



Faculty of Cognitive Sciences & Human Development

**Leveraging sMRI, Self-Attention Mechanisms, and Evolving Spiking
Neural Networks for Enhanced Suicide Ideation Detection in Depressed
Young Adults**

Corrine Francis

**Master of Science
2024**

Leveraging sMRI, Self-Attention Mechanisms, and Evolving Spiking Neural
Networks for Enhanced Suicide Ideation Detection in Depressed Young
Adults

Corrine Francis

A thesis submitted

In fulfillment of the requirements for the degree of Master of Science

(Intelligent Systems)

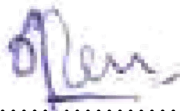
Faculty of Cognitive Sciences & Human Development

UNIVERSITI MALAYSIA SARAWAK

2024

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



.....
Signature

Name: Corrine Francis

Matric No.: 21020350

Faculty of Cognitive Sciences & Human Development

Universiti Malaysia Sarawak

Date: 03 June 2024

ACKNOWLEDGEMENT

I want to extend my profound and sincere gratitude to my main supervisor, Dr. Abdulrazak Yahya Saleh Al-Hababi, whose steadfast support, guidance, and mentorship were instrumental throughout the two years of my graduate education. Dr. Al-Hababi played an indispensable role in helping me navigate the complexities of this study, and his invaluable insights significantly contributed to its success.

I also extend my heartfelt appreciation to the Faculty of Cognitive Sciences and Human Development and the dedicated staff at the Centre for Graduate Studies at Universiti Malaysia Sarawak. Their consistent assistance and resources were crucial in facilitating my academic journey, from access to state-of-the-art facilities to expert advice.

Furthermore, I am profoundly grateful to my friends and family, who provided the unwavering encouragement and support needed to persevere through the challenges and triumphs of this educational pursuit. Their belief in me was a constant source of motivation.

Lastly, I offer my gratitude to the divine for granting me the strength and resilience to overcome the obstacles encountered on this educational path. I am humbled by the blessings that allowed me to navigate these difficulties with relative ease.

ABSTRACT

Accurate assessment of suicide ideation (SI) risk in depressed young adults remains a critical challenge, with existing methods exhibiting limited effectiveness. This study proposes a novel machine learning approach leveraging Evolving Spiking Neural Networks (ESNN) to enhance SI risk detection utilizing structural magnetic resonance imaging (sMRI) data. ESNNs, inspired by the brain's information processing mechanisms, excel at capturing temporal and spatial patterns in data, making them well-suited for modeling the complex dynamics of SI risk factors. Unlike traditional neural networks, ESNNs employ spiking neurons and adaptive learning mechanisms that continuously update internal representations, enhancing their robustness to changing risk factors and individual SI trajectories. However, their application in SI detection has been largely underexplored, creating a gap in leveraging their unique capabilities for this critical task.

To address this gap, the self-AM-ESNN model is introduced, which integrates self-attention mechanisms (self-AM) with ESNN to enable effective feature extraction and learning from sMRI data. By integrating self-AM with ESNN's dynamic learning capabilities, the model can capture complex neuroanatomical patterns associated with SI risk while adapting to individual variations. Evaluated on a dataset of 20 depressed individuals and 60 healthy controls, the self-AM-ESNN model demonstrated exceptional performance in classifying depression, achieving 94% test accuracy, 100% sensitivity, 92% specificity, and an area under the curve of 0.96.

These promising results highlight the potential of ESNN-based approaches to augment clinical decision-making and mental health interventions for SI risk assessment. Furthermore, the study incorporates a user-centric evaluation framework that enables mental

health professionals and service users to assess the model's detections and rationale, facilitating informed decision-making processes. By providing interpretable insights into the underlying factors contributing to SI risk, this approach empowers stakeholders to make more informed choices and tailor interventions accordingly.

Keywords: Suicide ideation; evolving spiking neural networks; structural MRI; depression; clinical decision-making

Memanfaatkan sMRI, Mekanisme Perhatian Kendiri, dan Rangkaian Neural Berduri Berubah untuk Meningkatkan Pengesanan Ideasi Bunuh Diri dalam Kalangan Dewasa Muda yang Mengalami Kemurungan

ABSTRAK

Penilaian yang tepat terhadap risiko ideasi bunuh diri (SI) dalam kalangan dewasa muda yang mengalami kemurungan masih menjadi cabaran kritikal, dengan kaedah sedia ada menunjukkan keberkesanan yang terhad. Kajian ini mencadangkan pendekatan pembelajaran mesin baharu yang memanfaatkan Rangkaian Neural Berduri Berubah (ESNN) untuk meningkatkan pengesanan risiko SI menggunakan data pengimejan resonans magnetik struktur (sMRI). ESNN, yang diilhamkan oleh mekanisme pemprosesan maklumat otak, cemerlang dalam menangkap corak temporal dan spatial dalam data, menjadikannya sesuai untuk memodelkan dinamik kompleks faktor risiko SI. Tidak seperti rangkaian neural tradisional, ESNN menggunakan neuron berduri dan mekanisme pembelajaran adaptif yang sentiasa mengemas kini representasi dalaman, meningkatkan ketahanannya terhadap faktor risiko yang berubah-ubah dan trajektori SI individu. Walau bagaimanapun, penggunaannya dalam pengesanan SI sebahagian besarnya belum diterokai, mewujudkan jurang dalam memanfaatkan kemampuan unik mereka untuk tugas kritikal ini.

Untuk mengatasi jurang ini, model self-AM-ESNN diperkenalkan, yang mengintegrasikan mekanisme perhatian kendiri (self-AM) dengan ESNN untuk membolehkan pengekstrakan ciri dan pembelajaran yang berkesan daripada data sMRI. Dengan mengintegrasikan self-AM dengan keupayaan pembelajaran dinamik ESNN, model ini dapat menangkap corak neuroanatomi kompleks yang berkaitan dengan risiko SI sambil menyesuaikan diri dengan variasi individu. Dinilai berdasarkan dataset yang terdiri daripada 20 individu yang mengalami kemurungan dan 60 kawalan yang sihat, model self-AM-ESNN menunjukkan

prestasi yang luar biasa dalam mengklasifikasikan kemurungan, mencapai ketepatan ujian sebanyak 94%, sensitiviti 100%, kekhususan 92%, dan kawasan di bawah lengkung sebanyak 0.96.

Hasil yang menjanjikan ini menonjolkan potensi pendekatan berasaskan ESNN untuk meningkatkan proses membuat keputusan klinikal dan intervensi kesihatan mental untuk penilaian risiko SI. Selain itu, kajian ini menggabungkan rangka kerja penilaian berpusatkan pengguna yang membolehkan profesional kesihatan mental dan pengguna perkhidmatan menilai pengesanan dan rasional model, memudahkan proses membuat keputusan yang lebih berinformasi. Dengan menyediakan wawasan yang boleh ditafsirkan mengenai faktor-faktor asas yang menyumbang kepada risiko SI, pendekatan ini memperkasakan pihak berkepentingan untuk membuat pilihan yang lebih berinformasi dan menyesuaikan intervensi dengan sewajarnya.

Kata kunci: *Ideasi bunuh diri; Rangkaian neural berduri berubah; MRI struktur; kemurungan; Membuat keputusan klinikal*

TABLE OF CONTENTS

	Page
DECLARATION	i
ACKNOWLEDGEMENT	ii
ABSTRACT	iii
<i>ABSTRAK</i>	v
TABLE OF CONTENTS	vii
LIST OF TABLES	xi
LIST OF FIGURES	xii
LIST OF ABBREVIATIONS	xvi
CHAPTER 1 INTRODUCTION	1
1.1 Overview	1
1.2 Study Background	1
1.3 Problem Statement	5
1.4 Research Questions	11
1.5 Research Objectives	11
1.6 Research Scopes	11
1.7 Research Significance	12
1.8 Summary	13

CHAPTER 2 LITERATURE REVIEW	14
2.1 Overview	14
2.2 Suicide Ideation (SI) and Depression	15
2.3 Traditional SI Assessment Methods and Its Limitation	19
2.4 Machine Learning (ML) and Digital Data in SI Assessment	20
2.5 ML and Neuroimaging in SI Assessments	22
2.6 Challenges in ML with Medical Images	24
2.7 Key Studies Utilizing Structural Magnetic Resonance Imaging (sMRI) and ML in SI Research	27
2.7.1 Key Studies Limitations	31
2.8 Proposed Model: Self-Attention (Self-AM) and Evolving Spiking Neural Network (ESNN) Integration in SI Assessment	33
2.9 Attention Mechanism (AM) and Spiking Neural Networks (SNN)	37
2.9.1 Relevance to SI Assessment	39
2.9.2 Integration of AM and SNN in the Proposed Model	40
2.10 Self-Attention Mechanism (self-AM)	41
2.11 Evolving Spiking Neural Networks (ESNN)	45
2.12 Summary	52
CHAPTER 3 RESEARCH METHODOLOGY	53
3.1 Overview	53
3.2 Dataset	56

3.3	Data Preprocessing	56
3.3.1	Reorientation	57
3.3.2	Segmentation	58
3.3.3	Diffeomorphic Anatomical Registration Through Exponential Lie Algebra (DARTEL)	60
3.3.4	Normalization and Smoothing	61
3.3.5	Image Format Conversion	63
3.4	Experimental Designs	64
3.4.1	Self-AM Feature Extraction	67
3.4.2	ESNN Encoder – Radial Basis Function (RBF) Transformations	69
3.4.3	Self-AM-ESNN Design	72
3.5	Experimental Settings	75
3.5.1	Exploratory Data Analysis (EDA)	77
3.5.2	Min-Max Normalization	81
3.5.3	Imbalanced Data Implementation Process	82
3.5.4	Hyperparameter Tuning: Genetic Algorithm (GA)	87
3.6	Performance Evaluations	89
3.7	Comparative Analyses	92
3.8	Summary	94
CHAPTER 4 RESULTS AND DISCUSSIONS		95

4.1	Overview	95
4.2	Hyperparameter Optimization	96
4.3	Comprehensive Evaluation and Analysis	108
4.4	Comparative Analyses	114
4.4.1	Traditional ML Classifiers and ESNN Standalone Model Analysis	114
4.4.2	Key Studies Analyses	117
4.5	Discussion	124
4.5.1	Verification and Validation Process	127
4.5.2	Empirical Study Integration	129
4.5.3	Performance Evaluation Processes	130
4.6	Summary	131
CHAPTER 5 CONCLUSION AND RECOMMENDATIONS		132
5.1	Overview	132
5.2	Summary of Key Findings	132
5.3	Study Contributions	133
5.4	Study Limitations	135
5.5	Recommendations for Future Research	136
5.6	Summary	138
REFERENCES		140
APPENDICES		193

LIST OF TABLES

	Page
Table 1.1: Research scope	12
Table 2.1: Risk factors contributing to depression	18
Table 2.2: DASS 21 scales (Perez, 2024)	20
Table 2.3: The key studies utilizing sMRI data and ML for SI research	30
Table 2.4: Limitation in key studies	32
Table 2.5: Applications of self-AM in medical data analysis	43
Table 2.6: Applications of self-AM in suicide research with digital data	44
Table 2.7: Summary of ESNN applications in detection tasks	47
Table 2.8: Summary of ESNN applications in prediction tasks	48
Table 2.9: Applications of ESNN in medical data analysis	49
Table 3.1: Datasets details	56
Table 3.2: Experimental Design Components	66
Table 3.3: Summary of Self-AM Feature Extraction Process	68
Table 3.4: Summary of encoding process	71
Table 3.5: Proposed model key parameters	75
Table 4.1: Hyperparameter configuration	96
Table 4.2: Hyperparameter configuration generated by the GA (*Best results highlighted in bold)	99
Table 4.3: Parameters of the KNN, LR, and SVM models	115
Table 4.4: Proposed model hyperparameter values (hyperparameter 3)	125

LIST OF FIGURES

	Page
Figure 1.1: sMRI visualization - potential biomarkers for depression (Wu & Mori, 2023)	3
Figure 1.2: Understanding young adults' experiences during the pandemic (Ashwin et al., 2022)	5
Figure 1.3: High rates of depression persist among young adults in France (OECD, 2021)	6
Figure 1.4: The Ask Suicide-Screening Questions (Horowitz et al., 2020)	7
Figure 1.5: Shifting suicide research focus to precision detections with ML (Fonseka et al., 2019)	8
Figure 1.6: Key cerebral areas associated with SI and behavior in neuroimaging research (Schmaal et al., 2020)	9
Figure 2.1: Chapter 2 overview	14
Figure 2.2: Emerging trends – Surge in SI among Filipino youth in 2021 (UP Population Institute, 2022)	15
Figure 2.3: SI patterns during the COVID-19 pandemic era across eight countries on four continents for young adults aged 18 and above (Schluter et al., 2022)	16
Figure 2.4: The application of ML and digital data for SI detection with textual content (Diniz et al., 2022)	21
Figure 2.5: Frontal and prefrontal cortex regions (Sabater, 2021)	22
Figure 2.6: Dorsal and ventral cortex regions (Michel & Morales, 2020)	23
Figure 2.7: Example of balanced and imbalanced data (Tripathi, 2019)	25
Figure 2.8: Classification task utilizing sMRI (Bajaj et al., 2023)	28
Figure 2.9: Summary of the proposed self-AM-ESNN model for SI assessment	36
Figure 2.10: Attention mechanism (Malingan, 2023)	37
Figure 2.11: SNN operation, (a) neuron threshold surpassed and impulse transmission; (b) neuron value decay and return to the original state (Lyashenko, 2021).	38
Figure 3.1: Chapter 3 overview	53
Figure 3.2: Overall research design environment	55

Figure 3.3: Data preprocessing steps	57
Figure 3.4: (a) The initial position of the MRI scan image before manual reorientation utilizing the MNI template, and (b) the resulting position after reorientation.	58
Figure 3.5: Segmentation of (a) GM, (b) WM, and (c) CSF tissue	59
Figure 3.6: (a) The GM segmentation utilizing the native space, and (b) the GM segmentation utilizing the registered space	60
Figure 3.7: Contrast between, (a) ‘Template_0’, and (b) ‘template_6’	61
Figure 3.8: Comparison between, (a) Subject’s ‘template_6’, and (b) the smoothed and normalized image of their MRI scan	62
Figure 3.9: Comparison between the normalized image and ‘template_6’, highlighting template_6 with red outline	63
Figure 3.10: Image background cropping process	64
Figure 3.11: Self-AM-ESNN design	65
Figure 3.12: Self-AM-ESNN design	74
Figure 3.13: Proposed model design of the classification task for SI assessment	76
Figure 3.14: Proposed model design of the classification task for SI assessment	77
Figure 3.15: Class distribution before splitting into train and testing sets	78
Figure 3.16: The brain image differences between “0” and “1” subjects	78
Figure 3.17: Age distribution	79
Figure 3.18: Count of individuals in each group categorized by gender	80
Figure 3.19: Age distribution by group	80
Figure 3.20: Imbalanced data implementation techniques	83
Figure 3.21: PCA visualization of the initial data after splitting into training and test groups	84
Figure 3.22: Stratified K-fold cross-validation (Turing, 2023)	85
Figure 3.23: Data distribution after the implementation of SMOTE and stratified 5-fold cross-validation	86
Figure 3.24: Data augmentation examples after augmentation process	86

Figure 3.25: Data distribution after data augmentation	87
Figure 3.26: Confusion matrix and performance metrics formula (Sirsat, 2019)	90
Figure 4.1: Chapter 4 overview	95
Figure 4.2: Hyperparameter 1 ten trials result	100
Figure 4.3: Hyperparameter 2 ten trials result	100
Figure 4.4: Hyperparameter 3 ten trials result	101
Figure 4.5: Hyperparameter 4 ten trials result	101
Figure 4.6: Hyperparameter 5 ten trials result	102
Figure 4.7: Hyperparameter 6 ten trials result	102
Figure 4.8: Hyperparameter 7 ten trials result	103
Figure 4.9: Hyperparameter 8 ten trials result	103
Figure 4.10: Hyperparameter 9 ten trials result	104
Figure 4.11: Hyperparameter 10 ten trials result	104
Figure 4.12: Hyperparameter configuration based on ten trials performance comparison	107
Figure 4.13: Model summary	109
Figure 4.14: Self-AM-ESNN ten trials performance metrics across different criteria (average, high and low)	110
Figure 4.15: Training progress visualization for the final models' results	111
Figure 4.16: ROC-AUC curve	112
Figure 4.17: Confusion matrix	112
Figure 4.18: Self-attention maps for brain images	113
Figure 4.19: KNN evaluation metrics vs. number of neighbors	115
Figure 4.20: Comparison of ML classifiers with proposed model (average results)	116
Figure 4.21: Comparison of key studies with proposed model (highest results)	118
Figure 4.22: Comparison of Weng et al. (2020) with the proposed model	119
Figure 4.23: Comparison of Chen et al. (2021a) with the proposed model	120

Figure 4.24: Comparison of Hong et al. (2021) with the proposed model	121
Figure 4.25: Comparison of Bajaj et al. (2023) with the proposed model	122
Figure 4.26: Comparison of Hu et al. (2023) with the proposed model	123
Figure 5.1: Summary of key findings	133
Figure 5.2: Study's limitations	136
Figure 5.3: Future research recommendations	137

LIST OF ABBREVIATIONS

2D	Two-dimensional
3D	Three-dimensional
ACC	Accuracy
AM	Attention Mechanism
AUC	Area Under the Curve
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
CSF	Cerebrospinal Fluid
DARTEL	Diffeomorphic Anatomical Registration Through Exponentiated Lie Algebra
DASS-21	Depression Anxiety & Stress Scale Questionnaire – 21 Questions
DenseNet	Densely Connected Convolutional Networks
DL	Deep Learning
ECOS	Evolutionary Computation of Structures
EDA	Exploratory Data Analysis
EEG	Electroencephalography
ESNN	Evolving Spiking Neural Network
FC	Frontal Cortex
FCNN	Fully Connected Neural Network
FN	False Negative
FP	False Positive
GA	Genetic Algorithm
GM	Gray Matter

GMV	Gray Matter Volume
HC	Healthy Controls
HP	Hyperparameter
INDI	International Neuroimaging Data-Sharing Initiative
KNN	K-Nearest Neighbors
LR	Logistic Regression
MDD	Major Depressive Disorder
ML	Machine Learning
MNI	Montreal Neurological Institute
MRI	Magnetic Resonance Imaging
NIfTI	Neuroimaging Informatics Technology Initiative Neuroimaging Informatics Technology Initiative
NLP	Natural Language Processing
PCA	Principal Component Analysis
PFC	Prefrontal Cortex
PNG	Portable Network Graphics
RBF	Radial Basis Functions
RF	Random Forest
ROC	Receiver Operating Characteristics
ROC-AUC	Receiver Operating Characteristics-Area Under the Curve
ROI	Regions of Interest
SA	Suicide Attempters
Self-AM	Self-Attention Mechanism
Self-AM-ESNN	Self-Attention Mechanism and Evolving Spiking Neural Network
SEN	Sensitivity

SI	Suicide Ideation
SIB	Suicide Ideation and Behaviors
SLIM	Southwest University Longitudinal Imaging Multimodal
sMRI	Structural Magnetic Resonance Imaging
SMOTE	Synthetic Minority Over-sampling Technique
SNN	Spiking Neural Network
SPEC	Specificity
SPM12	Statistical Parametric Mapping 12
SVM	Support Vector Machine
SVM-RFE	Support Vector Machine - Recursive Feature Elimination
T1w	T1 weighted
TN	True Negative
TP	True Positive
UNIMAS	Universiti Malaysia Sarawak
VBM	Voxel-Based Morphometry
WM	White Matter
XGB	Extreme Gradient Boosting

CHAPTER 1

INTRODUCTION

1.1 Overview

This study aims to improve suicide ideation (SI) assessment accuracy in depressed young adults by integrating machine learning (ML) methods such as Attention Mechanism (AM) and Spiking Neural Network (SNN) on structural magnetic resonance imaging (sMRI) data. The model involves the integration of self-AM and evolving SNN (ESNN), filling a critical gap in mental health assessment and offering insights for better intervention and support.

1.2 Study Background

The coronavirus disease (COVID-19) pandemic has intensified mental health issues, contributing to increased suicidal tendencies (Sher, 2020a; Sher, 2020b). Suicide ideation (SI), characterized by distressing death-related thoughts, predicts suicide attempts across various age groups (Harmer et al., 2020; Cheung et al., 2021). Additionally, Moller et al. (2023) found a correlation between SI and depression, highlighting the interconnectedness of these mental health issues. Since the onset of the pandemic, the prevalence of depression has remarkably increased, affecting over 8% of the US population, with nearly 17% affected in the 18 – 25 age group (Wang et al., 2024). Existing SI assessment tools lack accuracy, necessitating a novel method focusing on the SI-depression association (Deming et al., 2021).

ML has become foundational in suicide detection, offering faster and more accurate detection of SI (Yang et al., 2024). Models such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Neural Networks show promise in classifying mental illnesses such as depression (Barua et al., 2024). KNN, in particular, demonstrated exceptional accuracy of 91.45% in predicting SI among university students (Sara et al., 2024). Moreover, ML's ability to integrate diverse data sources enhances detection accuracy, emphasizing its importance in future research (Pigoni et al., 2024). Thus, integrating ML with diverse data sources is crucial for refining SI detection models and guiding future investigations in this critical area.

Understanding the neural underpinnings of psychiatric disorders is important in mental health research (Hauser et al., 2022). sMRI data, as depicted in Figure 1.1, provides insights into depression's biomarkers (Schmaal et al., 2020; Guy-Evans, 2023). However, existing studies utilizing sMRI and ML for SI detection have limitations (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023). These studies lack crucial performance metrics such as sensitivity, specificity, and area under the curve (AUC) (Suragala et al., 2021; Carrington et al., 2022). Thus, further research and methodological advancements are needed to improve SI detection accuracy in depressed individuals.

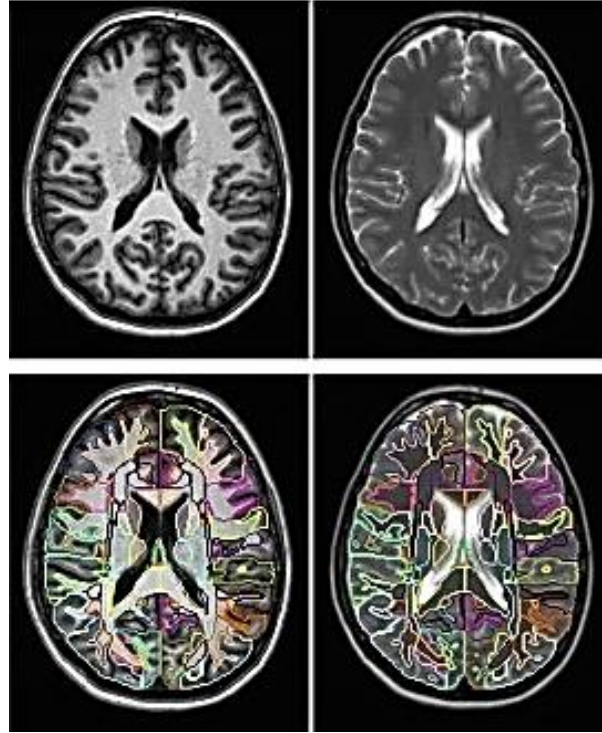


Figure 1.1: sMRI visualization - potential biomarkers for depression (Wu & Mori, 2023)

This study employed an integrated ML model called self-AM-ESNN to perform SI assessment based on the sMRI data of depressed young adults. The self-AM component emphasized crucial features within the input images (Choi & Yang, 2024), aiding ESNN in classification. Inspired by the brain's adaptability, ESNN continuously evolves to capture meaningful patterns (Kasabov, 2019). Integrating self-AM enhances feature focus, improving prediction accuracy.

The self-AM-ESNN model was trained on datasets from publicly available repositories of OpenNeuro¹ and the International Neuroimaging Data-Sharing Initiative (INDI)². It primarily integrates selected data from studies focusing on depression within OpenNeuro (Bezmaternykh, 2021a; Bezmaternykh, 2021b; Manelis et al., 2021). The data

¹ <https://openneuro.org/>

² https://fcon_1000.projects.nitrc.org/

for healthy controls (HC) were sourced from the Southwest University Longitudinal Imaging Multimodal (SLIM) dataset within INDI, as detailed in Liu et al. (2017). To address imbalances in the datasets, various techniques are employed, including stratified train-test split, Synthetic Minority Over-sampling Technique (SMOTE), stratified 5-fold cross-validation, and data augmentation (Brownlee, 2020c; Singh, 2020; Muralidhar, 2021; Mathews & Seetha, 2022).

Moreover, hyperparameter tuning utilizing the Genetic Algorithm (GA) was employed to optimize the configuration of the self-AM-ESNN model (Nikbakht et al., 2021). GAs, inspired by natural selection (Mehdary et al., 2024), excel in exploring vast solution spaces (Díaz-Álvarez et al., 2022). Performance evaluation employs metrics such as accuracy (ACC), sensitivity (SEN), specificity (SPEC), and AUC. Furthermore, comparative analyses include established ML classifiers such as ESNN, KNN, Logistic Regression (LR), and SVM (Kharel, 2020; Das, 2024; GeeksforGeeks, 2024), along with key studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023).

In essence, this study aims to improve SI detection accuracy among depressed young adults by utilizing ML models and their sMRI data. By leveraging advanced ML models, such as self-AM and ESNN, and employing techniques for handling imbalanced data, the research seeks to develop a more precise method for detecting SI. Comprehensive evaluations, including comparisons with traditional classifiers, key studies, and a thorough literature review, will advance intervention strategies at the intersection of mental health and technology.

1.3 Problem Statement

The COVID-19 pandemic has significantly impacted global mental health, leading to increased depression and SI among young adults (Rogers et al., 2020; OECD, 2021; Vahratian et al., 2021; Macalli et al., 2024). Pandemic-related uncertainties and coping challenges exacerbate their vulnerability (Meherali et al., 2021; Ashwin et al., 2022, refer to Figure 1.2). Additionally, social isolation and economic strains further intensify depressive symptoms and suicide risk (Que et al., 2020; Torales et al., 2020; Nomura et al., 2021; Barberis et al., 2022; Schluter et al., 2022). Kim et al. (2022a) highlights the significant role of depression in SI, emphasizing the urgent need to understand their complex relationship.

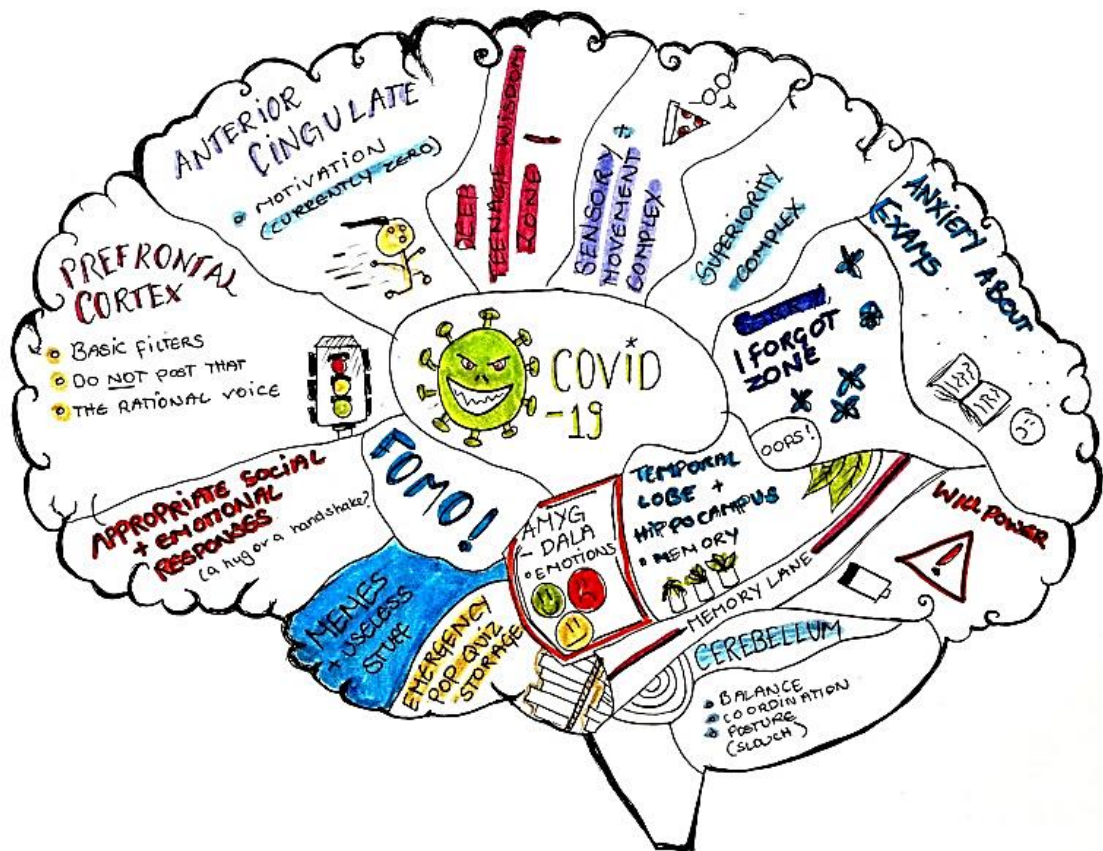


Figure 1.2: Understanding young adults' experiences during the pandemic (Ashwin et al., 2022)

The progression of suicide heavily relies on SI as a key predictor (Large et al., 2021; Hu et al., 2022). As seen in Figure 1.3, the COVID-19 pandemic has remarkably increased depression rates among young adults aged 18–24, consequently elevating SI (OECD, 2021; Schluter et al., 2022). Depression, characterized by neurochemical alterations, profoundly affects mood, cognition, and problem-solving skills (Bailey, 2024), significantly heightening suicide risk (Pompili, 2019; Lázaro-Pérez et al., 2023). Moreover, around 80% of suicide cases involve depression, emphasizing their strong correlation (Chiang et al., 2022). Given depression's role as a key predictor, effective assessment methods are crucial for identifying at-risk individuals.

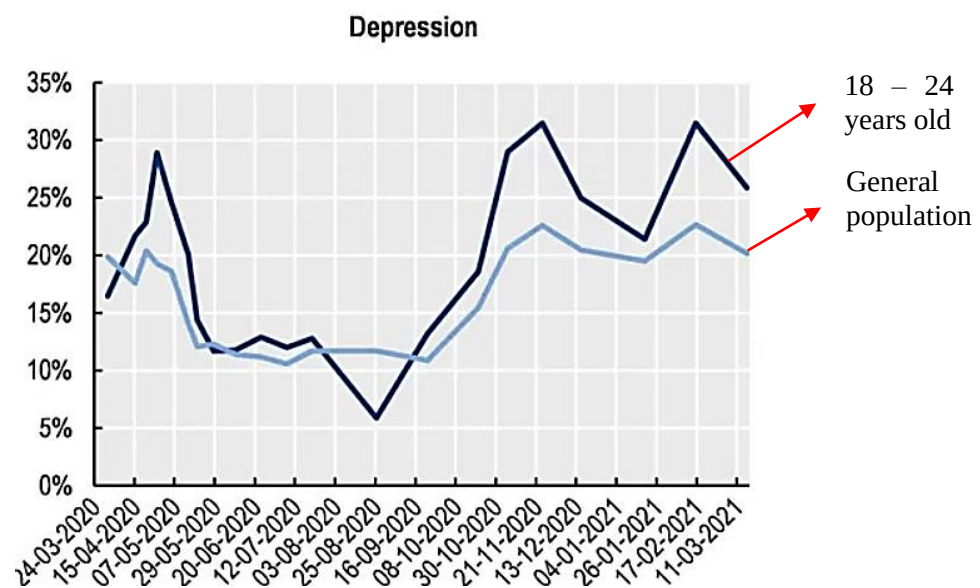


Figure 1.3: High rates of depression persist among young adults in France (OECD, 2021)

Psychologists commonly utilize established screening tools such as the Ask Suicide-Screening Questions Toolkit and the Columbia-Suicide Severity Rating Scale to predict SI (Horowitz et al., 2020; Simpson et al., 2021, refer to Figure 1.4). Despite their widespread

utilization, concerns persist about their efficacy, raising doubts about their ability to address critical areas (Clay, 2022). Moreover, reliance on conventional methods not only delays understanding of suicide vulnerability but also complicates the identification of specific physiological mechanisms (Barron et al., 2021). Despite various assessment tools available, none consistently predicts SI risk (Harmer et al., 2020). Thus, innovative approaches and novel techniques in SI detection are urgently needed.

ASQ
Ask Suicide-Screening Questions

Ask the patient:

1. In the past few weeks, have you wished you were dead?	Yes	No
2. In the past few weeks, have you felt that you or your family would be better off if you were dead?	Yes	No
3. In the past week, have you been having thoughts about killing yourself?	Yes	No
4. Have you ever tried to kill yourself?	Yes	No

If yes, how? _____ When? _____

If the patient answers yes to any of the above, ask the following question:

5. Are you having thoughts of killing yourself right now?	Yes	No
---	-----	----

If yes, please describe: _____

National Institute of Mental Health

Figure 1.4: The Ask Suicide-Screening Questions (Horowitz et al., 2020)

Recognizing the challenges in suicide detection, researchers are shifting from traditional to ML-based methods, aiming to overcome inherent limitations (Van Mens et al., 2020, refer to Figure 1.5). These modern approaches combine sophisticated statistical methods such as LR with various ML techniques, prioritizing detection accuracy over traditional methods (Kessler et al., 2020; Van Mens et al., 2020). ML's advantage lies in its

ability to integrate diverse predictors, including neuroimaging data, offering deeper insights into suicide risk complexity (Jankowsky et al., 2024). Thus, integrating ML with neuroimaging data holds promise for enhancing precision in suicide detection.

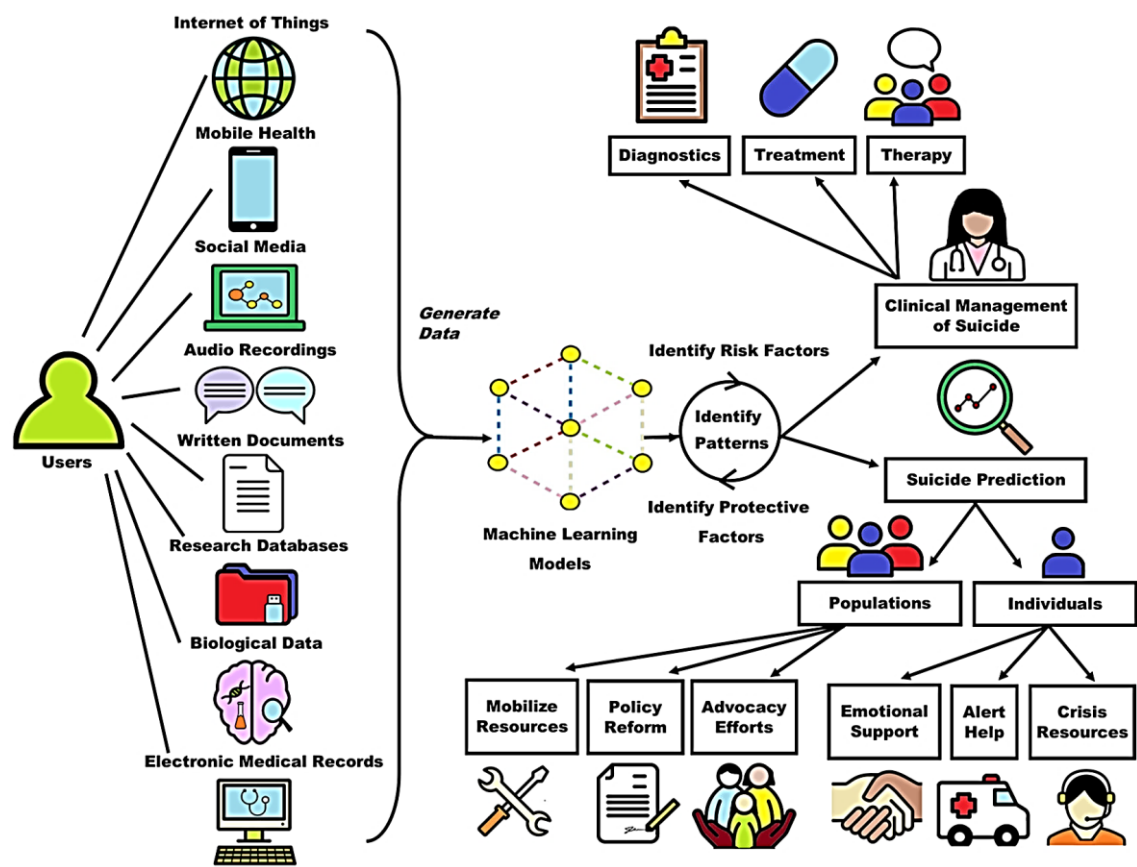


Figure 1.5: Shifting suicide research focus to precision detections with ML (Fonseka et al., 2019)

In current suicide research, combining neuroimaging techniques with ML uncovers new areas for managing suicide vulnerability (Ballard et al., 2021; Vidal-Ribas et al., 2021; Van Velzen et al., 2022a). Despite challenges such as varying sample sizes and neuroimaging methods, emerging evidence links specific brain regions and circuits to suicidal ideation and behavior (SIB) (Lai, 2019; Schmaal et al., 2020; Chen et al., 2021a, refer to Figure 1.6). Analyzing sMRI data aids in detecting abnormalities in mental health

disorders (Guy-Evans, 2023), including depression. Thus, the application of ML in examining sMRI data related to depression and SI deepens understanding and identifies potential treatment advancements.

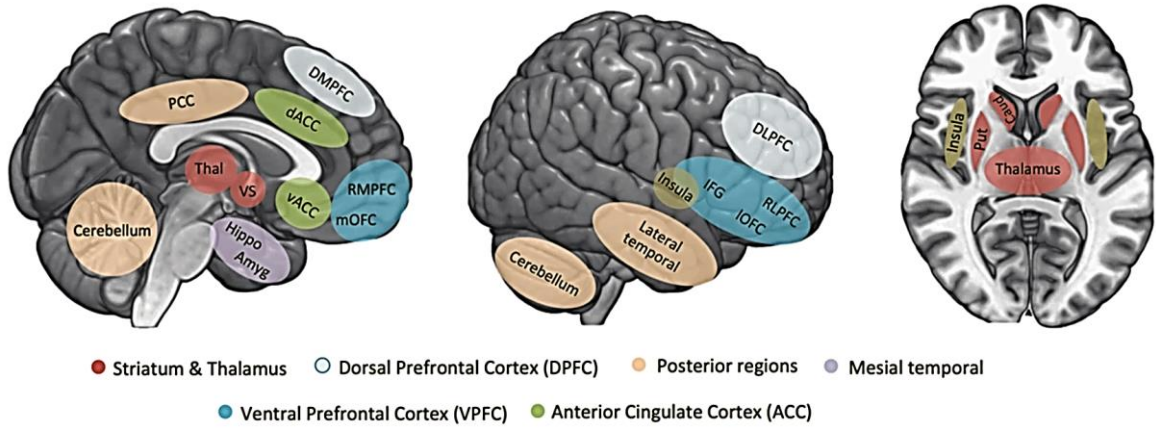


Figure 1.6: Key cerebral areas associated with SI and behavior in neuroimaging research (Schmaal et al., 2020)

Several studies have utilized ML and sMRI data to detect and predict suicide risk, achieving accuracy rates of 70.15% to 85% (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023). These findings highlight ML's effectiveness in identifying suicide risk factors, thoughts, and behaviors in depression. However, limitations exist. For instance, Weng et al. (2020) relied on traditional ML classifiers, potentially impacting accuracy. Furthermore, the absence of clinical controls in studies by Hong et al. (2021) and Bajaj et al. (2023) could affect model reliability. While valuable, these studies emphasize the need for more robust models to address observed limitations.

This study introduces a novel method, self-AM-ESNN, to enhance SI detection in depressed young adults utilizing sMRI data. Integrating self-AM into the ESNN framework, which has shown promise in SI detection models (Yang et al., 2023), the self-AM-ESNN

approach aims to further enhance detection accuracy. Self-AM is crucial as it enables ESNN to efficiently extract temporal and spatial features and capture distant relationships in the sMRI data (Verstynen & Kording, 2021). Moreover, self-AM also improves the model's capacity to merge temporal-spatial features and utilize end-to-end learning methods, vital for precise SI detection from complex sMRI data (Chadha & Kaushik, 2022). Therefore, integrating self-AM with ESNNs enhances sMRI data processing, improving the identification of individuals vulnerable to SI.

The application of ESNN in the context of depression and SI among young adults is a critically important area of investigation (Haque et al., 2021; López-Ramírez et al., 2023). Depression raises suicide risk, especially among young adults aged 15-29, with suicide ranking as the second leading cause of death for this age group in 2020 (Shankar et al., 2020; Rappai & Ramasamy, 2022). Utilizing advanced neural network models such as ESNN has the potential to improve early detection and intervention, which is essential for reducing suicide risk in vulnerable populations (Li, 2023).

ESNN, inspired by brain function, excels in predicting and classifying data with temporal and spatial features, akin to the brain's learning abilities (Saravanan et al., 2022). It excels at seamlessly integrating new information, making it ideal for monitoring changes in sMRI data over time (Kasabov, 2019; Ibad et al., 2020). Besides that, ESNNs, primarily utilized for depression classification, show promise in predicting SI among individuals with depression (Doborjeh et al., 2019; Shah et al., 2019; Tan et al., 2020a). Despite limited direct references to depression and SI, the adaptability and effectiveness of ESNNs in analogous domains justify their adoption in this study. It aims to advance SI detection in depressed young adults by leveraging ESNNs' unique abilities in handling temporal and spatial data (Dora & Kasabov, 2021).

1.4 Research Questions

This study is guided by the following questions:

1. What methods can be employed to enhance the non-invasive assessment of SI in depressed young adults through sMRI data?
2. How effective is the proposed model in identifying SI in depressed young adults utilizing sMRI data?
3. How do methodological advancements contribute to the accuracy and reliability of SI detection models based on sMRI data in depressed young adults?

1.5 Research Objectives

This study is driven by the following objectives:

1. To develop and implement the self-AM-ESNN model for enhancing the non-invasive assessment of SI in depressed young adults utilizing sMRI data.
2. To evaluate the effectiveness of the proposed model in accurately identifying SI in depressed young adults through the analysis of sMRI data.
3. To analyze how integrating self-AM and ESNN impacts the accuracy and reliability of SI detection models utilizing sMRI data in depressed young adults.

1.6 Research Scopes

This study is grounded upon research scopes as displayed in Table 1.1:

Table 1.1: Research scope

No.	Research Component	Details
1.	Dataset Repository	i. OpenNeuro ii. INDI
2.	Software and Program Language	i. Matlab R2021a ii. Statistical Parametric Mapping 12 (SPM12) iii. Spyder 5.4.3 iv. Anaconda Navigator 2.4.3 v. Python in Tensorflow environment
3.	Algorithms	i. Self-Attention Mechanism (self-AM) ii. Evolving Spiking Neural Network (ESNN) iii. Genetic Algorithm (GA) iv. K-Nearest Neighbor (KNN) v. Logistic Regression (LR) vi. Self-AM-ESNN vii. Support Vector Machine (SVM)
4.	Performance Key Metrics	i. Accuracy (ACC) ii. Sensitivity (SEN) iii. Specificity (SPEC) iv. Area Under the Curve (AUC)

1.7 Research Significance

Social isolation and quarantine are fueling a 'secondary pandemic,' causing a substantial increase in global cases of depression, SI, and self-harm (Ganesan et al., 2021). Even a slight increase in depressive symptoms can significantly impact the population's well-being, both physically and mentally (Shah et al., 2019; Robinson et al., 2022). Despite progress in preventing self-harm, there is inadequacy in identifying SI, especially among young adults aged 18-24.

Therefore, this study aims to contribute by enhancing the assessment of SI in depressed young adults. The specific focus is on the complex relationship between depression and SI, utilizing advanced sMRI data for depression biomarkers. Through these objectives, the study seeks to offer valuable insights and innovative approaches for addressing the mental health challenges posed by the 'secondary pandemic.'

1.8 Summary

This study aims to enhance SI assessment in young adults with depression utilizing advanced ML techniques and neuroimaging analysis. The proposed self-AM-ESNN model shows promise for SI assessment, potentially advancing mental health outcomes. Ultimately, the research seeks to enhance early detection and management strategies for SI, fostering more effective interventions and better mental health for young adults.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter lays the groundwork for enhancing SI assessment in depressed young adults utilizing sMRI data. It introduces advanced ML models, self-AM, and ESNN, highlighting their transformative potential. Figure 2.1 serves as a visual guide, ensuring clarity and comprehension throughout the chapter.

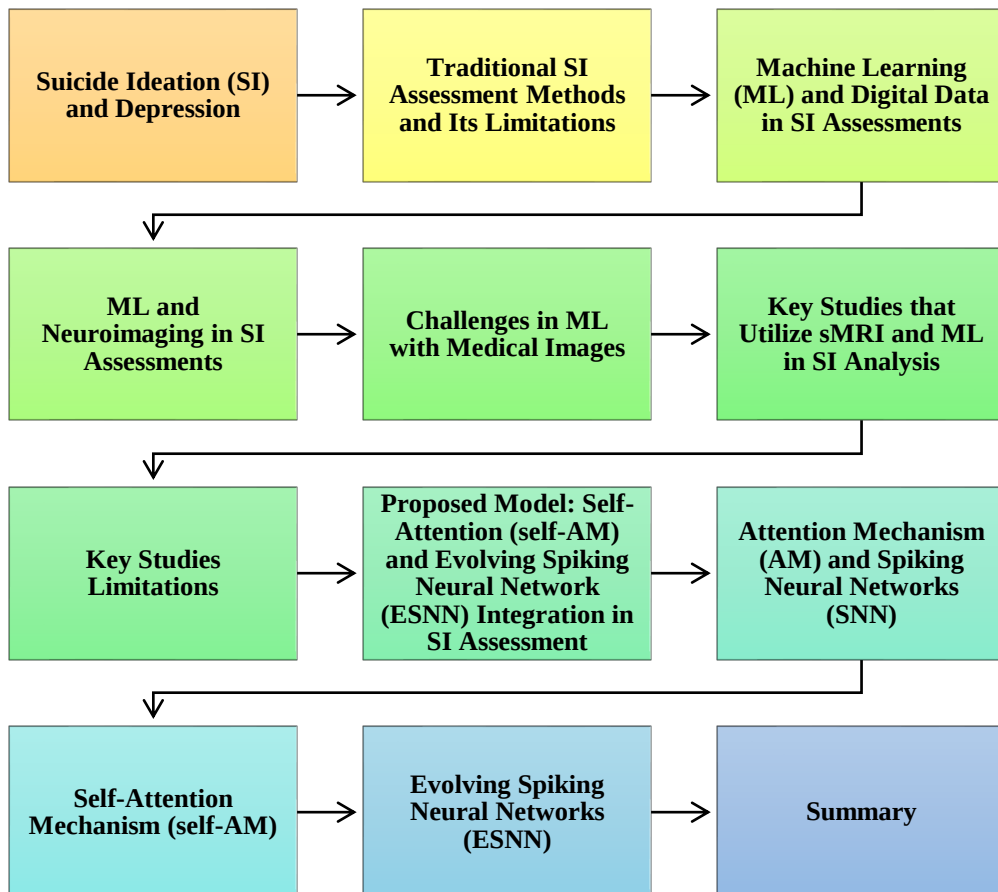


Figure 2.1: Chapter 2 overview

2.2 Suicide Ideation (SI) and Depression

SI varies from contemplation to self-harm planning, preceding suicidal behaviors and necessitating prompt interventions (Harmer et al., 2020; Large et al., 2021). Individuals with SI often struggle to cope with stressors, experiencing disrupted cognitive processes (Hatkevich et al., 2019; Zapata, 2023). Detecting SI poses challenges, as individuals tend to withdraw (Cliffe et al., 2021). Hence, timely mental health care is crucial to address underlying causes and alleviate the risk of self-harm (Shafir, 2023).

Despite a decline in suicide-related deaths, persistent SI remains a significant mental health concern (Lewis et al., 2023). The prolonged effects of COVID-19 have heightened SI, particularly among youth, as depicted in Figure 2.2. This strain on mental health services emphasizes the urgent requirement for improved risk detection and intervention strategies (Barzilay & Apter, 2022; Efstathiou et al., 2022).

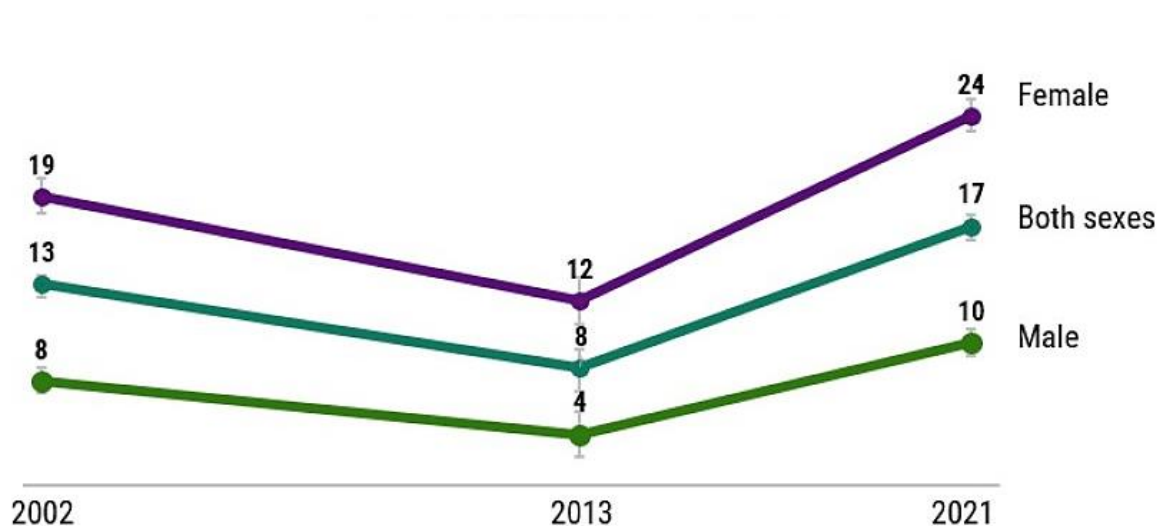


Figure 2.2: Emerging trends – Surge in SI among Filipino youth in 2021 (UP Population Institute, 2022)

In recent years, SI has become increasingly prevalent, especially among individuals aged 20 to 34, and is expected to rise due to recent global events, including COVID-19, climate change, conflicts, and environmental crises (Arowosegbe & Oyelade, 2023a). Schluter et al. (2022) discovered a gradual increase in SI throughout the pandemic's second wave, particularly among individuals aged 18 and above (refer to Figure 2.3). This finding aligns with other studies (Czeisler, 2020; Mamun, 2021; O'Connor et al., 2021), highlighting an elevated vulnerability to SI among young adults aged 18 and above during the pandemic.

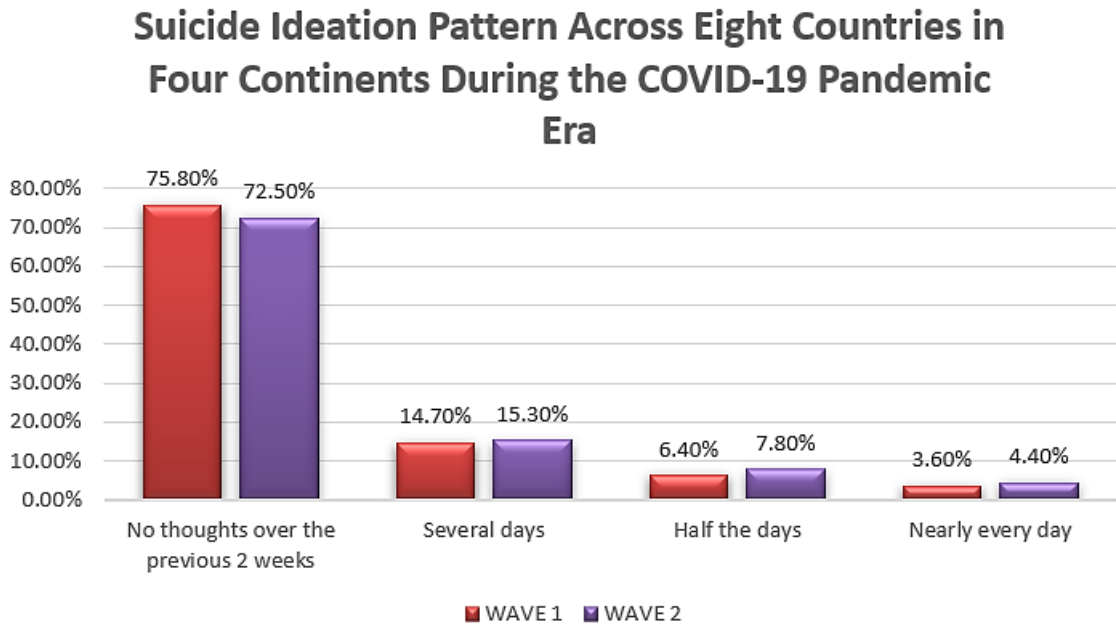


Figure 2.3: SI patterns during the COVID-19 pandemic era across eight countries on four continents for young adults aged 18 and above (Schluter et al., 2022)

The stressors of COVID-19, as shown in Table 2.1, negatively impacted individuals' psychological welfare, particularly young adults, leading to increased levels of depression and SI (Czeisler, 2020; Sewall et al., 2021). Early adulthood, characterized by brain development and structural maturation, becomes crucial as individuals face growing hardship and pressure, serving as standalone risk factors for emotional health conditions and

suicidal tendencies (Vanes et al., 2020). Moreover, depression is prevalent among those with suicidal tendencies, as mood disorders significantly predict SI and behaviors across different age groups (Oppenheimer et al., 2021). This highlights the complex interplay between stressors, depression, and SI among young adults.

Understanding the link between depression and suicide is crucial, as depression, a significant risk factor, can disrupt daily activities and increase suicidal tendencies (Lai, 2019; Pompili, 2019; Ergenzinger, 2022). Studies verify that individuals with depression are more prone to SI (Tasnim et al., 2020; Canady, 2021; Liu et al., 2022a; Moller et al., 2023). For instance, depression was identified as the main predictive factor for SI during Greece's second lockdown, emphasizing the importance of addressing depression in suicide prevention through targeted interventions (Efstathiou et al., 2021).

Table 2.1: Risk factors contributing to depression

No.	Factor	Descriptions
1.	Aged 18 to 24	Young adults, prone to high psychological distress and SI (Czeisler, 2020; Tasnim et al., 2020; Cheung et al., 2021; Batterham et al., 2022; López Steinmetz et al., 2022; Bridge et al., 2023).
2.	University students	Disruption-prone due to the pandemic, increasing susceptibility to SI (Pramukti et al., 2020; Son et al., 2020; Tasnim et al., 2020; Mamun et al., 2021).
3.	Financial problem	Affected young workers (Tanaka & Okamoto, 2021; Owens et al., 2022) as well as students in poor financial status (Son et al., 2020; Runkle et al., 2022).
4.	Loneliness	The pandemic intensified feelings of loneliness among 18 to 24-year-olds, leading to increased depression and SI (Antonelli-Salgado et al., 2021; Mental Health Foundation, 2023).
5.	Sleep problem	Predictor of SI during the COVID-19 crisis (Killgore et al., 2020) within people aged 18 to 24 (Tasnim et al., 2020; Yuan et al., 2020; Zhou et al., 2020a).
6.	Fear	Increased fear during the pandemic contributes to depression and SI (Killgore et al., 2020; Soto-Sanz et al., 2021), particularly among young adults (Hasan & Bao, 2020; Pramukti et al., 2020; Son et al., 2020; Mamun et al., 2021).

2.3 Traditional SI Assessment Methods and Its Limitation

Exploring traditional methods of assessing SI reveals various complexities. Psychological assessments, crucial for SI evaluation, encounter challenges when individuals with intense SI hesitate to engage in traditional therapeutic methods due to concerns about social stigma (Orsolini et al., 2020; Zissi, 2022). Moreover, those at higher suicide risk may prefer seeking support quietly through technology rather than in-person interventions (Wilks et al., 2021).

Challenges extend to clinical assessments, where varied approaches, including immediate referral and medication, may discourage open discussion about SI due to fears of involuntary hospitalization (Pappas, 2021; Ryan & Bartels, 2021). In addition, disagreement among primary care providers on assessment and management adds another layer of complexity (Harmer et al., 2020; Clay, 2022).

Diagnosing SI from patient self-reports is challenging. Approximately 80% of individuals who died by suicide denied such thoughts at their last mental health appointment (Vieira et al., 2023). Self-reporting methods, such as the Depression Anxiety & Stress Scale Questionnaire – 21 Questions (DASS 21), rely on patients' willingness to share information, which introduces errors and reduces precision, making them prone to bias and limiting their applicability (Bernert et al., 2020; Wisłowska-Stanek et al., 2021; Nadeem et al., 2022). Despite the availability of scales (refer to Table 2.2), enduring limitations persist (Harmer et al., 2020).

Table 2.2: DASS 21 scales (Perez, 2024)

No.	Level	Depression	Anxiety	Stress
1.	0 – 9	0 – 7	0 – 7	0 – 14
2.	10 – 13	8 – 9	8 – 9	15 – 18
3.	14 – 20	10 – 14	10 – 14	19 - 25
4.	21 – 27	15 – 19	15 – 19	26 – 33
5.	28+	20+	20+	34+

The analysis of traditional SI assessments uncovers remarkable challenges, emphasizing the complexities in this domain. While these assessments are crucial, they come with their own set of complexities. Recognizing the fundamental limitations in traditional psychological assessments for SI highlights the need for advanced methods.

2.4 Machine Learning (ML) and Digital Data in SI Assessment

Utilizing technology for suicide risk screening via social media shows promise for early identification (Arowosegbe & Oyelade, 2023b). Publicly accessible social media posts can reveal indicators of SI by detecting abrupt changes in user behavior (Renjith et al., 2021). Analyzing an individual's social media presence provides insights into their psychological well-being, making digital platforms an effortless monitoring mechanism for suicide risk (Nadeem et al., 2022). For instance, ML, as illustrated in Figure 2.4, focuses on classifying suicide risk through the analysis of textual content on social media, identifying individuals with SI or inclinations toward self-harm (Ji et al., 2020).

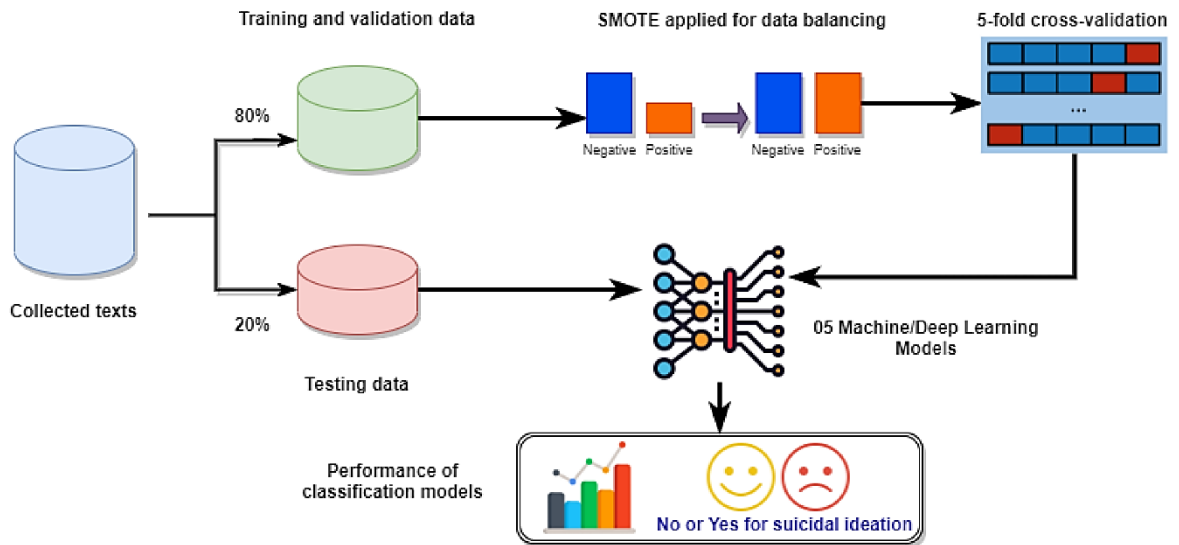


Figure 2.4: The application of ML and digital data for SI detection with textual content (Diniz et al., 2022)

Despite their promise, these methods have limitations. Understanding depression severity is crucial, and ML struggles to reason about suicide risk factors, relying on statistical clues (McHugh et al., 2019; Ji et al., 2020; Nadeem et al., 2022). Differentiating SI from other disorders is also challenging due to similar language patterns (Ji et al., 2022). Moreover, cultural and ethical considerations in utilizing personal data from social media are important, raising privacy concerns (Ji et al., 2020). Linthicum et al. (2019) highlighted ethical dilemmas, including bias in ML algorithms, predicting the timing of SIB, and legal questions from false predictions.

Addressing these concerns is crucial for the ethical utilization of digital data in suicide risk assessment. Ongoing research and advancements in ML aim to address these issues, emphasizing the importance of a balanced approach that values both technological innovation and ethical standards in suicide risk assessment.

2.5 ML and Neuroimaging in SI Assessments

Neuroimaging data provide objective measurements, enhancing accuracy compared to subjective information from questionnaires (Wang et al., 2024). Magnetic resonance imaging (MRI), a flexible and non-intrusive technique, offers high-quality brain images, crucial for identifying medical conditions through brain anatomy visualization (AFSP, 2020; Woolrich et al., 2020; Vieira et al., 2023). Changes in frontal, limbic, and temporal lobes are linked to SI, reflecting deficits in emotional processing (Vieira et al., 2023). As seen in Figure 2.5, the frontal cortex (FC) and prefrontal cortex (PFC), which govern 'executive functions,' influence cognitive processes, stress responses, impulse control, and moral decision-making (Sabater, 2021; Wisłowska-Stanek et al., 2021; Abou Chahla et al., 2023).

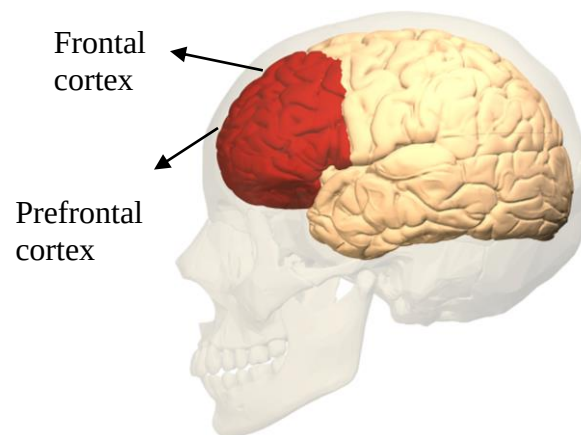


Figure 2.5: Frontal and prefrontal cortex regions (Sabater, 2021)

The PFC influences self-perception and emotional evaluation, contributing to negative thought patterns in individuals with SI (Yasin et al., 2022). Multiple studies consistently link specific brain regions such as the ventral and dorsal PFC to SIB (Segreti et al., 2019; Schmaal et al., 2020; Wang et al., 2020a; Ergenzinger, 2022; Van Velzen et al.,

2022b; Zheng et al., 2023). Dysfunctions in the ventral PFC, as shown in Figure 2.6, contribute to heightened negative states, potentially initiating SI, and are associated with compromised behavioral control, impaired decision-making, and diminished planning capacities (Schmaal et al., 2020; Ergenzinger, 2022).

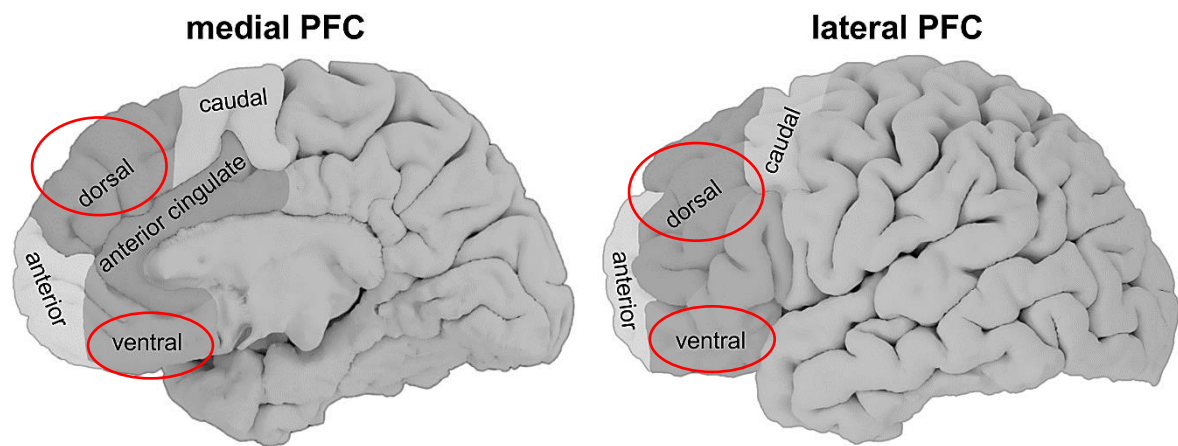


Figure 2.6: Dorsal and ventral cortex regions (Michel & Morales, 2020)

Previous research utilizing voxel-based morphometry (VBM) has associated gray matter volume (GMV) irregularities with suicidal tendencies in mood disorders (Wang et al., 2020b). Depressed individuals with SI show reduced GMV in specific brain regions compared to those with depression or HC (Zhang et al., 2020; Guo et al., 2023). Reduced GMV in the ventral PFC and hippocampus has been found among previous suicide attempters (Schmaal et al., 2020). However, neuroimaging research on the suicidal brain yields diverse outcomes and conflicting findings, including larger GMV in the PFC and insula among depressed individuals who attempted suicide (Rizk et al., 2019; Huang et al., 2020; Kang et al., 2020). Despite inconsistencies, the collective body of GMV studies

underlines its potential role in the development of suicidal behaviors among individuals coping with depression.

Neural features are linked to suicidality, necessitating advanced processing for categorization (Nemeroff, 2020). ML, favored in psychiatry for its handling of multi-scale variables, can predict associations with suicidal behavior from neuroimaging data (Parsaei et al., 2023; Vieira et al., 2023). Common supervised ML methods such as deep learning (DL), gradient boosting, KNN, LR, Random Forest (RF), and SVM create prediction models classifying different groups (Arbet et al., 2021). Reported ACC values range from 51% and above, and AUC values range from 0.50 to 1, with many studies achieving ACC or AUC values not less than 0.8 (Parsaei et al., 2023).

In essence, combining ML techniques with neuroimaging data shows promise for enhancing SI assessment. Neuroimaging studies reveal structural brain differences linked to depression and SI, offering valuable insights. ML methods, including DL and other classifiers, can predict suicidal behavior from neuroimaging data, showing promising accuracy values. After establishing the fundamental concepts of ML and neuroimaging for SI assessment, the focus now shifts to addressing the challenges encountered in applying ML to medical images. The subsequent subsection explores these challenges, providing essential context for understanding the innovative solutions presented in this study.

2.6 Challenges in ML with Medical Images

Medical image analysis poses complex challenges for ML, especially in detecting subtle features indicative of disorders such as depressive conditions and SI (Aboutalebi et al., 2022). For instance, manifestations of depression within individuals experiencing SI,

such as alterations in GMV, show significant variability among patients and across different phases of the illness (Wang et al., 2020b; Guo et al., 2023; Hao et al., 2023). Moreover, the substantial diversity in visual traits further complicates distinguishing between different diseases or defining specific ailments utilizing imaging data (Aboutaleb et al., 2022). This complexity is illustrated by the varied patterns of GMV density observed in depressed patients, highlighting the challenges in accurately interpreting medical images for clinical diagnoses (Huang et al., 2020).

In medical and healthcare datasets, imbalance is a general issue (Roy et al., 2024). Imbalanced classes bias toward the majority class, impeding the recognition of minority classes (Zhou et al., 2020b). As illustrated in Figure 2.7, imbalance arises when one or more target variable values have significantly fewer instances compared to others (Thabtah et al., 2020).

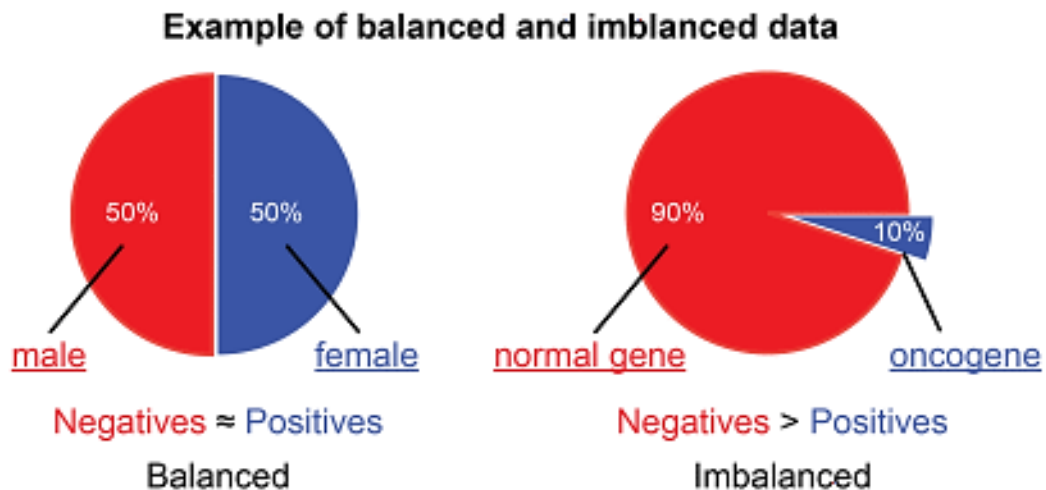


Figure 2.7: Example of balanced and imbalanced data (Tripathi, 2019)

In ML and DL, imbalanced datasets pose challenges as conventional algorithms, designed for balanced data, may overlook the minority class, which often holds critical predictive insights (Gholampour, 2024). This imbalance can detrimentally affect the accuracy of class label predictions in classification tasks and hinder the effectiveness of algorithms in data mining and ML, thereby impacting overall accuracy and decision-making capabilities (Tyagi & Mittal, 2020; Rekha et al., 2021).

In conclusion, while the significance of medical imaging in healthcare has grown, concerns about biased analyses due to varying physician expertise persist. Hence, the strategic integration of ML methodologies is essential in effectively addressing these challenges (Awe et al., 2024). By leveraging ML algorithms in medical imaging analysis, we can moderate subjective interpretation, promoting consistent and objective diagnostic evaluations.

In the upcoming subsection, this study reviews pioneering research that combines sMRI methods with ML models to explore SI. Authored by esteemed researchers, these studies significantly advance our understanding of SI and the development of robust diagnostic and prognostic frameworks. Noteworthy contributions include works by Weng et al. (2020), Chen et al. (2021a), Hong et al. (2021), Bajaj et al. (2023), and Hu et al. (2023). By analyzing these key studies, the aim is to synthesize current knowledge at the intersection of sMRI, ML, and SI, fostering scholarly discourse and guiding future research.

2.7 Key Studies Utilizing Structural Magnetic Resonance Imaging (sMRI) and ML in SI Research

Weng et al. (2020) employed a diverse cohort of depressive patients with and without SI alongside HC. Utilizing a Convolutional Neural Network (CNN)-based autoencoder, Extreme Gradient Boosting (XGB), and LR models, they achieved an impressive ACC of 85% in the prediction task. This high accuracy rate emphasizes the potential of ML approaches in analyzing neuroimaging data to identify biomarkers associated with suicide risk. The findings of this study hold significant implications for clinical practice, suggesting the feasibility of utilizing neuroimaging-based predictive models to aid in the early identification and intervention of individuals at risk of suicidal behavior.

Chen et al. (2021a) contributed significantly to predicting SI utilizing sMRI data. Despite the imbalanced nature of the dataset, their study effectively leveraged DL techniques such as CNN and Densely Connected Convolutional Networks (DenseNet) to discriminate among individuals with various levels of suicidal behavior and HCs. As highlighted in Table 2.3, the study achieved impressive ACC rates, ranging from 79.2% to 91.6%, demonstrating the potential of sMRI-based DL algorithms in stratifying individuals based on suicide risk.

Hong et al. (2021) addressed concerns specific to teens and youth by employing the Support Vector Machine - Recursive Feature Elimination (SVM-RFE) algorithm. They differentiated individuals diagnosed with major depressive disorder (MDD) who attempted suicide from those with SI but without attempts. Achieving a commendable ACC of 78.59%, the study not only showcases the potential of utilizing sMRI data to assess suicide risk among MDD patients but also demonstrates effective strategies for handling imbalanced data in machine learning-based classification tasks.

In their study, Bajaj et al. (2023) analyzed sMRI data from youth at critical suicide risk points, employing advanced ML techniques such as SVM, KNN, and ensemble methods (refer to Figure 2.8). Despite dataset imbalance, they achieved an outstanding classification ACC of 74.79%, highlighting the robustness of their ML framework in assessing structural biomarkers associated with suicide risk. Additionally, specific neuroanatomical regions, such as reduced cortical volume in the anterior and temporal lobes, and increased volume in the cuneus/precuneus, significantly contributed to the classification process.

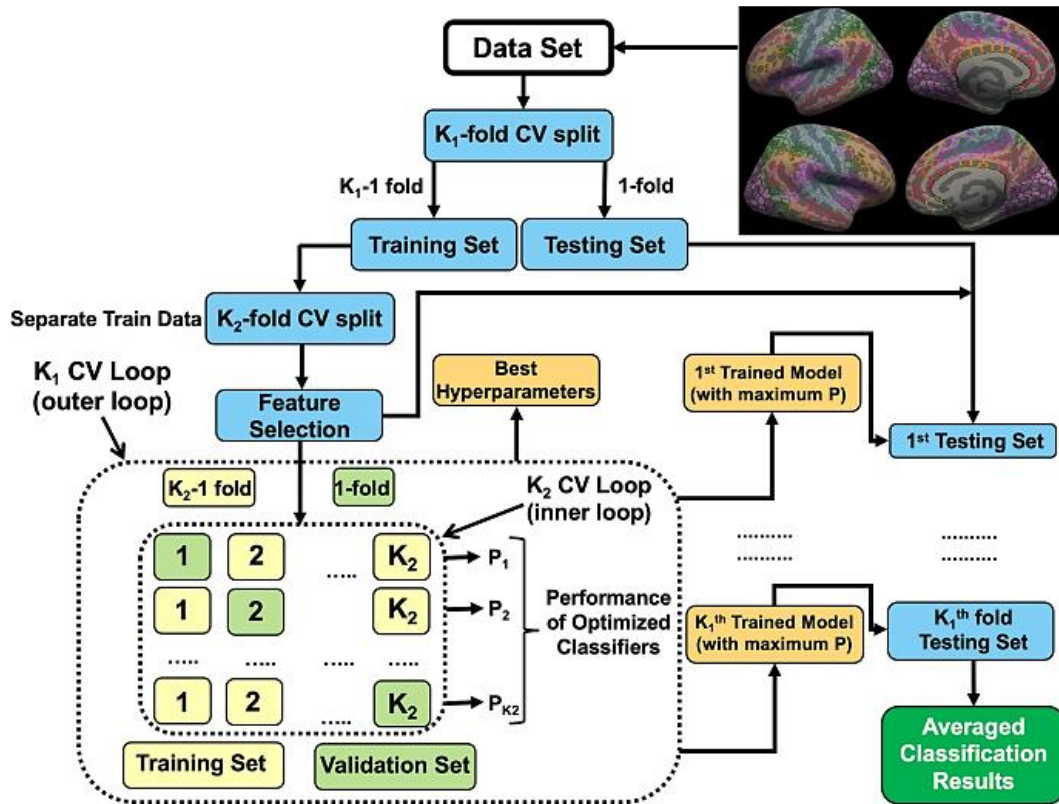


Figure 2.8: Classification task utilizing sMRI (Bajaj et al., 2023)

Hu et al. (2023) utilized fully connected neural network (FCNN) models to classify MDD patients into groups, including those with SI, suicide attempts (SA), and HC. Achieving a classification ACC of up to 70.15%, their study demonstrated robust

performance. They prioritized interpretability by extracting critical features, enhancing the model's decision-making capacity. While not explicitly addressing imbalanced data challenges, their utilization of FCNN models and comprehensive evaluation metrics suggests a sophisticated approach to handling complex datasets.

These key studies advance understanding of the interaction between sMRI and ML in assessing depression and SI, with implications for suicide risk assessment research. They provide insights into the development and application of ML techniques in predicting suicide risk from neuroimaging data. These findings contribute to more precise clinical assessments and interventions, potentially improving mental health care practices. Furthermore, the utilization of advanced technologies in these key studies underlines the value of interdisciplinary approaches in addressing complex psychological issues. These insights offer potential for developing software tools, decision support systems, and risk assessment algorithms to assist healthcare professionals in effectively identifying and managing suicide risk. Moreover, the broader implications for healthcare practice and policy development emphasize the importance of ongoing research and collaboration to address mental health issues and lower suicide rates.

Table 2.3 summarizes the key studies discussed in this section, aiding in understanding their methodologies, findings, and implications.

Table 2.3: The key studies utilizing sMRI data and ML for SI research

No.	Author/Year	Model	Objective	Results			
				ACC	SEN	SPEC	AUC
1.	Weng et al. (2020)	CNN, XGB, and LR.	Predict SI in depressed patients.	85%	75%	100%	–
2.	Chen et al. (2021a)	CNN and DenseNet.	CNN for accurate prediction of SI in depressed patients utilizing sMRI data.	79.2%	–	–	–
3.	Hong et al. (2021)	SVM-RFE.	Identification of SI and SA.	78.59%	73.1%	84%	0.80
4.	Bajaj et al. (2023)	SVM, KNN, and ensemble.	Utilized ML algorithms to classify suicide risk.	74.79%	75.90%	7407%	0.87
5.	Hu et al. (2023)	FCNN.	Identify MDD patients of SA and SI.	70.15%	71%	69.45%	–

2.7.1 Key Studies Limitations

This section outlines the limitations of the key studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023), ranging from small sample sizes to the neglect of certain behavioral dimensions, as detailed in Table 2.4. By addressing these issues, this study aims to enhance SI assessment precision for depressed young adults, contributing to more effective prevention and management strategies for suicidal behaviors.

The limitations outlined in Table 2.4 shed light on important constraints encountered in key studies, offering valuable insights into the challenges faced in SI assessment research. These studies struggled with issues such as small sample sizes, which ranged from 66 to 288 subjects, impacting both the reliability and generalizability of their findings. Utilizing small training datasets to build algorithms with numerous features can lead to challenges when deploying these algorithms in real-world scenarios (Topol, 2019; Berisha et al., 2021). Moreover, accurately estimating true data distributions becomes challenging due to limited sample sizes, hindering the development of robust and dependable ML models for medical image analysis (Guan et al., 2024).

The absence of clinical controls in studies such as those conducted by Hong et al. (2021) and Bajaj et al. (2023) may compromise the reliability of their findings. Clinical controls play a crucial role in ensuring the validity and robustness of research outcomes by providing a comparison group against which the results can be evaluated (Novotech, 2021). Their absence may introduce confounding variables or biases that could undermine the interpretation of the findings.

Table 2.4: Limitation in key studies

No.	Author/Year	Limitations
1.	Weng et al. (2020)	i. 153 subjects (21 – 60 years). ii. Reliance on XGB and LR. iii. Limited ML models predictive capabilities.
2.	Chen et al. (2021a)	i. 186 subjects. ii. Limited practical validation for DL methods. iii. Limited populations.
3.	Hong et al. (2021)	i. 66 subjects (14 – 25 years). ii. No consideration for medication effects. iii. Lack of exploration into variability in suicide attempt dimensions. iv. Absence of HC group. v. Potential evolving diagnostic profiles > 25 years.
4.	Bajaj et al. (2023)	i. 158 subjects (15 – 19 years). ii. Lacked clinical controls. iii. Limited interpretation of identified regions of interest (ROI). iv. Participants with psychiatric comorbidities. v. Difficulty distinguishing effects of suicide risk and depression/anxiety symptoms.
5.	Hu et al. (2023)	i. 288 subjects (15 – 35 years). ii. Lack consideration for behavioral dimensions in patients with MDD.

Furthermore, the study by Chen et al. (2021a) lacked practical validation for their DL methods, potentially hindering their real-world applicability. The absence of practical validation in DL models may introduce biases and impede their ability to be generalized for routine clinical application (Eelbode et al., 2021). Additionally, Weng et al. (2020) predominantly utilized traditional ML methods with constrained predictive capacities, potentially impacting accuracy. Traditional statistical approaches have faced challenges in capturing the diversity present within psychiatric phenotypes, particularly when analyzing small experimental samples (Koppe et al., 2021).

These limitations highlight the challenges in identifying suicide risk factors, particularly in individuals with depression. Recognizing and addressing these limitations is crucial for advancing the field and ensuring the reliability of research outcomes. Reflecting on the implications of these limitations for suicide risk assessment research is essential for guiding future studies and improving the efficacy of SI assessment methodologies.

2.8 Proposed Model: Self-Attention (Self-AM) and Evolving Spiking Neural Network (ESNN) Integration in SI Assessment

The proposed model, which combines self-AM and ESNN in SI assessment, addresses challenges identified in key studies, presenting a novel and comprehensive approach to improve accuracy and reliability. By integrating self-AM and ESNN, the model synergistically leverages their strengths, providing an advanced understanding of the complex factors influencing suicidal behavior. Built on decision-making theories and software quality principles, the model ensures a robust framework that captures cognitive processes related to SI while adhering to high standards of reliability and scalability.

To address the limitations outlined in Section 2.7.1, it is important to examine challenges faced by previous key studies in SI assessment (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023). These include small sample sizes, which can compromise the generalizability of findings. Selecting an appropriate model architecture can simplify training and alleviate sample size requirements (Koppe et al., 2021). Thus, advanced techniques such as self-AM and ESNN may compensate for smaller sample sizes by extracting more meaningful information and improving predictive performance.

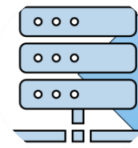
The proposed model addresses the challenge of distinguishing suicide risk from depression symptoms in Bajaj et al. (2023) study by utilizing sMRI data to visualize alterations in brain anatomy, enhancing precision in exploring SI dynamics within the target demographic. While MRI brain images offer high resolution, extracting actionable insights remains challenging (Berisha et al., 2021). To overcome this, our study integrates self-AM, enhancing representation capabilities and interpretability by focusing on significant brain regions. By integrating self-AM into the ESNN model, we dynamically adjust attention to different brain regions, optimizing predictive accuracy and interpretability (Yan et al., 2022).

Furthermore, the inclusion of a HC group alongside depressed young adults aged 19 to 24 addresses concerns raised by Hong et al. (2021) and Bajaj et al. (2023) regarding the absence of control groups. The HC group serves as a crucial reference point for comparison, enabling researchers to discern specific differences associated with depression and SI within this age demographic (Jayatilake & Ganegoda, 2021). This comparative analysis enhances the reliability and validity of our study's findings, providing a clearer understanding of the neural correlates of suicidal behaviors.

All key studies have typically focused on individuals aged 18 to 65, yet young adults aged 18 to 24 exhibit heightened vulnerability to depression and SI (Hill et al., 2021; Schluter et al., 2022; Bridge et al., 2023). Mental health trajectories vary over time, emphasizing the importance of tracking changes (Durstewitz et al., 2021). Therefore, this study targets depressed young adults aged 19 to 24 to minimize age-related variations, thereby refining the exploration of SI dynamics. This approach ensures a standardized sample, enhancing the precision and accuracy of predictive models for more effective prevention strategies against suicidal behaviors.

ESNN dynamically adapt and evolve, mirroring the plasticity of biological neural systems (Kasabov, 2019). Their predictive capabilities enable the analysis of complex neuroimaging data, identifying subtle patterns indicative of SI and providing actionable information for clinicians to improve risk management strategies (Abdullah et al., 2019; Kumarasinghe et al., 2021). Similarly, self-AM selectively focuses on relevant neuroanatomical features associated with suicide risk, enhancing model interpretability and clinical utility (Ahmed, 2022; Otten, 2023). Its adaptability to varying data distributions ensures robust performance across diverse datasets, revolutionizing SI assessment and facilitating more informed decision-making in clinical practice (Sharique, 2021).

In conclusion, our model promises to advance SI assessment by addressing key study limitations and leveraging self-AM and ESNN capabilities. It enhances detection accuracy and reliability, potentially revolutionizing neuroimaging-based assessment for more effective interventions. Continued research in this area shows promise for better understanding and targeted interventions. Figure 2.9 summarizes the proposed model of this study.



Sample Size Concerns:

- Self-AM's feature extraction enhances clarity (Otten, 2023).
- ESNN's adaptability refines understanding of neural patterns (Ibad et al., 2020).



Incorporating Control Groups:

- Healthy controls (HC) aid in accurate assessment.



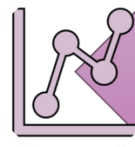
Neuroimaging Data:

- Analyzing sMRI data helps visualize brain anatomy, detect alteration linked to SI.



Depressed Young Adults:

- Aged 19 – 24 → reduce age-related variations in brain structures and mental health.
- Enhances precision in exploring SI dynamics.



Comparative Analyses:

- Proposed model performance evaluated against traditional ML classifiers, ESNN standalone model, and key studies.
- Provide insights into its superiority and unique contributions.

Figure 2.9: Summary of the proposed self-AM-ESNN model for SI assessment

2.9 Attention Mechanism (AM) and Spiking Neural Networks (SNN)

AM and SNN represent two fundamental concepts within the domain of artificial intelligence and computational neuroscience, respectively. AM refers to a computational paradigm inspired by human cognitive processes, particularly in the realm of selective attention (Gonçalves et al., 2022; Cristina, 2023). This mechanism enables models to focus on relevant information while filtering out irrelevant data (Ahmed, 2022, refer to Figure 2.10).

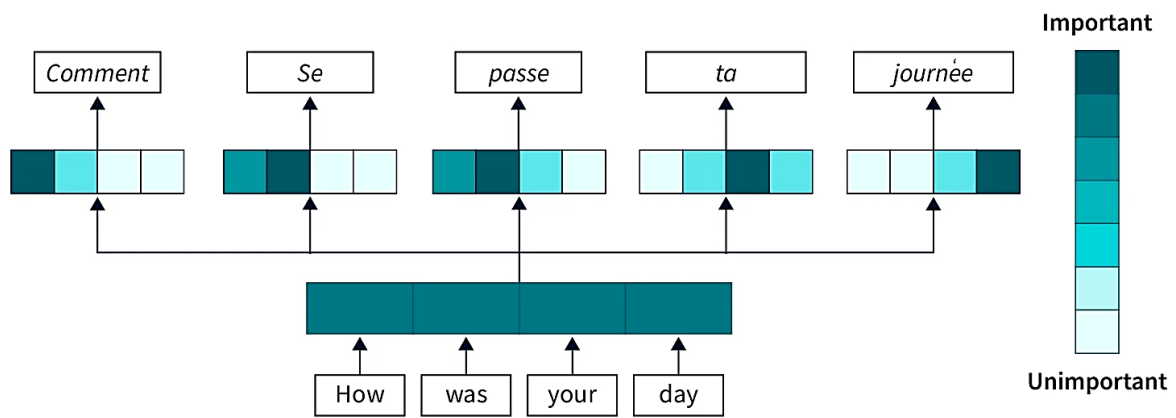
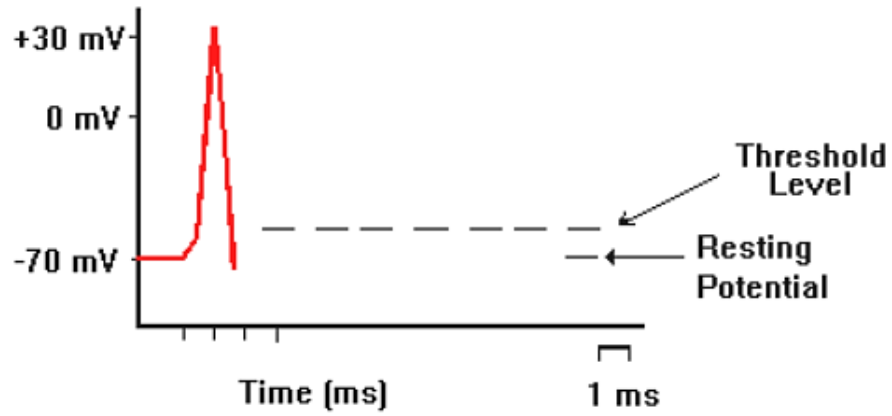


Figure 2.10: Attention mechanism (Malingan, 2023)

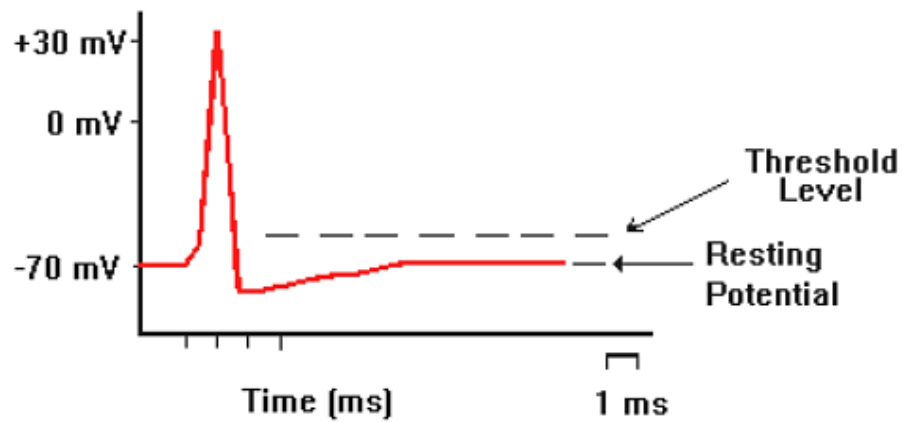
AM is one of the most significant discoveries in ML and in recent times, it has been employed to accomplish remarkable outcomes in nearly every domain of ML (Erdem, 2021). The integration of AM in DL has led to significant advancements in medical image analysis (Yao et al., 2019; Ranjbarzadeh et al., 2021; Xiao et al., 2021; Cheng et al., 2022; Guo et al., 2022; Rondinella et al., 2023; Takagi et al., 2023; Ullah et al., 2023).

On the other hand, SNNs constitute a class of artificial neural networks that mimic the functionality of biological neural networks more closely compared to traditional neural

network models (Taherkhani et al., 2020). SNNs utilize a representation of information through discrete spikes or neuronal action potentials, facilitating efficient and biologically plausible computation (Tan et al., 2020a; Kim & Panda, 2021, refer to Figure 2.11).



(a)



(b)

Figure 2.11: SNN operation, (a) neuron threshold surpassed and impulse transmission; (b) neuron value decay and return to the original state (Lyashenko, 2021).

This framework enables SNNs to exhibit capabilities such as temporal processing, asynchronous communication, and low-power operation (Kumarasinghe et al., 2021). In healthcare settings, SNN algorithms have been implemented in medical data classification

as they are excellent contenders for the classification of medical images due to the benefits of natural power-efficiency, biological plausibility, and commendable image recognition performance (Zhou et al., 2020a; Fu & Dong, 2022).

2.9.1 Relevance to SI Assessment

Both AM and SNN hold significant relevance in the context of SI assessment, contributing distinct methodologies and insights to enhance the understanding and detection of suicidal behaviors.

AM facilitates the identification and prioritization of relevant features within heterogeneous data sources such as text, audio, or visuals (Ma & Cao, 2020; Ji et al., 2022; Devika et al., 2023). In SI assessment, AM helps detect linguistic, semantic, and contextual cues indicative of distress (Cao et al., 2020; Sawhney et al., 2021; Chadha & Kaushik, 2022). By focusing on these features, AM-based models enhance suicide risk assessment tools' accuracy and sensitivity, aiding early intervention (Li et al., 2023a).

SNNs, known for their temporal processing and event-driven computation capabilities (Yamazaki et al., 2022), show promise in modeling the dynamic nature of SIB. They excel at capturing temporal dependencies and subtle patterns within longitudinal data streams (Lou et al., 2020; Zhou et al., 2020a; Alzhrani et al., 2021; Doborjeh et al., 2021b; Turkson et al., 2021; Niepceron et al., 2022; Yue et al., 2023), providing insights into evolving suicide risk trajectories. Leveraging these dynamics, SNN-based models offer detailed insights into SI progression, enabling personalized risk assessment and intervention strategies (Yamazaki et al., 2022).

2.9.2 Integration of AM and SNN in the Proposed Model

The proposed integrated model combining AM and SNN serves as a novel approach to predicting SI among depressed young adults, leveraging the insights and methodologies offered by both computational paradigms.

AMs are integral to the proposed model, aiding in the identification and prioritization of important neuroanatomical features in sMRI data (Hua et al., 2023). By directing attention to brain regions linked with depression, AM enhances the model's ability to focus on neurobiological markers relevant to SI and depressive symptoms (Chi et al., 2022). This selective attention improves the model's interpretability and discriminative power, facilitating the extraction of meaningful patterns from complex neuroimaging data while minimizing the influence of confounding variables (Gonçalves et al., 2022).

Utilizing SNN alongside sMRI data of depressed young adults holds potential for identifying SI (Haque et al., 2021). Recent research has highlighted the effectiveness of advanced DL techniques such as CNN and DenseNet in analyzing sMRI data to distinguish individuals across various levels of suicide risk, spanning from depression to SI and attempts (Chen et al., 2021a). Moreover, the fusion of ML algorithms with sMRI data has proven successful in forecasting SI based on patterns in brain imaging, offering an objective tool for assessing suicide risk in depressed patients (Weng et al., 2020). By integrating SNN with sMRI data, we aim to improve the accuracy and speed of detecting SI in young adults with depression, thereby contributing to more effective prevention and intervention strategies.

The integration of AM and SNN in our model provides synergistic benefits, boosting both predictive accuracy and explanatory depth. By merging feature selection with dynamic brain processing, the model can detect neurobiological markers of SI while capturing the

complex interactions among brain regions linked to depression (Vieira et al., 2023). Furthermore, by employing AM, SNNs optimize membrane potentials and regulate spiking responses based on neuroscience principles, leading to improved performance and energy efficiency (Yao et al., 2023). This integrated strategy not only enhances suicide risk detection but also enables tailored interventions for depressed young adults.

2.10 Self-Attention Mechanism (self-AM)

Self-AM, derived from the broader concept of AM, empowers models to capture long-range dependencies within input data by assigning varying degrees of importance to different elements based on their contextual relevance (Li et al., 2020; LinkedIn, 2023; Liu & Xu, 2023). In the context of sMRI data analysis, self-AM enables each voxel or region within the brain to selectively attend to informative features within its spatial context while filtering out irrelevant information (Jiang et al., 2022; Li et al., 2023b; Hassanin et al., 2024). This selective attention enhances the model's interpretability, discriminative power, and ability to extract meaningful neuroanatomical patterns associated with depression and suicide risk (Hu, 2020; Otten, 2023). Overall, self-AM captures complex interactions in the brain, improving the models' accuracy and reliability of detections for depressive symptoms and SI (Rao et al., 2021; Sharique, 2021).

In the proposed model, self-AM plays a crucial role in extracting features from sMRI data of depressed young adults. It identifies ROI related to depressive symptoms and suicide risk by assigning attention weights to each voxel or region (Li et al., 2023b). The attention output is then fed into the ESNN encoder, where it is transformed into a spike train representation compatible with the spatiotemporal processing capabilities of ESNNs. By

utilizing self-AM for initial feature extraction, the model enhances its ability to identify and prioritize neuroanatomical features relevant to depression and suicide risk in sMRI data, contributing to more accurate and personalized SI detection among depressed young adults.

In essence, self-AM is fundamental in our model, facilitating the selective integration of spatial information and capturing complex neuroanatomical patterns within sMRI data of depressed young adults. This empowers the model to identify relevant features linked to depressive symptoms and suicide risk, enhancing the accuracy of SI detection. Tables 2.5 and 2.6 provide further insights into the utilization of self-AM in medical image analysis and suicide research, accentuating its importance across diverse domains.

Table 2.5: Applications of self-AM in medical data analysis

No.	Author/Year	Domain	Objective	Results
1.	Tao et al. (2020)	EEG	Emotion recognition.	ACC improves by roughly 27% to 30% on different datasets.
2.	Altaheri et al. (2022)	EEG	Motor imagery categorization.	Framework surpasses current methods with ACCs (70% to 80%) for individualized and universal subject-specific modes, respectively.
3.	Jiang et al. (2022)	MRI	Novel approach for Alzheimer's disease image classification.	Outperforms comparable models with ACC improves from 86.8% to 89.4%.
4.	Li et al. (2023b)	MRI	Cardiac segmentation.	Achieved excellent segmentation outcomes.
5.	Wang et al. (2023b)	ECG	Arrhythmia categorization.	i. ACC: 99.4% ii. SPEC: 99.4% iii. SEN: 97.36%
6.	Yang et al. (2023b)	X-rays	Chest X-ray classification.	Outperforms other models with an ACC of 98.0%.
7.	Yuan et al. (2023)	ECG	Anomaly detection for irregular heart rhythms.	ACC of 98.33% on initial dataset and 99.12% on the enhanced dataset.

Table 2.6: Applications of self-AM in suicide research with digital data

No.	Author/Year	Objective	Results
1.	Fang et al. (2021)	Suicide risk identification with text.	F1-score improved with AM implementation.
2.	He et al. (2021)	Automated identification of depression from videos.	• Mean absolute error: 7.51 • Root mean error: 9.14
3.	Toto et al. (2021)	Categorization of depression utilizing audio.	• F1-score increase of 6% to 30%
4.	Zhang et al. (2021a)	Automated classification of suicide notes.	• Precision: 87.5% • Recall: 88.5% • F1-score: 88%
5.	Kumar & Sachdeva (2022)	Cyberbullying identification on social media.	F1-score of above 90%.
6.	Ghosh et al. (2022)	Identifying interpersonal risk elements of suicide in suicide letters.	Outperformed others in the same study with a macro-F1 score of: • 54.02 (Perceived Burdensomeness). • 56.64 (Thwarted Belongingness).
7.	Roy et al. (2022)	Forecasting suicidal trends – indication, ideation, and behavior or attempt.	• Accuracy: 83% • AUC: 78

2.11 Evolving Spiking Neural Networks (ESNN)

Renowned for their ability to model neural dynamics, ESNNs play a crucial role in capturing the temporal patterns of brain activity associated with SI (Kasabov, 2019; Roy et al., 2020). Unlike traditional artificial neural networks (ANNs), ESNNs offer transparency, providing valuable insights into decision-making processes critical for applications such as SI detection. They also address the issue of "catastrophic forgetting," where ANNs forget previously learned information when adapting to new data (Kaushik et al., 2021; Aleixo et al., 2023). In our proposed model, ESNNs convert attention-weighted neuroanatomical features from self-AM into spike train representations, facilitating effective modeling of suicide risk factors through spatiotemporal processing.

Furthermore, ESNNs combine the principles of SNNs and evolutionary computation of structures (ECOS) (Yamazaki et al., 2022; Wu et al., 2024). Their adaptability and evolutionary traits render ESNNs advantageous in suicide risk detection (Ibad et al., 2020). ESNNs offer significant advantages for SI detection from sMRI data:

1. Spatial pattern learning capabilities, enabling them to capture complex anatomical patterns and structural brain changes associated with depressive states and suicide risk (Shen et al., 2021; Wu et al., 2022). Their adaptive learning mechanisms continuously update internal representations and predictive models based on new sMRI data, enhancing robustness and adaptability to evolving neuroanatomical markers of individual SI trajectories (Jiang et al., 2023).
2. Integration of adaptive synaptic plasticity and neurogenesis mechanisms, allowing ESNNs to dynamically adjust neuron connections' strength and generate new neurons based on changing sMRI input patterns (Ibad et al., 2022). This network restructuring

optimizes predictive models over time, adapting to evolving neuroanatomical patterns associated with suicide risk while maintaining high predictive accuracy (Laña et al., 2019; Ibad et al., 2020).

Tables 2.7, 2.8, and 2.9 provide a comprehensive overview of the versatile applications of ESNNs in detection and prediction tasks. These tables highlight the significance of ESNNs across various domains, showcasing specific instances where their utility shines in the analysis of medical data. Through these examples, the tables highlight how ESNNs are not only powerful tools for addressing complex challenges in healthcare but also extend their efficacy to other fields, demonstrating their broad applicability and potential impact on advancing technological solutions for diverse problems.

Table 2.7: Summary of ESNN applications in detection tasks

No.	Author/Year	Objective	Results
1.	Demertzis et al. (2020)	Improves anomaly detection in large-scale industrial data.	ACC for dataset of: • Water tower: 98.03% • Gas: 97.68% • Electric: 96.92%
2.	Liu et al. (2021)	ESNN model for air pollution detection in Beijing and Shanghai.	Superior performance compared to other models.
3.	Maciąg et al. (2021)	Anomalies detection in two different datasets.	ACCs of 69% and 96%, respectively.
4.	Bäßler et al. (2022)	Real-time detection in multivariate time series utilizing modified online ESNN based on Maciąg et al. (2021) research.	Enhanced outlier identification and reduced runtime.

Table 2.8: Summary of ESNN applications in prediction tasks

No.	Author/Year	Objective	Results
1.	Abdullah et al. (2019)	Flood risk prediction with dynamic ESNN.	Highest ACC (92.86%) for 1-day and 3-day flood risk compared to others.
2.	Laña et al. (2019)	ESNN for long-term road traffic volume forecasting.	Decreased error, accurate categorization, and forecasting (>0.8) on test data.
3.	Maciąg et al. (2019)	Air pollution forecasting with ESNN based on NeuCube.	Outperforming basic NeuCube model ACC in all scenarios.
4.	Maciąg et al. (2020)	Air pollution prediction.	Competitive outcomes compared to cutting-edge techniques and algorithms.
5.	Ibad et al. (2022)	ESNN hyperparameter optimization.	ACC for datasets: i. Spoken Arabic digits: 0.96 ii. Articulatory word recognition: 0.97 iii. Character trajectories: 0.94 iv. Wafer: 1.0 v. GunPoint: 0.94

Table 2.9: Applications of ESNN in medical data analysis

No.	Author/Year	Domain	Objective	Results
1.	Doborjeh (2019)	EEG and MRI	Spatio-temporal neuroimaging data analysis.	Enhanced classification up to 92% ACC – present 20% improvement compared to other ML methods.
2.	Doborjeh et al. (2019)	EEG	Classification of depressed subjects.	ACC: 87%.
3.	Shah et al. (2019)	EEG	Classify depressed versus HC subjects with several conditions.	ACCs of 68.18% and 72.13%, respectively.
4.	Kumarasinghe et al. (2020)	EEG	Revealing temporal and spatial patterns in spatio-temporal data.	Successfully extracted neural pathways and providing insight into brain's motor cortex.
5.	Tan et al. (2020b)	EEG	Emotional valence classification utilizing diverse data.	ACC 73.15% in binary sentiment classification.
6.	Chen et al. (2021b)	MRI	Mimic neural activities of specific hippocampal brain regions.	Simulates brain areas and the evolved parameters enhance model performance.
7.	Kumarasinghe et al. (2021)	EEG	Predicting upper limb muscle activity and kinematics.	Enhanced ACC.
8.	Sabri et al. (2022)	-	Classification of scoliosis images with photogrammetry.	Outperforms traditional ML with 90.01% ACC.

ESNNs have shown promise in broader suicide research, yet their specific role in predicting SI remains largely unexplored. While previously primarily utilized for classifying emotions such as depression (Doborjeh et al., 2019; Shah et al., 2019), ESNNs offer potential in SI research due to their ability to capture temporal dynamics and subtle neural patterns (Kasabov, 2019). Moreover, ESNNs can integrate various data sources such as neuroimaging, genetics, and clinical variables, enhancing suicide risk assessment models (Ibad et al., 2022; Shen et al., 2023). Leveraging ESNNs in SI research can deepen our understanding of the neural correlates of suicidal behavior, leading to more effective prevention and intervention strategies.

Integrating ESNNs with decision-making theories can enhance the interpretability and applicability of these models in the context of suicide risk assessment. Theories such as prospect theory and bounded rationality provide frameworks for understanding human decision-making processes, including the evaluation of suicide risk (Bauer & Capron, 2020; McDermott, 2024). By incorporating decision boundaries and thresholds into ESNNs, these models can emulate the cognitive processes involved in assessing suicide risk, shedding light on the underlying factors that shape such critical decisions (Qiu & Klonsky, 2021; Wang et al., 2021).

Moreover, the consideration of SI is crucial in developing accurate and comprehensive predictive models for suicide risk. SI, a multifaceted construct encompassing thoughts, intentions, and behaviors related to suicide (Gökbayrak, 2021), provides valuable insights into an individual's risk profile. By training ESNNs on datasets that incorporate measures of SI, these models can effectively capture the complex interplay between SI and other risk factors, ultimately improving the accuracy of suicide risk detections. This

approach aligns with decision-making frameworks that recognize the importance of integrating diverse sources of information for informed decision-making.

The implementation of software tools designed for suicide risk assessment can facilitate collaboration and knowledge sharing within the community of practice, thereby enhancing the effectiveness and efficiency of decision-making processes. These tools enable healthcare professionals to access and analyze large datasets, leading to more informed decisions and personalized intervention strategies (Sadek, 2019; Bentley et al., 2022). By integrating ESNN-based predictive models into such software platforms, clinicians can streamline the process of model development, deployment, and application, ultimately enhancing the accuracy and timeliness of suicide risk assessments. Additionally, these tools can empower frontline healthcare providers to assess suicide risk more accurately and intervene proactively, reducing the burden on specialized mental health services (Velupillai et al., 2019; Barak-Corren et al., 2020).

In conclusion, ESNNs play a crucial role in the proposed model by facilitating the transformation of neuroanatomical features into a spike train representation for predictive modeling of suicide risk. Although ESNNs demonstrate remarkable adaptability and dynamic learning capabilities, their application in suicide research remains relatively unexplored. However, by harnessing ESNNs, this study strive to uncover the neural correlates of SI, thereby enhancing our predictive models for more effective prevention and intervention strategies.

2.12 Summary

This study aims to enhance SI assessment for depressed young adults by employing self-AM-ESNN integrated model with sMRI data. Beyond immediate objectives, the proposed model may establish a methodological benchmark for future research. Acknowledging the psychological distress in the youth population, this study emphasizes the crucial link between depression and SI. Subsequent chapters examine methodology, data collection, and model development, seeking to advance SI assessment and facilitate a broader understanding of psychological wellness for better outcomes and timely interventions.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview

This chapter serves as a link between the foundational principles established in Chapter 1 and the methodological approach outlined in Chapter 2, aiming to provide a seamless transition and coherence throughout the research process. Figure 3.1 provides a general overview of Chapter 3.

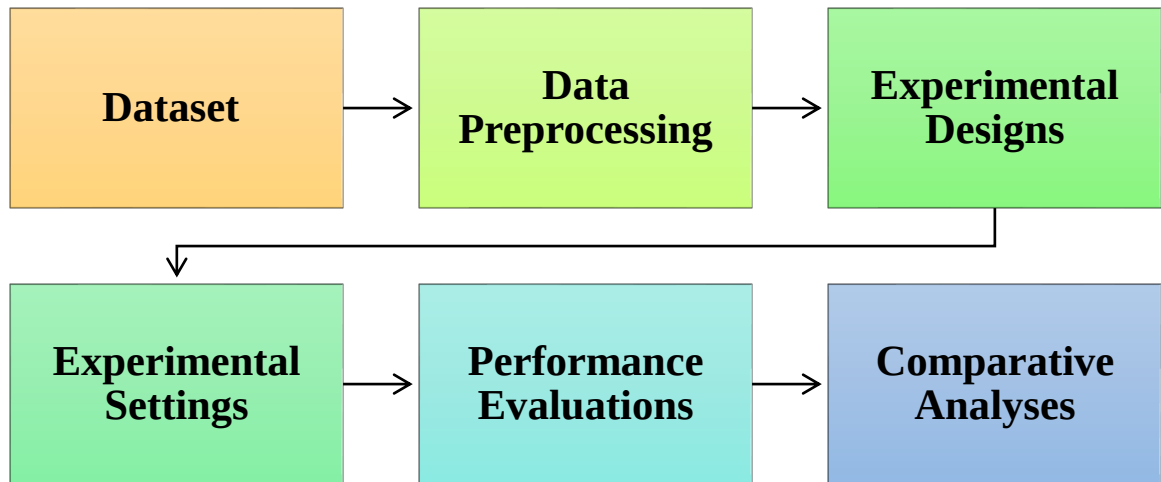


Figure 3.1: Chapter 3 overview

The ESNN algorithm was selected for this study due to its demonstrated efficacy in predicting SI among depressed young adults utilizing sMRI data (Chen et al., 2021b; Nikam et al., 2023). Additionally, ESNN's ability to capture temporal dynamics and sparse representations aligns well with the characteristics of sMRI data, making it a suitable choice for this task. The decision to explore ESNN was further motivated by its potential for refining SI detection and aiding early intervention in mental health care (Choi et al., 2021). By employing a quantitative approach, this study aims to rigorously evaluate the performance of ESNN in predicting SI among depressed young adults, leveraging the rich information contained in sMRI data.

Integrating self-AM and ESNN is essential for accurately predicting SI in depressed young adults utilizing sMRI data (Ibode et al., 2022). This approach capitalizes on the strengths of both techniques: self-attention enhances feature extraction, while ESNN captures temporal dynamics and sparse representations. This synergy offers a promising avenue for developing precise predictive models for SI in this vulnerable population (Wu et al., 2023; Dai et al., 2024).

Figure 3.2 illustrates the research design environment, visually depicting the connections between Chapters 1, 2, 4, and 5. This visualization clarifies the evolution of the research methodology and its alignment with the overarching research objectives, aiding in a thorough comprehension of the study's framework and its elements.

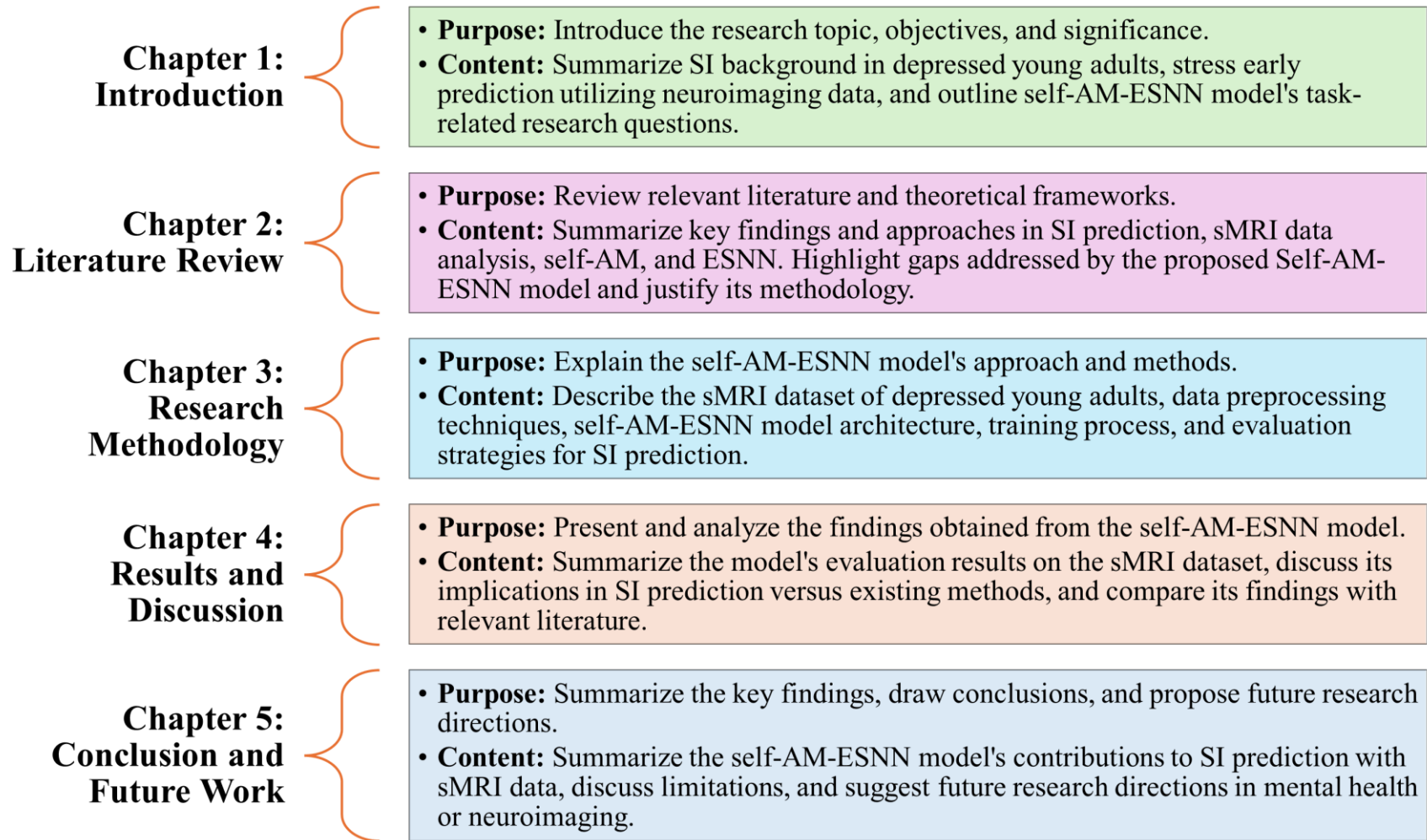


Figure 3.2: Overall research design environment

3.2 Dataset

This study employed a dataset consisting of 80 sMRI scans of young adults aged 19 to 24, comprising 20 scans from depressed individuals and 60 scans from HC subjects, as specified in Table 3.1.

Table 3.1: Datasets details

No.	Dataset	OpenNeuro	INDI
1.	Research object	Depressive	HC
2.	Number of samples	20	60
3.	Average age	21.95 (19 – 24)	19.78 (19 – 22)
4.	Gender (Male/ Female)	5/ 15	20/ 40

The relationships within the dataset exhibit non-linear characteristics, reflecting the complex interactions between the sMRI data, demographic variables, and the detection of SI (Moller et al., 2023). Therefore, it is essential to employ modeling techniques that can effectively capture and leverage this non-linearity.

3.3 Data Preprocessing

The raw Neuroimaging Informatics Technology Initiative (NIfTI) data underwent preprocessing to ensure readiness for analysis and classification tasks on the three-dimensional (3D) sMRI images, despite potential delays due to data complexity (Heindl, 2022; Singh et al., 2022; Akindele et al., 2023). The preprocessing pipeline as described in

Figure 3.3, drew inspiration from Volodymyr Bogdanov’s tutorials (Bogdanov, 2015³; Bogdanov, 2017⁴), and was tailored to our dataset.

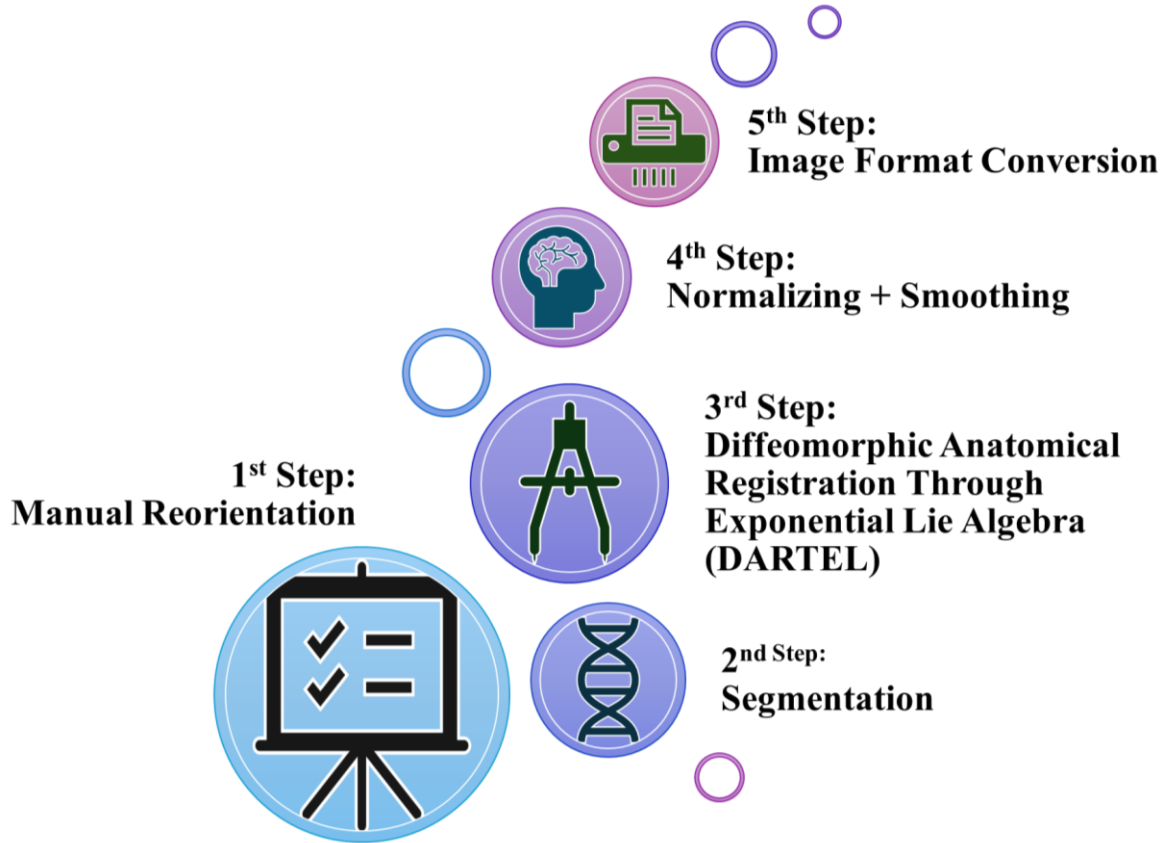


Figure 3.3: Data preprocessing steps

3.3.1 Reorientation

Reorientation is crucial for the accurate interpretation of neuroimaging data, as it ensures central positioning and consistent calibration post ML model training (Sert, 2021; Brainlife, 2022). The process was conducted manually utilizing the Montreal Neurological

³ <https://www.youtube.com/watch?v=sUFRnWv9Mg&t=119s>

⁴ <https://www.youtube.com/watch?v=YVDG9cjmUPU&t=370s>

Institute's (MNI) T1-weighted (T1w) brain templates via SPM12 software (Bogdanov, 2015). This practice integrates existing anatomical information, establishing a unified coordinate system for group-level analyses and comparisons (Dadar et al., 2021). Furthermore, manual adjustments to the raw image's orientation, as shown in Figure 3.4, ensure meticulous reorientation, promoting data consistency and accuracy.

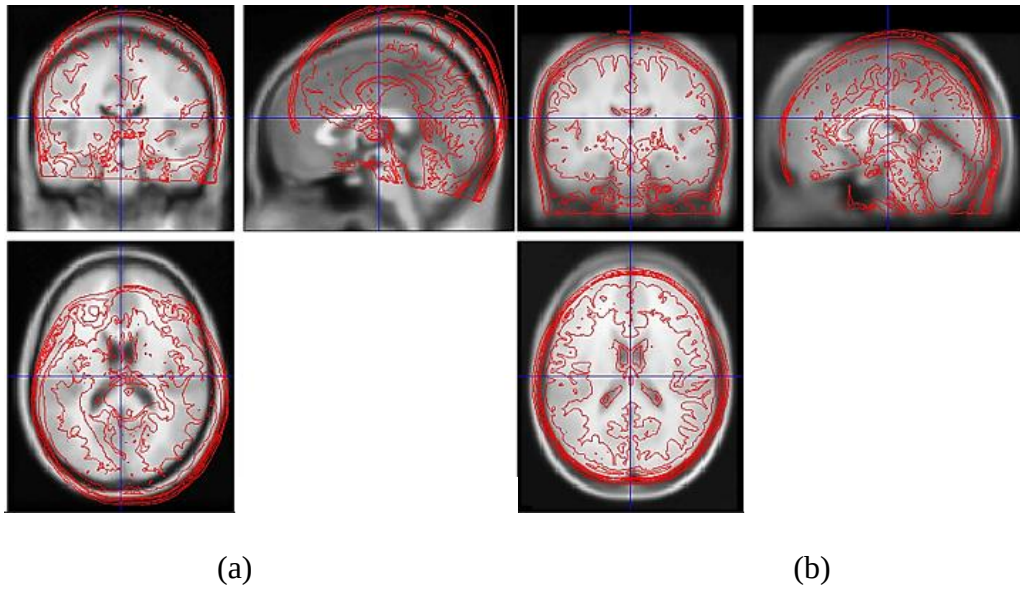


Figure 3.4: (a) The initial position of the MRI scan image before manual reorientation utilizing the MNI template, and (b) the resulting position after reorientation.

3.3.2 Segmentation

The segmentation process, conducted utilizing SPM12 software, autonomously classifies tissue groups based on the brain's division. This division encompasses three key elements: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF), as visually depicted in Figure 3.5. Among these components, the GM structural graphics were designated as the primary data source for the proposed model.

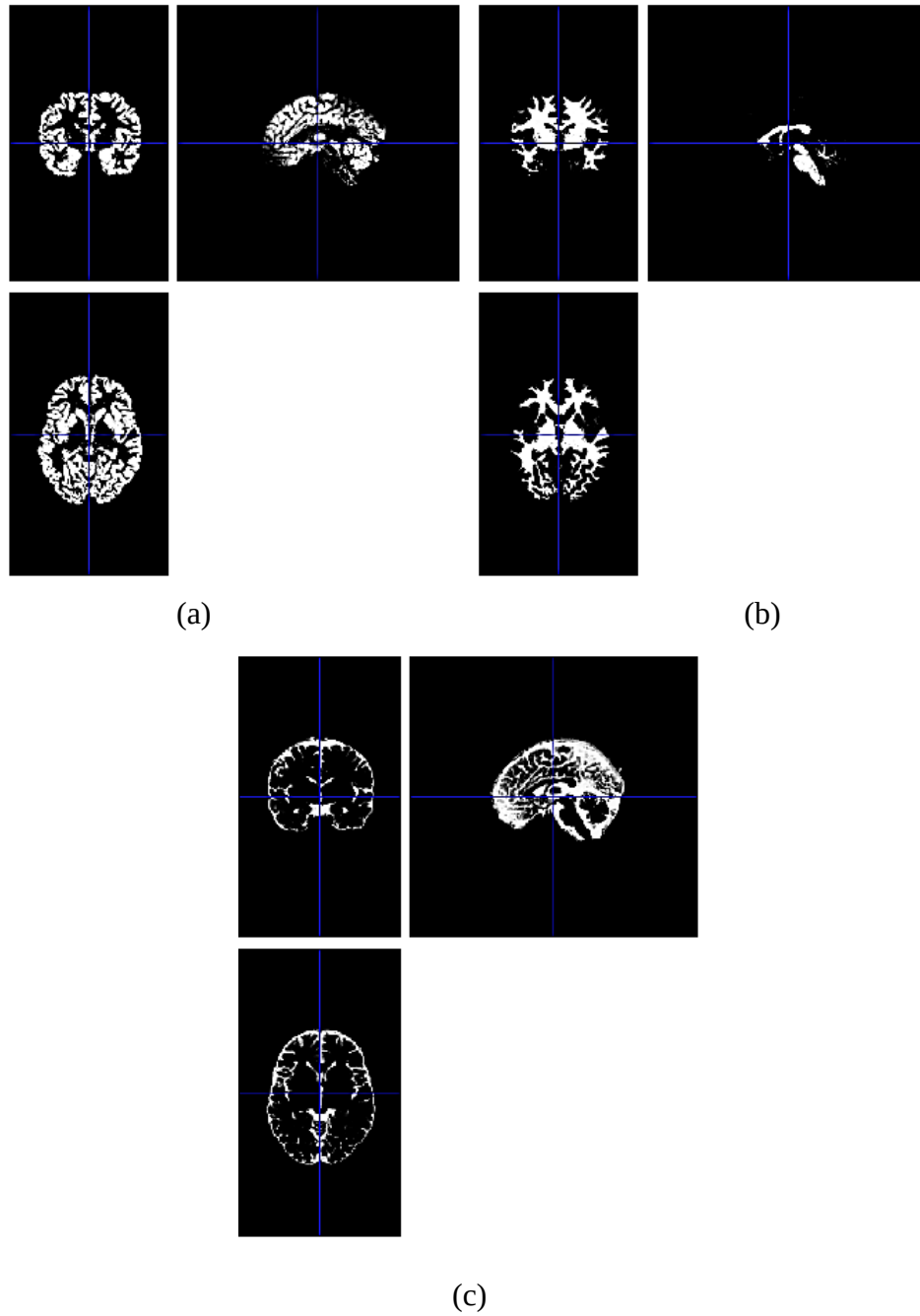


Figure 3.5: Segmentation of (a) GM, (b) WM, and (c) CSF tissue

Figure 3.6 illustrates the distinction between native and registered spaces. Native space represents the original MRI acquisition setting, closely resembling the original T1w image (Pinto et al., 2020). In the registered space, native and DARTEL spaces are integrated utilizing a GM template for segmentation. The registered space aligns multiple MRI data

sets utilizing techniques such as DARTEL to ensure precise alignment despite anatomical differences (Visser et al., 2020). The utilization of DARTEL demonstrates effective segmentation, ensuring alignment and consistency for data analysis and model development (Bogdanov, 2017).

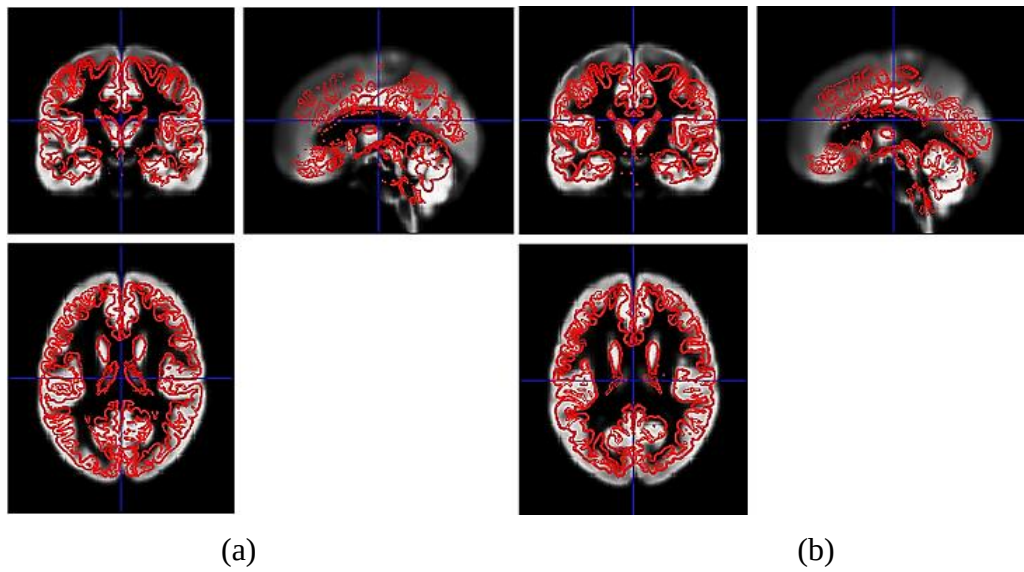


Figure 3.6: (a) The GM segmentation utilizing the native space, and (b) the GM segmentation utilizing the registered space

3.3.3 Diffeomorphic Anatomical Registration Through Exponential Lie Algebra (DARTEL)

DARTEL significantly enhances image fitting precision by constructing regional templates for GM and WM through six iterative registrations of unnormalized tissue class images (Ashburner, 2007; Bogdanov, 2017). With each iteration, the alignment of individual images improves, leading to the creation of progressively sharper templates. This enhancement is illustrated in Figure 3.7, where 'template_0' appears blurry and indistinct, whereas 'template_6' exhibits a sharper representation.

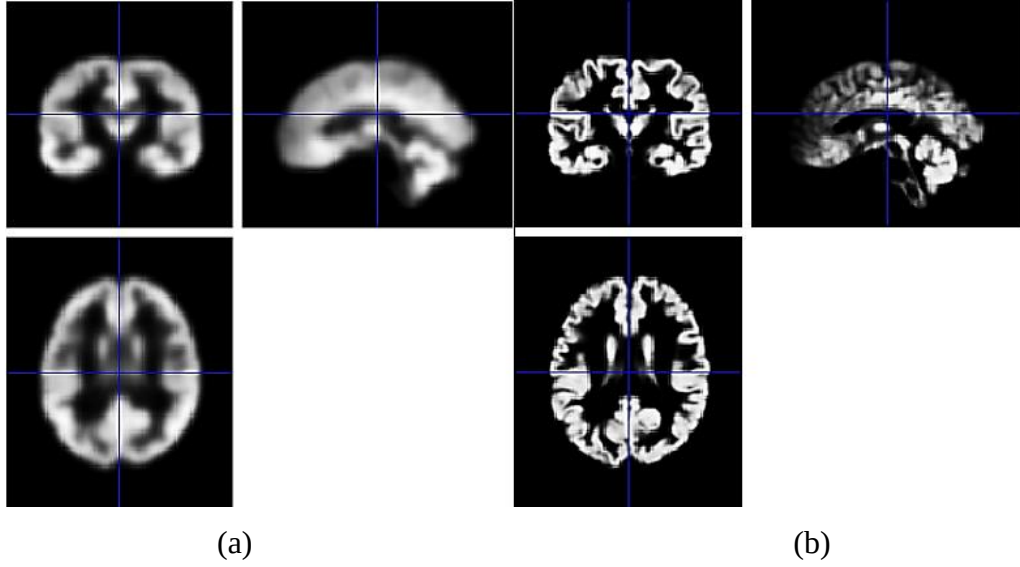


Figure 3.7: Contrast between, (a) ‘Template_0’, and (b) ‘template_6’

3.3.4 Normalization and Smoothing

In the normalization and smoothing step, structural images are adjusted to align with an MNI brain template utilizing two templates: the original and global templates. Simultaneously, smoothing, a technique to reduce noise and enhance structure visibility, is crucial in the normalization phase (Candemir, 2023). The procedures utilizing the ‘template_6’ is visually depicted in Figure 3.8.

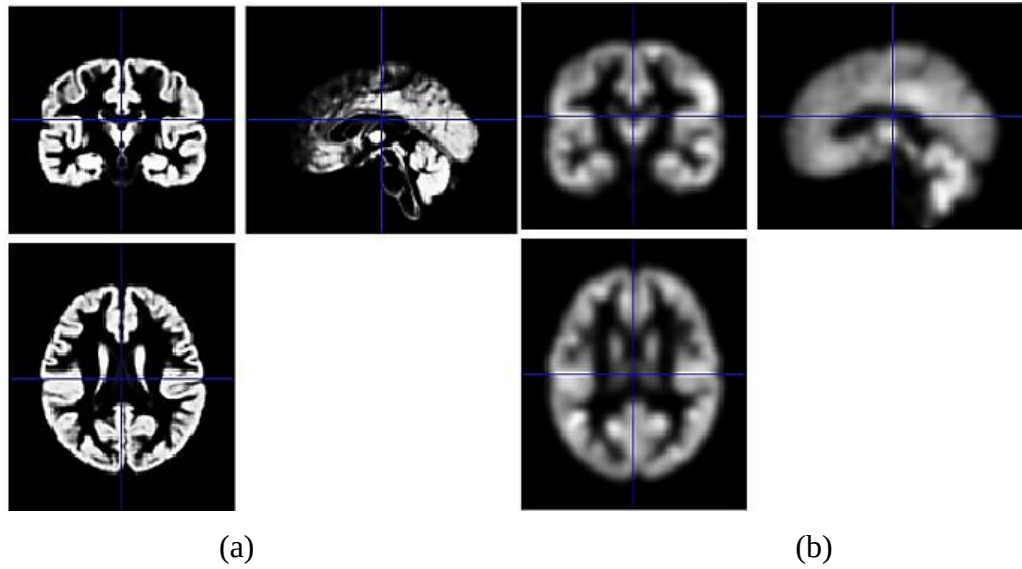


Figure 3.8: Comparison between, (a) Subject's 'template_6', and (b) the smoothed and normalized image of their MRI scan

In Figure 3.9, the contrast between the normalized image and 'template_6' from DARTEL is showcased during the orientation phase. 'Template_6' undergoes warping to align with the standard MNI template. This visual representation emphasizes the effectiveness of the orientation process, highlighting the achieved alignment and compatibility with the standard MNI template.

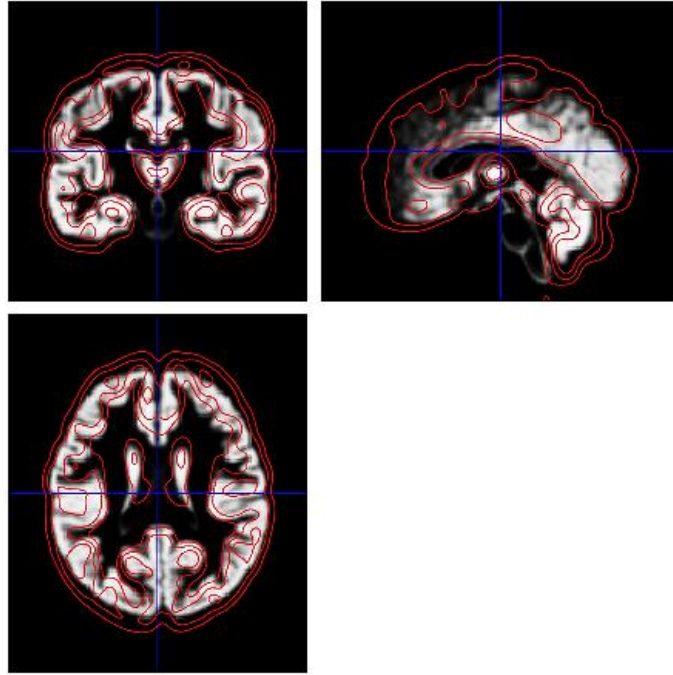


Figure 3.9: Comparison between the normalized image and ‘template_6’, highlighting template_6 with red outline

3.3.5 Image Format Conversion

In the fifth step, raw 3D NIFTI images are converted into a suitable format for ML applications (Heindl, 2022). Converting medical formats to digital formats is crucial for subsequent processing and image visualization (Akindele et al., 2023). The primary goal is to convert all visual data from the input dataset into web-compatible Portable Network Graphic (PNG) format, preserving original data integrity and preventing image data loss (Parahar, 2019). For detailed instructions on the conversion procedure, refer to Laurence (2020)⁵.

After preprocessing, the data underwent a 90° rotation, and a PNG file was generated for each subject. Each of these output files comprises 121 brain slice images, as shown in

⁵ <https://alexlaurence.github.io/NIfTI-Image-Converter/>

appendices, with the 61st section image selected as the primary data representation for each subject. This choice was grounded in the fact that the image effectively captures the central region of the brain, serving as a representative point for the data analysis and modeling processes.

All chosen images were uniformly resized to a standardized dimension of 50×50 pixels, enhancing the efficiency of feature extraction by the proposed model. Subsequently, the images underwent cropping to eliminate any unnecessary background elements, as depicted in Figure 3.10.

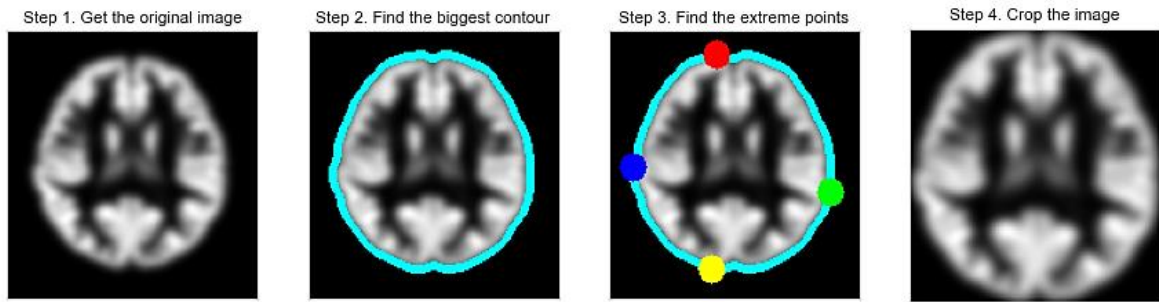


Figure 3.10: Image background cropping process

The next section explores the design and development of the proposed self-AM-ESNN models, outlining their roles and significance in this study.

3.4 Experimental Designs

This section explores the design and development of the self-AM and ESNN models, fundamental components of the novel method for improving SI assessment in depressed

young adults utilizing sMRI data. It provides insights into the design principles, methodologies, and architecture underlying these models within the broader research framework. Figure 3.11 offers an overview of the content discussed in this section.



Figure 3.11: Self-AM-ESNN design

Table 3.2 provides a breakdown of the key components of the experimental design. Each row corresponds to a specific component, including its designation, description of its role, and the process it undergoes within the research framework. This tabular format offers a concise summary of the experimental design, aiding in the comprehension and navigation of the subsequent detailed explanations.

The following section offers a detailed explanation of the self-AM-ESNN models and their frameworks. Moreover, the provided equations represent the mathematical expressions derived from the implemented codes.

Table 3.2: Experimental Design Components

No.	Design	Description	Process
1.	Self-AM Feature Extraction	Utilizes self-AM to extract features from sMRI data post-processed from depressed young adults.	Self-AM analyzes the input data to identify relevant features and patterns indicative of depression.
2.	ESNN Encoder: Encoding	Employs an ESNN encoder to transform the attention output from self-AM into a spike train representation.	The attention output is processed by the ESNN encoder, which applies radial basis function (RBF) transformation to convert it into a spike train format.
3.	ESNN Component: Classification	Utilizes the ESNN components to perform the classification task based on the spike train representation generated by the ESNN encoder.	The spike train representation is inputted into the ESNN components, which leverage its temporal dynamics to classify the input data into relevant categories, such as depressed individual or HC.

3.4.1 Self-AM Feature Extraction

In this study, the self-AM layers consist of three main components: Query (Q), Key (K), and Value (V). The input images, represented as two-dimensional (2D) arrays with pixel values of 50×50 , undergo convolutional layers to obtain representations for Q, K , and V . These representations are linear transformations of the input images, where $Q = W_Q$, $K = w_K$, and $V = W_V$. After obtaining Q, K , and V , they undergo reshaping for self-AM calculation, converting each element in the 2D grid to a sequence of vectors. The core of self-AM involves calculating attention scores, representing the similarity or relevance between Q and K for each element in the sequence.

$$A = \text{matmul}(Q \cdot K^T) \quad (3.1)$$

Here, ' A ' represents the attention scores, ' $\text{matmul}(X, Y)$ ' denotes the matrix multiplication of Q and K , and ' K^T ' represents the transpose of the K matrix. Subsequently, the *softmax* activation function is applied to normalize the attention scores, representing them as probabilities.

$$\text{Softmax}(A)_{ij} = \frac{e^{A_{ij}}}{\sum_{k=2}^n e^{A_{ik}}} \quad (3.2)$$

In this context, $\text{Softmax}(A)_{ij}$ represents the component at the i -th row and j -th row of the *softmax*-transformed matrix. Here, ' n ' is the number of K vectors, and ' A_{ij} ' is the corresponding element in the original attention scores matrix. The final step involves calculating the weighted sum of the V vectors utilizing the normalized attention scores.

$$O = A \cdot V \quad (3.3)$$

Here, O represents the output matrix, A is the attention scores matrix, and V is the value matrix. This process results in the output of the self-AM.

In summary, the self-AM architecture calculates attention scores to capture relationships between different pixels within the input images. This involves linear transformations of Q, K , and V representations, followed by *softmax* normalization, and a weighted sum operation, resulting in an attention-based representation of the input. Table 3.3 summarizes the self-AM feature extraction process.

Table 3.3: Summary of Self-AM Feature Extraction Process

No.	Process
1.	Input images represented as 2D arrays (50×50 pixels).
2.	Convolutional layers to obtain Q, K , and V representations.
3.	Linear transformation: $Q = W_Q, K = W_K, V = W_V$
4.	Reshaping for self-AM calculation, converting the grid to vectors.
5.	Calculation of attention scores: $A = \text{matmul}(Q \cdot K^T)$
6.	<i>Softmax</i> activation for normalization: $\text{Softmax}(A)_{ij} = \frac{e^{A_{ij}}}{\sum_{k=2}^n e^{A_{ik}}}$
7.	Weighted sum of V vectors utilizing normalized attention scores: $O = A \cdot V$
8.	Output: Attain attention output for ESNN encoder input data.

3.4.2 ESNN Encoder – Radial Basis Function (RBF) Transformations

The ESNN encoder, utilizing Radial Basis Function (RBF) transformation, is a fundamental component responsible for converting the attention output from the self-AM into spike train representations (Kasabov, 2019). This transformation is essential for further processing by the ESNN components and enables effective pattern recognition and classification. RBF is a mathematical function characterized by real values, with its output dependent on the distance from the origin (Dua et al., 2019; Simplilearn, 2023). The RBF function is defined as:

$$\phi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right) \quad (3.4)$$

Here, $\phi(r)$ signifies the RBF function, ' r ' is the distance from the central point, and ' σ ' is a parameter that controls the width of the RBF.

In the encoding process, each encoding field (μ_i) is systematically determined, and the calculation of the ' μ_i ' center involves a systematic approach based on the parameters such as ' num_fields ', ' i_{min} ', and ' i_{max} '. The center ' μ_i ' for the i -th encoding field is determined utilizing the following equation:

$$\mu_i = i_{min} + \frac{(2i - 3) \cdot (i_{max} - i_{min})}{2 \cdot (num_fields - 2)} \quad (3.5)$$

In this equation, ' i ' denotes the index of the value, ranging from 1 to ' num_fields '. Furthermore, ' i_{min} ', and ' i_{max} ' correspond to the minimum and maximum values of ' i ', respectively. This systematic calculation procedure is crucial for determining the precise centers for each encoding field, ensuring their effective alignment with the context of this study and the architectural requirements of the ESNN model.

Then, the standard deviation (σ_i) is calculated for each encoding field based on the ‘*beta*’ parameter. The ‘ σ_i ’ relates to the i -th encoding field and is determined through the following formula:

$$\sigma_i = \frac{i_{max} - i_{min}}{\beta \cdot (num_fields - 2)} \quad (3.6)$$

The encoding function for each field follows the RBF-like encoding of a Gaussian distribution, assigning higher values to input values near the center and lower values to those farther away. This encoding function for the i -th encoding field is as follows:

$$rcf_i(x) = \frac{1}{\sigma_i \cdot \sqrt{2\pi}} \cdot \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right) \quad (3.7)$$

In this equation, $rcf_i(x)$ represents the encoding function for the i -th encoding field, where ‘ x ’ represents the input value. Parameters ‘ σ_i ’ and ‘ μ_i ’ control the standard deviation and the center (mean) of the encoding field, respectively.

The calculation of encoding values for a given input value ‘ x ’ is systematically executed. These values are compiled into an array, ‘*encoding_values*’, which includes all individual field-based encoding values and is represented by the following equation:

$$encoding_values = [rcf_0(x), rcf_1(x), rcf_2(x), \dots, rcf_{num_fields-1}(x)] \quad (3.8)$$

This process ensures that encoding values are meticulously computed for all encoding fields, establishing a comprehensive array of encoding representations. It serves as a fundamental step in preparing input data for the ESN model. The transformation from encoding values to a spike train representation is accomplished by inverting these values, where each value is subtracted from 1. This inversion process is represented by the equation:

$$spike_train[i] = 1 - encoding_values[i] \quad (3.9)$$

Here, ‘ i ’ represents the index of the elements in the lists. This inversion is a conventional approach in spike encoding techniques and is instrumental in transforming encoding values to spike train data. The encoding procedure is summarized in Table 3.4.

Table 3.4: Summary of encoding process

No.	Process
1.	Define encoding parameters: num_fields , i_{min} , and i_{max} .
2.	Determine centers (μ_i): $\mu_i = i_{min} + \frac{(2i - 3) \cdot (i_{max} - i_{min})}{2 \cdot (num_fields - 2)}$
3.	Calculate standard deviations (σ_i): $\sigma_i = \frac{i_{max} - i_{min}}{beta \cdot (num_fields - 2)}$
4.	Gaussian encoding function ($rcf_i(x)$): $rcf_i(x) = \frac{1}{\sigma_i \cdot \sqrt{2\pi}} \cdot \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right)$
5.	Encoding process for all fields: $encoding_values = [rcf_0(x), rcf_1(x), rcf_2(x), \dots, rcf_{num_fields-1}(x)]$
6.	Inverted spike train representation: $spike_train[i] = 1 - encoding_values[i]$
7.	Output: Obtain spike train representations for input data.

3.4.3 Self-AM-ESNN Design

In the proposed model design, the self-AM acts as the feature extractor, identifying important parts of the images before encoding them into spike patterns with RBFs in the ESNN encoder (Yadav et al., 2023). Then, the encoder output was fed into the ESNN component to perform the classification task. In the ESNN framework, neurons are critical for processing spike train inputs, performing essential functions such as activation computation, synaptic weight adaptation, and firing threshold determination (Zhang et al., 2021b; Patel & Schuman., 2023). These attributes collectively enable the network to learn and execute image classification tasks on the dataset.

During the forward pass of the training process, neuron activation occurs, where each neuron in the network computes its activation based on the input spikes, current synaptic weights and thresholds:

$$A = \sum_i S_i \cdot w_i - t \quad (3.10)$$

Here, the variables are defined as follows:

- ‘ A ’ denotes the activation level of the neuron.
- ‘ S_i ’ represents the input spike received at the i -th synapse.
- ‘ w_i ’ signifies the synaptic weight at the i -th synapse.
- ‘ t ’ corresponds to the neuron’s threshold value.

After the activation are computed for all neurons in the networks, the neurons update and adapt based on input data and labels. These update rules ensure that the synaptic weights and thresholds of the neurons in the ESNN model are adjusted iteratively during the training process, enabling the model to learn and adapt to the input data effectively. This update

mechanism is crucial for the neuron's learning process, allowing it to adjust and optimize synaptic weights (w) and threshold (t) over time. The updates occur as follows:

$$w_{ij}^{new} = \frac{merge_{count} \cdot w_{ij}^{old} + w_{ij}}{merge_{count} + 1} \quad (3.11)$$

$$t_j^{new} = \frac{merge_{count} \cdot t_j^{old} + t_j}{merge_{count} + 1} \quad (3.12)$$

Where:

- ' w_{ij}^{new} ': Denotes the new value of the synaptic weight between neuron ' j ' and input spike ' i ' after the update.
- ' $merge_{count}$ ': Represents the count of merges that have occurred for the neuron.
- ' w_{ij}^{old} ': The previous value of the synaptic weight between neuron ' j ' and input spike ' i '.
- ' w_{ij} ': The weight associated with the connection between neuron ' j ' and input spike ' i '.
- ' t_j^{new} ': Denotes the new value of the threshold for neuron ' j ' after the update.
- ' t_j^{old} ': The previous value of the threshold for neuron ' j '.
- ' t_j ': Represents the threshold of neuron ' j '.

The entire classification process is visually represented in Figure 3.12.

Input: Dataset $D = \{(X_i, Y_i)\}_{i=1}^N$, where ' X_i ' is the i -th input image and ' Y_i ' is the corresponding binary label (0 or 1).

1. Data Preprocessing:
for each image X_i in D :
 Normalize X_i #Apply normalization if needed
2. Feature Extraction:
for each image X_i in D :
 $A_i = \text{SelfAttention}(X_i)$ #Apply self-attention layer
3. ESNN Encoding:
for each feature representation A_i in D :
 $S_i = \text{Encoder}(A_i)$ #Encode into spike train
4. Initialize ESNN Model Parameters:
 Initialize neuron weights w and biases b
5. Model Training:
for each (S_i, Y_i) in D :
 #Compute neuron activation
 $A_i = \text{sum}(S_i * w) + b$

 #Update neuron parameters
 $\text{merge}_{count} = \text{sum}(Y_i)$
 $w_{new} = \frac{(\text{merge}_{count} \cdot w_{old} + w_i)}{(\text{merge}_{count} + 1)}$
 $b_{new} = \frac{(\text{merge}_{count} \cdot b_{old} + b_i)}{(\text{merge}_{count} + 1)}$
6. Model Detection:
for each new input image X_{test} :
 $A_{test} = \text{SelfAttention}(X_{test})$
 $S_{test} = \text{Encoder}(A_{test})$
 $Y_{pred} = \text{Activate}(S_{test}, w, b)$ #Propagate through adapted neurons
return Y_{pred}
7. Evaluation:
 $\text{Evaluate}(Y_{pred}, Y_{true})$ #Compute classification metrics

Figure 3.12: Self-AM-ESNN design

The proposed model is initialized with key parameters as shown in Table 3.5:

Table 3.5: Proposed model key parameters

No.	Parameter	Explanation
1.	num_fields	Defines the number of fields or dimensions in the encoding process.
2.	β	Determines RBF spread, shaping encoding characteristics.
3.	i_{min}	Minimum normalized value (0.0).
4.	i_{max}	Maximum normalized value (1.0).
5.	$attention_unit$	Number of attention units in the self-AM layer.
6.	mod	Regulates synaptic weights adaptation speed during merging.
7.	sim	Determines neuron firing threshold based on synaptic weights.
8.	C	Threshold for assessing neuron similarity during merging.

3.5 Experimental Settings

This section presents strategies to improve model training, focusing on addressing imbalanced data utilizing techniques such as stratified train-test splitting, Synthetic Minority Over-sampling Technique (SMOTE), cross-validation, and data augmentation. Genetic Algorithms are utilized to optimize hyperparameters for the self-AM-ESNN model, enhancing its effectiveness in brain image classification. Figures 3.13 and 3.14 provide overviews of the classification task design and the main elements of the experimental settings.

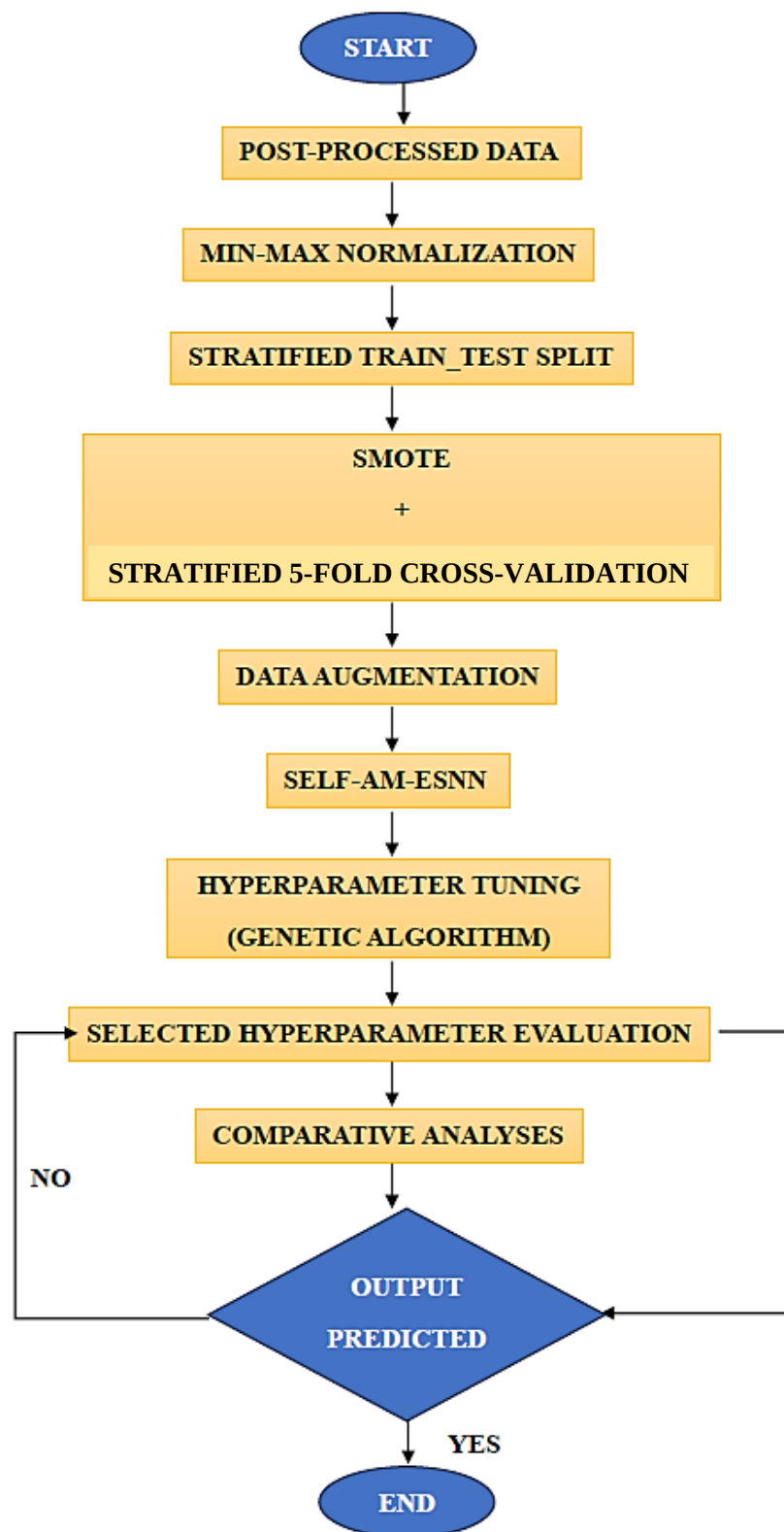


Figure 3.13: Proposed model design of the classification task for SI assessment

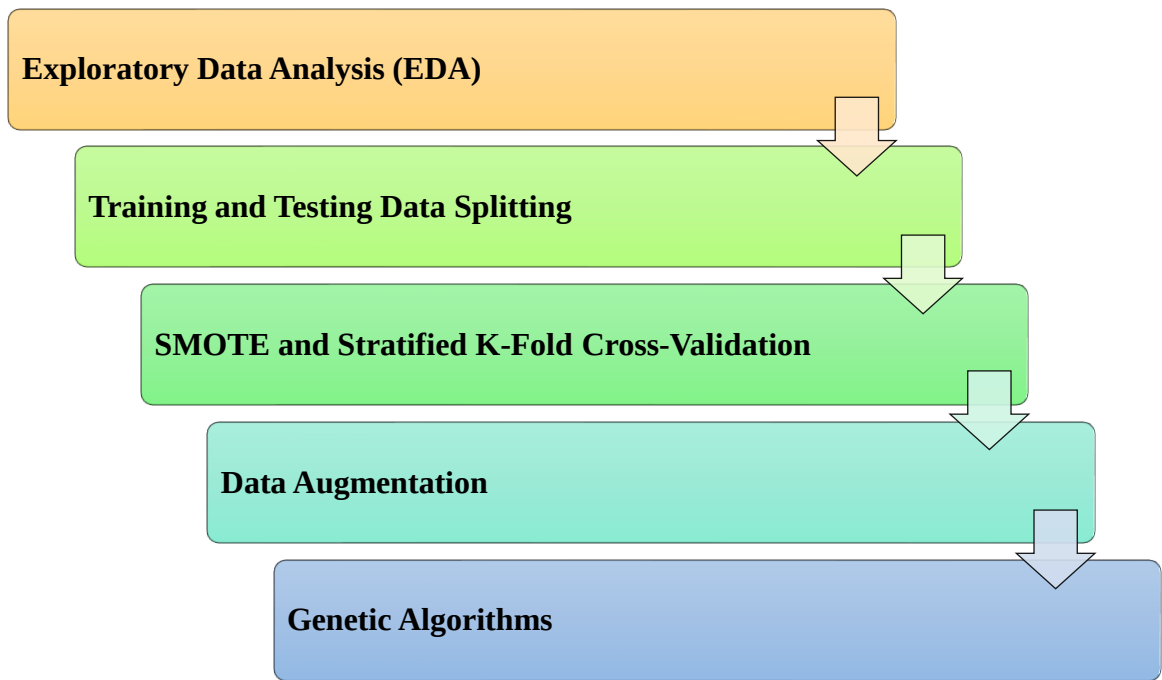


Figure 3.14: Proposed model design of the classification task for SI assessment

3.5.1 Exploratory Data Analysis (EDA)

In this study, Exploratory Data Analysis (EDA) was carefully performed on the dataset to enhance understanding of its structural characteristics and inherent features after raw data preprocessing. The dataset includes a total of 80 samples, with 20 from individuals with depression (label '1') and 60 from the HC group (label '0') c, as illustrated in Figure 3.15.

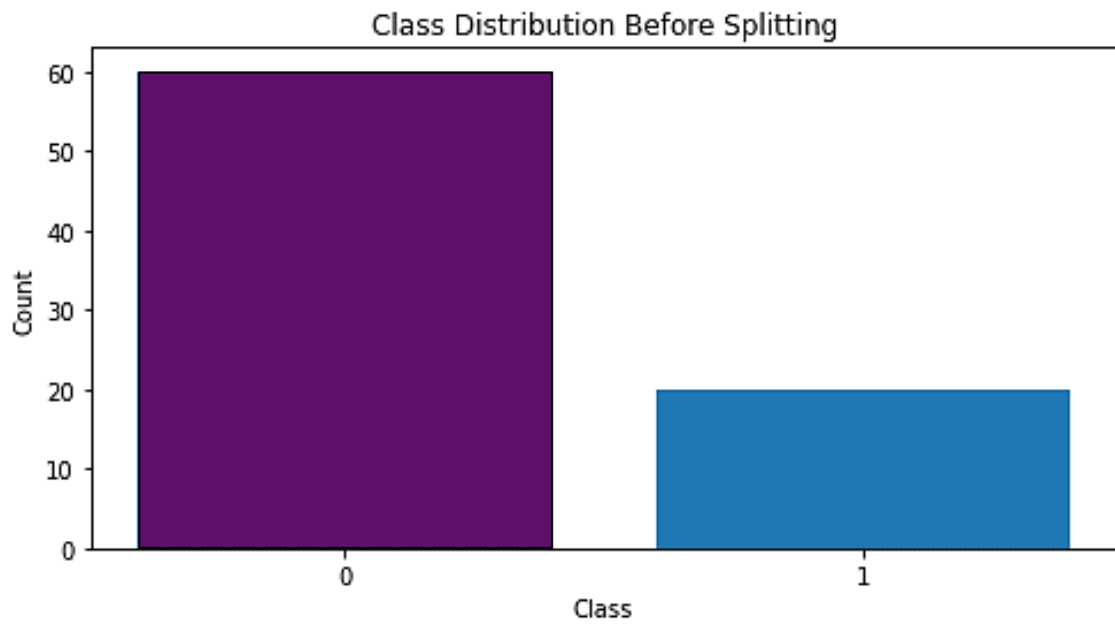


Figure 3.15: Class distribution before splitting into train and testing sets

Each image in the dataset contains a 50×50 pixel grid, with brightness values assigned to each pixel; higher values denote darker pixels. Figure 3.16 illustrates this pixel distribution.

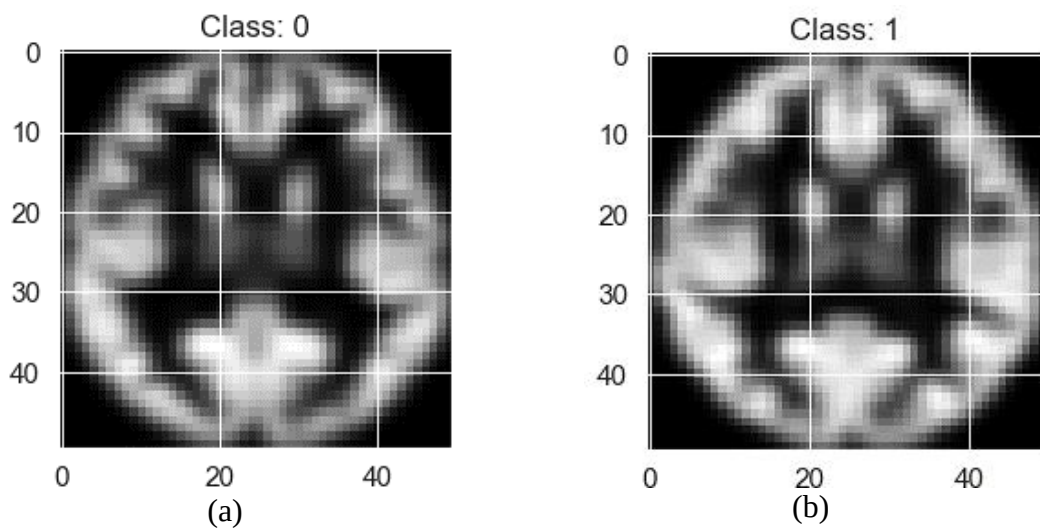


Figure 3.16: The brain image differences between “0” and “1” subjects

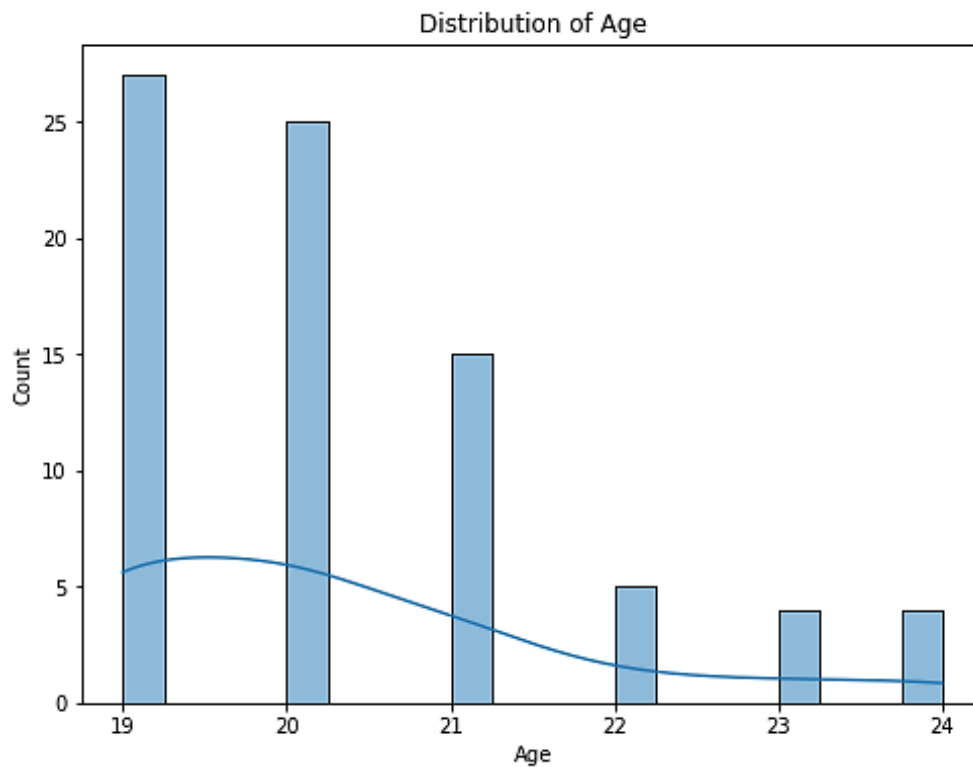


Figure 3.17: Age distribution

Figure 3.17 reveals the data distribution, with subjects averaging 20.325 years old, ranging from 19 to 24 years. Then, Figure 3.18 shows that the '1' category includes 15 female subjects and 5 male subjects, while the '0' category includes 40 female subjects and 20 male subjects.

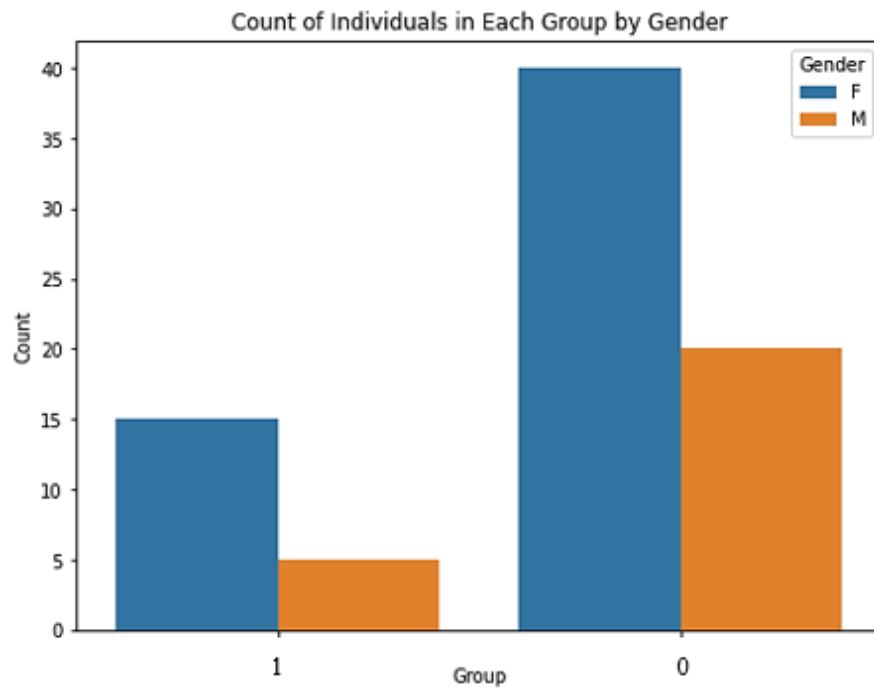


Figure 3.18: Count of individuals in each group categorized by gender

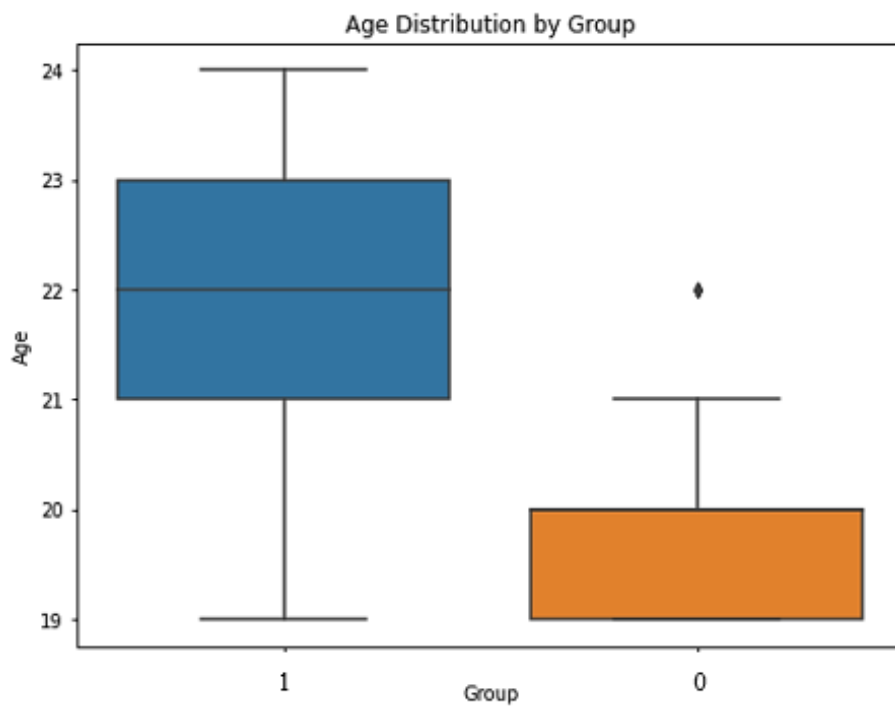


Figure 3.19: Age distribution by group

The data analysis in Figure 3.19 indicates a significant age distribution gap, with most subjects in category '1' aged 21-23 and those in category '0' aged 19-20. This imbalance, evident from the EDA visualizations, highlights a disparity between depressive individuals ('1') and HC subjects ('0'). Such class imbalance, where samples are unevenly distributed, may introduce bias in the proposed self-AM-ESNN model (López, 2021; Stocksieker et al., 2023).

In conclusion, the comprehensive EDA conducted in this section has provided valuable insights into the structural characteristics of the dataset. The examination of demographic information, gender distribution, and age ranges within the '1' and '0' categories has unveiled noticeable imbalances. These findings inform the implementation of strategies in subsequent stages to effectively address identified imbalances.

3.5.2 Min-Max Normalization

During the data preprocessing phase for the proposed model, a crucial min-max normalization process was applied to the sMRI input data. This normalization involved scaling pixel values by a factor of 255.0, transforming them into a range between 0 and 1 (Theintactone, 2023). The primary objective of this normalization was to optimize image contrast, thereby enhancing the visibility of inherent features for subsequent analyses (Theintactone, 2023).

In addition to enhancing feature visibility, the min-max normalization process plays a crucial role in facilitating efficient and accurate computations when integrating self-AM with ESNN (Richter & Wattenhofer, 2020). By scaling pixel values to a standardized range, normalization ensures consistent and stable input data, which is essential for achieving

convergence during model training (Tomar et al., 2021). Furthermore, normalization alleviates the risk of assigning unequal weight to variables with a broad range when utilizing the original scale (Liu, 2022). This ensures that the self-AM-ESNN model can effectively learn from the entire range of pixel values, without being disproportionately influenced by outliers or extreme values.

In conclusion, min-max normalization is essential for optimizing sMRI data, enhancing feature visibility, and ensuring computational efficiency when integrating self-AM with ESNN. By standardizing pixel values, this process lays the groundwork for accurate model detections and contributes to the success of this research.

3.5.3 Imbalanced Data Implementation Process

This section outlines a systematic approach aimed at addressing the challenges associated with imbalanced data. A suite of four techniques was tailored to address the inherent class imbalance, as seen in Figure 3.20. By utilizing these techniques, we aim to overcome the challenges posed by imbalanced data, thus improving the predictive performance and overall reliability of our proposed model. Importantly, these techniques are crucial for preparing the data for subsequent analysis with the self-AM-ESNN model.

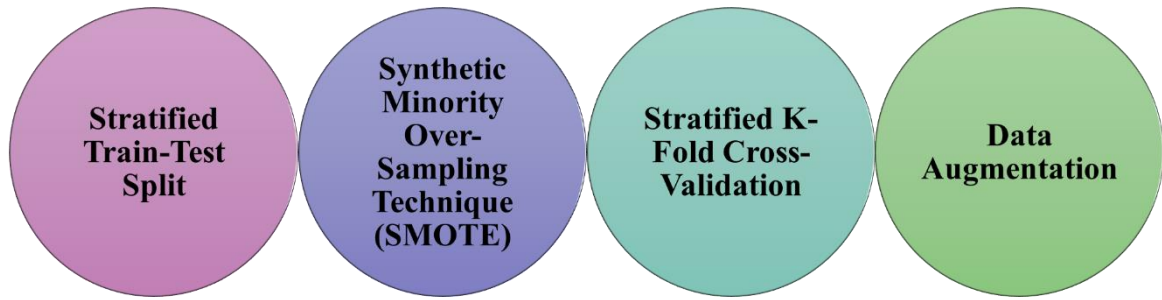


Figure 3.20: Imbalanced data implementation techniques

The original dataset was split into training and testing sets with a standard 80-20 ratio, resulting in 48 samples for training and 16 for testing (Tokuç, 2024). This partitioning utilized the stratified train-test split method to maintain balanced class proportions (Brownlee, 2020b). The 20% testing set was reserved for evaluating the model's performance on unseen data, ensuring an unbiased assessment. Utilizing a Principal Component Analysis (PCA) visualization, as shown in Figure 3.21, provides insight into the structure of the data post-split, offering valuable insights into its characteristics and distribution within the training and testing sets (Tam, 2021).

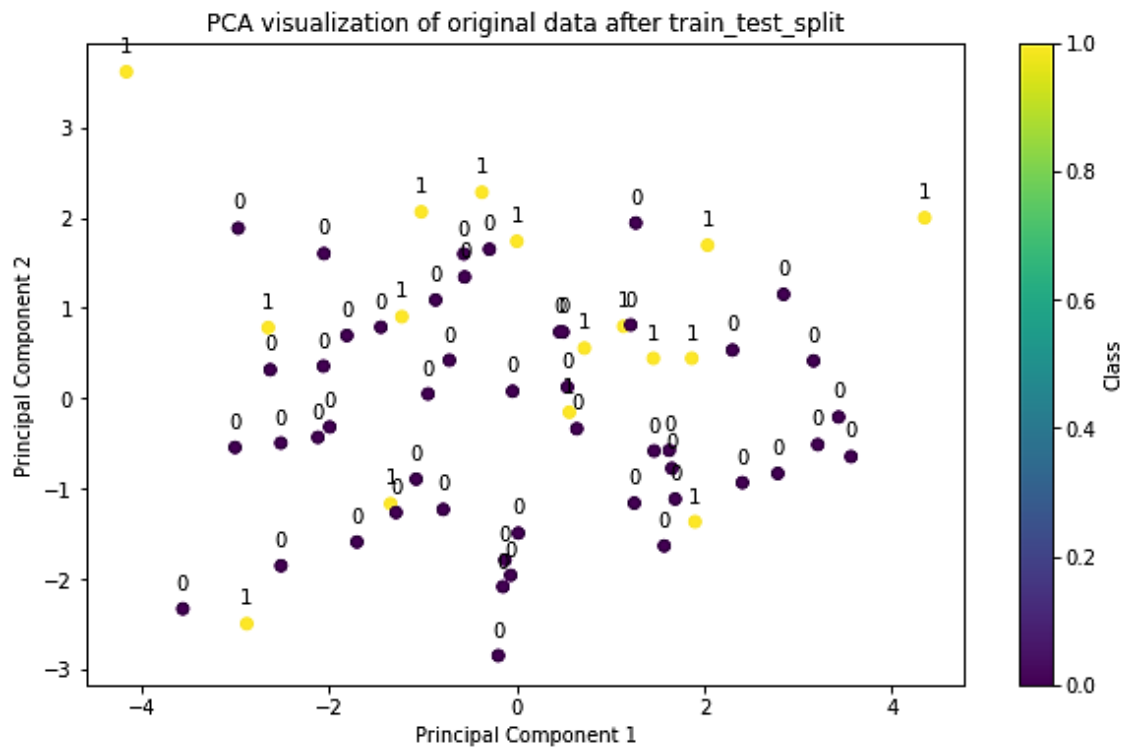


Figure 3.21: PCA visualization of the initial data after splitting into training and test groups

After splitting the data, the SMOTE algorithm was applied (Mathews & Seetha, 2022), which involves identifying the K-nearest neighbors of minority data points and generating synthetic samples along the lines between them (Brownlee, 2021; Kosolwattana et al., 2023). This was complemented by stratified 5-fold cross-validation to improve the training set quality, dividing the data into five sections for cross-validation, with one section reserved for testing in each iteration (Brownlee, 2020a). Thölke et al. (2023) recommended this approach as it can maintain balance within folds for more dependable results.

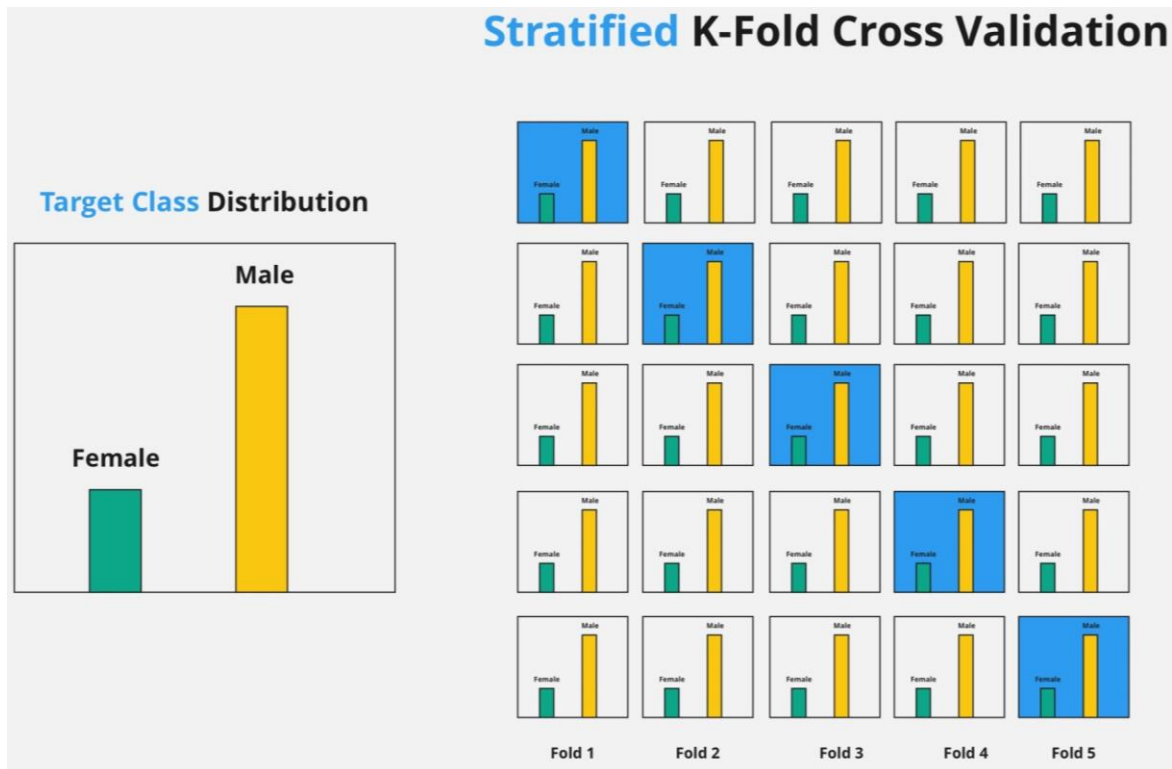


Figure 3.22: Stratified K-fold cross-validation (Turing, 2023)

Figure 3.22 illustrates the utilization of stratified K-fold cross-validation to maintain consistent class proportions across the dataset, training set, and test set, ensuring balanced and accurate performance evaluation (Muralidhar, 2021). Additionally, in this study, SMOTE increased the training dataset size by 96 samples, achieving better balance between classes. The results of this balanced approach, combining SMOTE and stratified 5-fold cross-validation, are depicted in Figure 3.23.

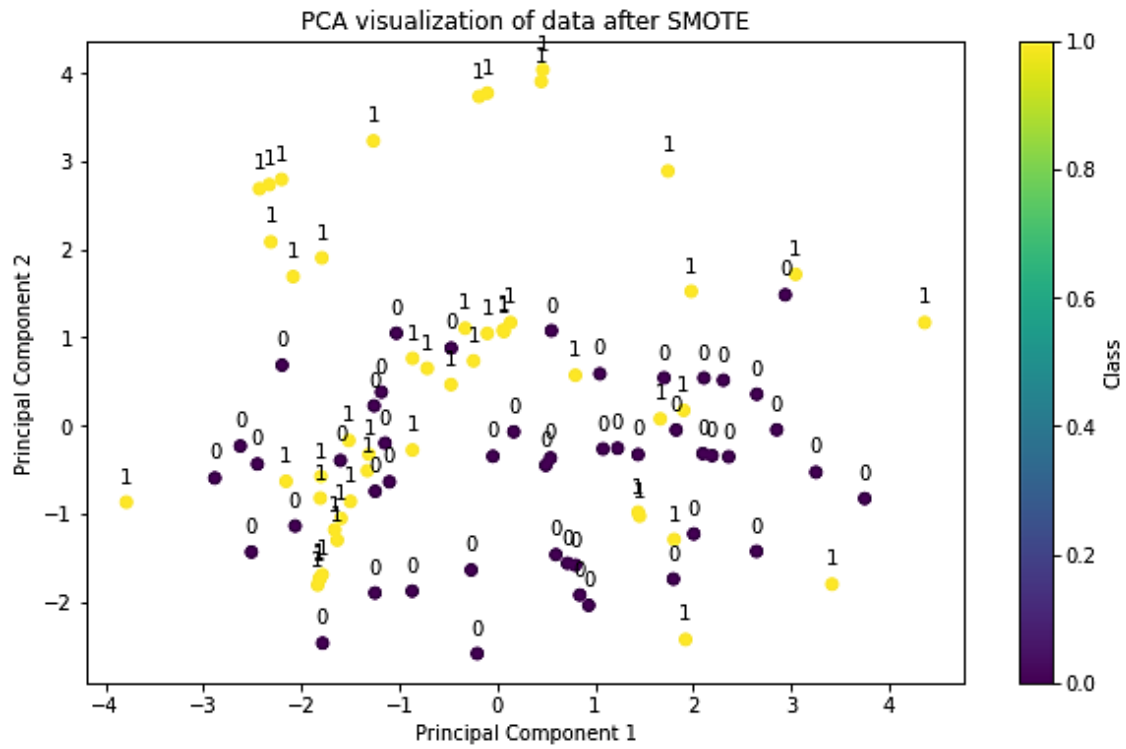


Figure 3.23: Data distribution after the implementation of SMOTE and stratified 5-fold cross-validation

This study utilized data augmentation to augment the training dataset, increasing the quantity of images to capture more data patterns and improve model performance (Picsellia, 2022). Examples of data augmentation are shown in Figure 3.24, and Figure 3.25 illustrates the distribution of training data, which includes 858 samples.

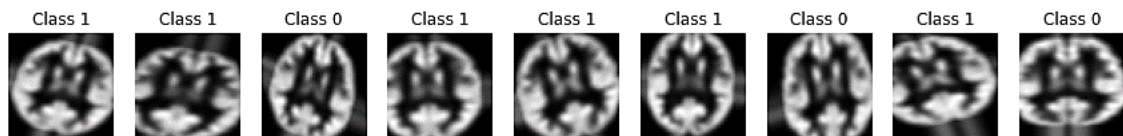


Figure 3.24: Data augmentation examples after augmentation process

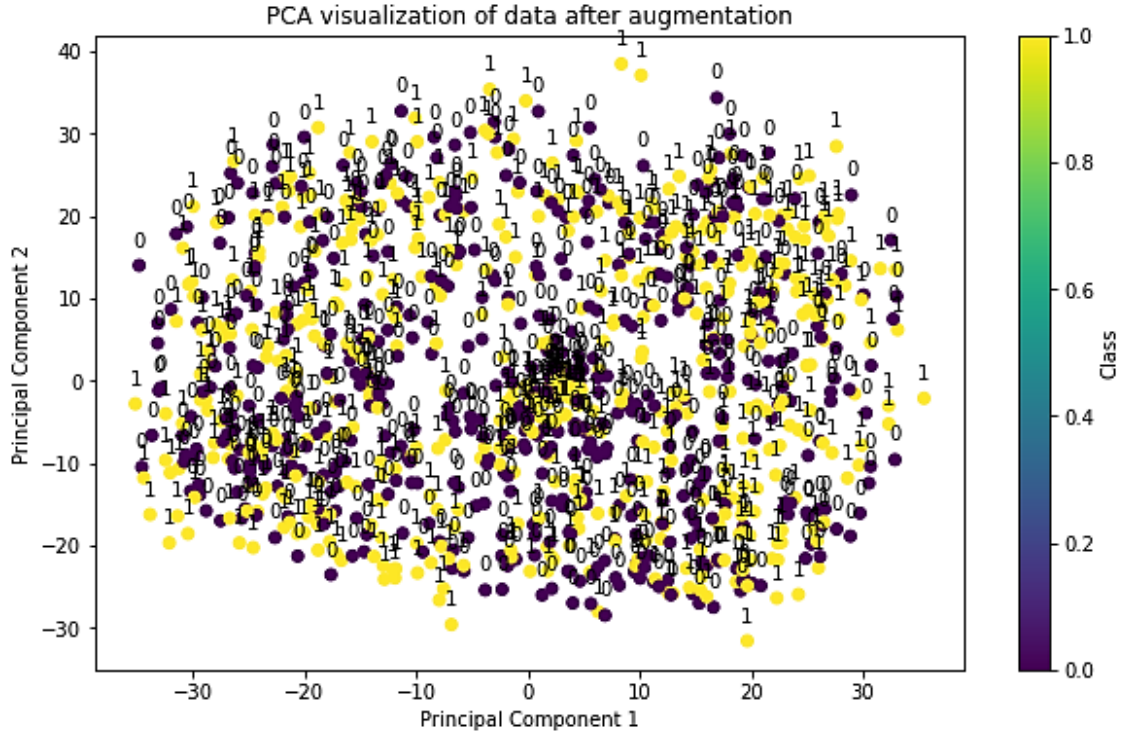


Figure 3.25: Data distribution after data augmentation

In summary, the implementation of strategies to address class imbalances, including stratified train-test split, SMOTE with stratified 5-fold cross-validation, and data augmentation, establishes a robust foundation for improving model performance. These approaches ensure unbiased evaluation and enhance the model's ability to generalize, setting the stage for subsequent hyperparameter optimization utilizing Genetic Algorithm.

3.5.4 Hyperparameter Tuning: Genetic Algorithm (GA)

Optimizing hyperparameters is crucial for maximizing the performance of the proposed self-AM-ESNN model. In this section, we employ Genetic Algorithms (GA) to determine the optimal values for the parameters of the proposed model.

GA, inspired by evolutionary principles, has demonstrated efficacy in optimizing complex real-world applications (Alhijawi & Awajan, 2023). Specifically, in computational biology, GA has proven effective in identifying economical solutions for parameter optimization (Sohail, 2023). Importantly, GA has been effectively utilized for optimizing hyperparameters in ESNN (Parsa et al., 2021; Al-Hyari, 2022; Japa et al., 2022). Studies have demonstrated that GAs effectively navigate the extensive hyperparameter space inherent in SNNs, which are distinguished by their spiking neuron communication (Liu et al., 2021). Therefore, utilizing GA can efficiently navigate the hyperparameter space of the self-AM-ESNN model, enhancing its predictive performance. This approach offers a systematic method for fine-tuning parameters, contributing to a more accurate SI detection method.

In this investigation, considering the dataset's modest size (858 for training, 16 for testing), manual selection of hyperparameter configurations from GA outcomes may offer advantages. This approach is particularly beneficial for small datasets, where automatic hyperparameter tuning methods may not be optimal (Thavasimani & Srinath, 2022). This method enables a more customized and accurate fine-tuning of hyperparameters, potentially enhancing model effectiveness, particularly in scenarios with restricted data (Johnson et al., 2020). By leveraging the outcomes of the GA and manually selecting hyperparameter configurations, researchers can efficiently optimize model settings, even with limited datasets.

In addition, the decision to select a batch size of 22 was influenced by practical considerations. Attempts to execute the GA with batch sizes exceeding 22 resulted in hardware memory overload and rapid overheating. Conversely, utilizing batch sizes below 22 significantly slowed down the GA process. Therefore, a batch size of 22 was chosen as it

represents a pragmatic compromise between computational efficiency and hardware limitations, ensuring smooth operation of the GA while maximizing model performance. Furthermore, existing research suggests that batch sizes ranging from 16 to 64 are more likely to yield highly accurate models in neural networks (Lin, 2022).

In summary, the hyperparameter tuning approach balances methodical exploration, resource efficiency, and a commitment to enhancing the proposed model's performance. As the study progresses, the researchers remain flexible to adjust the hyperparameter range based on emerging insights. Detailed parameter configurations are provided in Chapter 4, offering a concise overview of the experimental design.

3.6 Performance Evaluations

To evaluate the proposed model performance, this study utilizes metrics such as Accuracy (ACC), Sensitivity (SEN), Specificity (SPEC), and Area Under the Curve (AUC), accompanied by the crucial confusion matrix for imbalanced datasets (Mohajon, 2020). The matrix enables a comprehensive analysis beyond traditional measures (Selvaraj, 2022), incorporating key metrics such as:

1. *True Positive (TP)*: This metric quantifies how effectively the model correctly identifies positive cases as positive.
2. *True Negative (TN)*: It evaluates the model's capability to accurately group negative cases as negative.
3. *False Negative (FN)*: This metric tracks instances where the model mistakenly categorizes negative cases as positive.

4. *False Positive (FP)*: It reflects the model's performance when it inaccurately classifies positive samples as negative.

The confusion matrix provides a breakdown of the proposed model's detections compared to the actual class labels (Araf et al., 2024). Figure 3.26 presents the confusion matrix, offering a clear assessment of the model's performance with imbalanced data. The figure not only displays the confusion matrix but also breaks down the key performance metrics directly within the classification assessment. This includes the formulas for ACC, SEN, and SPEC, providing a concise reference for understanding these critical evaluation measures.

		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{(TP + FN)}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN + FP)}$
		Precision $\frac{TP}{(TP + FP)}$	Negative Predictive Value $\frac{TN}{(TN + FN)}$	Accuracy $\frac{TP + TN}{(TP + TN + FP + FN)}$

Figure 3.26: Confusion matrix and performance metrics formula (Sirsat, 2019)

ACC serves as a standard evaluation measure in ML, employed to assess a model's proficiency in accurately predicting class labels (Araf et al., 2024). Despite its limitations

with imbalanced datasets (Müller et al., 2022), ACC remains widely utilized as it offers a straightforward assessment of model effectiveness, valuable for clinicians and researchers alike (Hicks et al., 2022). Therefore, ACC was chosen as a key metric in this study to provide a basic understanding of the model's performance, although supplementary metrics are essential for a more refined evaluation (Thieme, 2021).

In the medical domain, the choice of SEN and SPEC as key metrics is grounded in their fundamental importance for accurate diagnosis and patient care (Swift et al., 2020; Müller et al., 2022). SEN is critical for identifying all positive cases, minimizing the risk of missing critical diagnoses and enabling prompt treatment to alleviate health risks (Araf et al., 2024). Similarly, SPEC plays a crucial role in reducing false alarms, ensuring that negative cases are correctly identified and averting unnecessary interventions that could burden both patients and healthcare resources (Araf et al., 2024). Utilizing these key metrics, this study aims to establish a robust SI detection model that aligns with the critical imperative of precision and patient safety.

In addition to traditional metrics such as ACC, SEN, and SPEC, this study incorporates the AUC to assess the overall performance of the classification model (Geeksforgeeks, 2023). In contemporary contexts, the AUC metric has become a prevalent method for validating ML classifiers (Müller et al., 2022). The AUC metric measures a model's ability to distinguish between positive and negative cases (Mienye et al., 2021). It ranges from 0 to 1, with higher values indicating better performance (Owusu-Adjei et al., 2023). By incorporating the AUC, this study ensures a thorough evaluation that accounts for the proposed model's ability to distinguish between different classes, enhancing the robustness of the analysis.

In summary, the thorough evaluation of model performance in this study, utilizing metrics such as ACC, SEN, SPEC, and AUC, alongside the utilization of the confusion matrix, provides a robust framework for assessing the self-AM-ESNN classification task. By considering a range of metrics, including supplementary ones such as SEN and SPEC, alongside traditional measures such as ACC, we can gain deeper insights into the capabilities and limitations of the proposed model, thereby improving decision-making in clinical settings. This holistic approach ensures a comprehensive evaluation essential for advancing the reliability and applicability of ML models in SI research.

3.7 Comparative Analyses

In this study, a series of analyses comprehensively evaluated the proposed model within a broader context. This involved benchmarking against traditional ML classifiers, a standalone ESNN model, and making a comparative assessment against relevant results from past key studies. To benchmark against ML classifiers, this study selected K-Nearest Neighbors (KNN), Logistic Regression (LR), Support Vector Machine (SVM), and a standalone ESNN model.

The KNN algorithm is widely esteemed in suicide research for predicting suicidal tendencies (Rahaman et al., 2022; Ghosh et al., 2023). Guidère's (2020) study achieved remarkable accuracy, with a 91% success rate in forecasting suicidal behavior. By leveraging KNN, researchers can effectively analyze suicide rates and foresee demographic changes following suicide incidents (Aslan et al., 2022). The extensive utilization of KNN highlights its effectiveness in predictive modeling and risk assessment in this crucial domain.

LR is widely utilized in suicide research for predictive modeling (Jain et al., 2022; Wongnontae et al., 2023). It plays a crucial role in identifying significant contributors to suicide fatalities and forecasting suicidal behavior based on diverse demographics, behavioral, and other influential factors (Jankowsky et al., 2024). In the context of depression and SI, LR collaborates with other ML algorithms such as Naïve Bayes and SVM to accurately predict posts indicating depression (Mitchell et al., 2021). Thus, LR's application in suicide research underlines its effectiveness in analyzing and forecasting suicidal tendencies across various populations and scenarios.

The SVM stands as a prevalent tool in suicide research, employed for the examination and anticipation of suicidal tendencies (Patel & Soni, 2021). Investigations have demonstrated SVM's commendable performance in detecting patterns of suicide in social media data, achieving an accuracy rate of 0.886 (Saha et al., 2023). Furthermore, studies have contrasted the accuracy of SVM with that of RF in predicting SI, revealing superior accuracy with RF (Linthicum et al., 2019). Overall, SVM plays a crucial role in suicide research by facilitating the identification and prognosis of suicidal behavior through the analysis of social media content and psychological stress indicators.

The standalone ESNN model was employed to assess whether the incorporation of self-AM enhances performance. ESNN offers unique capabilities in handling spatiotemporal data and capturing dynamic patterns, making it a promising candidate for enhancing SI detection accuracy (Ibad et al., 2020). By evaluating ESNN alongside popular ML classifiers, this study aims to explore its potential for innovation in brain image classification.

Next, a thorough comparison with past key studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023) positioned the findings of this

study. Assessing the proposed model against previous research provided insights into its innovative potential and relevance in brain image classification. Furthermore, this evaluation enhanced the understanding of the proposed model's capabilities, aiding in refining and developing more effective solutions in this challenging field.

3.8 Summary

In summary, Chapter 3 has laid the foundation for this study, encompassing essential components such as dataset description, data preprocessing, and the development of self-AM-ESNN models. The chapter delved into EDA, data preparation techniques, strategies for addressing imbalanced datasets, and hyperparameter tuning. These outlined strategies form a robust groundwork for the proposed model evaluation, which be explained upon in Chapter 4.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Overview

This chapter presents a thorough examination of the outcomes and insights obtained from evaluating the self-AM-ESNN model. It is divided into key sections, focusing on optimization and comparative analyses.

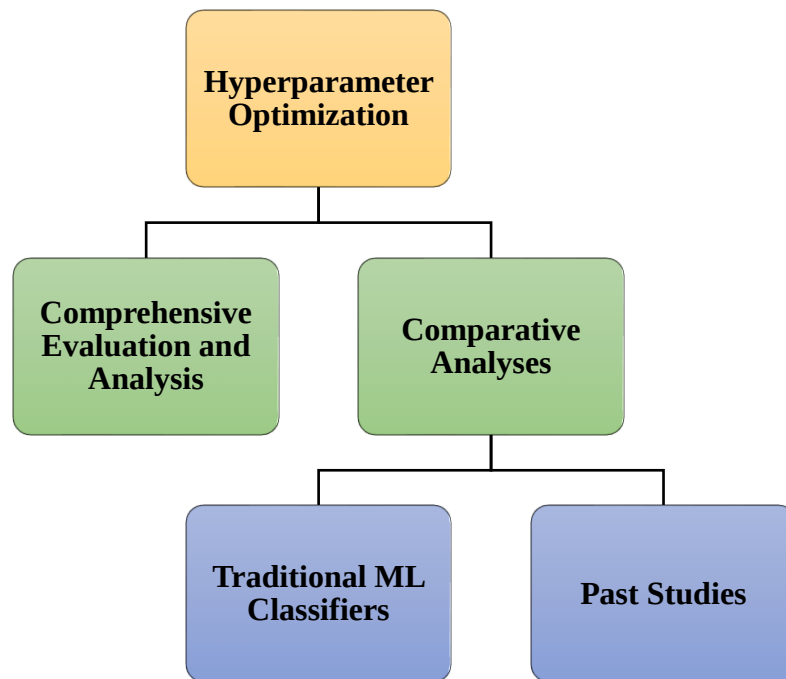


Figure 4.1: Chapter 4 overview

4.2 Hyperparameter Optimization

In this study, a GA was employed to systematically optimize the proposed model by exploring key parameters within the hyperparameter space (Rendyk, 2024). The specific configuration values utilized for the GA hyperparameter optimization are detailed in Table 4.1.

Table 4.1: Hyperparameter configuration

No.	Hyperparameter	Configuration
Self-AM-ESNN parameter		
1.	<i>Num_fields</i>	[5, 26]
2.	<i>Beta</i>	[0.0, 1.0]
3.	<i>I_{min}</i>	0.0
4.	<i>I_{max}</i>	1.0
5.	<i>Attention_units</i>	[5, 26]
6.	<i>Mod</i>	[0.0, 1.0]
7.	<i>C</i>	[0.0, 1.0]
8.	<i>Sim</i>	[0.0, 1.0]
9.	<i>Learning_rate</i>	[0.001, 0.1]
10.	<i>Epoch</i>	[5, 26]
GA Parameter		
11.	<i>Max_num_generation</i>	5
12.	<i>Num_population</i>	5
13.	<i>Mutation_chance</i>	0.3

It is crucial to note that as the number of hyperparameters involved in the tuning process increases, the optimization procedure tends to slow down. Hence, in the context of our study, we emphasize the importance of focusing on a minimal subset of model hyperparameters during the search and tuning process, as advocated by Brownlee (2020b). The chosen configuration values for the GA, as observed in Table 4.1, were meticulously selected to maintain a balanced approach between examination and development, aligning with the characteristics of our dataset and the objectives of our study. With a dataset comprising 858 training and 16 testing samples, it was necessary to tailor the hyperparameters to suit the data's complexity adequately.

The constants ' I_{min} ' and ' I_{max} ' were determined through prior min-max normalization, ensuring the model's compatibility with the dataset's [0.0, 1.0] range. Furthermore, parameters such as '*num_fields*', '*epoch*', and '*attention_units*' were set within a range of 5 to 26 for adaptability in capturing complex data patterns. The selection of the '*epoch*' range was carefully determined to ensure convergence without overfitting. This approach was integral to our research methodology, aiming to optimize model performance while maintaining generalizability and robustness.

The ESNN parameters '*mod*', '*C*', '*sim*,' as well as the encoder parameter of '*beta*,' are recommended to fall within the range of 0 to 1, as emphasized by Kasabov (2019), Ibad et al. (2020), and Shen et al. (2023). This range is advocated to facilitate effective evolutionary structure learning and optimal learning outcomes. In addition, the '*learning_rate*' bounds ([0.001, 0.1]) enable the optimizer to adjust weights effectively. GA parameters, on the other hand, balance efficiency and population diversity, aiding in the exploration of the hyperparameter space.

Selecting the model's hyperparameter is a complex task, requiring multiple iterations to experiment with various combinations and identify the optimal configuration (Avberšek & Repovš, 2022). Employing this approach, the GA produced ten unique hyperparameter configurations (refer to Table 4.2) and it systematically evaluated all ten hyperparameters based on performance metrics of ACC, SEN, SPEC, and AUC (refer to Figures 4.2 to 4.11).

The decision to evaluate ten hyperparameter configurations strikes a balance between thorough exploration and computational efficiency. This number allows for sufficient coverage of settings without overwhelming resources or risking overfitting. Moreover, it provides a robust sample size for the analysis and comparison of performance metrics. However, practical constraints, such as time and complexity, also influenced this decision. Overall, ten configurations offer a comprehensive yet feasible approach to identifying an optimal setting.

Table 4.2: Hyperparameter configuration generated by the GA (*Best results highlighted in bold)

Hyperparameter (HP)	Epoch	Num_fields	Beta	I _{min}	I _{max}	Attention_units	Mod	C	Sim	Learning_rate
1.	23	20	0.74	0.0	1.0	20	0.86	0.11	0.20	0.05
2.	10	23	0.61	0.0	1.0	24	0.83	0.56	0.60	0.03
3.	25	7	0.31	0.0	1.0	20	0.17	0.13	0.55	0.001
4.	5	20	0.14	0.0	1.0	5	0.16	0.4	0.4	0.1
5.	15	19	0.53	0.0	1.0	20	0.72	0.19	0.49	0.1
6.	25	15	0.42	0.0	1.0	20	0.53	0.94	0.33	0.1
7.	25	24	0.30	0.0	1.0	20	0.61	0.96	0.90	0.001
8.	25	7	0.32	0.0	1.0	20	0.44	0.32	0.77	0.001
9.	25	5	0.10	0.0	1.0	20	0.02	0.97	0.94	0.001
10.	7	24	0.36	0.0	1.0	12	0.93	0.99	0.74	0.03

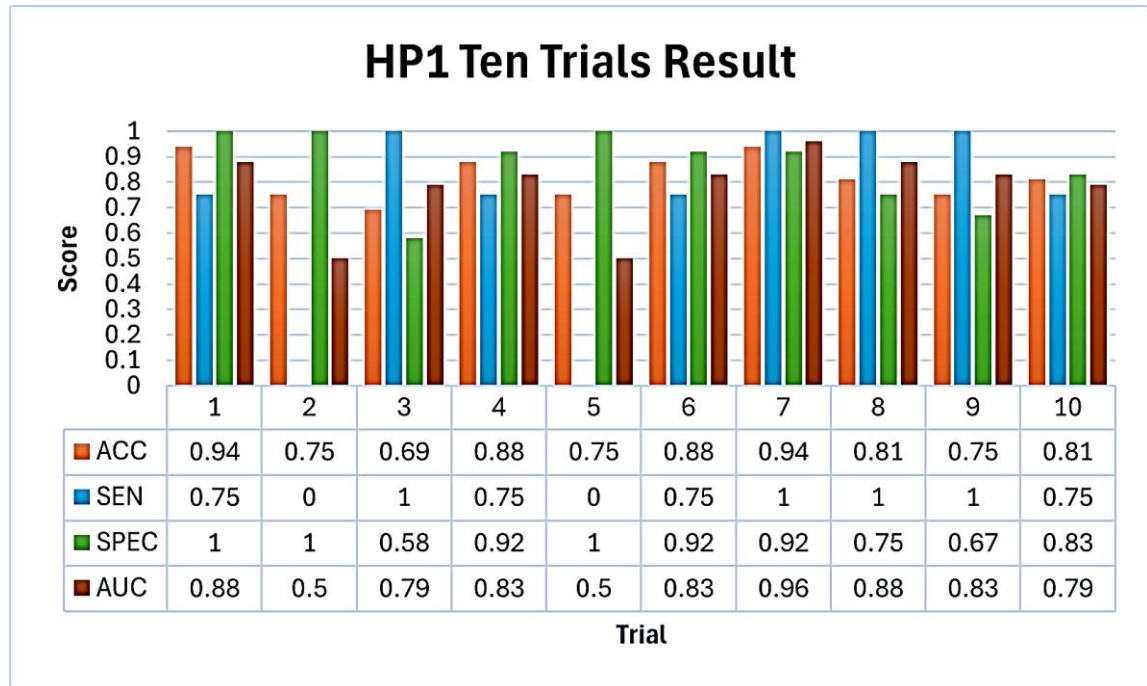


Figure 4.2: Hyperparameter 1 ten trials result

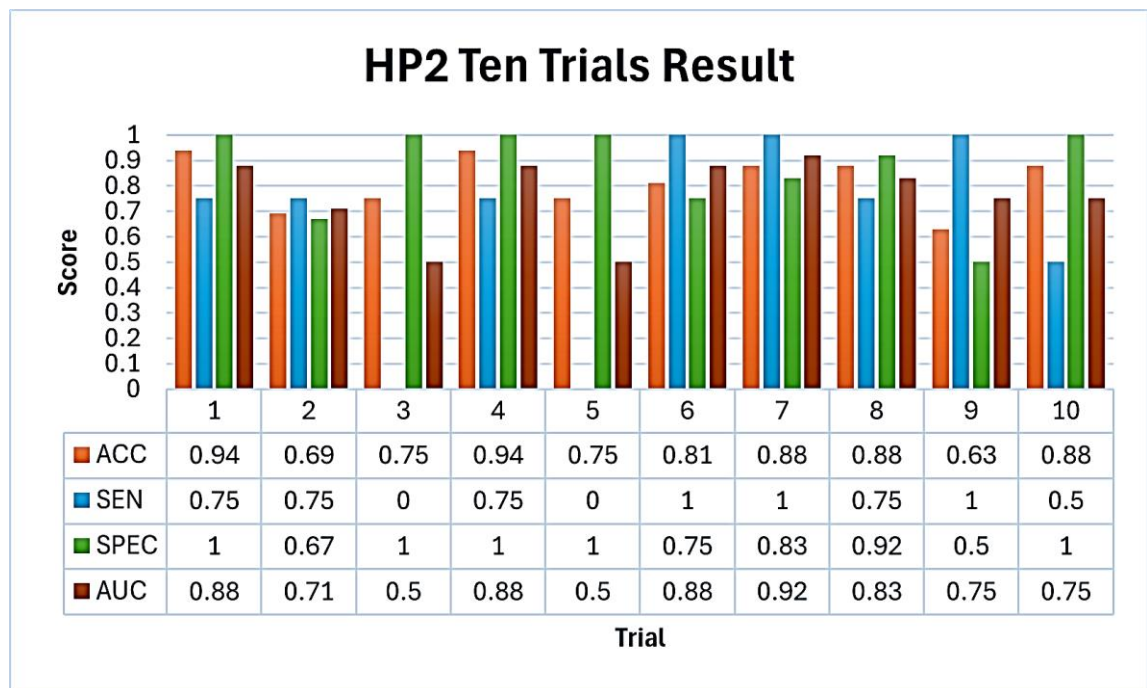


Figure 4.3: Hyperparameter 2 ten trials result

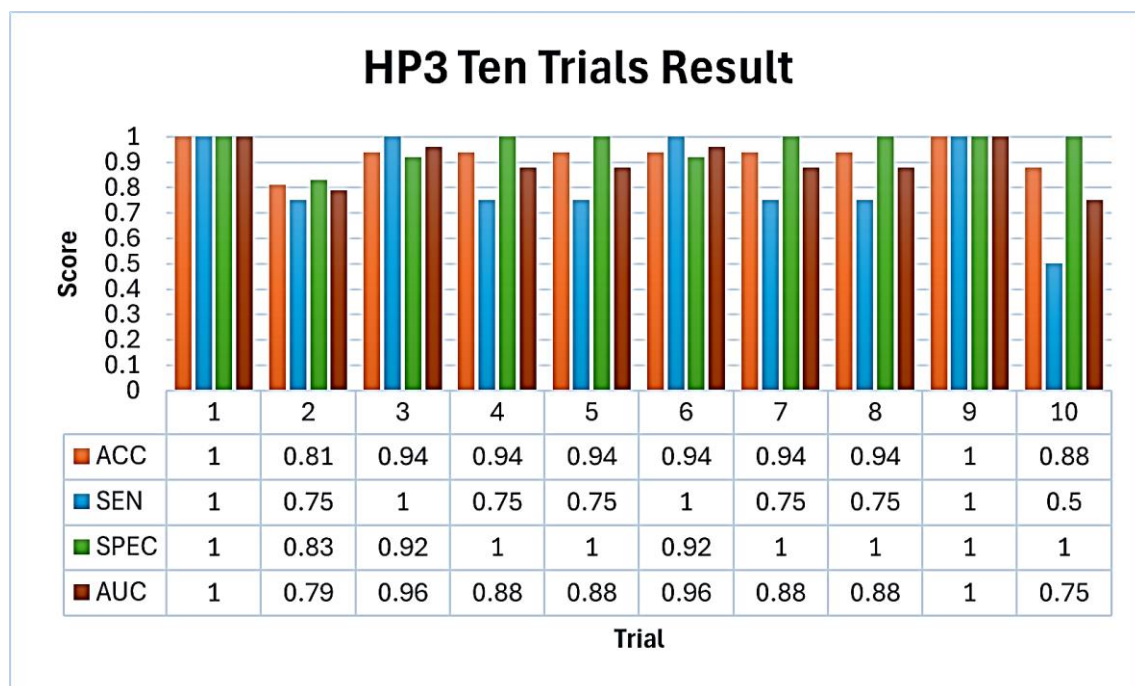


Figure 4.4: Hyperparameter 3 ten trials result

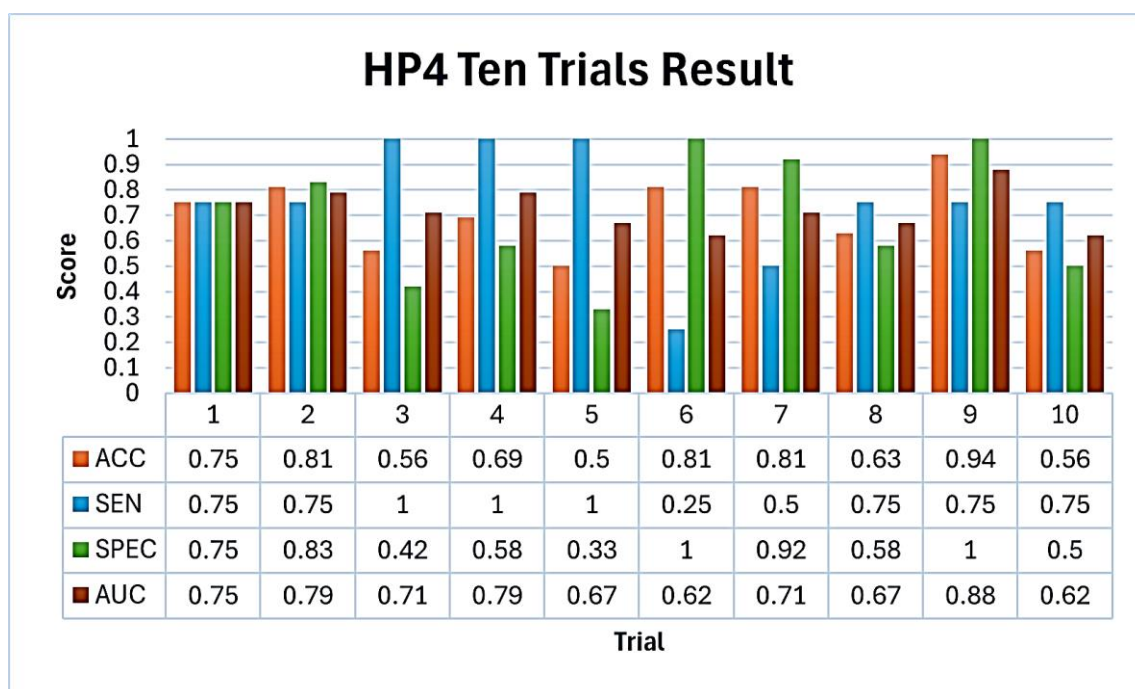


Figure 4.5: Hyperparameter 4 ten trials result

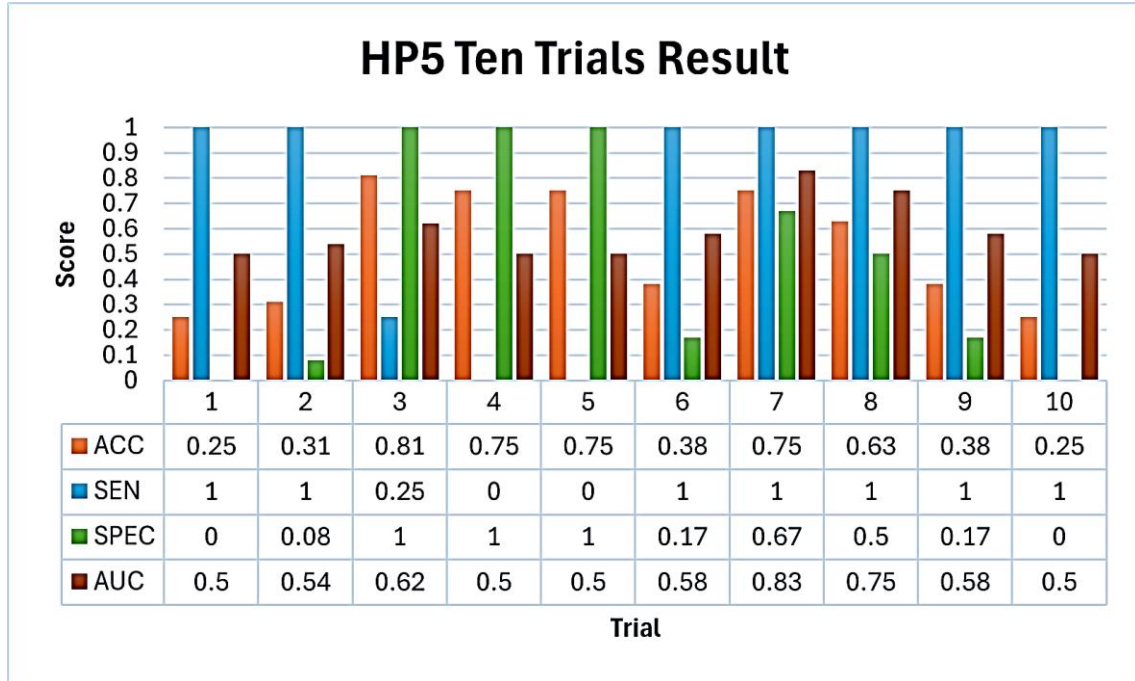


Figure 4.6: Hyperparameter 5 ten trials result

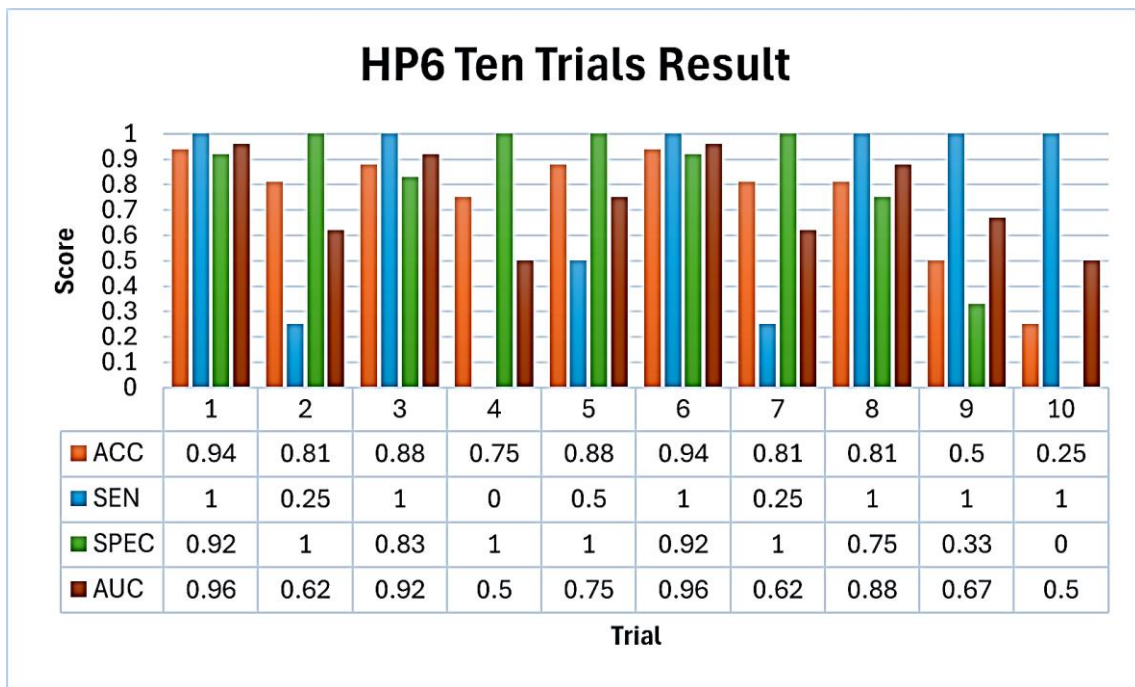


Figure 4.7: Hyperparameter 6 ten trials result

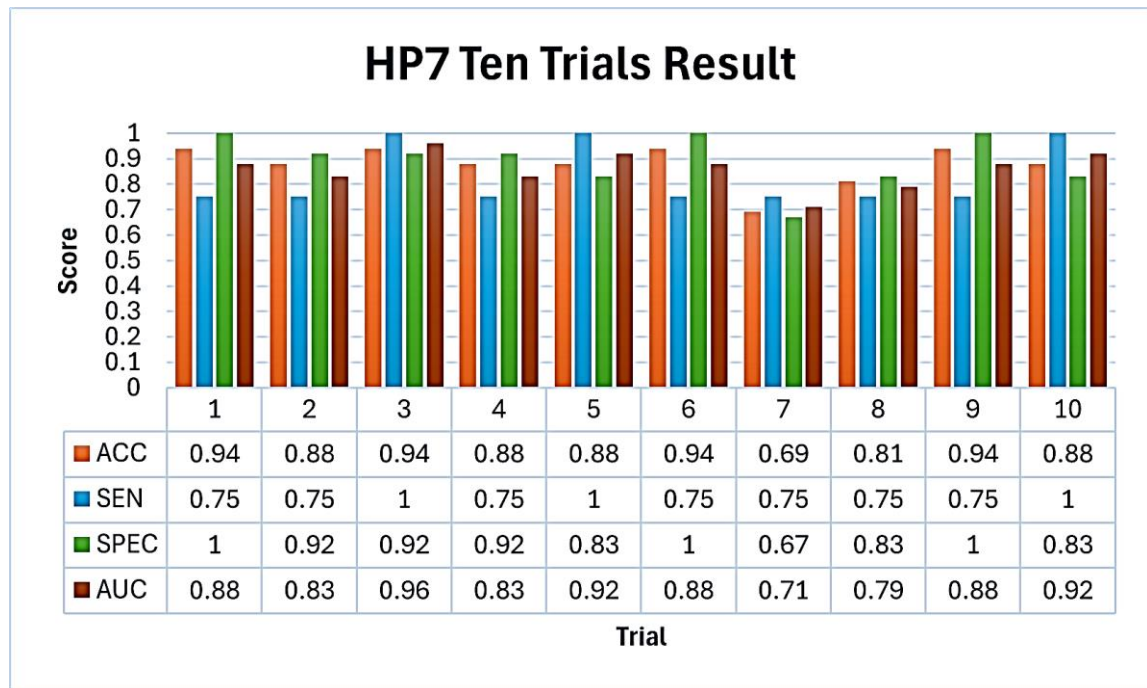


Figure 4.8: Hyperparameter 7 ten trials result

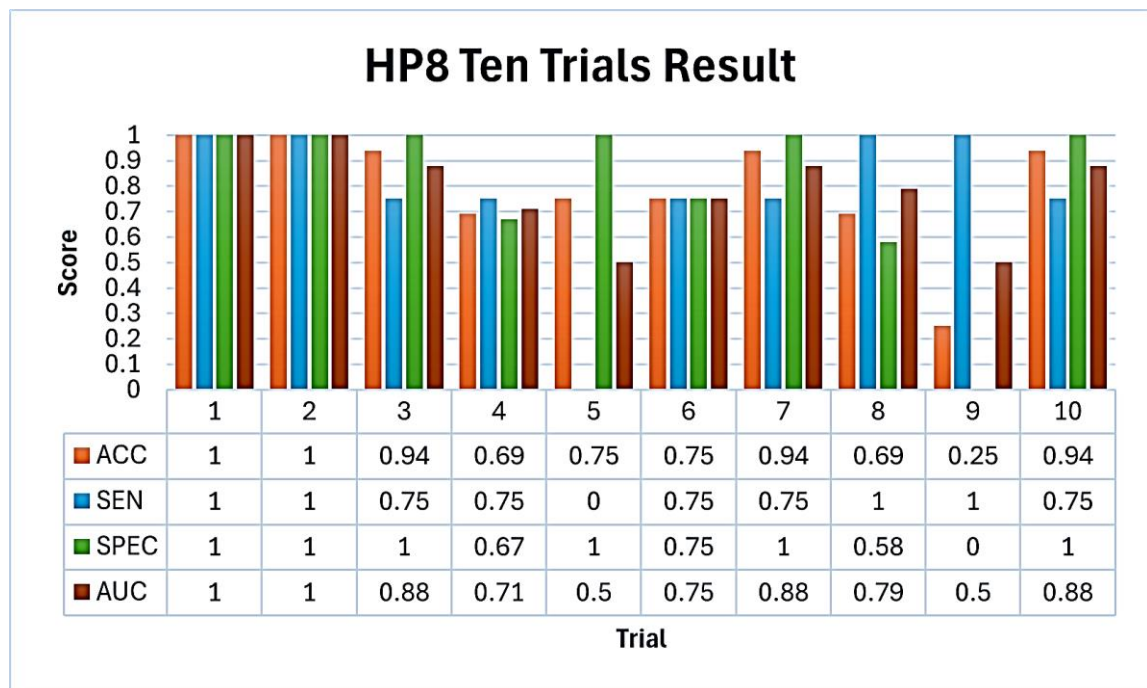


Figure 4.9: Hyperparameter 8 ten trials result

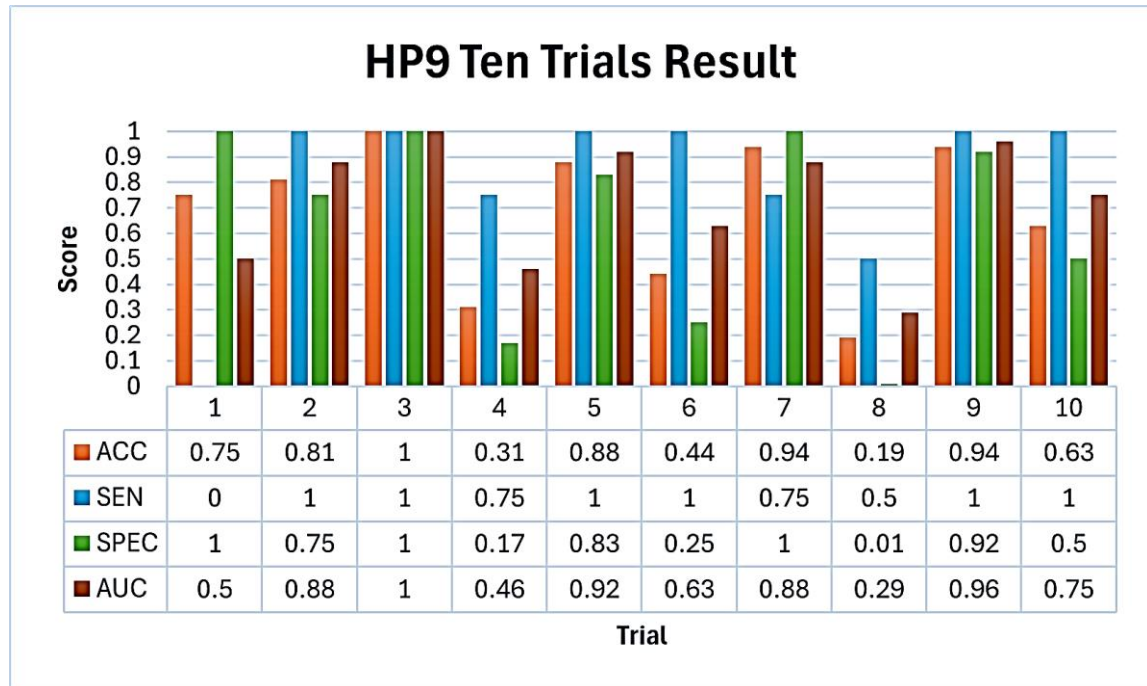


Figure 4.10: Hyperparameter 9 ten trials result

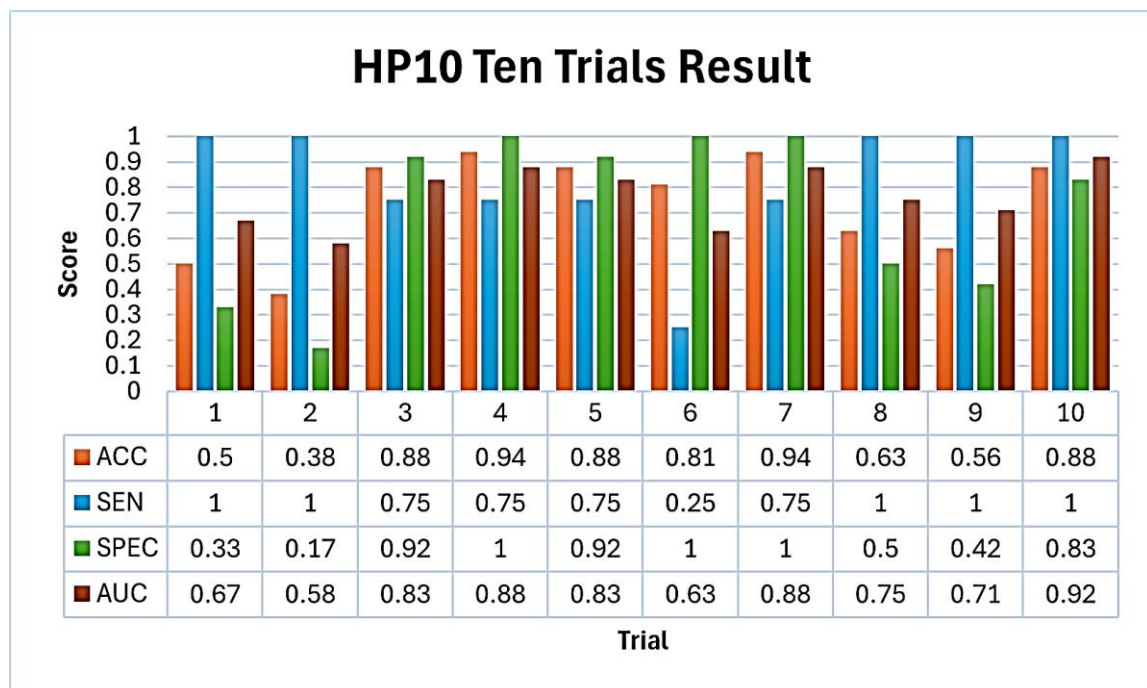


Figure 4.11: Hyperparameter 10 ten trials result

Hyperparameter 1 (refer to Figure 4.2) demonstrates overall effectiveness with an average ACC of 82%. SEN averages 70%, indicating its ability to identify positive instances, although with variability from 0% to 100% across trials. SPEC is robust, averaging 86%, accurately identifying negative instances. The AUC is 0.78, suggesting balanced performance. While the model consistently exhibits robust ACC and SPEC, attention is needed for trials with lower SEN.

Similarly, hyperparameter 2 results (refer to Figure 4.3), with an average ACC of 82%, demonstrate commendable ACC and SPEC, effectively classifying instances. However, there is variability in trial-specific ACC (ranging from 63% to 94%) and SEN (ranging from 0% to 100%). The model's strong SPEC (average of 87%) and balanced AUC (average of 0.76) indicate reliability, yet variations in SEN are observed.

As seen in Figure 4.4, hyperparameter 3 highlights impressive performance with an average ACC of 93.3%. SEN averages 82.5%, and SPEC is exceptional at 96.7%. The average AUC is 0.90, showcasing a harmonious balance. Across trials, the HP3 model consistently displays excellence, instilling strong confidence in its predictive capabilities.

On the contrary, hyperparameter 4 (refer to Figure 4.5) presents mixed performance with an average ACC of 71%. SEN varies from 25% to a perfect 100%, indicating inconsistency. SPEC averages 69%, with trial-specific values ranging from 33% to 100%, suggesting variability in performance. The average AUC stands at 0.72, reflecting a fair balance, although with some variability. Noticeably, Trial 3 exhibits signs of overfitting, potentially due to data leakage, wherein the training data unintentionally influences the testing data, resulting in inflated model performance (Barla, 2023).

Furthermore, as depicted in Figure 4.6, hyperparameter 5 presents a challenging performance, with an average ACC of 53%. SEN averages 73%, albeit with trial-to-trial variability. SPEC averages 45%, with individual trial values spanning from 0% to 100%, indicating inconsistency in correctly identifying negative instances. The average AUC is 0.59, reflecting a fair balance. However, Trials 2, 6, and 9 display signs of overfitting.

Hyperparameter 6 (refer to Figure 4.7) demonstrates moderately successful performance, with an average ACC of 76%. SEN averages 70%, with trial-specific values varying, and SPEC shows a strong average of 78%, showcasing the model's proficiency in correctly identifying negative instances. The average AUC is 0.74, indicating a balanced performance. While the model consistently demonstrates robust ACC and SPEC, there are variations in SEN across trials.

However, as seen in Figure 4.8, hyperparameter 7 results demonstrate a strong overall performance, with an average ACC of 87.8%. SEN averages an impressive 82.5%, and SPEC displays a robust average of 89.2%. The average AUC is 0.86, suggesting a well-balanced performance. While the model consistently exhibits strong ACC and SPEC, two trials (2 and 7) show signs of overfitting. Similarly, hyperparameter 8 (refer to Figure 4.9) also performs well, with an average ACC of 83.9%. SEN averages 77.5%, and SPEC shows an average of 80%. The average AUC is 0.79, reflecting a balanced performance. Regardless of this, two trials (8 and 9) exhibit signs of overfitting.

Hyperparameter 9 (refer to Figure 4.10) results present a challenging performance, with an average ACC of 68.9%. SEN averages at 80%, while SPEC averages at 64.2%, suggesting the model's struggle in correctly identifying negative instances. The average AUC is 0.73, reflecting a balanced performance. Nevertheless, several trials (1, 4, 6, 8, and 10) exhibit signs of overfitting.

Lastly, hyperparameter 10 (refer to Figure 4.11) results exhibit a moderate performance, with an average ACC of 74%. SEN averages 83%, while SPEC shows a reasonable average of 71%. The average AUC is 0.77, reflecting a balanced performance. Conversely, several trials (2, 8, 9, and 10) display signs of overfitting.

The performance of the ten hyperparameter configurations varies. Some trials achieve perfect scores without overfitting, indicating effective generalization. On average, hyperparameter 3 excels in accuracy and reliability, hyperparameters 1 and 2 perform consistently, hyperparameter 4 shows mixed results, hyperparameter 5 faces overfitting, and hyperparameter 6 has moderate success. Hyperparameters 7 and 8 perform well but with overfitting concerns, hyperparameter 9 struggles with accuracy and specificity, and hyperparameter 10 performs moderately with occasional overfitting.

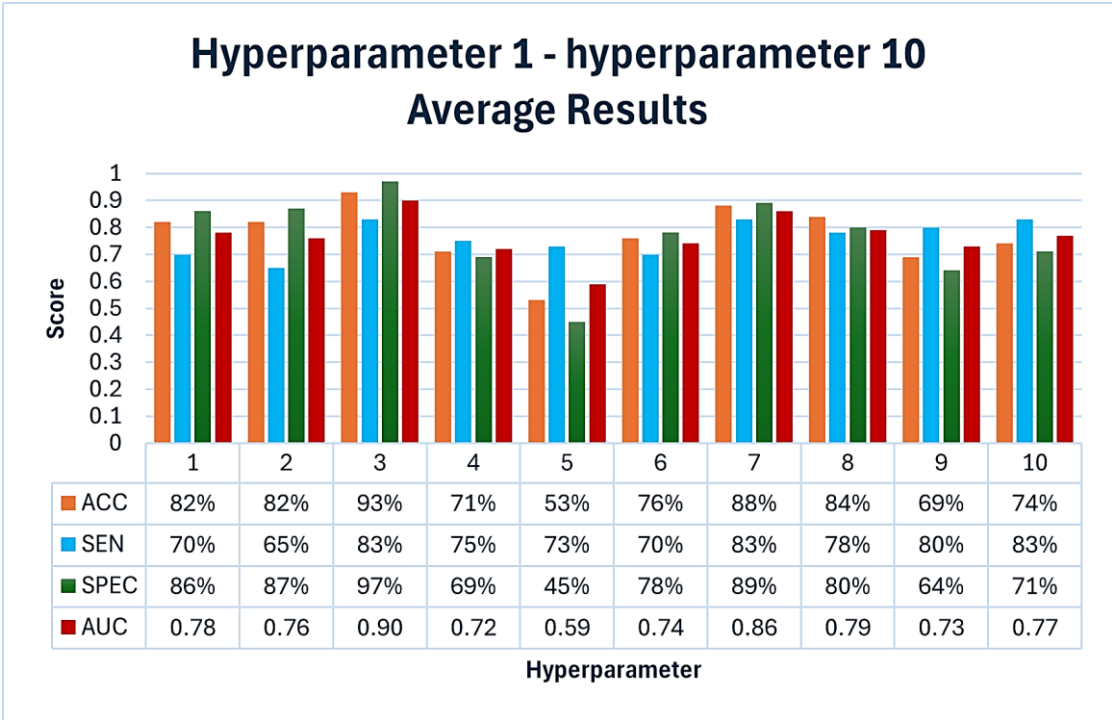


Figure 4.12: Hyperparameter configuration based on ten trials performance comparison

As depicted in Figure 4.12, the AUC metric highlights hyperparameter 3's robustness in balancing SEN and SPEC, suggesting an optimal trade-off. These findings provide a basis for selecting hyperparameter 3 as the most suitable hyperparameter configuration, informing subsequent model development and refinement. The iterative and adaptive nature of hyperparameter tuning aligns with the overarching goal of enhancing model performance.

4.3 Comprehensive Evaluation and Analysis

To comprehensively evaluate the hyperparameter 3 configuration, an in-depth analysis is conducted, assessing its performance across key metrics and its ten trials. This detailed evaluation intends to present refined exploration of the effectiveness of hyperparameter 3 in enhancing the model's capability to perform the classification task.

Figure 4.13 presents the model summary for hyperparameter 3's configuration, representing the proposed model's architecture. This configuration integrates a self-AM for efficient feature extraction from 50×50 pixel grayscale images, ultimately culminating in a dense layer with 50,121 parameters customized for binary classification.

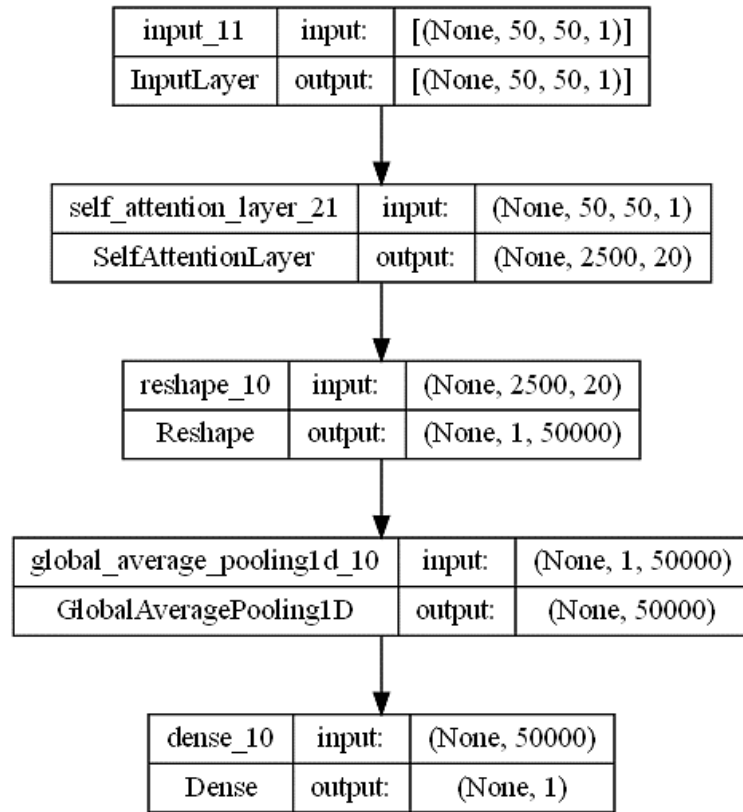


Figure 4.13: Model summary

In previous Figure 4.4, the comprehensive analysis of ten trials reveals that the proposed model consistently maintains a high level of ACC, ranging from 81% to 100%. However, there is noticeable variability in SEN, ranging from 50% to 100%, indicating differing success rates in correctly identifying positive instances. On the other hand, SPEC remains consistently high, ranging from 83% to 100%, affirming the model's proficiency in correctly identifying negative instances. The AUC scores ranging from 0.75 to 1.00 further highlight the model's varying discriminative ability across trials.

The analysis showcased outstanding performance metrics, with the highest achieving 94% ACC, 100% SEN, 92% SPEC, and an impressive AUC of 0.96. Conversely, hyperparameter 3 exhibited lower metrics, registering 81% ACC, 75% SEN, 83% SPEC,

and an AUC of 0.79. On average, hyperparameter 3 attained 93% ACC, 83% SEN, 87% SPEC, and an AUC of 0.90, as illustrated in Figure 4.14.

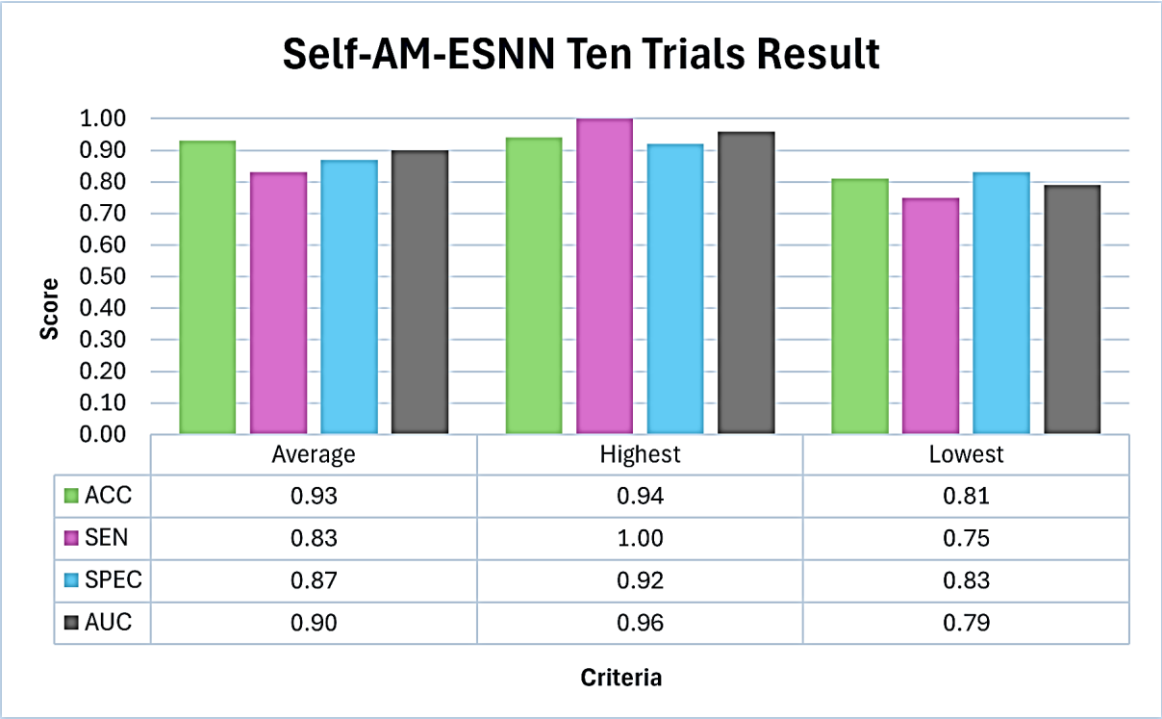


Figure 4.14: Self-AM-ESNN ten trials performance metrics across different criteria (average, high and low)

Figure 4.15 illustrates the training progress of trial 3 (highest results), demonstrating a consistent reduction in training loss. This decline indicates the model's improving predictive capabilities, resulting in the highest performance. Furthermore, the decreasing training loss reflects successful learning and adaptation to data patterns, highlighting the effectiveness of the chosen hyperparameter in cultivating improved model performance.

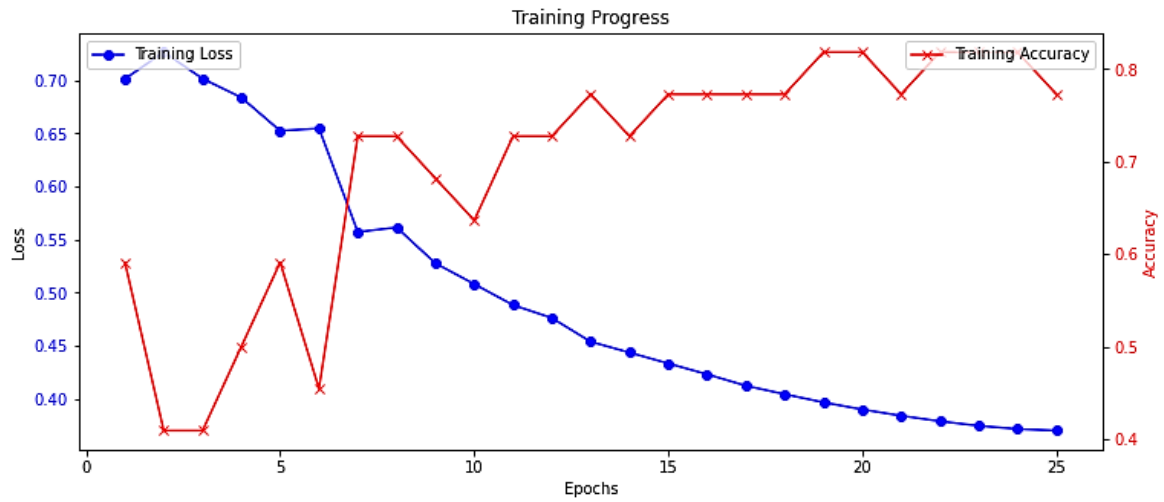


Figure 4.15: Training progress visualization for the final models' results

Furthermore, Figure 4.16 displays the Receiver Operating Characteristics-Area Under the Curve (ROC-AUC) curve. The orange curve represents the ROC for the classifier under evaluation, with an AUC of 0.96, indicating excellent performance in distinguishing between the two classes (Nahm, 2022). The closer the ROC curve is to the top-left corner, the higher the true positive rate and the lower the false positive rate, indicating better classifier performance.

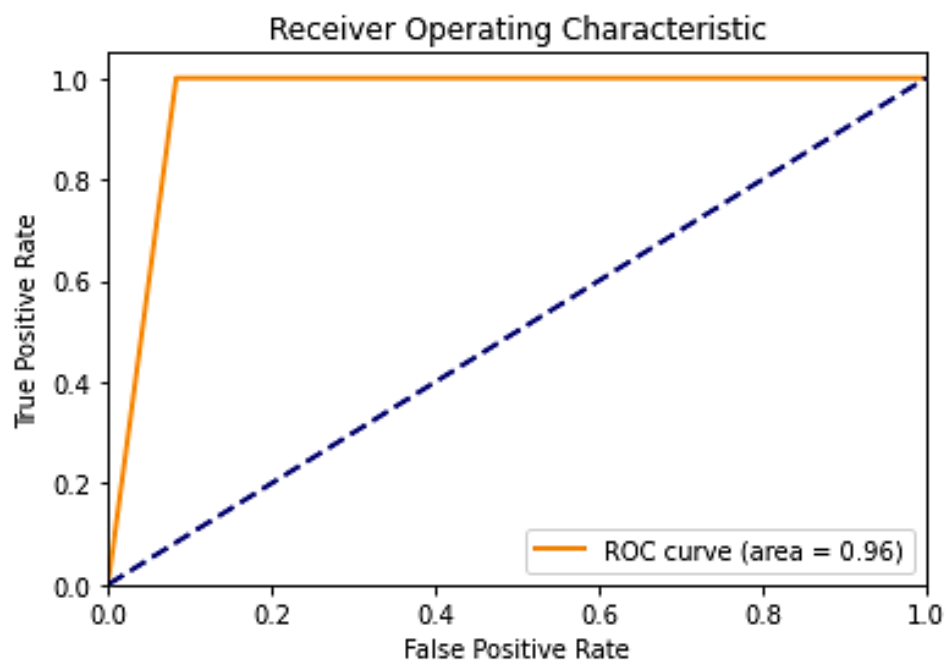


Figure 4.16: ROC-AUC curve

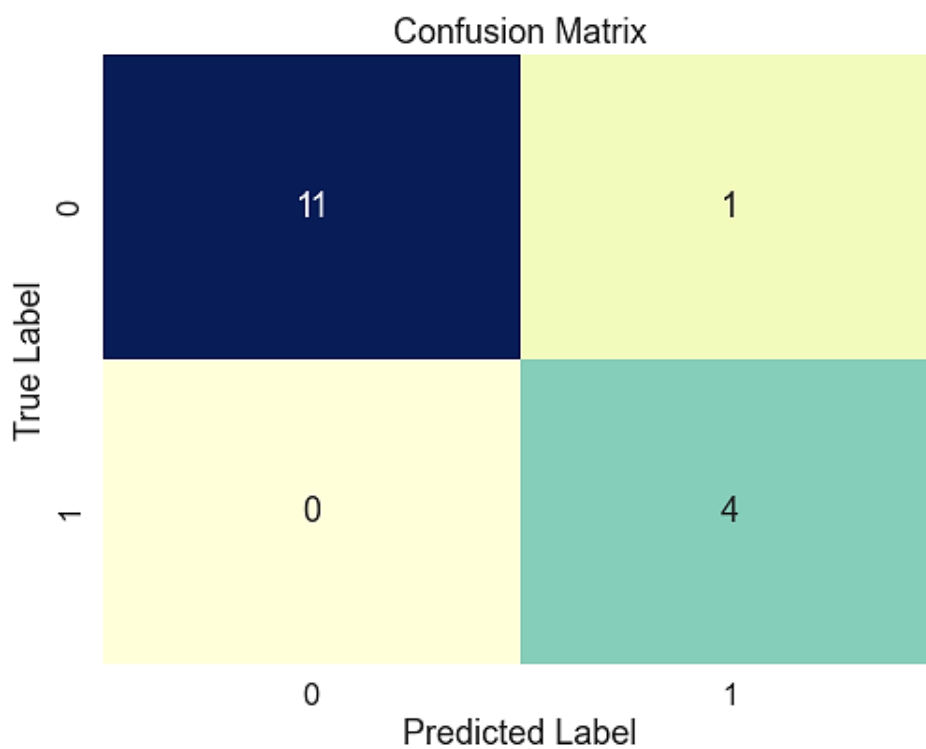


Figure 4.17: Confusion matrix

In Figure 4.17, the confusion matrix analyzes the proposed model's proficiency in the classification task. With 11 TP and 4 TN, the model accurately classified HC ('0') and depressive ('1') subjects. The absence of FP showcases the model's precision in avoiding misclassification. However, a single FN indicates an area for refinement to minimize instances of failing to identify HC subjects.

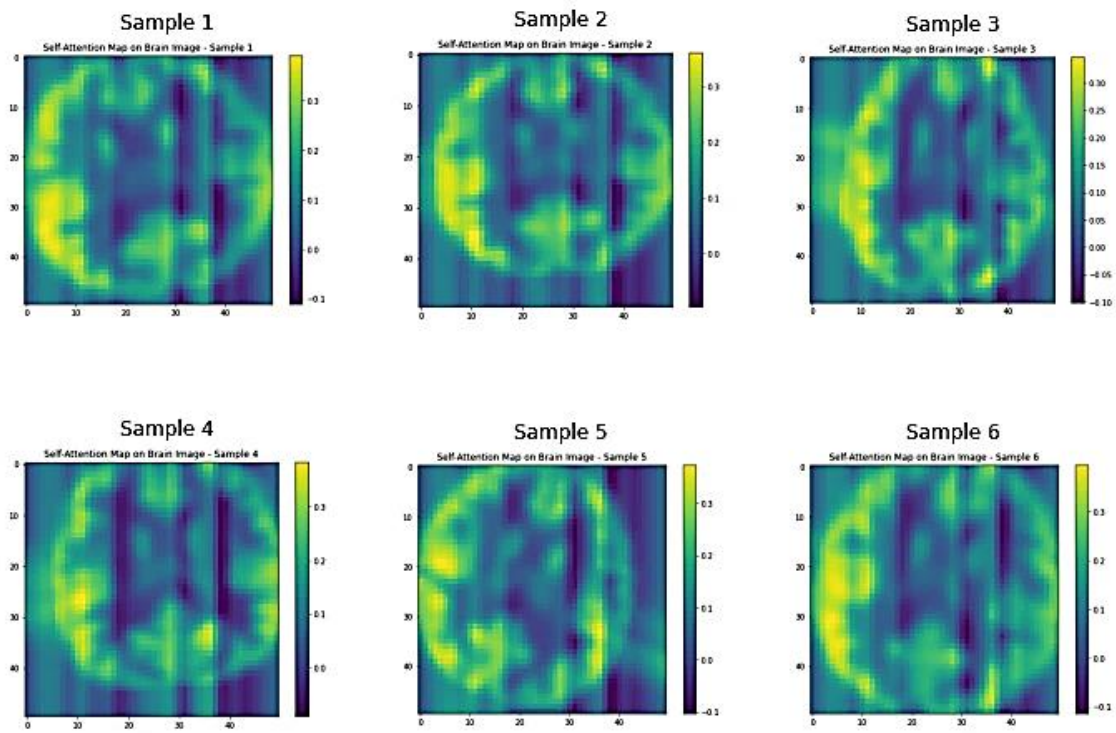


Figure 4.18: Self-attention maps for brain images

In Figure 4.18, self-attention maps unveil central points within the ESNN, displaying regions with heightened attention. The distinct yellow color indicates areas with attention values exceeding 0.3. Though not always directly linked with optimal performance, these visualizations offer crucial insights into the self-AM's functionality within the network (Xu et al., 2019).

In conclusion, the proposed model demonstrates strong overall performance, especially in ACC and SPEC. While SEN exhibits some variability, the model consistently achieves good discriminative ability, as indicated by the AUC scores. This assessment provides insights into the consistency and variability of the model's performance across the 10 trials, offering a comprehensive understanding of hyperparameter 3's behavior.

4.4 Comparative Analyses

In this section, we conduct thorough comparative analyses to evaluate the proposed model against traditional ML classifiers, alongside the ESNN standalone model, and insights from prior key studies. Our goal is to highlight the proposed self-AM-ESNN model's strengths and areas for improvement, offering valuable insights for broader model evaluation and understanding its unique contributions.

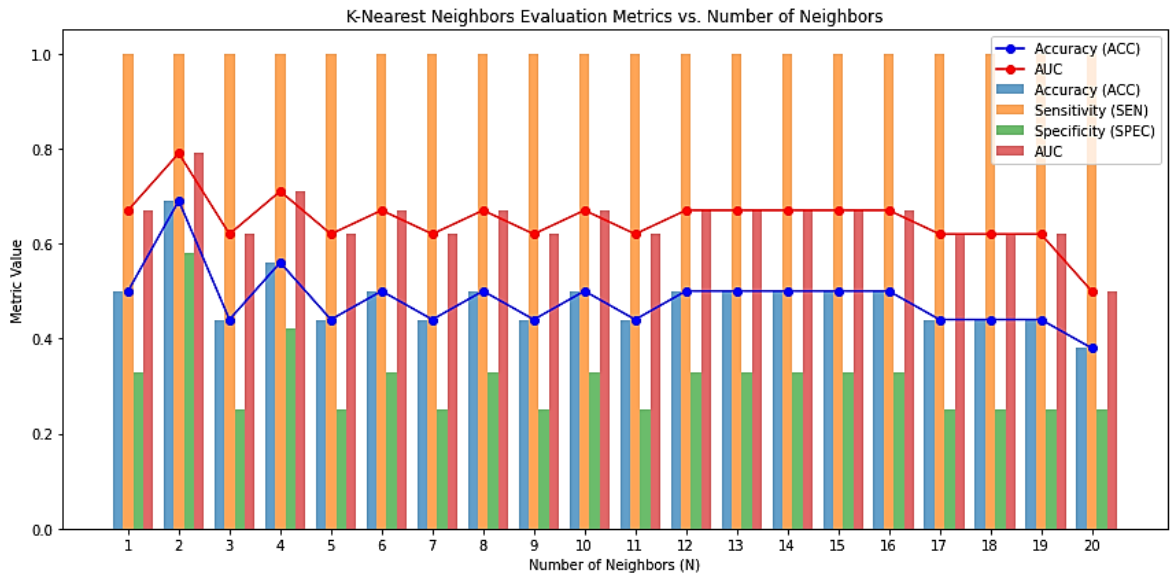
4.4.1 Traditional ML Classifiers and ESNN Standalone Model Analysis

The comparative analysis evaluates the proposed model against three traditional ML classifiers: KNN, LR, and SVM. Additionally, the standalone ESNN model is compared with the proposed model. Table 4.3 provides an overview of the parameters utilized for each classifier, with specific adjustments made based on the values in Table 4.4 to customize them to the study's context and objectives. The ESNN model utilizes the HP3 configuration but excludes the '*attention_units*' parameter.

Table 4.3: Parameters of the KNN, LR, and SVM models

No.	Model	Parameter	Values
1.	KNN	$N_neighbors$	2
2.	LR	Max_iter	1000
3.	SVM	$Probability$ $Random_state$	True 42

The investigation into the optimal number of neighbors for the KNN model, ranging from 1 to 20, aimed to strike a balance between computational efficiency and performance. Figure 4.19 illustrates the results across ten trials, indicating that a ‘ k ’ value of 2 consistently yielded optimal results. Subsequent increases in ‘ k ’ showed diminishing returns in performance gains.

**Figure 4.19:** KNN evaluation metrics vs. number of neighbors

The ‘*max_iter*’ parameter for the LR model was set to 1000 to address a convergence warning, ensuring effective convergence during training. SVM parameters were intentionally selected to optimize performance and interpretation. Enabling the ‘*probability*’ parameter offered insights into prediction confidence, especially for imbalanced datasets. In addition, setting the ‘*random_state*’ parameter to 42 ensured result reproducibility for consistent and reliable evaluation. Figure 4.20 illustrates the average results from ten trials across all models.

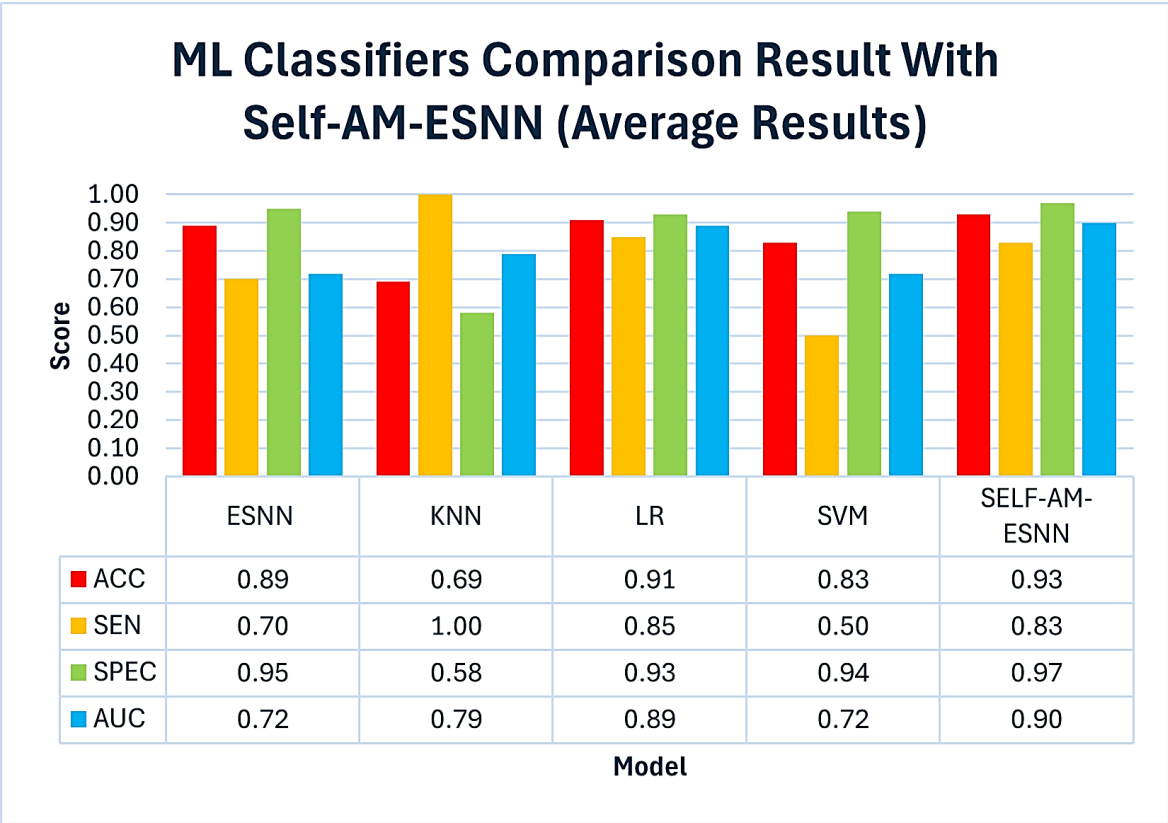


Figure 4.20: Comparison of ML classifiers with proposed model (average results)

In Figure 4.20, the proposed self-AM-ESNN model demonstrates an average ACC of 93%, surpassing other models. Although KNN achieves the highest SEN at 100%, the

proposed model closely follows with 83%. Regarding SPEC, the proposed model leads with a score of 97%, closely followed by the ESNN model at 95%. Overall, the proposed self-AM-ESNN model exhibits balanced and competitive performance, particularly excelling in ACC and SPEC compared to other models. The AUC values further support the model's discriminative ability, with both the proposed model and LR outperforming ESNN, KNN and SVM. However, despite LR's strong performance, it still falls short of matching the exceptional capabilities of the proposed model.

4.4.2 Key Studies Analyses

To demonstrate the efficiency and advancements of the self-AM-ESNN model, a comprehensive exploration against previous approaches for SI assessment has been conducted (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023). This analysis includes a discussion of key studies in the field. Figure 4.21 presents a comparison of the highest results achieved in prior studies with those of the proposed model.

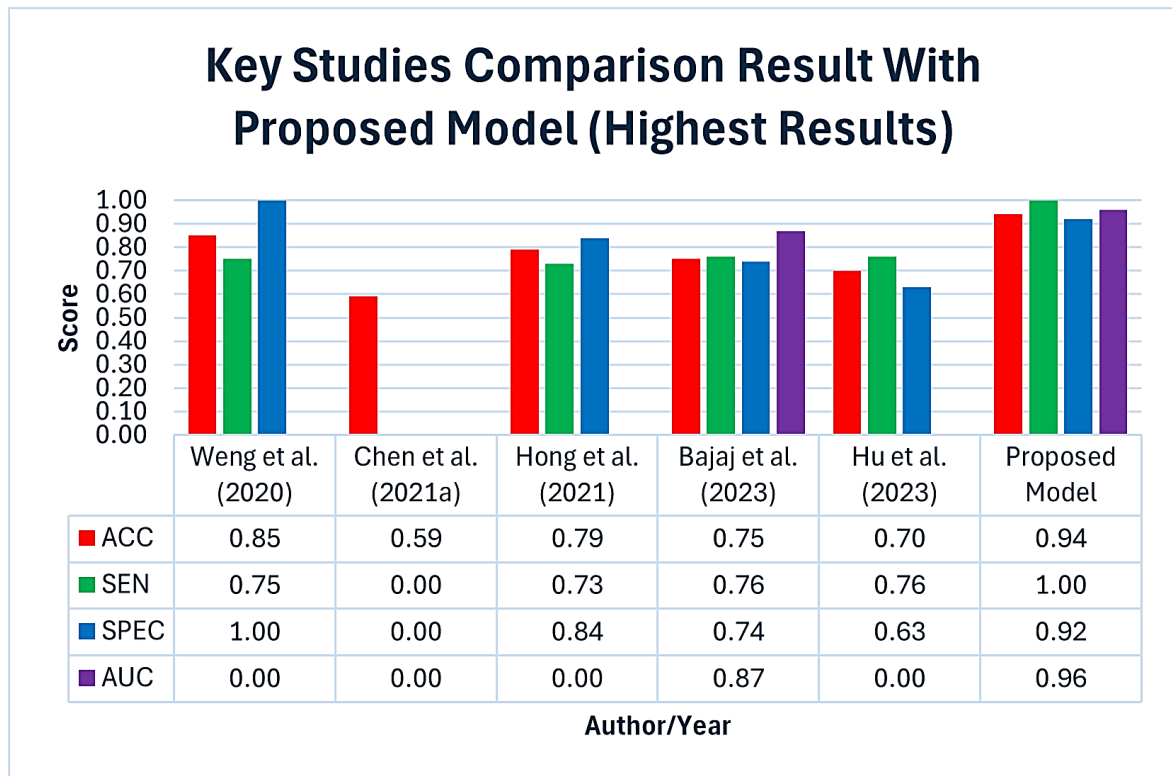


Figure 4.21: Comparison of key studies with proposed model (highest results)

In Figure 4.21, the proposed model emerges as a leader in SI assessment, surpassing previous studies across key metrics. With an ACC of 94%, the proposed model demonstrates superior precision in classification. While Bajaj et al. (2023) and Hu et al. (2023) exhibit reasonable SEN, the proposed model excels in this aspect. Additionally, the proposed model shows high SPEC at 92%, indicating its proficiency in correctly identifying negative cases. Though Weng et al. (2020) achieved a perfect SPEC (100%), the proposed model maintains competitive performance. Furthermore, its impressive AUC score of 0.96 emphasizes its effective discrimination ability.

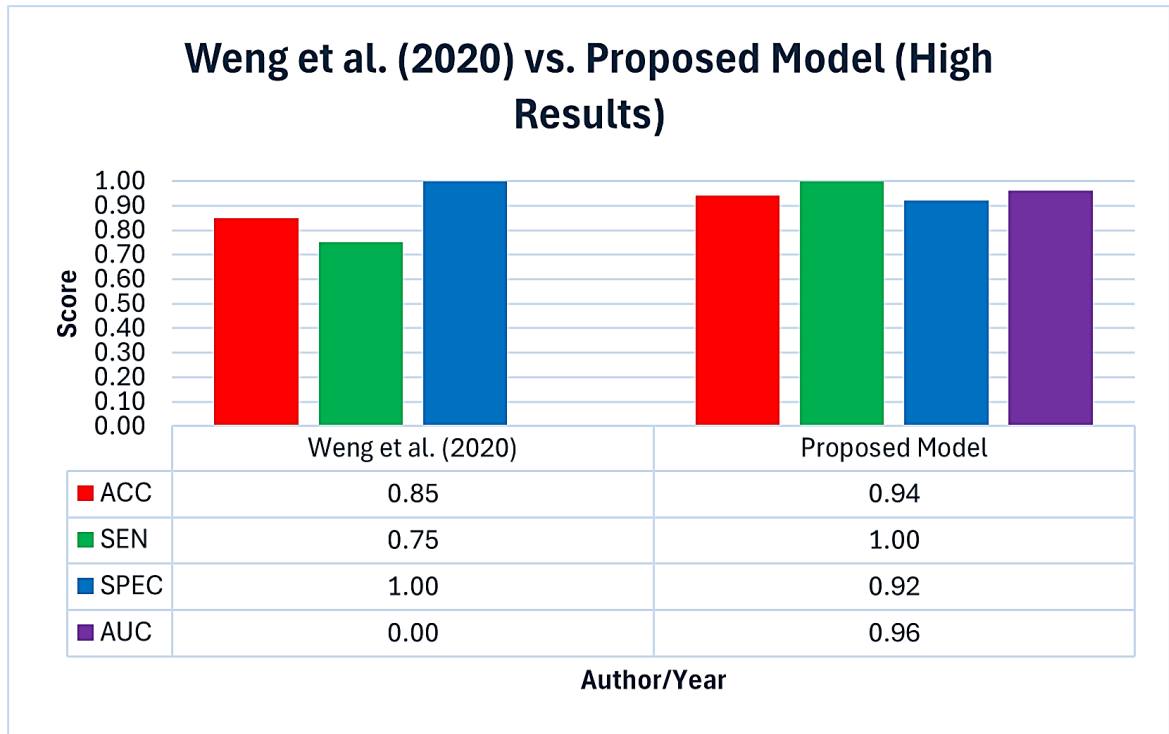


Figure 4.22: Comparison of Weng et al. (2020) with the proposed model

In the comparison presented in Figure 4.22, the proposed model demonstrates superior performance over Weng et al.'s (2020) model. With an ACC score of 94%, the proposed model significantly outperforms Weng et al.'s 85%. Impressively, the proposed model achieves a perfect SEN score of 100%, contrasting with Weng et al.'s 75%. However, it is important to note that Weng et al. achieved a perfect SPEC score of 100%, while the proposed model achieved 92%. Additionally, the proposed model exhibits a robust performance in terms of the AUC, scoring 0.96, while Weng et al.'s model falls short with a score of 0.00.

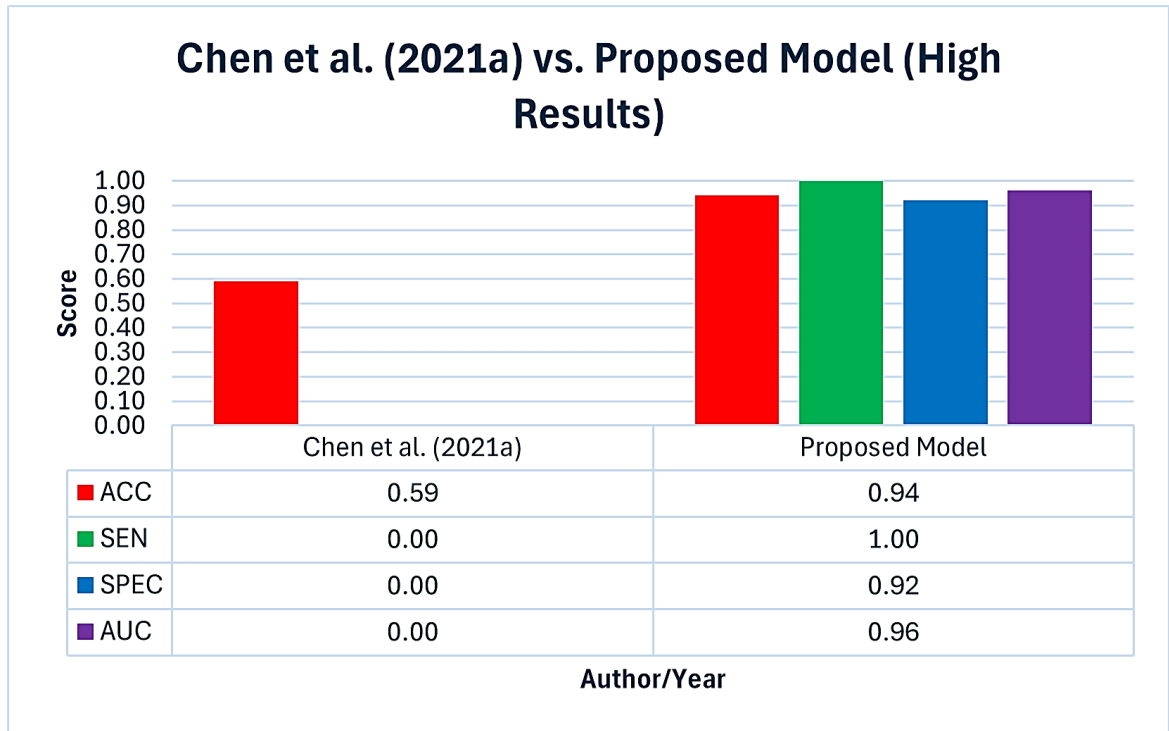


Figure 4.23: Comparison of Chen et al. (2021a) with the proposed model

In Figure 4.23, the performance of Chen et al.'s (2021a) model is compared with the proposed model, revealing the latter's dominance across all metrics. Particularly, the proposed model achieves an ACC score of 94%, surpassing Chen et al.'s score of 59%. Impressively, the proposed model attains high scores for both SEN and AUC of 100% and 0.96, respectively, while Chen et al. falter with scores of 0.00 for both metrics, as well as for SPEC.

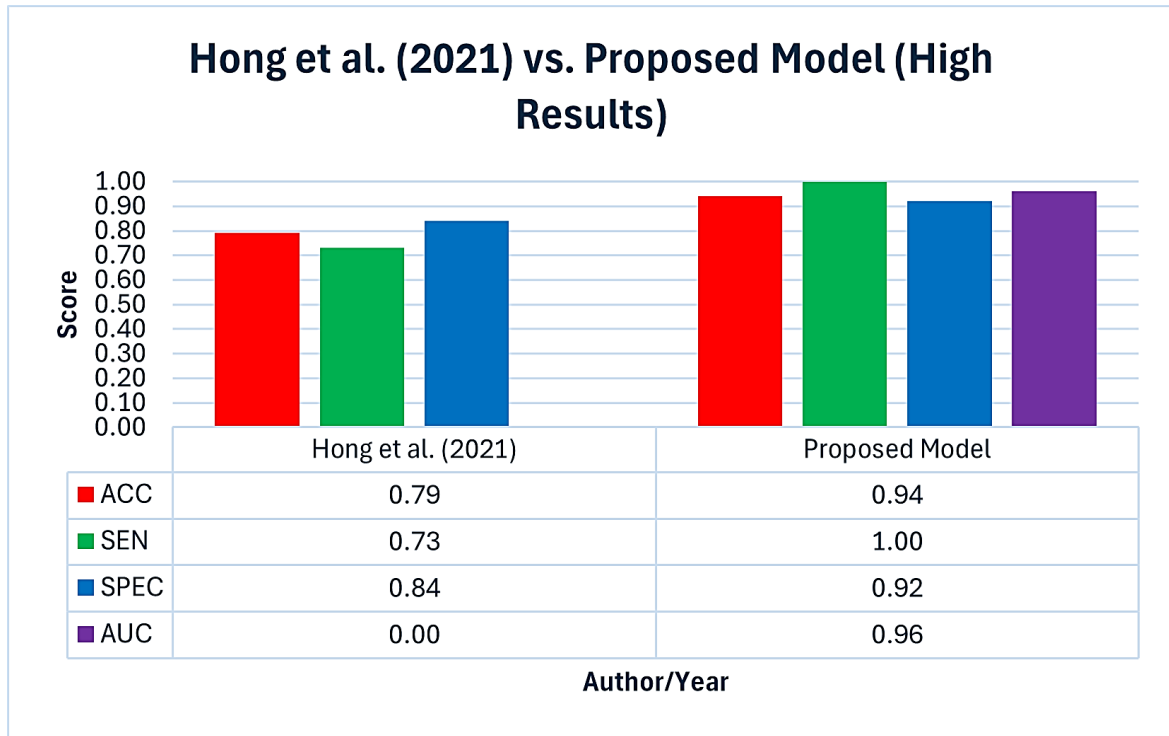


Figure 4.24: Comparison of Hong et al. (2021) with the proposed model

In the comparison depicted in Figure 4.24, the proposed model outperforms Hong et al.'s (2021) model across all evaluated metrics. For ACC, the proposed model achieves an impressive score of 94%, outperforming Hong et al.'s score of 79%. Moreover, the proposed model demonstrates perfect SEN with a score of 100%, contrasting sharply with Hong et al.'s score of 73%. Additionally, in terms of SPEC, the proposed model excels with a score of 92%, surpassing Hong et al.'s score of 84%. Most strikingly, the proposed model exhibits a robust performance with an AUC score of 0.96, while Hong et al.'s model falls short with a score of 0.00.

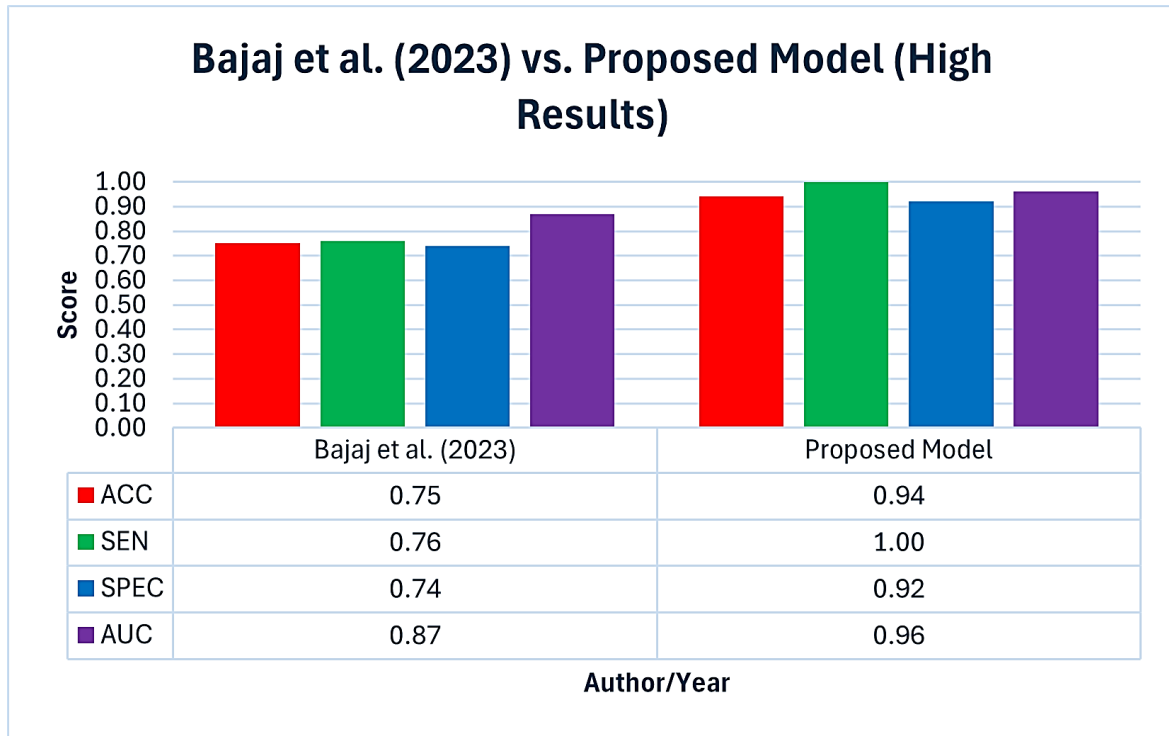


Figure 4.25: Comparison of Bajaj et al. (2023) with the proposed model

In Figure 4.25, the proposed model clearly surpasses Bajaj et al.'s (2023) model across all assessed metrics. With an ACC score of 94%, the proposed model outshines Bajaj et al.'s 75%. Remarkably, the proposed model achieves a flawless SEN score of 100%, contrasting sharply with Bajaj et al.'s 76%. The proposed model demonstrates superior SPEC with a score of 92%, compared to Bajaj et al.'s 74%. In addition, the proposed model exhibits a robust performance in terms of AUC, scoring 0.96, while Bajaj et al.'s model achieves a respectable yet lower score of 0.87.

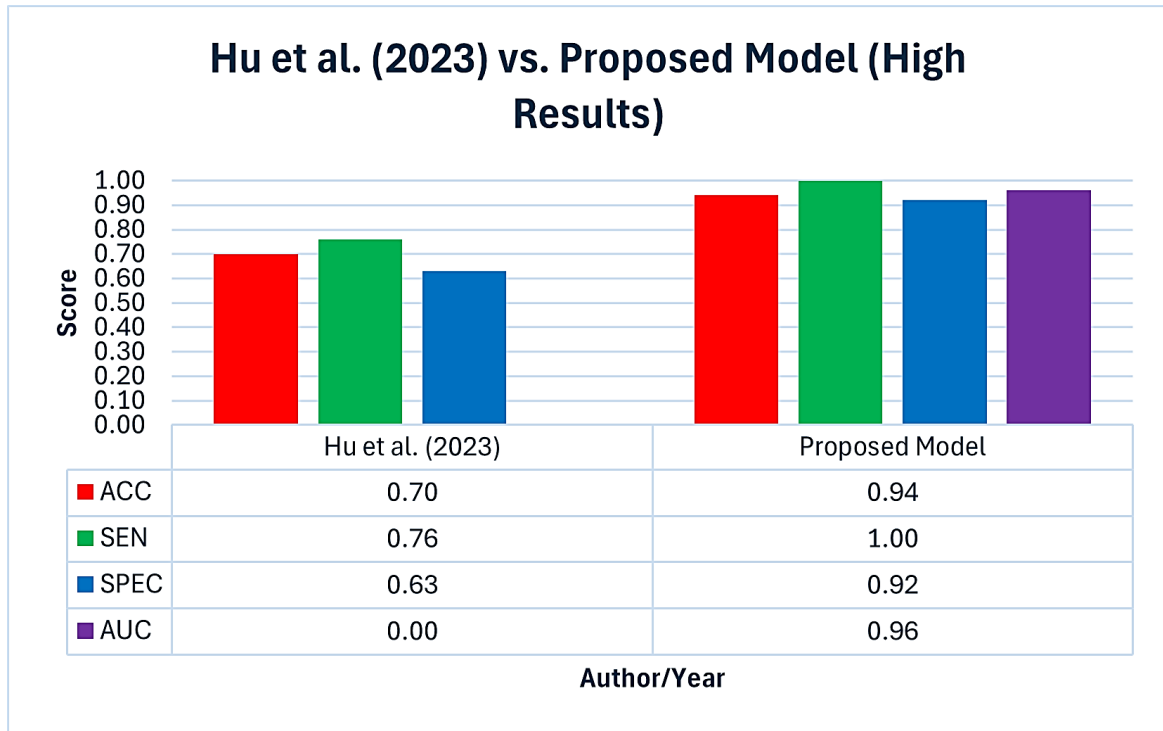


Figure 4.26: Comparison of Hu et al. (2023) with the proposed model

In Figure 4.26, the proposed model emerges as the superior performer when compared to Hu et al.'s (2023) model across all metrics. With an ACC score of 94%, the proposed model significantly surpasses Hu et al.'s 70%. The proposed model achieves a perfect SEN score of 100%, contrasting starkly with Hu et al.'s 76%. Furthermore, the proposed model demonstrates superior SPEC with a score of 92%, compared to Hu et al.'s 63%. Outstandingly, the proposed model exhibits robust performance in terms of the AUC, scoring 0.96, while Hu et al.'s model falls short with a score of 0.00.

The comprehensive analysis presented herein showcases the superiority of the proposed self-AM-ESNN model over existing approaches for SI assessment. By outperforming prior key studies across various metrics, including ACC, SEN, SPEC, and AUC, the proposed model demonstrates its efficacy and potential for real-world applications. Nonetheless, it is necessary to take into consideration the limitations in data reporting for

some studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Hu et al., 2023) when interpreting these comparative analyses comprehensively. These studies lack data for certain metrics (SEN, SPEC, and AUC), making direct comparison challenging.

4.5 Discussion

This study proposes a new method for SI assessment in depressed young adults, leveraging sMRI data and the ESNN model with self-AM. Combining ESNN and self-AM provides a robust and adaptable solution suitable for standard utilization in organizational environments for detecting SI (Kasabov, 2019). The strength of ESNNs lies in their adaptability and ability to discern significant patterns from data, overcoming the constraints typically associated with traditional neural networks (Ibad et al., 2022).

By harnessing the adaptive nature and optimization features of ESNN, organizations can effectively employ this technology in detecting and addressing SI (Elbrecht & Schuman, 2020). Utilizing ESNN's adaptability and pattern-recognition alongside self-AM enables organizations to develop accurate detection models for identifying and addressing suicide risk factors (Shin et al., 2022; Arowosegbe & Oyelade, 2023b). This standardized method ensures reliable detections, facilitating prompt interventions and effectively moderating SI within organizational settings (Datta, 2023).

ESNNs, inspired by the brain's functionality, present challenges due to the inherent discontinuous nature of spiking neurons. However, employing a GA for ESNN hyperparameter optimization ensured the model's peak performance (Japa et al., 2022). The suggested hyperparameter 3 configuration (refer to Table 4.4) demonstrated consistency and reliability across different evaluation metrics, effectively managing training iterations and

feature selection. The responsiveness of hyperparameter 3's performance to changes in datasets underlines the significance of meticulous tuning and iterative enhancements, guaranteeing ongoing advancements in model effectiveness and adaptability to varied scenarios.

Table 4.4: Proposed model hyperparameter values (hyperparameter 3)

No.	Parameter	Value
1.	<i>Epoch</i>	25
2.	<i>Num_field</i>	7
3.	<i>Beta</i>	0.31
4.	<i>I_{min}</i>	0.0
5.	<i>I_{max}</i>	1.0
6.	<i>Attention_units</i>	20
7.	<i>Mod</i>	0.17
8.	<i>C</i>	0.13
9.	<i>Sim</i>	0.55
10.	<i>Learning_rate</i>	0.001

The integration of self-AM within the ESNN model represents a significant advancement in SI assessment and intervention strategies within organizational contexts (Ji et al., 2022). Through self-AM visualizations (refer to Figure 4.18), the model effectively highlights regions with heightened attention, emphasizing the importance of specific features in decision-making processes (Ruiz-Serra et al., 2022). The ESNN model gains a heightened ability to capture complex patterns and relationships crucial for accurate

classification (Škrlić et al., 2020). This enhancement not only optimizes the model's performance by aligning with refined parameter values but also ensures the optimal utilization of configuration values, leading to improved classification accuracy and performance.

Comparative analyses against both conventional ML classifiers and standalone ESNN models, as well as against key studies, provide further validation of the superiority of the self-AM-ESNN approach (Dewangan et al., 2023). Its effectiveness in precise classification and improved discriminative capability positions it as a promising solution for accurately assessing and intervening in SI within organizational contexts. These comparative studies contribute to the development of efficient models for detecting SI, potentially saving lives by enabling timely interventions (Verma et al., 2023).

Recognizing and incorporating the neural correlates of SIBs is essential for expanding understanding and crafting precise strategies to prevent suicide (Vieira et al., 2023). Thus, the integration of sMRI data in this research marks a prominent progression, enriching the accuracy and thoroughness of SI assessments by leveraging into the wealth of information contained within these images (Nawaz et al., 2023). This integration of advanced imaging methods aligns with the forefront of advancements in neuroimaging, indicating a collective move towards more sophisticated analyses in mental health studies.

In summary, the findings presented in this study emphasize the dynamic and evolving landscape of SI assessments. The need for methods that not only push the boundaries of knowledge but also find practical applications in diverse settings is now more evident than ever. Bridging the gap between theoretical advancements and real-world impact becomes crucial, paving the way for more effective and applicable solutions in the field of SI assessment.

4.5.1 Verification and Validation Process

To ensure model robustness and efficacy, thorough verification and validation are essential (Beyer, 2024). This study emphasizes the importance of validation, critical for assessing the proposed model's suitability for decision-making with ESNN (Haddad et al., 2022). Through rigorous testing of hyperparameter configurations, the aim is to measure the effectiveness and efficiency of integrating self-AM and ESNN in addressing the research problem.

For verification, a GA was utilized for hyperparameter tuning of the self-AM-ESNN model. The optimization process, as discussed in Wang et al. (2023c), is crucial for training SNNs due to their unique traits. Utilizing evolutionary algorithms, as highlighted by Pradhan et al. (2023), is important for capturing complex behaviors akin to biological neurons. The evolving connectivity framework proposed by Liu et al. (2022b) highlights the necessity for accurate and hardware-friendly training methods. Incorporating these insights, hyperparameter optimization with GA boosts the performance and reliability of the ESNN model.

In the validation phase, the performance of the ESNN model in SI detection in depressed young adults utilizing sMRI data was assessed. The model's performance was evaluated on imbalanced sMRI datasets obtained from the OpenNeuro and INDI repositories. After preprocessing the datasets according to standard techniques, various evaluation metrics were employed, including ACC, SEN, SPEC, and AUC. These metrics play a crucial role in validating the model's performance, assessing its predictive abilities, and evaluating its effectiveness in handling spatial and temporal information (Agebure et al., 2020; Saravanan et al., 2022).

The validation experiments compared the performance of the proposed self-AM-ESNN model against relevant baselines and existing methods reported in the literature. The results demonstrated the superiority of the self-AM-ESNN model, achieving an ACC of 94%, SEN of 100%, SPEC of 92%, and AUC of 0.96. These results outperformed other models in key studies, including CNN, XGB, and LR (Weng et al., 2020); SVM, KNN, and ensemble models (Chen et al., 2021a); SVM-RFE (Hong et al., 2021); and CNN, DenseNet (Bajaj et al., 2023), and FCNN (Hu et al., 2023). The exceptional performance of the self-AM-ESNN model highlights its capability in handling spatial and temporal information, making it suitable for decision-making tasks based on input data, particularly in the context of SI detection utilizing neuroimaging data.

The integration of self-AM and ESNN components in the self-AM-ESNN model significantly contributed to its enhanced performance. The self-AM component facilitated dynamic adaptation and feature extraction, while the ESNN component leveraged the temporal dynamics of spiking neurons, enhancing the model's capability to capture and process complex patterns in the sMRI data.

The thorough verification and validation processes demonstrated the effectiveness and efficiency of the proposed self-AM-ESNN model in addressing the research problem of SI detection in depressed young adults utilizing sMRI data. By outperforming existing methods in key studies and offering a robust solution, this study contributes to the advancement of knowledge in neuroimaging-based depression diagnosis. It also paves the way for further exploration and application in related domains, such as mental health research and clinical practice.

4.5.2 Empirical Study Integration

In addition to the comparative analyses discussed in Section 4.4.2, an empirical study was conducted to validate the performance of the self-AM-ESNN model in real-world scenarios. This empirical study complements the findings from previous studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023) and provides further insights into the model's effectiveness and applicability. The sMRI dataset of depressed individuals utilized in this study, as detailed in Section 3.2, shares similarities with those utilized in previous studies, facilitating direct comparisons of results and enabling an assessment of the performance of the self-AM-ESNN model across different datasets.

The proposed self-AM-ESNN model was trained and evaluated utilizing this dataset to assess its performance in identifying individuals at risk of SI. Figure 4.14 presents the results of the empirical study, illustrating the model's performance across ten trials. These results demonstrate the model's effectiveness in accurately classifying individuals at risk of SI, with the highest trial yielding an ACC of 94%, SEN of 100%, SPEC of 92%, and AUC of 0.96.

By integrating the empirical study into the analysis, this study aims not only to validate the model's performance but also to understand its comparative strengths and weaknesses in relation to other approaches highlighted in key studies. The exceptional performance of the self-AM-ESNN model, particularly in terms of sensitivity, highlights its ability to accurately identify individuals at risk of SI, minimizing false negatives and enabling timely interventions.

4.5.3 Performance Evaluation Processes

Ensuring the reliability and significance of the performance evaluation for the self-AM-ESNN model was paramount in this study. Rigorous measures were taken to minimize biases and validate the obtained results. Data preprocessing steps, detailed in Section 3.3, and the feature extraction process utilizing self-AM, as explained in Section 3.4.1, were meticulously conducted to ensure high-quality input data.

Furthermore, techniques discussed in Section 3.5.3 were employed to address class imbalances, alleviate overfitting, and ensure robust evaluations, thereby preventing skewed performance metrics. Stratified k -fold cross-validation ($k=5$) was utilized to ensure a fair and unbiased evaluation of the model's performance, moderating the risk of overfitting, and enhancing the generalizability of the results.

The interpretation of performance metrics underwent meticulous examination to gain meaningful insights into the model's efficacy in distinguishing between healthy and depressive subjects. The selection of evaluation metrics, including ACC, SEN, SPEC, and AUC, was based on their widespread acceptance and relevance in binary classification tasks, particularly in the medical domain (Hicks et al., 2022). The utilization of these metrics helps to standardize evaluation methods, improve reproducibility, and enable comparison across various medical studies.

It is important to acknowledge the potential limitations and biases inherent in the evaluation process. Despite our best efforts, the study may be subject to biases associated with the dataset utilized, such as demographic factors or comorbidities. Additionally, the performance of the model may vary across different datasets or populations, highlighting the need for further validation and generalization studies.

By addressing these aspects comprehensively, the reliability and significance of the performance evaluation of the self-AM-ESNN model were effectively demonstrated, reinforcing the validity of the study outcomes. Nonetheless, continuous efforts to improve the evaluation processes and address potential limitations are essential for enhancing the robustness and applicability of the proposed model.

4.6 Summary

In recent years, advanced ML techniques in neuroimaging have paved the way for innovative approaches to SI assessment. This study introduces a novel integrated model that combines self-AM and ESNN, specifically designed for SI detection utilizing sMRI data in depressed young adults. Remarkably, the model surpasses the performance of both traditional ML classifiers, the standalone ESNN model, and previous key studies, marking a significant advancement in SI prevention. In addition, it offers a more precise and adaptable approach to mental health care.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Overview

This section concludes the in-depth research by presenting clear findings and recommendations based on the proposed model. It highlights the innovative potential of this model in reshaping SI assessment in mental health.

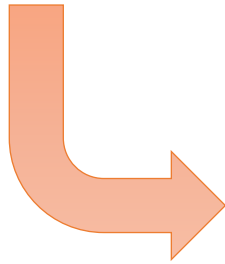
5.2 Summary of Key Findings

The essential outcomes are summarized in Figure 5.1. This study emphasizes the challenges among depressed young adults, particularly in understanding the complex link between depression and SI. Traditional assessment methods face limitations, necessitating innovative approaches, especially those leveraging ML and neuroimaging data. Additionally, key studies in this field faced limitations, with their model accuracy falling below 90%.

Thus, this study introduces an innovative classification model by integrating self-AM and ESNN, utilizing sMRI data of depressed young adults. Through careful experiments and hyperparameter tuning with GA, the proposed model achieves remarkable performance, with the highest result showing 94% ACC, 100% SEN, 92% SPEC, and AUC of 0.96, surpassing conventional models (KNN, LR, and SVM), the standalone ESNN model, and key studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023).

Challenges post COVID-19 Pandemic:

- **Focus:** Exploring the complex link between depression and SI.
- **Concerns:** Limitations in traditional SI assessment as well as in existing key studies.
- **Demand:** Need for advanced methods, combining ML techniques and neuroimaging data.



ML Classification Model:

- **Description:** Innovative novel self-AM-ESNN model for predicting SI utilizing sMRI data of depressed young adults.
- **Results:** Highest ACC of 94%, SEN of 100%, SPEC of 92%, and an AUC value of 0.96.
- **Performance Comparison:** Outperforms ML classifiers (ESNN, KNN, LR, SVM) and prior studies.

Figure 5.1: Summary of key findings

5.3 Study Contributions

This study makes significant contributions to the field of SI assessment and mental health research. The key contributions can be summarized as follows:

1. *Innovative Classification Model:* The study proposes a novel classification model that integrates self-AM with ESNN and utilizes sMRI data. This integration of cutting-edge techniques represents a pioneering approach to enhancing SI assessment for depressed young adults.
2. *Exceptional Performance:* The proposed self-AM-ESNN model achieves remarkable performance, surpassing conventional ML models (e.g., KNN, LR, SVM) and standalone ESNN models. With an ACC of 94%, SEN of 100%, SPEC of 92%, and

an AUC of 0.96, the model outperforms previous key studies in the field, making a significant contribution to neuroimaging-based SI assessment.

3. *Adaptability and Pattern Recognition:* The self-AM-ESNN model's strength lies in its ability to capture complex patterns and adapt to individual variations and changing risk factors. This adaptability and dynamic learning capability make the model well-suited for diverse organizational environments, enabling accurate assessment of SI risk among employees or target populations.
4. *Enabling Prompt Interventions:* By leveraging the self-AM-ESNN model, organizations can precisely assess SI risk, facilitating prompt interventions and tailor mental health support strategies. This contribution has the potential to significantly improve mental health support and well-being within organizational settings.
5. *Driving Innovation:* This study inspires comprehensive innovation in SI assessment and the broader mental health field. The proposed model reshapes the landscape of SI assessment, laying the groundwork for more precise and effective interventions, and advancing our understanding of mental well-being, particularly among young adults.

The key contributions highlighted in this section emphasize the novelty of the proposed model, its outstanding performance, adaptability to organizational contexts, potential for enabling prompt interventions, and its role in driving innovation in the field of SI assessment and mental health research.

5.4 Study Limitations

While this study offers valuable insights, it is essential to acknowledge several limitations that may impact the interpretation of results and the generalizability of findings (refer to Figure 5.2). Firstly, the dataset utilized in this study comprised only 80 samples, which is a relatively small dataset size. Small dataset sizes can limit the model's ability to generalize and may not capture the full variability present in the broader population.

Secondly, there is a significant class imbalance in the dataset, with 60 HC and only 20 depressed subjects. This class imbalance could introduce bias and affect the model's ability to generalize accurately to broader populations.

Thirdly, the availability of suitable sMRI data specifically for individuals with depression was limited. This constraint may compromise the representativeness of the sample and could influence the model's performance and generalizability in capturing the neuroanatomical patterns associated with depression and SI.

Additionally, the computational demands associated with processing large features, such as brain images, pose significant challenges, particularly for researchers with limited access to computational resources. Processing and analyzing high-dimensional data can be computationally intensive, requiring substantial computational power and resources.

While efforts were made to address these limitations within the scope of the study, it is important to recognize that they may impact the study's outcomes and conclusions. Future research endeavors should consider these constraints and aim to alleviate them to enhance the robustness and applicability of findings in real-world contexts.

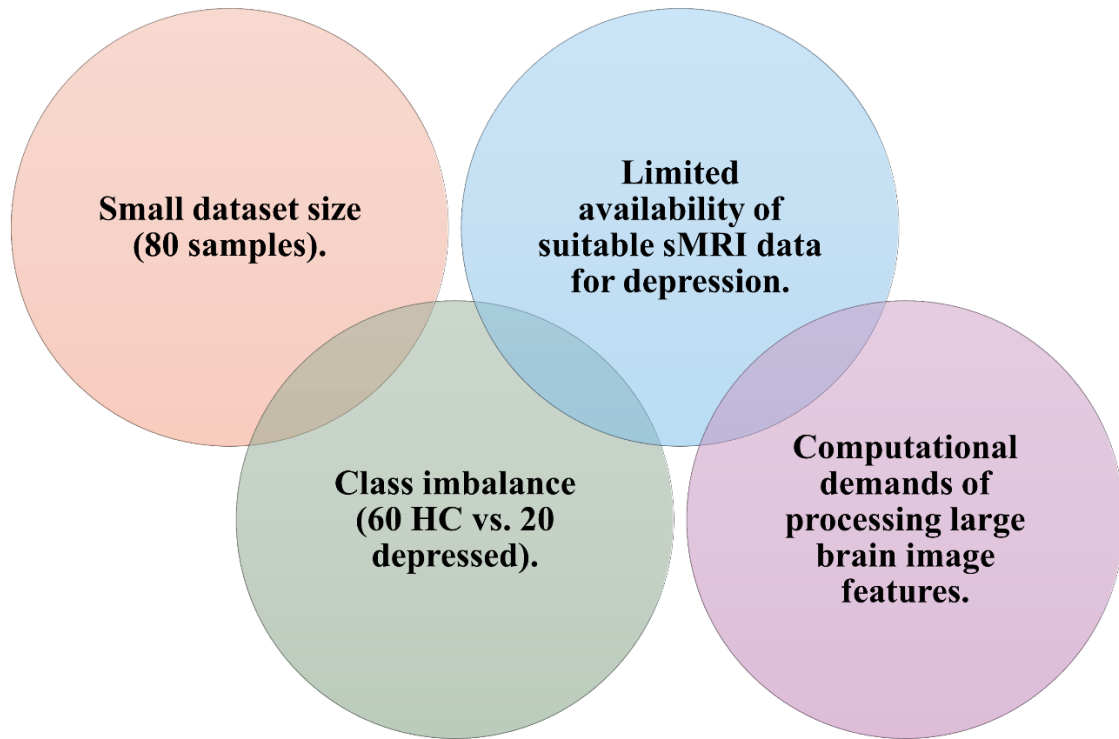


Figure 5.2: Study's limitations

5.5 Recommendations for Future Research

Given the limitations discussed and the insights gained from the proposed self-AM-ESNN model, future research should prioritize overcoming these constraints and advancing the field of SI assessment among depressed young adults, utilizing neuroimaging data. Figure 5.3 illustrates key areas that offer opportunities for further investigation.

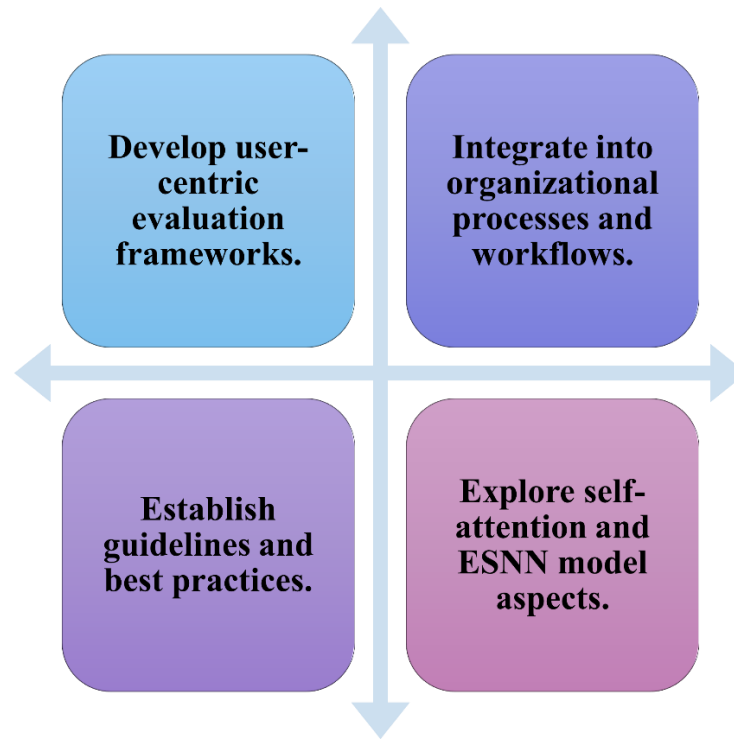


Figure 5.3: Future research recommendations

A crucial area for future exploration is the practical implementation and validation of the self-AM-ESNN model as a standardized approach for SI assessment and control within organizational settings. Research efforts should focus on developing user-centric evaluation frameworks that enable mental health professionals and service users to effectively interpret the model's detections and rationale. This would facilitate informed decision-making processes and the tailoring of interventions to individual needs.

Additionally, future studies should investigate the integration of the self-AM-ESNN model into existing organizational processes and workflows, ensuring seamless adoption and effective utilization. Guidelines and best practices for interpreting the model's outputs and translating them into actionable strategies for SI management within organizational contexts should be developed and validated.

By prioritizing these research directions, future studies can contribute to the successful adoption of the self-AM-ESNN model as a common standard for SI assessment and intervention in organizational environments, ultimately enhancing the well-being and mental health support for employees and target populations.

In future research, prioritizing exploration of aspects related to self-AM and ESNN holds the potential to significantly advance the assessment of SI in depressed young adults. This advancement could yield innovative solutions, deepen the understanding of mental health, and inform interventions with increased precision and ethical rigor.

5.6 Summary

Amidst the COVID-19 pandemic, mental health challenges, particularly among depressed young adults, have surged, emphasizing the need for innovative solutions to assess and alleviate SI risk. This study introduces a novel classification model, integrating self-AM with ESNN and leveraging sMRI data. This self-AM-ESNN model demonstrates outstanding performance, surpassing traditional methods and prior key studies with 94% ACC, 100% SEN, 92% SPEC, and an AUC of 0.96. Its adaptability suits various organizational settings, enabling precise SI risk assessment and tailored interventions.

Despite limitations such as small dataset size and computational challenges, this study lays the groundwork for future research to overcome these constraints and advance SI assessment in depressed young adults. Prioritizing exploration of self-AM and ESNN model aspects, alongside developing user-centric evaluation frameworks and practical implementation guidelines, will facilitate widespread adoption. In essence, our study

pioneers the application of state-of-the-art techniques to address SI assessment challenges, fostering more precise interventions and inspiring innovation in mental health research.

REFERENCES

- Abdullah, M. H. A., Othman, M., Kasim, S., & Mohamed, S. A. (2019). Evolving spiking neural networks methods for classification problem: a case study in flood events risk assessment. *Indonesian Journal of Electrical Engineering and Computer Science*, 16(1), 222-229. 10.11591/ijeecs.v16.i1.pp222-229
- About Chahla, M. N., Khalil, M. I., Comai, S., Brundin, L., Erhardt, S., & Guillemin, G. J. (2023). Biological factors underpinning suicidal behaviour: an update. *Brain Sciences*, 13(3), 505. 10.3390/brainsci13030505
- Aboutalebi, H., Pavlova, M., Gunraj, H., Shafiee, M. J., Sabri, A., Alaref, A., & Wong, A. (2022). MEDUSA: multi-scale encoder-decoder self-attention deep neural network architecture for medical image analysis. *Frontiers in Medicine*, 8, 821120. 10.3389/fmed.2021.821120
- AFSP. (2020). Neuroimaging and Suicide Prevention Research: Reviewing the Last Two Decades. *American Foundation for Suicide Prevention*. Available at: <https://afsp.org/story/neuroimaging-and-suicide-prevention-research-reviewing-the-last-two-decades> [Accessed on 5 February 2023]
- Agebure, M. A., Baagyere, E. Y., & Oyetunji, E. O. (2020). Spiking Neural Network Learning Models for Spike Sequence Learning and Data Classification. *Asian Journal of Research in Computer Science*, 1-17.
- Ahmed, I. (2022). Image classification with attention. *Paperspace*. Available at: <https://blog.paperspace.com/image-classification-with-attention/> [Accessed on 28 March 2023]

- Akindele, R. G., Yu, M., Kanda, P. S., Owoola, E. O., & Aribilola, I. (2023). Denoising of Nifti (MRI) images with a regularized neighborhood pixel similarity wavelet algorithm. *Sensors*, 23(18), 7780. 10.3390/s23187780
- Al-Hyari, A. (2022). Hyperparameters Optimization of Convolutional Neural Networks using Evolutionary Algorithms. In *2022 International Conference on Emerging Trends in Computing and Engineering Applications (ETCEA)* (pp. 1-6). IEEE. 10.1109/ETCEA57049.2022.10009778
- Aleixo, E. L., Colonna, J. G., Cristo, M., & Fernandes, E. (2023). *Catastrophic forgetting in deep learning: A comprehensive taxonomy*. arXiv. 10.48550/arXiv.2312.10549.
- Alhijawi, B., & Awajan, A. (2023). Genetic algorithms: Theory, genetic operators, solutions, and applications. *Evolutionary Intelligence*, 1-12. 10.1007/s12065-023-00822-6
- Altaheri, H., Muhammad, G., & Alsulaiman, M. (2022). Physics-informed attention temporal convolutional network for EEG-based motor imagery classification. *IEEE Transactions on Industrial Informatics*, 19(2), 2249-2258. 10.1109/TII.2022.3197419
- Antonelli-Salgado, T., Monteiro, G. M. C., Marcon, G., Roza, T. H., Zimerman, A., Hoffmann, M. S., ... & Passos, I. C. (2021). Loneliness, but not social distancing, is associated with the incidence of suicidal ideation during the COVID-19 outbreak: a longitudinal study. *Journal of Affective Disorders*, 290, 52-60. 10.1016/j.jad.2021.04.044
- Araf, I., Idri, A., & Chair, I. (2024). Cost-sensitive learning for imbalanced medical data: a review. *Artificial Intelligence Review*, 57(4), 1-72. 10.1007/s10462-023-10652-8

- Arbet, J., Brokamp, C., Meinen-Derr, J., Trinkley, K. E., & Spratt, H. M. (2021). Lessons and tips for designing a machine learning study using EHR data. *Journal of Clinical and Translational Science*, 5(1), e21. 10.1017/cts.2020.513
- Arowosegbe, A., & Oyelade, T. (2023a). Advances in Suicide Prevention in the UK. *Preprints 2023*. 10.20944/preprints202308.1116.v1
- Arowosegbe, A., & Oyelade, T. (2023b). Application of Natural Language Processing (NLP) in Detecting and Preventing Suicide Ideation: A Systematic Review. *International Journal of Environmental Research and Public Health*, 20(2), 1514. 10.3390/ijerph20021514
- Ashburner, J. (2007). A fast diffeomorphic image registration algorithm. *Neuroimage*, 38(1), 95-113. 10.1016/j.neuroimage.2007.07.007
- Ashwin, A., Cherukuri, S. D., & Rammohan, A. (2022). Negative effects of COVID-19 pandemic on adolescent health: Insights, perspectives, and recommendations. *Journal of Global Health*, 12, 03009. 10.7189/jogh.12.03009.
- Aslan, H. İ., Yılmaz, A. B., Jeong, N., Lee, S., & Choi, C. (2022, February). Prediction of number of suicidal people based on KNN. In *2022 International Conference on Electronics, Information, and Communication (ICEIC)* (pp. 1-4). IEEE. 10.1109/ICEIC54506.2022.9748557.
- Avberšek, L. K., & Repovš, G. (2022). Deep learning in neuroimaging data analysis: applications, challenges, and solutions. *Frontiers in Neuroimaging*, 1, 981642. 10.3389/fnimg.2022.981642
- Awe, O. O., Ojumu, J. B., Ayanwoye, G. A., Ojumoola, J. S., & Dias, R. (2024). Machine Learning Approaches for Handling Imbalances in Health Data Classification. In

Sustainable Statistical and Data Science Methods and Practices: Reports from LISA 2020 Global Network, Ghana, 2022 (pp. 375-391). Cham: Springer Nature Switzerland. 10.1007/978-3-031-41352-0_19

Bäßler, D., Kortus, T., & Gühring, G. (2022). Unsupervised anomaly detection in multivariate time series with online evolving spiking neural networks. *Machine Learning*, 111(4), 1377-1408. 10.1007/s10994-022-06129-4

Bailey, L. (2024). Depression | Coping with suicidal thoughts. *Familydoctor.org*. Available at: <https://familydoctor.org/depression-coping-with-suicidal-thoughts/>. [Accessed on 21 April 2024]

Bajaj, S., Blair, K. S., Dobbertin, M., Patil, K. R., Tyler, P. M., Ringle, J. L., ... & Blair, R. J. R. (2023). Machine learning based identification of structural brain alterations underlying suicide risk in adolescents. *Discover Mental Health*, 3(1), 6. 10.1007/s44192-023-00033-6

Ballard, E.D., Gilbert, J.R., Wusinich, C., & Zarate Jr., C.A. (2021). New methods for assessing rapid changes in suicide risk. *Frontiers in Psychiatry*, 12, 598434. 10.3389/fpsyt.2021.598434

Barak-Corren, Y., Castro, V. M., Nock, M. K., Mandl, K. D., Madsen, E. M., Seiger, A., ... & Smoller, J. W. (2020). Validation of an electronic health record–based suicide risk prediction modeling approach across multiple health care systems. *JAMA Network Open*, 3(3), e201262-e201262. 10.1001/jamanetworkopen.2020.1262

Barberis, N., Cannavò, M., Cuzzocrea, F., & Verrastro, V. (2022). Suicidal behaviours during COVID-19 pandemic: A review. *Clinical Neuropsychiatry*, 19(2), 84. 10.36131/cnfioritieditore20220202.

- Barla, N. (2023). Overfitting vs Underfitting in Machine Learning: Everything You Need to Know. *Neptune.ai*. Available at: <https://neptune.ai/blog/overfitting-vs-underfitting-in-machine-learning> [Accessed on 12 November 2023]
- Barron, D. S., Baker, J. T., Budde, K. S., Bzdok, D., Eickhoff, S. B., Friston, K. J., ... & Krystal, J. H. (2021). Decision models and technology can help psychiatry develop biomarkers. *Frontiers in Psychiatry*, 12, 706655. 10.3389/fpsyt.2021.706655
- Barua, P. D., Vicnesh, J., Lih, O. S., Palmer, E. E., Yamakawa, T., Kobayashi, M., & Acharya, U. R. (2024). Artificial intelligence assisted tools for the detection of anxiety and depression leading to suicidal ideation in adolescents: a review. *Cognitive Neurodynamics*, 18(1), 1-22. 10.1007/s11571-022-09904-0
- Barzilay, S., & Apter, A. (2022). Recent research advances in identification and prevention of youth suicide risk. *Current Opinion in Psychiatry*, 35(6), 395-400. 10.1097/YCO.0000000000000816
- Batterham, P. J., Calear, A. L., Shou, Y., Farrer, L. M., Gulliver, A., McCallum, S. M., & Dawel, A. (2022). Effects of the COVID-19 pandemic on suicidal ideation in a representative Australian population sample—Longitudinal cohort study. *Journal of Affective Disorders*, 300, 385-391. 10.1016/j.jad.2022.01.022
- Bauer, B. W., & Capron, D. W. (2020). How behavioral economics and nudges could help diminish irrationality in suicide-related decisions. *Perspectives on Psychological Science*, 15(1), 44-61. 10.1177/1745691619866463
- Bentley, K. H., Zuromski, K. L., Fortgang, R. G., Madsen, E. M., Kessler, D., Lee, H., ... & Smoller, J. W. (2022). Implementing machine learning models for suicide risk

- prediction in clinical practice: focus group study with hospital providers. *JMIR Formative Research*, 6(3), e30946. 10.2196/30946
- Berisha, V., Krantsevich, C., Hahn, P. R., Hahn, S., Dasarathy, G., Turaga, P., & Liss, J. (2021). Digital medicine and the curse of dimensionality. *NPJ Digital Medicine*, 4(1), 153. 10.1038/s41746-021-00521-5
- Bernert, R. A., Hilberg, A. M., Melia, R., Kim, J. P., Shah, N. H., & Abnoui, F. (2020). Artificial intelligence and suicide prevention: a systematic review of machine learning investigations. *International Journal of Environmental Research and Public Health*, 17(16), 5929. 10.3390/ijerph17165929
- Beyer, D. (2024, April). State of the art in software verification and witness validation: SV-COMP 2024. In *International Conference on Tools and Algorithms for the Construction and Analysis of Systems* (pp. 299-329). Cham: Springer Nature Switzerland. 10.1007/978-3-031-57256-2_15
- Bezmaternykh, D. D., Meinikov, M. E., Savelov, A. A., & Petrovskii, E. D. (2021a). Resting state with closed eyes for patients with depression and healthy participants. *OpenNeuro*. [Dataset]. 10.18112/openneuro.ds002748.v1.0.5
- Bezmaternykh, D. D., Meinikov, M. E., Savelov, A. A., & Petrovskii, E. D. (2021b). Two sessions of resting state with closed eyes for patients with depression in treatment course (NFB, CBT or No treatment groups). *OpenNeuro*. [Dataset]. 10.18112/openneuro.ds003007.v1.0.1
- Bogdanov, V. B. (2015, Dec 2). *SPM12 (Kyiv 2015): part 2 – reorientation 2/3* [Video]. Youtube. <https://www.youtube.com/watch?v=sUFRFnWv9Mg&t=119s>

- Bogdanov, V. B. (2017, May 5). *DARTEL VBM Lyon presentation 20170505* [Video]. Youtube. <https://www.youtube.com/watch?v=YVDG9cjnUPU&t=370s>
- Brainlife. (2022). Anatomical (T1w) preprocessing. *Brainlife Documentation*. Available at: <https://brainlife.io/docs/tutorial/t1w-preprocessing/> [Accessed on 25 May 2023]
- Bridge, J. A., Ruch, D. A., Sheftall, A. H., Hahm, H. C., O’Keefe, V. M., Fontanella, C. A., ... & Horowitz, L. M. (2023). Youth suicide during the first year of the COVID-19 pandemic. *Pediatrics*, 151(3), e2022058375. 10.1542/peds.2022-058375
- Brownlee, J. (2020a). Autoencoder Feature Extraction for Classification. *Machine Learning Mastery*. Available at: <https://machinelearningmastery.com/autoencoder-for-classification/> [Accessed on 11 November 2023]
- Brownlee, J. (2020b). Tune Hyperparameters for Classification Machine Learning Algorithms. *Machine Learning Mastery*. Available at: <https://machinelearningmastery.com/hyperparameters-for-classification-machine-learning-algorithms/> [Accessed on 11 November 2023]
- Brownlee, J. (2020c). Train-Test Split for Evaluating Machine Learning Algorithms. *Machine Learning Mastery*. Available at: <https://machinelearningmastery.com/train-test-split-for-evaluating-machine-learning-algorithms/> [Accessed on 12 November 2023]
- Brownlee, J. (2021). SMOTE for Imbalanced Classification with Python. *Machine Learning Mystery*. Available at: <https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/> [Accessed on 12 November 2023]
- Canady, V.A. (2021). New literature review examines suicide risk during COVID-19. *Mental Health Weekly*, 31(4), 3-4. 10.1002/mhw.32654

- Candemir, C. (2023). Spatial smoothing effect on group-level functional connectivity during resting and task-based fMRI. *Sensors*, 23(13), 5866. 10.3390/s23135866
- Cao, L., Zhang, H., & Feng, L. (2020). Building and using personal knowledge graph to improve suicidal ideation detection on social media. *IEEE Transactions on Multimedia*, 24, 87-102. 10.1109/TMM.2020.3046867
- Carrington, A. M., Manuel, D. G., Fieguth, P. W., Ramsay, T., Osmani, V., Wernly, B., ... & Holzinger, A. (2022). Deep ROC analysis and AUC as balanced average accuracy, for improved classifier selection, audit and explanation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(1), 329-341. 10.1109/TPAMI.2022.3145392
- Chadha, A., & Kaushik, B. (2022). A hybrid deep learning model using grid search and cross-validation for effective classification and prediction of suicidal ideation from social network data. *New Generation Computing*, 40(4), 889-914. 10.1007/s00354-022-00191-1
- Chen, V. C. H., Wong, F. T., Tsai, Y. H., Cheok, M. T., Chang, Y. P. E., McIntyre, R. S., & Weng, J. C. (2021a). Convolutional neural network-based deep learning model for predicting differential suicidality in depressive patients using brain generalized q-sampling imaging. *The Journal of Clinical Psychiatry*, 82(2), 28302. 10.4088/JCP.19m13225
- Chen, K., Johnson, A., Scott, E. O., Zou, X., De Jong, K. A., Nitz, D. A., & Krichmar, J. L. (2021b). Differential spatial representations in hippocampal CA1 and subiculum emerge in evolved spiking neural networks. In *2021 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE. 10.1109/IJCNN52387.2021.9534139

- Cheng, J., Tian, S., Yu, L., Gao, C., Kang, X., Ma, X., ... & Lu, H. (2022). ResGANet: Residual group attention network for medical image classification and segmentation. *Medical Image Analysis*, 76, 102313. 10.1016/j.media.2021.102313
- Cheung, T., Lam, S. C., Lee, P. H., Xiang, Y. T., Yip, P. S. F., & International Research Collaboration on COVID-19. (2021). Global imperative of suicidal ideation in 10 countries amid the COVID-19 pandemic. *Frontiers in Psychiatry*, 11, 588781. 10.3389/fpsyt.2020.588781
- Chi, Z., Zhang, G., & Guo, X. (2022, March). A new attention mechanism based on inner product for medical image classification. In *International Conference on Computer Graphics, Artificial Intelligence, and Data Processing (ICCAID 2021)* (Vol. 12168, pp. 138-143). SPIE. 10.1117/12.2631117
- Chiang, Y. H., Ma, Y. C., Lin, Y. C., Jiang, J. L., Wu, M. H., & Chiang, K. C. (2022). The relationship between depressive symptoms, rumination, and suicide ideation in patients with depression. *International Journal of Environmental Research and Public Health*, 19(21), 14492. 10.3390/ijerph192114492.
- Choi, K. S., Kim, S., Kim, B. H., Jeon, H. J., Kim, J. H., Jang, J. H., & Jeong, B. (2021). Deep graph neural network-based prediction of acute suicidal ideation in young adults. *Scientific Reports*, 11(1), 15828. 10.1038/s41598-021-95102-7
- Choi, H. S., & Yang, J. (2024). Innovative Use of Self-Attention-Based Ensemble Deep Learning for Suicide Risk Detection in Social Media Posts. *Applied Sciences*, 14(2), 893. 10.3390/app14020893
- Clay, R. A. (2022). How to assess and intervene with patients at risk of suicide. *AMERICAN PSYCHOLOGICAL ASSOCIATION*. Available at:

<https://www.apa.org/monitor/2022/06/continuing-education-intervene-suicide>

[Accessed on 22 October 2023]

- Cliffe, C., Seyedsalehi, A., Vardavoulia, K., Bittar, A., Velupillai, S., Shetty, H., ... & Dutta, R. (2021). Using natural language processing to extract self-harm and suicidality data from a clinical sample of patients with eating disorders: a retrospective cohort study. *BMJ Open*, 11(12), e053808. 10.1136/bmjopen-2021-053808
- Cristina, S. (2023). The Attention Mechanism from Scratch. *Machine Learning Mastery*. Available at: <https://machinelearningmastery.com/the-attention-mechanism-from-scratch/> [Accessed on 10 November 2023]
- Czeisler, M. É. (2020). Mental health, substance use, and suicidal ideation during the COVID-19 pandemic—United States, June 24–30, 2020. *MMWR. Morbidity and Mortality Weekly Report*, 69(32), 1049–1057. 10.15585/mmwr.mm6932a1
- Dadar, M., Manera, A. L., Fonov, V. S., Ducharme, S., & Collins, D. L. (2021). MNI-FTD templates, unbiased average templates of frontotemporal dementia variants. *Scientific Data*, 8(1), 222. 10.1038/s41597-021-01007-5
- Dai, P., Zhou, Y., Shi, Y., Lu, D., Chen, Z., Zou, B., ... & REST-meta-MDD Consortium. (2024). Classification of MDD using a Transformer classifier with large-scale multisite resting-state fMRI data. *Human Brain Mapping*, 45(1), e26542. 10.1002/hbm.26542
- Das, A. (2024). Logistic regression. In *Encyclopedia of Quality of Life and Well-Being Research* (pp. 3985-3986). Cham: Springer International Publishing. 10.1007/978-3-319-69909-7_1689-2

- Datta, G. (2023). *Towards Efficient Edge Intelligence with In-Sensor and Neuromorphic Computing: Algorithm-Hardware Co-Design* (Doctoral dissertation, University of Southern California).
- Demertzis, K., Iliadis, L., & Bougoudis, I. (2020). Gryphon: a semi-supervised anomaly detection system based on one-class evolving spiking neural network. *Neural Computing and Applications*, 32(9), 4303-4314. 10.1007/s00521-019-04363-x
- Deming, C. A., Harris, J. A., Castro-Ramirez, F., Glenn, J. J., Cha, C. B., Millner, A. J., & Nock, M. K. (2021). Inconsistencies in self-reports of suicidal ideation and attempts across assessments methods. *Psychological Assessment*, 33(3), 218-229. 10.1037/pas0000976.
- Devika, S. P., Pooja, M. R., Arpitha, M. S., & Vinayakumar, R. (2023, March). BERT-based approach for suicide and depression identification. In *Proceedings of Third International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2022* (pp. 435-444). Singapore: Springer Nature Singapore. 10.1007/978-981-19-9228-5_36
- Dewangan, D., Selot, S., & Panicker, S. (2023). The Accuracy Analysis of Different Machine Learning Classifiers for Detecting Suicidal Ideation and Content. *Asian Journal of Electrical Sciences*, 12(1). 10.51983/ajes-2023.12.1.3694
- Díaz-Álvarez, J., Matias-Guiu, J. A., Cabrera-Martín, M. N., Pytel, V., Segovia-Ríos, I., García-Gutiérrez, F., ... & Alzheimer's Disease Neuroimaging Initiative. (2022). Genetic algorithms for optimized diagnosis of Alzheimer's disease and Frontotemporal dementia using Fluorodeoxyglucose positron emission tomography imaging. *Frontiers in Aging Neuroscience*, 13, 708932. 10.3389/fnagi.2021.708932

- Diniz, E. J., Fontenele, J. E., de Oliveira, A. C., Bastos, V. H., Teixeira, S., Rabêlo, R. L., ... & Teles, A. S. (2022, April). Boamente: A natural language processing-based digital phenotyping tool for smart monitoring of suicidal ideation. In *Healthcare* (Vol. 10, No. 4, p. 698). MDPI. 10.3390/healthcare10040698
- Doborjeh, M. (2019). *Development of Spiking Neural Network Methods for Spatio-temporal Brain Data Analysis* (Doctoral dissertation, Auckland University of Technology).
- Doborjeh, Z., Doborjeh, M., Taylor, T., Kasabov, N., Wang, G. Y., Siegert, R., & Sumich, A. (2019). Spiking neural network modelling approach reveals how mindfulness training rewires the brain. *Scientific Reports*, 9(1), 6367. 10.1038/s41598-019-42863-x
- Dora, S., & Kasabov, N. (2021). Spiking neural networks for computational intelligence: an overview. *Big Data and Cognitive Computing*, 5(4), 67. 10.3390/bdcc5040067
- Dua, M., Gupta, R., Khari, M., & Crespo, R. G. (2019). Biometric iris recognition using radial basis function neural network. *Soft Computing*, 23(22), 11801-11815. 10.1007/s00500-018-03731-4
- Durstewitz, D., Huys, Q. J., & Koppe, G. (2021). Psychiatric illnesses as disorders of network dynamics. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 6(9), 865-876. 10.1016/j.bpsc.2020.01.001
- Eelbode, T., Sinonquel, P., Maes, F., & Bisschops, R. (2021). Pitfalls in training and validation of deep learning systems. *Best Practice & Research Clinical Gastroenterology*, 52, 101712. 10.1016/j.bpg.2020.101712
- Efstathiou, V., Michopoulos, I., Yotsidi, V., Smyrnis, N., Zompola, C., Papadopoulou, A., ... & Gournellis, R. (2021). Does suicidal ideation increase during the second

- COVID-19 lockdown?. *Psychiatry Research*, 301, 113990. 10.1016/j.psychres.2021.113990
- Efstathiou, V., Stefanou, M. I., Siafakas, N., Makris, M., Tsivgoulis, G., Zoumpourlis, V., ... & Rizos, E. (2022). Suicidality and COVID-19: Suicidal ideation, suicidal behaviors and completed suicides amidst the COVID-19 pandemic. *Experimental and Therapeutic Medicine*, 23(1), 1-8. 10.3892/etm.2021.11030
- Elbrecht, D., & Schuman, C. (2020, July). Neuroevolution of spiking neural networks using compositional pattern producing networks. In *International Conference on Neuromorphic Systems 2020* (pp. 1-5). 10.1145/3407197.3407198
- Erdem, K. (2021). Interactive guide to Attention Mechanism. *Towards Data Science*. Available at: <https://towardsdatascience.com/introduction-to-attention-mechanism-8d044442a29> [Accessed on 25 April 2024]
- Ergenzinger, E. (2022). The neurobiology of suicide: Research points to specific circuits for active vs. passive suicidal thoughts. *Psychology Today*. Available at: <https://www.psychologytoday.com/us/blog/night-sweats-and-delusions-grandeur/202202/the-neurobiology-suicide> [Accessed on 6 June 2023]
- Fang, Y., Yang, S., Zhao, B., & Huang, C. (2021). Cyberbullying detection in social networks using Bi-gru with self-attention mechanism. *Information*, 12(4), 171. 10.3390/info12040171
- Fonseka, T. M., Bhat, V., & Kennedy, S. H. (2019). The utility of artificial intelligence in suicide risk prediction and the management of suicidal behaviors. *Australian & New Zealand Journal of Psychiatry*, 53(10), 954-964. 10.1177/0004867419864428

- Fu, Q., & Dong, H. (2022). Spiking Neural Network Based on Multi-Scale Saliency Fusion for Breast Cancer Detection. *Entropy*, 24(11), 1543. 10.3390/e24111543.
- Ganesan, B., Al-Jumaily, A., Fong, K. N., Prasad, P., Meena, S. K., & Tong, R. K. Y. (2021). Impact of coronavirus disease 2019 (COVID-19) outbreak quarantine, isolation, and lockdown policies on mental health and suicide. *Frontiers in Psychiatry*, 12, 565190. 10.3389/fpsyt.2021.565190
- Geeksforgeeks. (2023). Guide to AUC ROC Curve in Machine Learning. *Geeksforgeeks*. Available at: <https://www.geeksforgeeks.org/auc-roc-curve/> [Accessed on 19 October 2023]
- GeeksforGeeks. (2024). K-Nearest Neighbours (KNN) Algorithm. *GeeksforGeeks*. Available at: <https://www.geeksforgeeks.org/k-nearest-neighbours/> [Accessed on 09 May 2024]
- Gholampour, S. (2024). Impact of Nature of Medical Data on Machine and Deep Learning for Imbalanced Datasets: Clinical Validity of SMOTE Is Questionable. *Machine Learning and Knowledge Extraction*, 6(2), 827-841. 10.3390/make6020039
- Ghosh, S., Ekbal, A., & Bhattacharyya, P. (2022). *Am I no good? towards detecting perceived burdensomeness and thwarted belongingness from suicide notes*. arXiv. 10.48550/arXiv.2206.06141.
- Ghosh, D., Sing, M., Adhikary, A., & Nayek, A. K. (2023). Machine Learning-Based Approaches in the Detection of Suicide From Social Media Comments. In *Cognitive Cardiac Rehabilitation Using IoT and AI Tools* (pp. 91-104). IGI Global. 10.4018/978-1-6684-7561-4.ch007

- Gökbayrak, N. S. (2021). What is suicidal ideation? *PsychCentral*. Available at: <https://psychcentral.com/depression/what-is-suicidal-ideation> [Accessed on 25 April 2024]
- Gonçalves, T., Rio-Torto, I., Teixeira, L. F., & Cardoso, J. S. (2022). A survey on attention mechanisms for medical applications: are we moving towards better algorithms? *IEEE Access*, 10, 98909 – 98935. 10.1109/ACCESS.2022.3206449.
- Guan, H., Yap, P. T., Bozoki, A., & Liu, M. (2024). Federated learning for medical image analysis: A survey. *Pattern Recognition*, 151, 110424. 10.1016/j.patcog.2024.110424
- Guidère, M. (2020). Nlp applied to online suicide intention detection. In *HealTAC 2020*. <https://inserm.hal.science/inserm-02521389/>
- Guy-Evans, O. (2023). Neuroimaging: Brain Scanning Techniques in Psychology. *Simply Psychology*. Available at: <https://www.simplypsychology.org/neuroimaging.html> [Accessed on 12 November 2023]
- Guo, K., Li, X., Fan, T., & Hu, X. (2022). VANet: a medical image fusion model based on attention mechanism to assist disease diagnosis. *BMC Bioinformatics*, 23(1), 548. 10.1186/s12859-022-05072-4
- Guo, Y., Jiang, X., Jia, L., Zhu, Y., Han, X., Wu, Y., ... & Tang, Y. (2023). Altered gray matter volumes and plasma IL-6 level in major depressive disorder patients with suicidal ideation. *NeuroImage: Clinical*, 38, 103403. 10.1016/j.nicl.2023.103403
- Haddad, J., Bynum, M., Eydenberg, M., Blakely, L., Kilwein, Z., Boukouvala, F., ... & Jalving, J. (2022). Verification of neural network surrogates. In *Computer Aided*

Chemical Engineering (Vol. 51, pp. 583-588). Elsevier. 10.1016/B978-0-323-95879-0.50098-9

Hao, Z., Li, H., Ouyang, L., Sun, F., Wen, X., & Wang, X. (2023). Pain avoidance and functional connectivity between insula and amygdala identifies suicidal attempters in patients with major depressive disorder using machine learning. *Psychophysiology*, 60(1), e14136. 10.1111/psyp.14136

Haque, A., Reddi, V., & Giallanza, T. (2021). Deep learning for suicide and depression identification with unsupervised label correction. In *Artificial Neural Networks and Machine Learning–ICANN 2021: 30th International Conference on Artificial Neural Networks, Bratislava, Slovakia, September 14–17, 2021, Proceedings, Part V* 30 (pp. 436-447). Springer International Publishing. 10.1007/978-3-030-86383-8_35

Harmer, B., Lee, S., Duong, T. V. H., & Saadabadi, A. (2020). Suicidal ideation. 2020 Nov 23. *StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing*.

Hasan, N., & Bao, Y. (2020). Impact of “e-Learning crack-up” perception on psychological distress among college students during COVID-19 pandemic: A mediating role of “fear of academic year loss”. *Children and Youth Services Review*, 118, 105355. 10.1016/j.chilyouth.2020.105355

Hassanin, M., Anwar, S., Radwan, I., Khan, F. S., & Mian, A. (2024). Visual attention methods in deep learning: An in-depth survey. *Information Fusion*, 108, 102417. 10.1016/j.inffus.2024.102417

Hatkevich, C., Venta, A., & Sharp, C. (2019). Theory of mind and suicide ideation and attempt in adolescent inpatients. *Journal of Affective Disorders*, 256, 17-25. 10.1016/j.jad.2019.05.051

- Hauser, T. U., Skvortsova, V., De Choudhury, M., & Koutsouleris, N. (2022). The promise of a model-based psychiatry: building computational models of mental ill health. *The Lancet Digital Health*, 4(11), e816-e828. 10.1016/S2589-7500(22)00152-2
- He, L., Chan, J. C. W., & Wang, Z. (2021). Automatic depression recognition using CNN with attention mechanism from videos. *Neurocomputing*, 422, 165-175. 10.1016/j.neucom.2020.10.015
- Heindl, A. (2022). What's the Difference Between DICOM and NIfTI?. *Encord*. Available at: <https://encord.com/blog/dicom-and-nifti-comparison/> [Accessed on 10 September 2023]
- Hicks, S. A., Strümke, I., Thambawita, V., Hammou, M., Riegler, M. A., Halvorsen, P., & Parasa, S. (2022). On evaluation metrics for medical applications of artificial intelligence. *Scientific Reports*, 12(1), 5979. 10.1038/s41598-022-09954-8
- Hill, R.M., Rufino, K., Kurian, S., Saxena, J., Saxena, K., & Williams, L. (2021). Suicide ideation and attempts in a pediatric emergency department before and during COVID-19. *Pediatrics*, 147(3). 10.1542/peds.2020-029280
- Hong, S., Liu, Y. S., Cao, B., Cao, J., Ai, M., Chen, J., Greenshaw, A., & Kuang, L. (2021). Identification of suicidality in adolescent major depressive disorder patients using sMRI: A machine learning approach. *Journal of Affective Disorders*, 280, 72-76. 10.1016/j.jad.2020.10.077
- Horowitz, L. M., Snyder, D. J., Boudreaux, E. D., He, J. P., Harrington, C. J., Cai, J., ... & Bridge, J. A. (2020). Validation of the ask suicide-screening questions for adult medical inpatients: a brief tool for all ages. *Psychosomatics*, 61(6), 713-722. 10.1016/j.psych.2020.04.008

- Hu, D. (2020). An introductory survey on attention mechanisms in NLP problems. In *Intelligent Systems and Applications: Proceedings of the 2019 Intelligent Systems Conference (IntelliSys) Volume 2* (pp. 432-448). Springer International Publishing. 10.1007/978-3-030-29513-4_31
- Hu, S., Mo, D., Guo, P., Zheng, H., Jiang, X., & Zhong, H. (2022). Correlation between suicidal ideation and emotional memory in adolescents with depressive disorder. *Scientific Reports*, 12(1), 5470. 10.1038/s41598-022-09459-4
- Hu, J., Huang, Y., Zhang, X., Liao, B., Hou, G., Xu, Z., ... & Li, P. (2023). Identifying suicide attempts, ideation, and non-ideation in major depressive disorder from structural MRI data using deep learning. *Asian Journal of Psychiatry*, 82, 103511. 10.1016/j.ajp.2023.103511
- Hua, X., Du, Z., Yu, H., & Maa, J. (2023). *Convolutional neural network based on sparse graph attention mechanism for MRI super-resolution.* arXiv. 10.48550/arXiv.2305.17898
- Huang, X., Rootes-Murdy, K., Bastidas, D. M., Nee, D. E., & Franklin, J. C. (2020). Brain differences associated with self-injurious thoughts and behaviors: a meta-analysis of neuroimaging studies. *Scientific Reports*, 10(1), 2404. 10.1038/s41598-020-59490-6
- Ibad, T., Kadir, S. J. A., & Ab Aziz, N. (2020). Evolving spiking neural network: A comprehensive survey of its variants and their results. *Journal of Theoretical and Applied Information Technology*, 98(24), 4061-4081.
- Ibad, T., Abdulkadir, S. J., Aziz, N., Ragab, M. G., & Al-Tashi, Q. (2022). Hyperparameter optimization of evolving spiking neural network for time-series classification. *New Generation Computing*, 40(1), 377-397. 10.1007/s00354-022-00165-3

- Ibode, R. T., Tunde-Francis, A. A., Afeye, A. F., Anifowose, O. T., Owolola, O. I., & Ogidan, O. A. (2022). Assessment Of The Prevalence Of Suicide Among Young Adults Using Machine Learning. *Global Journal of Pure and Applied Sciences*, 28(2), 177-184. 10.4314/gjpas.v28i2.7
- Jain, P., Srinivas, K. R., & Vichare, A. (2022). Depression and suicide analysis using machine learning and NLP. In *Journal of Physics: Conference Series* (Vol. 2161, No. 1, p. 012034). IOP Publishing. 10.1088/1742-6596/2161/1/012034
- Jankowsky, K., Steger, D., & Schroeders, U. (2024). Predicting lifetime suicide attempts in a community sample of adolescents using machine learning algorithms. *Assessment*, 31(3), 557-573. 10.1177/10731911231167490
- Japa, L., Serqueira, M., Mendonça, I., Bezerra, E., Aritsugi, M., & González, P. H. (2022, July). A conjugated evolutionary algorithm for hyperparameter optimization. In *2022 IEEE Congress on Evolutionary Computation (CEC)* (pp. 1-9). IEEE. 10.1109/CEC55065.2022.9870442
- Jayatilake, S. M. D. A. C., & Ganegoda, G. U. (2021). Involvement of machine learning tools in healthcare decision making. *Journal of Healthcare Engineering*, 2021. 10.1155/2021/6679512
- Ji, S., Pan, S., Li, X., Cambria, E., Long, G., & Huang, Z. (2020). Suicidal ideation detection: A review of machine learning methods and applications. *IEEE Transactions on Computational Social Systems*, 8(1), 214-226. 10.1109/TCSS.2020.3021467.
- Ji, S., Li, X., Huang, Z., & Cambria, E. (2022). Suicidal ideation and mental disorder detection with attentive relation networks. *Neural Computing and Applications*, 34(13), 10309-10319. 10.1007/s00521-021-06208-y

- Jiang, M., Yan, B., Li, Y., Zhang, J., Li, T., & Ke, W. (2022). Image classification of Alzheimer's disease based on external-attention mechanism and fully convolutional network. *Brain Sciences*, 12(3), 319. 10.3390/brainsci12030319
- Jiang, T., Xu, Q., Ran, X., Shen, J., Lv, P., Zhang, Q., & Pan, G. (2023, October). Adaptive deep spiking neural network with global-local learning via balanced excitatory and inhibitory mechanism. In *The Twelfth International Conference on Learning Representations*.
- Johnson, F., Valderrama, A., Valle, C., Crawford, B., Soto, R., & Nanculef, R. (2020). Automating configuration of convolutional neural network hyperparameters using genetic algorithm. *IEEE Access*, 8, 156139-156152. 10.1109/ACCESS.2020.3019245
- Kang, S. G., Cho, S. E., Na, K. S., Lee, J. S., Joo, S. W., Cho, S. J., ... & Lee, Y. J. (2020). Differences in brain surface area and cortical volume between suicide attempters and non-attempters with major depressive disorder. *Psychiatry Research: Neuroimaging*, 297, 111032. 10.1016/j.pscychresns.2020.111032
- Kasabov, N. K. (2019). Evolving spiking neural networks. *Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence*, 169-199. 10.1007/978-3-662-57715-8_5
- Kaushik, P., Gain, A., Kortylewski, A., & Yuille, A. (2021). *Understanding catastrophic forgetting and remembering in continual learning with optimal relevance mapping*. arXiv. 10.48550/arXiv.2102.11343.
- Kessler, R. C., Bossarte, R. M., Luedtke, A., Zaslavsky, A. M., & Zubizarreta, J. R. (2020). Suicide prediction models: a critical review of recent research with recommendations

- for the way forward. *Molecular Psychiatry*, 25(1), 168-179. 10.1038/s41380-019-0531-0
- Kharel, S. (2020). Perceptron vs SVM: a quick comparison. *Medium*. Available at: <https://medium.com/@subashkharel/perceptron-vs-svm-a-quick-comparison-6b5d6b5d64f> [Accessed on 23 August 2023]
- Killgore, W. D., Cloonan, S. A., Taylor, E. C., Fernandez, F., Grandner, M. A., & Dailey, N. S. (2020). Suicidal ideation during the COVID-19 pandemic: the role of insomnia. *Psychiatry Research*, 290, 113134. 10.1016/j.psychres.2020.113134
- Kim, Y., & Panda, P. (2021). Visual explanations from spiking neural networks using inter-spike intervals. *Scientific Reports*, 11, 19037. 10.1038/s41598-021-98448-0
- Kim, S., Son, H. G., Lee, S., Park, H., & Jeong, K. H. (2022a). A Study on the Relationship between Depression Change Types and Suicide Ideation before and after COVID-19. In *Healthcare* (Vol. 10, No. 9, p. 1610). MDPI. 10.3390/healthcare10091610
- Kodati, D., & Tene, R. (2023). Identifying suicidal emotions on social media through transformer-based deep learning. *Applied Intelligence*, 53(10), 11885-11917. 10.1007/s10489-022-04060-8
- Koppe, G., Meyer-Lindenberg, A., & Durstewitz, D. (2021). Deep learning for small and big data in psychiatry. *Neuropsychopharmacology*, 46(1), 176-190. 10.1038/s41386-020-0767-z
- Kosolwattana, T., Liu, C., Hu, R., Han, S., Chen, H., & Lin, Y. (2023). A self-inspected adaptive SMOTE algorithm (SASMOTE) for highly imbalanced data classification in healthcare. *BioData Mining*, 16(1), 15. 10.1186/s13040-023-00330-4

- Kumar, A., & Sachdeva, N. (2022). A Bi-GRU with attention and CapsNet hybrid model for cyberbullying detection on social media. *World Wide Web*, 25(4), 1537-1550. 10.1007/s11280-021-00920-4
- Kumarasinghe, K., Kasabov, N., & Taylor, D. (2020). Deep learning and deep knowledge representation in Spiking Neural Networks for Brain-Computer Interfaces. *Neural Networks*, 121, 169-185. 10.1016/j.neunet.2019.08.029
- Kumarasinghe, K., Kasabov, N., & Taylor, D. (2021). Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements. *Scientific Reports*, 11(1), 2486. 10.1038/s41598-021-81805-4
- Lai, C-H. (2019). Promising neuroimaging biomarkers in depression. *Psychiatry Investigation*, 16(9), 662. 10.30773/pi.2019.07.25.2
- Laña, I., Lobo, J. L., Capecci, E., Del Ser, J., & Kasabov, N. (2019). Adaptive long-term traffic state estimation with evolving spiking neural networks. *Transportation Research Part C: Emerging Technologies*, 101, 126-144. 10.1016/j.trc.2019.02.011
- Large, M., Corderoy, A., & McHugh, C. (2021). Is suicidal behavior a stronger predictor of later suicide than suicidal ideation? A systematic review and meta-analysis. *Australian & New Zealand Journal of Psychiatry*, 55(3), 254-267. 10.1177/0004867420931161
- Laurence, A. (2020). NIfTI Image Converter. *GitHub*. Available at: <https://github.com/alexlaurence/NIfTI-Image-Converter> [Accessed on 11 June 2023]
- Lázaro-Pérez, C., Munuera Gómez, P., Martínez-López, J. Á., & Gómez-Galán, J. (2023). Predictive factors of suicidal ideation in Spanish university students: a health,

- preventive, social, and cultural approach. *Journal of Clinical Medicine*, 12(3), 1207.
10.3390/jcm12031207
- Lewis, K. C., Roche, M. J., Brown, F., & Tillman, J. G. (2023). Attachment, loneliness, and social connection as prospective predictors of suicidal ideation during the COVID-19 pandemic: A relational diathesis-stress experience sampling study. *Suicide and Life-Threatening Behavior*, 53(1), 64-74. 10.1111/sltb.12922
- Li, W., Qi, F., Tang, M., & Yu, Z. (2020). Bidirectional LSTM with self-attention mechanism and multi-channel features for sentiment classification. *Neurocomputing*, 387, 63-77. 10.1016/j.neucom.2020.01.006
- Li, Y. (2023). Depression and Suicide Risk Prediction Based on Machine Learning Models. *Journal of Education, Humanities and Social Sciences*, 15, 302-307.
10.54097/ehss.v15i.9312
- Li, X., Li, M., Yan, P., Li, G., Jiang, Y., Luo, H., & Yin, S. (2023a). Deep learning attention mechanism in medical image analysis: Basics and beyonds. *International Journal of Network Dynamics and Intelligence*, 93-116. 10.53941/ijndi0201006
- Li, Y. Z., Wang, Y., Huang, Y. H., Xiang, P., Liu, W. X., Lai, Q. Q., ... & Guo, Y. F. (2023b). RSU-Net: U-net based on residual and self-attention mechanism in the segmentation of cardiac magnetic resonance images. *Computer Methods and Programs in Biomedicine*, 231, 107437.
10.1016/j.cmpb.2023.107437
- Lin, R. (2022, February). Analysis on the selection of the appropriate batch size in CNN neural network. In *2022 International Conference on Machine Learning and*

Knowledge Engineering (MLKE) (pp. 106-109). IEEE.
10.1109/MLKE55170.2022.00026

Linkedin. (2023). What are the benefits and challenges of using self-attention for image recognition and generation?. *Linkedin*. Available at: <https://www.linkedin.com/advice/3/what-benefits-challenges-using-self-attention-image> [Accessed on 17 November 2023]

Linthicum, K. P., Schafer, K. M., & Ribeiro, J. D. (2019). Machine learning in suicide science: Applications and ethics. *Behavioral Sciences & The Law*, 37(3), 214-222.
10.1002/bsl.2392

Liu, W., Wei, D., Chen, Q., Yang, W., Meng, J., Wu, G., ... & Qiu, J. (2017). Longitudinal test-retest neuroimaging data from healthy young adults in southwest China. *Scientific Data*, 4(1), 1-9. 10.1038/sdata.2017.17

Liu, C., Shen, W., Zhang, L., Du, Y., & Yuan, Z. (2021). Spike neural network learning algorithm based on an evolutionary membrane algorithm. *IEEE Access*, 9, 17071-17082. 10.1109/ACCESS.2021.3053280

Liu, C. (2022). Data Transformation: Standardization vs Normalization. *KDNuggets*. Available at: <https://www.kdnuggets.com/2020/04/data-transformation-standardization-normalization.html> [Accessed on 12 November 2023]

Liu, L., Pollock, N. J., Contreras, G., Tonmyr, L., & Thompson, W. (2022a). Prevalence of suicidal ideation among adults in Canada: results of the second Survey on COVID-19 and mental health. *Health Reports*, 33(5), 13-21.
10.25318/82-003-x202200500002-eng

- Liu, C., Wang, H., Liu, N., & Yuan, Z. (2022b). Optimizing the neural structure and hyperparameters of liquid state machines based on evolutionary membrane algorithm. *Mathematics*, 10(11), 1844. 10.3390/math10111844
- Liu, L., & Xu, X. (2023). Self-attention Mechanism at the Token Level: Gradient Analysis and Algorithm Optimization. *Knowledge-Based Systems*, 277, 110784. 10.1016/j.knosys.2023.110784
- Lobo, J. L., Del Ser, J., Bifet, A., & Kasabov, N. (2020). Spiking neural networks and online learning: An overview and perspectives. *Neural Networks*, 121, 88-100. 10.1016/j.neunet.2019.09.004
- López, F. (2021). Class Imbalance: Random Sampling and Data Augmentation with Imbalanced-Learn. *Towards Data Science*. Available at: <https://towardsdatascience.com/class-imbalance-random-sampling-and-data-augmentation-with-imbalanced-learn-63f3a92ef04a> [Accessed on 12 November 2023]
- López-Ramírez, E., Pérez-Santiago, A. D., Sánchez-Medina, M. A., Matías-Pérez, D., & García-Montalvo, I. A. (2023). Neural bases of suicidal ideation and depression in young college students. *Frontiers in Psychology*, 14, 1141591. 10.3389/fpsyg.2023.1141591.
- López Steinmetz, L. C., Dutto Florio, M. A., Leyes, C. A., Fong, S. B., Rigalli, A., & Godoy, J. C. (2022). Levels and predictors of depression, anxiety, and suicidal risk during COVID-19 pandemic in Argentina: the impacts of quarantine extensions on mental health state. *Psychology, Health & Medicine*, 27(1), 13-29. 10.1080/13548506.2020.1867318

- Lyashenko, V. (2021). Basic Guide to Spiking Neural Networks for Deep Learning. *Cnvr.io*. Available at: <https://cnvr.io/spiking-neural-networks/> [Accessed on 5 December 2023]
- Ma, Y., & Cao, Y. (2020, June). Dual attention based suicide risk detection on social media. In *2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)* (pp. 637-640). IEEE. 10.1109/ICAICA50127.2020.9182380
- Macalli, M., Castel, L., Jacqmin-Gadda, H., Tournier, M., Galera, C., Pereira, E., & Tzourio, C. (2024). Frequency of Depressive Symptoms and Suicidal Ideation Among University Students Before and After the COVID-19 Pandemic. *medRxiv*, 2024-03. 10.1101/2024.03.14.24304160
- Maciąg, P. S., Kasabov, N., Kryszkiewicz, M., & Bembeník, R. (2019). Air pollution prediction with clustering-based ensemble of evolving spiking neural networks and a case study for London area. *Environmental Modelling & Software*, 118, 262-280. 10.1016/j.envsoft.2019.04.012
- Maciąg, P. S., Kryszkiewicz, M., & Bembeník, R. (2020). Online evolving spiking neural networks for incremental air pollution prediction. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE. 10.1109/IJCNN48605.2020.9206775
- Maciąg, P. S., Kryszkiewicz, M., Bembeník, R., Lobo, J. L., & Del Ser, J. (2021). Unsupervised anomaly detection in stream data with online evolving spiking neural networks. *Neural Networks*, 139, 118-139. 10.1016/j.neunet.2021.02.017

- Malingan, N. (2023). Attention mechanism in deep learning. *Scaler*. Available at: <https://www.scaler.com/topics/deep-learning/attention-mechanism-deep-learning/> [Accessed on 25 April 2024]
- Mamun, M. A. (2021). Suicide and suicidal behaviors in the context of COVID-19 pandemic in Bangladesh: a systematic review. *Psychology Research and Behavior Management*, 14, 695-704. 10.2147/PRBM.S315760
- Mamun, M. A., Al Mamun, F., Hosen, I., Hasan, M., Rahman, A., Jubayar, A. M., ... & Sikder, M. T. (2021). Suicidality in Bangladeshi young adults during the COVID-19 pandemic: the role of behavioral factors, COVID-19 risk and fear, and mental health problems. *Risk Management and Healthcare Policy*, 14, 4051-4061. 10.2147/RMHP.S330282
- Manelis, A., Baranger, D. A. A., & Satz, S. (2021). Cortical myelin measured by the T1w/T2w ratio in individuals with depressive disorders and healthy controls. *OpenNeuro*. [Dataset]. <https://openneuro.org/datasets/ds003653/versions/1.0.0>
- Mathews, L., & Seetha, H. (2022). Learning from imbalanced healthcare data using overlap pattern synthesis. In *Proceedings of International Conference on Computational Intelligence and Data Engineering: ICCIDE 2021* (pp. 447-456). Singapore: Springer Nature Singapore. 10.1007/978-981-16-7182-1_35
- McDermott, R. (2024, March 15). *Prospect theory* | *Psychology, Decision Making & Risk Analysis*. Encyclopedia Britannica. <https://www.britannica.com/topic/prospect-theory> [Accessed on 25 April 2024]
- McHugh, C. M., Corderoy, A., Ryan, C. J., Hickie, I. B., & Large, M. M. (2019). Association between suicidal ideation and suicide: meta-analyses of odds ratios, sensitivity,

- specificity and positive predictive value. *BJPsych Open*, 5(2), e18. 10.1192/bjo.2018.88
- McHugh, C.M., & Large, M.M. (2020). Can machine-learning methods really help predict suicide? *Current Opinion in Psychiatry*, 33(4), 369-374. 10.1097/YCO.0000000000000609
- Mehdary, A., Chehri, A., Jakimi, A., & Saadane, R. (2024). Hyperparameter Optimization with Genetic Algorithms and XGBoost: A Step Forward in Smart Grid Fraud Detection. *Sensors*, 24(4), 1230. 10.3390/s24041230
- Meherali, S., Punjani, N., Louie-Poon, S., Abdul Rahim, K., Das, J. K., Salam, R. A., & Lassi, Z. S. (2021). Mental health of children and adolescents amidst COVID-19 and past pandemics: a rapid systematic review. *International Journal of Environmental Research and Public Health*, 18(7), 3432. 10.3390/ijerph18073432
- Mental Health Foundation. (2023). Loneliness and mental health. *Mental Health Foundation*. Available at: <https://www.mentalhealth.org.uk/explore-mental-health/loneliness> [Accessed on 25 April 2024]
- Michel, M., & Morales, J. (2020). Minority reports: Consciousness and the prefrontal cortex. *Mind & Language*, 35(4), 493-513. 10.1111/mila.12264
- Mienye, I. D., Ainah, P. K., Emmanuel, I. D., & Esenogho, E. (2021, March). Sparse noise minimization in image classification using Genetic Algorithm and DenseNet. In *2021 Conference on Information Communications Technology and Society (ICTAS)* (pp. 103-108). IEEE. 10.1109/ICTAS50802.2021.9395014

- Mitchell, S. M., Cero, I., Littlefield, A. K., & Brown, S. L. (2021). Using categorical data analyses in suicide research: Considering clinical utility and practicality. *Suicide and Life-Threatening Behavior*, 51(1), 76-87. 10.1111/sltb.12670
- Mohajon, J. (2020). Accuracy on Imbalanced Datasets and Why, You Need Confusion Matrix!. *Medium*. Available at: <https://medium.com/analytics-vidhya/accuracy-on-imbalanced-datasets-and-why-you-need-confusion-matrix-937613bf89bf> [Accessed on 19 October 2023]
- Moller, C. I., Badcock, P. B., Hetrick, S. E., Rice, S., Berk, M., Witt, K., ... & Davey, C. G. (2023). Predictors of suicidal ideation severity among treatment-seeking young people with major depressive disorder: The role of state and trait anxiety. *Australian & New Zealand Journal of Psychiatry*, 57(8), 1150-1162. 10.1177/00048674221144262
- Müller, D., Soto-Rey, I., & Kramer, F. (2022). Towards a guideline for evaluation metrics in medical image segmentation. *BMC Research Notes*, 15(1), 210. 10.1186/s13104-022-06096-y
- Muralidhar, K. S. V. (2021). What is Stratified Cross-Validation in Machine Learning?. *Towards Data Science*. Available at: <https://towardsdatascience.com/what-is-stratified-cross-validation-in-machine-learning-8844f3e7ae8e> [Accessed on 14 October 2023]
- Nadeem, A., Naveed, M., Islam Satti, M., Afzal, H., Ahmad, T., & Kim, K. I. (2022). Depression Detection Based on Hybrid Deep Learning SSCL Framework Using Self-Attention Mechanism: An Application to Social Networking Data. *Sensors*, 22(24), 9775. 10.3390/s22249775

- Nahm, F. S. (2022). Receiver operating characteristic curve: overview and practical use for clinicians. *Korean Journal of Anesthesiology*, 75(1), 25. 10.4097/kja.21209
- Nawaz, H., Shah, I., & Ali, S. (2023). The amygdala connectivity with depression and suicide ideation with suicide behavior: A meta-analysis of structural MRI, resting-state fMRI and task fMRI. *Progress In Neuro-Psychopharmacology and Biological Psychiatry*, 124, 110736. 10.1016/j.pnpbp.2023.110736
- Nemeroff, C. B. (2020). The state of our understanding of the pathophysiology and optimal treatment of depression: glass half full or half empty?. *American Journal of Psychiatry*, 177(8), 671 – 685. 10.1176/appi.ajp.2020.20060845
- Nikam, O., Singh, S., Patil, S., Nair, S., Raut, A., Lobo, V. B., ... & Laban, R. M. (2023). A Machine Learning Prediction Model for Envisaging Future Risk of Suicide. In *2023 5th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)* (pp. 1-6). IEEE. 10.1109/ICNTE56631.2023.10146651.
- Nikbakht, S., Anitescu, C., & Rabczuk, T. (2021). Optimizing the neural network hyperparameters utilizing genetic algorithm. *Journal of Zhejiang University-Science A*, 22(6), 407-426. 10.1631/jzus.A2000384
- Nomura, K., Minamizono, S., Maeda, E., Kim, R., Iwata, T., Hirayama, J., ... & Yamamoto, F. (2021). Cross-sectional survey of depressive symptoms and suicide-related ideation at a Japanese national university during the COVID-19 stay-home order. *Environmental Health and Preventive Medicine*, 26, 1-9. 10.1186/s12199-021-00953-1

- Novotech. (2021). The importance of control groups in clinical trials. *NOVOTECH*. Available at: <https://novotech-cro.com/faq/importance-control-groups-clinical-trials> [Accessed on 24 April 2024]
- O'Connor, R. C., Wetherall, K., Cleare, S., McClelland, H., Melson, A. J., Niedzwiedz, C. L., ... & Robb, K. A. (2021). The COVID-19 pandemic should be last orders for poor care of people with neurodevelopmental disorders. *British Journal of Psychiatry*, 218(6), 326-333. 10.1192/bjp.2020.212
- OECD. (2021). Supporting young people's mental health through the COVID-19 crisis. *Organization for Economic Co-operation and Development*. Available at: <https://www.oecd.org/coronavirus/policy-responses/supporting-young-people-s-mental-health-through-the-covid-19-crisis-84e143e5/> [Accessed on 4 December 2023]
- Oppenheimer, C. W., Bertocci, M., Greenberg, T., Chase, H. W., Stiffler, R., Aslam, H. A., ... & Phillips, M. L. (2021). Informing the study of suicidal thoughts and behaviors in distressed young adults: the use of a machine learning approach to identify neuroimaging, psychiatric, behavioral, and demographic correlates. *Psychiatry Research: Neuroimaging*, 317, 111386. 10.1016/j.psychresns.2021.111386
- Otten, N. V. (2023). Self-attention Made Easy And How To Implement It In PyTorch. *SPOT INTELLIGENCE*. Available at: <https://spotintelligence.com/2023/01/31/self-attention/> [Accessed on 16 October 2023]
- Orsolini, L., Latini, R., Pompili, M., Serafini, G., Volpe, U., Vellante, F., ... & De Berardis, D. (2020). Understanding the complex of suicide in depression: from research to clinics. *Psychiatry Investigation*, 17(3), 207. 10.30773/pi.2019.0171

- Owens, M., Townsend, E., Hall, E., Bhatia, T., Fitzgibbon, R., & Miller-Lakin, F. (2022). Mental health and wellbeing in young people in the UK during lockdown (COVID-19). *International Journal of Environmental Research and Public Health*, 19(3), 1132. 10.3390/ijerph19031132
- Owusu-Adjei, M., Ben Hayfron-Acquah, J., Frimpong, T., & Abdul-Salaam, G. (2023). Imbalanced class distribution and performance evaluation metrics: A systematic review of prediction accuracy for determining model performance in healthcare systems. *PLOS Digital Health*, 2(11), e0000290. 10.1371/journal.pdig.0000290
- Pappas, S. (2021). New research in suicide prevention. *AMERICAN PSYCHOLOGICAL ASSOCIATION*. Available at: <https://www.apa.org/monitor/2021/09/news-suicide-prevention> [Accessed on 22 October 2023]
- Parahar, M. (2019). Difference between JPEG and PNG. *Tutorialspoint*. Available at: <https://www.tutorialspoint.com/difference-between-jpeg-and-png> [Accessed on 2 September 2023]
- Parsa, M., Kulkarni, S. R., Coletti, M., Bassett, J., Mitchell, J. P., & Schuman, C. D. (2021). Multi-objective hyperparameter optimization for spiking neural network neuroevolution. In *2021 IEEE Congress on Evolutionary Computation (CEC)* (pp. 1225-1232). IEEE. 10.1109/CEC45853.2021.9504897
- Parsaei, M., Taghavizanjani, F., Cattarinussi, G., Moghaddam, H. S., Di Camillo, F., Akhondzadeh, S., ... & Delvecchio, G. (2023). Classification of suicidality by training supervised machine learning models with brain MRI findings: A systematic review. *Journal of Affective Disorders*, 340, 766 – 791. 10.1016/j.jad.2023.08.034

- Patel, H., & Soni, N. (2021, October). Machine Learning Based Approach For Prediction Of Suicide Related Activity. In *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC)* (pp. 967-972). IEEE. 10.1109/ICOSEC51865.2021.9591836.
- Patel, K. P., & Schuman, C. D. (2023, April). Impact of Noisy Input on Evolved Spiking Neural Networks for Neuromorphic Systems. In *Proceedings of the 2023 Annual Neuro-Inspired Computational Elements Conference* (pp. 52-56). 10.1145/3584954.3584969
- Paul, R. (2023). Model Interpretability and Explainability: A Comprehensive Guide. *Medium*. Available at: <https://rudrendupaul.medium.com/model-interpretability-and-explainability-a-comprehensive-guide-d347799f554> [Accessed on 25 April 2024]
- Perez, A. L. (2024). Depression Anxiety and Stress Scale (DASS-21). *Care Patron*. Available at: <https://www.carepatron.com/templates/depression-anxiety-and-stress-scale-dass-21> [Accessed on 10 May 2024]
- Picsellia. (2022). How to Deal with Imbalanced Datasets in Computer Vision. *Picsellia*. Available at: <https://www.picsellia.com/post/improve-imbalanced-datasets-in-computer-vision> [Accessed on 9 November 2023]
- Pigoni, A., Delvecchio, G., Turtulici, N., Madonna, D., Pietrini, P., Cecchetti, L., & Brambilla, P. (2024). Machine learning and the prediction of suicide in psychiatric populations: a systematic review. *Translational Psychiatry*, 14(1), 140. 10.1038/s41398-024-02852-9

- Pinto, M. S., Paoletta, R., Billiet, T., Van Dyck, P., Guns, P. J., Jeurissen, B., ... & Sijbers, J. (2020). Harmonization of brain diffusion MRI: Concepts and methods. *Frontiers in Neuroscience*, 14, 485829. 10.3389/fnins.2020.00396
- Pompili, M. (2019). Critical appraisal of major depression with suicidal ideation. *Annals of General Psychiatry*, 18, 1-5. 10.1186/s12991-019-0232-8
- Pradhan, A., King, J., Pinisetty, S., & Roop, P. S. (2023). Model based verification of spiking neural networks in cyber physical systems. *IEEE Transactions on Computers*, 72(9), 2426-2439. 10.1109/TC.2023.3251841.
- Pramukti, I., Strong, C., Sitthimongkol, Y., Setiawan, A., Pandin, M. G. R., Yen, C. F., ... & Ko, N. Y. (2020). Anxiety and suicidal thoughts during the COVID-19 pandemic: cross-country comparative study among Indonesian, Taiwanese, and Thai university students. *Journal of Medical Internet Research*, 22(12), e24487. 10.2196/24487
- Qiu, T., & Klonsky, E. D. (2021). Deciding to die: the relations of decision-making styles to suicide ideation and attempts. *International Journal of Cognitive Therapy*, 14(2), 341-361. 10.1007/s41811-021-00107-9
- Que, J., Yuan, K., Gong, Y., Meng, S., Bao, Y., & Lu, L. (2020). Raising awareness of suicide prevention during the COVID-19 pandemic. *Neuropsychopharmacology Reports*, 40(4), 392-395. 10.1002/npr2.12141
- Rahaman, M. N., Chaki, S., Biswas, M. S., Biswas, M., Ahmed, S., Mahi, M. J. N., & Faruqi, N. (2022, April). Identifying the signature of suicidality: A machine learning approach. In *THEETAS 2022: Proceedings of The International Conference on Emerging Trends in Artificial Intelligence and Smart Systems, THEETAS 2022*,

16-17 April 2022 (p. 279). European Alliance for Innovation. 10.4108/eai.16-4-2022.2318160

Ranjbarzadeh, R., Bagherian Kasgari, A., Jafarzadeh Ghouschi, S., Anari, S., Naseri, M., & Bendeche, M. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. *Scientific Reports*, 11(1), 1-17. <https://doi.org/10.1038/s41598-021-90428-8>

Rao, A., Park, J., Woo, S., Lee, J-Y., & Aalami, O. (2021). Studying the Effects of Self-Attention for Medical Image Analysis. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops* (pp. 3416 – 3425). 10.1109/ICCVW54120.2021.00381

Rappai, S., & Ramasamy, G. (2022, January). Computational Methods to Predict Suicide Ideation among Adolescents. In *2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)* (pp. 1-11). IEEE. 10.1109/ACCAI53970.2022.9752645.

Rekha, G., Tyagi, A. K., Sreenath, N., & Mishra, S. (2021, January). Class imbalanced data: Open issues and future research directions. In *2021 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1-6). IEEE. 10.1109/ICCCI50826.2021.9402272

Rendyk. (2024). Tuning the Hyperparameters and Layers of Neural Network Deep Learning. *Analytics Vidhya*. Available at: <https://www.analyticsvidhya.com/blog/2021/05/tuning-the-hyperparameters-and-layers-of-neural-network-deep-learning/> [Accessed on 13 May 2024]

- Renjith, S., Abraham, A., Jyothi, S. B., Chandran, L., & Thomson, J. (2022). An ensemble deep learning technique for detecting suicidal ideation from posts in social media platforms. *Journal of King Saud University-Computer and Information Sciences*, 34(10), 9564 – 9575. 10.1016/j.jksuci.2021.11.010
- Richter, O., & Wattenhofer, R. (2020). *Normalized attention without probability cage*. arXiv. 10.48550/arXiv.2005.09561.
- Rizk, M. M., Rubin-Falcone, H., Lin, X., Keilp, J. G., Miller, J. M., Milak, M. S., ... & Mann, J. J. (2019). Gray matter volumetric study of major depression and suicidal behavior. *Psychiatry Research: Neuroimaging*, 283, 16-23. 10.1016/j.psychresns.2018.11.007
- Robinson, E., Sutin, A. R., Daly, M., & Jones, A. (2022). A systematic review and meta-analysis of longitudinal cohort studies comparing mental health before versus during the COVID-19 pandemic in 2020. *Journal of Affective Disorders*, 296, 567-576. 10.1016/j.jad.2021.09.098
- Rogers, J. P., Chesney, E., Oliver, D., Pollak, T. A., McGuire, P., Fusar-Poli, P., ... & David, A. S. (2020). Psychiatric and neuropsychiatric presentations associated with severe coronavirus infections: a systematic review and meta-analysis with comparison to the COVID-19 pandemic. *The Lancet Psychiatry*, 7(7), 611-627. 10.1016/S2215-0366(20)30203-0
- Rondinella, A., Crispino, E., Guarnera, F., Giudice, O., Ortis, A., Russo, G., ... & Battiato, S. (2023). Boosting multiple sclerosis lesion segmentation through attention mechanism. *Computers in Biology and Medicine*, 161, 107021. 10.1016/j.combiomed.2023.107021

- Roy, A., Nikolitch, K., McGinn, R., Jinah, S., Klement, W., & Kaminsky, Z. A. (2020). A machine learning approach predicts future risk to suicidal ideation from social media data. *NPJ Digital Medicine*, 3(1), 1-12.
- Roy, K., Zi, Y., Narayanan, V., Gaur, M., & Sheth, A. (2022). *KSAT: Knowledge-infused self attention transformer--integrating multiple domain-specific contexts*. arXiv. 10.48550/arXiv.2210.04307.
- Roy, D., Roy, A., & Roy, U. (2024). Learning from Imbalanced Data in Healthcare: State-of-the-Art and Research Challenges. *Computational Intelligence in Healthcare Informatics*, 1132, 19-32. 10.1007/978-981-99-8853-2_2
- Ruiz-Serra, J., White, J., Petrie, S., Kameneva, T., & McCarthy, C. (2022). *Towards self-attention based visual navigation in the real world*. arXiv. 10.48550/arXiv.2209.07043.
- Runkle, J. D., Yadav, S., Michael, K., Green, S., Weiser, J., & Sugg, M. M. (2022). Crisis response and suicidal patterns in US youth before and during COVID-19: a latent class analysis. *Journal of Adolescent Health*, 70(1), 48-56. 10.1016/j.jadohealth.2021.10.003
- Ryan, C. J., & Bartels, J. (2021). Involuntary hospitalization. *Psychiatric Ethics*, 5.
- Sabater, V. (2021). The Prefrontal Cortex: One of the Most Interesting Parts of the Brain. *Exploring Your Mind*. Available at: <https://exploringyourmind.com/prefrontal-cortex-interesting-parts-brain/> [Accessed on 27 June 2023]
- Sabri, N., Hamed, H. N. A., Ibrahim, Z., Ibrahim, K., Isa, M. A., & Diah, N. M. (2022). The hybrid feature extraction method for classification of adolescence idiopathic scoliosis

- using Evolving Spiking Neural Network. *Journal of King Saud University-Computer and Information Sciences*, 34(10), 8899 – 8908. 10.1016/j.jksuci.2022.08.019
- Sadek, J. (2019). Suicide Risk Assessment Tools and Instruments. *A Clinician's Guide to Suicide Risk Assessment and Management*, 33-44. 10.1007/978-3-319-77773-3_4
- Saha, S., Dasgupta, S., Anam, A., Saha, R., Nath, S., & Dutta, S. (2023). An Investigation of Suicidal Ideation from Social Media Using Machine Learning Approach. *Baghdad Science Journal*, 20(3 (Supl.)), 1164-1164. 10.21123/bsj.2023.8515
- Sara, S. S., Rahman, M. A., Rahman, R., & Talukder, A. (2024). Prediction of suicidal ideation with associated risk factors among university students in the southern part of Bangladesh: machine learning approach. *Journal of Affective Disorders*, 349, 502-508. 10.1016/j.jad.2024.01.092
- Saravanan, M., Bablani, A., & Rangisetty, N. (2022, April). Evolving Spiking Neural Network as a Classifier: An Experimental Review. In *International Conference on Advances in Computing and Data Sciences* (pp. 304-315). Cham: Springer International Publishing. 10.1007/978-3-031-12641-3_25
- Sawhney, R., Joshi, H., Gandhi, S., & Shah, R. R. (2021, March). Towards ordinal suicide ideation detection on social media. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining* (pp. 22-30). 10.1145/3437963.3441805
- Schluter, P. J., Génereux, M., Hung, K. K., Landaverde, E., Law, R. P., Mok, C. P. Y., ... & Roy, M. (2022). Patterns of suicide ideation across eight countries in four continents during the COVID-19 pandemic era: repeated cross-sectional study. *JMIR Public Health and Surveillance*, 8(1), e32140. 10.2196/32140

- Schmaal, L., van Harmelen, A. L., Chatzi, V., Lippard, E. T., Toenders, Y. J., Averill, L. A., ... & Blumberg, H. P. (2020). Imaging suicidal thoughts and behaviors: a comprehensive review of 2 decades of neuroimaging studies. *Molecular Psychiatry*, 25(2), 408-427. 10.1038/s41380-019-0587-x
- Segreti, A. M., Chase, H. W., Just, M., Brent, D., & Pan, L. (2019). Cortical thickness and volume reductions in young adults with current suicidal ideation. *Journal of Affective Disorders*, 245, 126-129. 10.1016/j.jad.2018.10.081
- Selvaraj, N. (2022). Confusion Matrix, Precision, and Recall Explained. *KDnuggets*. Available at: <https://www.kdnuggets.com/2022/11/confusion-matrix-precision-recall-explained.html> [Accessed on 14 October 2023]
- Sert, E. (2021). Medical Image Pre-Processing with Python. *Towards Data Science*. Available at: <https://towardsdatascience.com/medical-image-pre-processing-with-python-d07694852606> [Accessed on 21 August 2023]
- Sewall, C. J., Goldstein, T. R., & Rosen, D. (2021). Objectively measured digital technology use during the COVID-19 pandemic: Impact on depression, anxiety, and suicidal ideation among young adults. *Journal of Affective Disorders*, 288, 145-147. 10.1016/j.jad.2021.04.008
- Shafir, H. (2023). Suicidal ideation: Symptoms, causes, effects, & prevention. *Choosing Therapy*. Available at: <https://www.choosingtherapy.com/suicidal-ideation/> [Accessed on 25 April 2024]
- Shah, D., Wang, G. Y., Doborjeh, M., Doborjeh, Z., & Kasabov, N. (2019). Deep learning of eeg data in the neucube brain-inspired spiking neural network architecture for a better understanding of depression. In *Neural Information Processing: 26th*

International Conference, ICONIP 2019, Sydney, NSW, Australia, December 12–15, 2019, Proceedings, Part III 26 (pp. 195-206). Springer International Publishing.
10.1007/978-3-030-36718-3_17

Shankar, R., El Kady, R., & Aggarwal, A. (2020). Youth suicide: a population crying for help? A system overloaded? Who can help?. *Missouri Medicine*, 117(4), 370.
PMC7431062

Sharique, Md. (2021). Vision Transformer: “Attention in Images”. *Medium*. Available at:
<https://medium.com/analytics-vidhya/vision-transformer-attention-in-images-a86d0a8adc1b> [Accessed on 9 August 2023]

Shen, J., Liu, J. K., & Wang, Y. (2021). Dynamic spatiotemporal pattern recognition with recurrent spiking neural network. *Neural Computation*, 33(11), 2971-2995.
10.1162/neco_a_01432

Shen, J., Xu, Q., Liu, J. K., Wang, Y., Pan, G., & Tang, H. (2023, June). Esl-snns: An evolutionary structure learning strategy for spiking neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 37, No. 1, pp. 86-93).
10.1609/aaai.v37i1.25079

Sher, L. (2020a). The impact of the COVID-19 pandemic on suicide rates. *QJM: An International Journal of Medicine*, 113(10), 707-712. 10.1093/qjmed/hcaa202

Sher, L. (2020b). Are COVID-19 survivors at increased risk for suicide?. *Acta Neuropsychiatrica*, 32(5), 270-270. 10.1017/neu.2020.21

Shin, H. D., Zaheer, J., Rodak, T., Torous, J., & Strudwick, G. (2022). Information and communication technology-based interventions for suicide prevention implemented

in clinical settings: a scoping review protocol. *BMJ Open*, 12(1), e056232. 10.1136/bmjopen-2021-056232

Simplilearn. (2023). What are Radial Basis Functions Neural Networks? Everything You Need to Know. *Simplilearn*. Available at: <https://www.simplilearn.com/tutorials/machine-learning-tutorial/what-are-radial-basis-functions-neural-networks> [Accessed on 11 November 2023]

Simpson, S. A., Goans, C., Loh, R., Ryall, K., Middleton, M. C., & Dalton, A. (2021). Suicidal ideation is insensitive to suicide risk after emergency department discharge: Performance characteristics of the Columbia-Suicide Severity Rating Scale Screener. *Academic Emergency Medicine*, 28(6), 621-629. 10.1111/acem.14198

Singh, S. (2020). Data Augmentation to solve imbalanced training data for image classification. *Medium*. Available at: <https://medium.com/analytics-vidhya/data-augmentation-to-solve-imbalanced-training-data-for-image-classification-f6d888cbd596> [Accessed on 9 November 2023]

Singh, K. U., Kumar, A., Singh, T., & Ram, M. (2022). Image-based decision making for reliable and proper diagnosing in NIFTI format using watermarking. *Multimedia Tools and Applications*, 81(27), 39577-39603. 10.1007/s11042-022-12192-9

Sirsat, M. (2019). What is confusion matrix and advanced classification metrics?. *Data Science and Machine Learning*. Available at: <https://manisha-sirsat.blogspot.com/2019/04/confusion-matrix.html> [Accessed on 3 August 2023]

Škrlj, B., Džeroski, S., Lavrač, N., & Petković, M. (2020). Feature importance estimation with self-attention networks. In *24th European Conference on Artificial Intelligence (ECAI 2020)* (pp. 1491-1498). IOS Press. 10.3233/FAIA200256

- Sohail, A. (2023). Genetic algorithms in the fields of artificial intelligence and data sciences. *Annals of Data Science*, 10(4), 1007-1018. 10.1007/s40745-021-00354-9
- Son, C., Hegde, S., Smith, A., Wang, X., & Sasangohar, F. (2020). Effects of COVID-19 on college students' mental health in the United States: Interview survey study. *Journal of Medical Internet Research*, 22(9), e21279. 10.2196/21279
- Soto-Sanz, V., Falcó, R., Marzo, J. C., Piqueras, J. A., PSICO-RECURSOS COVID-19 study group, Lopez-Nuñez, A., ... & Vidal-Arenas, V. (2021). Socio-emotional strengths against psychopathology and suicidal ideation in fear of COVID-19. *Current Psychology*, 1-11. 10.1007/s12144-021-02185-6
- Stocksieker, S., Pommeret, D., & Charpentier, A. (2023). *Data augmentation for imbalanced regression*. arXiv. 10.48550/arXiv.2302.09288.
- Suragala, A., Venkateswarlu, P., & China Raju, M. (2021). A comparative study of performance metrics of data mining algorithms on medical data. In *ICCCE 2020: Proceedings of the 3rd International Conference on Communications and Cyber Physical Engineering* (pp. 1549-1556). Springer Singapore. 10.1007/978-981-15-7961-5_139
- Swift, A., Heale, R., & Twycross, A. (2020). What are sensitivity and specificity?. *Evidence-Based Nursing*, 23(1), 2-4. 10.1136/ebnurs-2019-103225
- Taherkhani, A., Belatreche, A., Li, Y., Cosma, G., Maguire, L. P., & McGinnity, T. M. (2020). A review of learning in biologically plausible spiking neural networks. *Neural Networks*, 122, 253-272. 10.1016/j.neunet.2019.09.036
- Takagi, Y., Hashimoto, N., Masuda, H., Miyoshi, H., Ohshima, K., Hontani, H., & Takeuchi, I. (2023). Transformer-based personalized attention mechanism for medical images

- with clinical records. *Journal of Pathology Informatics*, 14, 100185.
10.1016/j.jpi.2022.100185
- Tam, A. (2021). Principal component analysis for visualization. *Machine Learning Mystery*.
Available at: <https://machinelearningmastery.com/principal-component-analysis-for-visualization/> [Accessed on 13 December 2023]
- Tan, C., Šarlija, M., & Kasabov, N. (2020a). Spiking neural networks: background, recent development and the NeuCube architecture. *Neural Processing Letters*, 52(2), 1675-1701. 10.1007/s11063-020-10322-8
- Tan, C., Cebailos, G., Kasabov, N., & Puthanmadam Subramaniam, N. (2020b). Fusionsense: Emotion classification using feature fusion of multimodal data and deep learning in a brain-inspired spiking neural network. *Sensors*, 20(18), 5328. 10.3390/s20185328
- Tanaka, T., & Okamoto, S. (2021). Increase in suicide following an initial decline during the COVID-19 pandemic in Japan. *Nature Human Behaviour*, 5(2), 229-238. 10.1038/s41562-020-01042-z
- Tao, W., Li, C., Song, R., Cheng, J., Liu, Y., Wan, F., & Chen, X. (2020). EEG-based emotion recognition via channel-wise attention and self attention. *IEEE Transactions on Affective Computing*, 14(1), 382-393. 10.1109/TAFFC.2020.3025777
- Tasnim, R., Islam, M. S., Sujana, M. S. H., Sikder, M. T., & Potenza, M. N. (2020). Suicidal ideation among Bangladeshi university students early during the COVID-19 pandemic: Prevalence estimates and correlates. *Children and Youth Services Review*, 119, 105703. 10.1016/j.childyouth.2020.105703

- Thabtah, F., Hammoud, S., Kamalov, F., & Gonsalves, A. (2020). Data imbalance in classification: Experimental evaluation. *Information Sciences*, 513, 429-441. 10.1016/j.ins.2019.11.004
- Thavasimani, K., & Srinath, N. K. (2022). Hyperparameter optimization using custom genetic algorithm for classification of benign and malicious traffic on internet of things-23 dataset. *International Journal of Electrical & Computer Engineering (2088-8708)*, 12(4), 4031-4041. 10.11591/ijece.v12i4.pp4031-4041
- Theintactone. (2023). Min-Max Normalization. *The Intact One*. Available at: <https://theintactone.com/2023/01/22/min-max-normalization/> [Accessed on 12 November 2023]
- Thieme, C. (2021). Understanding Precision, Sensitivity, and Specificity In Classification Modeling and How To Calculate Them With A Confusion Matrix. *Towards Data Science*. Available at: <https://towardsdatascience.com/understanding-common-classification-metrics-titanic-style-8b8a562d3e32> [Accessed on 19 October 2023]
- Thölke, P., Mantilla-Ramos, Y. J., Abdelhedi, H., Maschke, C., Dehgan, A., Harel, Y., ... & Jerbi, K. (2023). Class imbalance should not throw you off balance: Choosing the right classifiers and performance metrics for brain decoding with imbalanced data. *NeuroImage*, 277, 120253. 10.1016/j.neuroimage.2023.120253
- Tokuç, A. A. (2024). Splitting a Dataset into Train and Test Sets. *Baeldung*. Available at: <https://www.baeldung.com/cs/train-test-datasets-ratio> [Accessed on 11 May 2024]
- Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44-56. 10.1038/s41591-018-0300-7

- Tomar, D., Lortkipanidze, M., Vray, G., Bozorgtabar, B., & Thiran, J. P. (2021). Self-attentive spatial adaptive normalization for cross-modality domain adaptation. *IEEE Transactions on Medical Imaging*, 40(10), 2926-2938. 10.1109/TMI.2021.3059265
- Torales, J., O'Higgins, M., Castaldelli-Maia, J. M., & Ventriglio, A. (2020). The outbreak of COVID-19 coronavirus and its impact on global mental health. *International Journal of Social Psychiatry*, 66(4), 317–320. 10.1177/0020764020915212
- Toto, E., Tlachac, M. L., & Rundensteiner, E. A. (2021). Audibert: A deep transfer learning multimodal classification framework for depression screening. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management* (pp. 4145-4154). 10.1145/3459637.3481895
- Tripathi, H. (2019). What is balanced and imbalanced dataset? *Medium*. Available at: <https://medium.com/analytics-vidhya/what-is-balance-and-imbalance-dataset-89e8d7f46bc5> [Accessed on 24 April 2024]
- Turing. (2023). Different types of cross-validations in machine learning and their explanations. *Turing*. Available at: <https://www.turing.com/kb/different-types-of-cross-validations-in-machine-learning-and-their-explanations> [Accessed on 13 December 2023]
- Tyagi, S., & Mittal, S. (2020). Sampling approaches for imbalanced data classification problem in machine learning. In *Proceedings of ICRIC 2019: Recent Innovations in Computing* (pp. 209-221). Springer International Publishing. 10.1007/978-3-030-29407-6_17

- Ullah, Z., Usman, M., Latif, S., & Gwak, J. (2023). Densely attention mechanism based network for COVID-19 detection in chest X-rays. *Scientific Reports*, 13(1), 261. 10.1038/s41598-022-27266-9
- UP Population institute. (2022). Pinoy youth in worse mental shape today, nationwide survey indicates. *UNIVERSITY OF THE PHILIPPINES POPULATION INSTITUTE*. Available at: <https://www.uppi.upd.edu.ph/news/2022/pinoy-youth-in-worse-mental-health-shape-today> [Accessed on 4 December 2023]
- Vahratian, A., Blumberg, S. J., Terlizzi, E. P., & Schiller, J. S. (2021). Symptoms of anxiety or depressive disorder and use of mental health care among adults during the COVID-19 pandemic – Unites States, August 2020 – February 2021. *Morbidity and Mortality Weekly Report*, 70(13), 490–494. 10.15585/mmwr.mm7013e2
- Van Mens, K., de Schepper, C. W. M., Wijnen, B., Koldijk, S. J., Schnack, H., de Looft, P., ... & De Beurs, D. (2020). Predicting future suicidal behaviour in young adults, with different machine learning techniques: A population-based longitudinal study. *Journal of Affective Disorders*, 271, 169–177. 10.1016/j.jad.2020.03.081
- Van Velzen, L. S., Toenders, Y. J., Avila-Parcet, A., Dinga, R., Rabinowitz, J. A., Campos, A. I., ... & Schmaal, L. (2022a). Classification of suicidal thoughts and behaviour in children: results from penalised logistic regression analyses in the Adolescent Brain Cognitive Development study. *The British Journal of Psychiatry*, 220(4), 210-218. 10.1192/bjp.2022.7
- Van Velzen, L. S., Dauvermann, M. R., Colic, L., Villa, L. M., Savage, H. S., Toenders, Y. J., ... & Schmaal, L. (2022b). Structural brain alterations associated with suicidal thoughts and behaviors in young people: results from 21 international studies from

- the ENIGMA Suicidal Thoughts and Behaviours consortium. *Molecular Psychiatry*, 27(11), 4550-4560. 10.1038/s41380-022-01734-0
- Vanes, L. D., Moutoussis, M., Ziegler, G., Goodyer, I. M., Fonagy, P., Jones, P. B., ... & Dolan, R. J. (2020). White matter tract myelin maturation and its association with general psychopathology in adolescence and early adulthood. *Human Brain Mapping*, 41(3), 827-839. 10.1002/hbm.24842
- Velupillai, S., Hadlaczky, G., Baca-Garcia, E., Gorrell, G. M., Werbeloff, N., Nguyen, D., ... & Dutta, R. (2019). Risk assessment tools and data-driven approaches for predicting and preventing suicidal behavior. *Frontiers in Psychiatry*, 10, 36. 10.3389/fpsyt.2019.00036
- Verma, A., Harper, M., Assi, S., Al-Hamid, A., Yousif, M. G., Mustafina, J., ... & Al-Jumeily OBE, D. (2023). Suicide ideation detection: a comparative study of sequential and transformer hybrid algorithms. In *The International Conference on Data Science and Emerging Technologies* (pp. 373-387). Singapore: Springer Nature Singapore. 10.1007/978-981-99-0741-0_27
- Verstynen, T., & Kording, K. (2021). *A critical reappraisal of predicting suicidal ideation using fMRI*. arXiv. 10.48550/arXiv.2103.06114.
- Vidal-Ribas, P., Janiri, D., Doucet, G. E., Pornpattananangkul, N., Nielson, D. M., Frangou, S., & Stringaris, A. (2021). Multimodal neuroimaging of suicidal thoughts and behaviors in a US population-based sample of school-age children. *American Journal of Psychiatry*, 178(4), 321-332. 10.1176/appi.ajp.2020.20020120
- Vieira, R., Faria, A. R., Ribeiro, D., Picó-Pérez, M., & Bessa, J. M. (2023). Structural and functional brain correlates of suicidal ideation and behaviors in depression: A

- scoping review of MRI studies. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, 126, 110799. 10.1016/j.pnpbp.2023.110799
- Visser, M., Petr, J., Müller, D. M., Eijelaar, R. S., Hendriks, E. J., Witte, M., ... & De Witt Hamer, P. C. (2020). Accurate MR image registration to anatomical reference space for diffuse glioma. *Frontiers in Neuroscience*, 14, 585. 10.3389/fnins.2020.00585
- Wang, L., Zhao, Y., Edmiston, E. K., Womer, F. Y., Zhang, R., Zhao, P., ... & Wei, S. (2020a). Structural and functional abnormalities of amygdala and prefrontal cortex in major depressive disorder with suicide attempts. *Frontiers in Psychiatry*, 10, 923.
- Wang, P., Zhang, R., Jiang, X., Wei, S., Wang, F., & Tang, Y. (2020b). Gray matter volume alterations associated with suicidal ideation and suicide attempts in patients with mood disorders. *Annals of General Psychiatry*, 19, 1–7. 10.1186/s12991-020-00318-y
- Wang, L., Li, J., Liu, H., Wang, Z., Yang, L., & An, L. (2021). Influence Factors for Decision-Making Performance of Suicide Attempters and Suicide Ideators: The Roles of Somatic Markers and Explicit Knowledge. *Frontiers in Psychology*, 12, 693879. 10.3389/fpsyg.2021.693879
- Wang, G., Sun, Y., Cheng, S., & Song, S. (2023a). Evolving connectivity for recurrent spiking neural networks. *Advances in Neural Information Processing Systems*, 36, 2991-3007.
- Wang, Y., Yang, G., Li, S., Li, Y., He, L., & Liu, D. (2023b). Arrhythmia classification algorithm based on multi-head self-attention mechanism. *Biomedical Signal Processing and Control*, 79, 104206. 10.1016/j.bspc.2022.104206

- Wang, G., Sun, Y., Cheng, S., & Song, S. (2023c). Evolving connectivity for recurrent spiking neural networks. *Advances in Neural Information Processing Systems*, 36, 2991-3007.
- Wang, J., Wu, D. D., DeLorenzo, C., & Yang, J. (2024). Examining factors related to low performance of predicting remission in participants with major depressive disorder using neuroimaging data and other clinical features. *Plos One*, 19(3), e0299625. 10.1371/journal.pone.0299625
- Weng, J. C., Lin, T. Y., Tsai, Y. H., Cheok, M. T., Chang, Y. P. E., & Chen, V. C. H. (2020). An autoencoder and machine learning model to predict suicidal ideation with brain structural imaging. *Journal of Clinical Medicine*, 9(3), 658. 10.3390/jcm9030658
- Wilks, C. R., Chu, C., Sim, D., Lovell, J., Gutierrez, P., Joiner, T., ... & Nock, M. K. (2021). User engagement and usability of suicide prevention apps: systematic search in app stores and content analysis. *JMIR Formative Research*, 5(7), e27018. 10.2196/27018
- Wisłowska-Stanek, A., Kolosowska, K., & Maciejak, P. (2021). Neurobiological basis of increased risk for suicidal behaviour. *Cells*, 10(10), 2519. 10.3390/cells10102519
- Wongnongtaey, K., Srisomboon, K., & Sutivong, D. (2023, April). Analyzing Suicide and Contributing Factors in Thailand Using Classification by Logistic Regression, Decision Tree and Support Vector Machine. In *2023 IEEE 3rd International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB)* (pp. 130-135). IEEE. 10.1109/ICEIB57887.2023.10170197
- Woolrich, M., Jenkinson, M., & Mackay, C. (2020). Neuroimaging technologies. *New Oxford Textbook of Psychiatry*, 101.

- Wu, L., Xu, Z., Wang, Z., Chen, Z., Huang, Z., Peng, C., ... & Zhao, H. (2022). Machine learning accelerated carbon neutrality research using big data—from predictive models to interatomic potentials. *Science China Technological Sciences*, 65(10), 2274-2296. 10.1007/s11431-022-2095-7
- Wu, D., & Mori, S. (2023). Structural Neuroimaging: From Macroscopic to Microscopic Scales. In *Handbook of Neuroengineering* (pp. 2917-2951). Singapore: Springer Nature Singapore. 10.1007/978-981-16-5540-1_84
- Wu, X., Song, Y., Zhou, Y., Jiang, Y., Bai, Y., Li, X., & Yang, X. (2023). STCA-SNN: self-attention-based temporal-channel joint attention for spiking neural networks. *Frontiers in Neuroscience*, 17, 1261543. 10.3389/fnins.2023.1261543
- Wu, J., Wang, Y., Li, Z., Lu, L., & Li, Q. (2024). A Review of Computing with Spiking Neural Networks. *Computers, Materials & Continua*, 78(3).
- Xiao, Y., Yin, H., Wang, S. H., & Zhang, Y. D. (2021). TReC: Transferred ResNet and CBAM for detecting brain diseases. *Frontiers in Neuroinformatics*, 15, 781551. 10.3389/fninf.2021.781551
- Xu, D., Ruan, C., Korpeoglu, E., Kumar, S., & Achan, K. (2019). Self-attention with functional time representation learning. *Advances in Neural Information Processing Systems*, 32.
- Yadav, H. S., Panchal, P., Manawat, D., S, G., & S, S. (2023). Self Attention in U-Net for Semantic Segmentation of Low Resolution SAR Images. In *Proceedings of the 2023 Asia Conference on Computer Vision, Image Processing and Pattern Recognition* (pp. 1-7). 10.1145/3596286.3596291

- Yamazaki, K., Vo-Ho, V. K., Bulsara, D., & Le, N. (2022). Spiking neural networks and their applications: A Review. *Brain Sciences*, 12(7), 863. 10.3390/brainsci12070863
- Yan, W., Qu, G., Hu, W., Abrol, A., Cai, B., Qiao, C., ... & Calhoun, V. D. (2022). Deep learning in neuroimaging: Promises and challenges. *IEEE Signal Processing Magazine*, 39(2), 87-98. 10.1109/MSP.2021.3128348
- Yang, H., Wang, L., Xu, Y., & Liu, X. (2023). CovidViT: a novel neural network with self-attention mechanism to detect Covid-19 through X-ray images. *International Journal of Machine Learning and Cybernetics*, 14(3), 973 – 987. 10.1007/s13042-022-01676-7
- Yang, C., Huebner, E. S., & Tian, L. (2024). Prediction of suicidal ideation among preadolescent children with machine learning models: a longitudinal study. *Journal of Affective Disorders*, 352, 403-409. 10.1016/j.jad.2024.02.070
- Yasin, S., Fierst, A., Keenan, H., Knapp, A., Gallione, K., Westlund, T., ... & Keenan, J. P. (2022). Self-Enhancement and the Medial Prefrontal Cortex: The Convergence of Clinical and Experimental Findings. *Brain Sciences*, 12(8), 1103. 10.3390/brainsci12081103
- Yao, H., Zhang, X., Zhou, X., & Liu, S. (2019). Parallel structure deep neural network using CNN and RNN with an attention mechanism for breast cancer histology image classification. *Cancers*, 11(12), 1901. 10.3390/cancers11121901
- Yao, M., Zhao, G., Zhang, H., Hu, Y., Deng, L., Tian, Y., ... & Li, G. (2023). Attention spiking neural networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(8), 9393-9410. 10.1109/TPAMI.2023.3241201.

- Yuan, S., Liao, Z., Huang, H., Jiang, B., Zhang, X., Wang, Y., & Zhao, M. (2020). Comparison of the indicators of psychological stress in the population of Hubei province and non-endemic provinces in China during two weeks during the coronavirus disease 2019 (COVID-19) outbreak in February 2020. *Medical Science Monitor: International Medical Journal of Experimental and Clinical Research*, 26, e923767-1. 10.12659/MSM.923767
- Yuan, C., Liu, Z., Wang, C., & Yang, F. (2023). Electrocardiogram signal classification based on fusion method of residual network and self-attention mechanism. *Sheng wu yi xue gong cheng xue za zhi= Journal of Biomedical Engineering= Shengwu Yixue Gongchengxue Zazhi*, 40(3), 474-481. 10.7507/1001-5515.202210062
- Zapata, K. (2023). What it's like to live with suicidal thoughts. *Everyday Health Blogs*. Available at: <https://www.everydayhealth.com/emotional-health/what-its-like-to-live-with-suicidal-thoughts/> [Accessed on 25 April 2024]
- Zhang, R., Wei, S., Chang, M., Jiang, X., Tang, Y., & Wang, F. (2020). Dorsolateral and ventrolateral prefrontal cortex structural changes relative to suicidal ideation in patients with depression. *Acta Neuropsychiatrica*, 32(2), 84-91. <https://doi.org/10.1017/neu.2019.45>
- Zhang, T., Schoene, A. M., & Ananiadou, S. (2021a). Automatic identification of suicide notes with a transformer-based deep learning model. *Internet Interventions*, 25, 100422. 10.1016/j.invent.2021.100422
- Zhang, A., Han, Y., Niu, Y., Gao, Y., Chen, Z., & Zhao, K. (2021b). Self-evolutionary neuron model for fast-response spiking neural networks. *IEEE Transactions on*

Cognitive and Developmental Systems, 14(4), 1766-1777.
10.1109/TCDS.2021.3139444

Zheng, M., Da, H., Pan, X., Bian, Y., Li, X., Xiao, Q., ... & Zhang, Y. (2023). Dorsolateral prefrontal activation in depressed young adults with and without suicidal ideation during an emotional autobiographical memory task: A fNIRS study. *Journal of Affective Disorders*, 326, 216-224. 10.1016/j.jad.2023.01.115

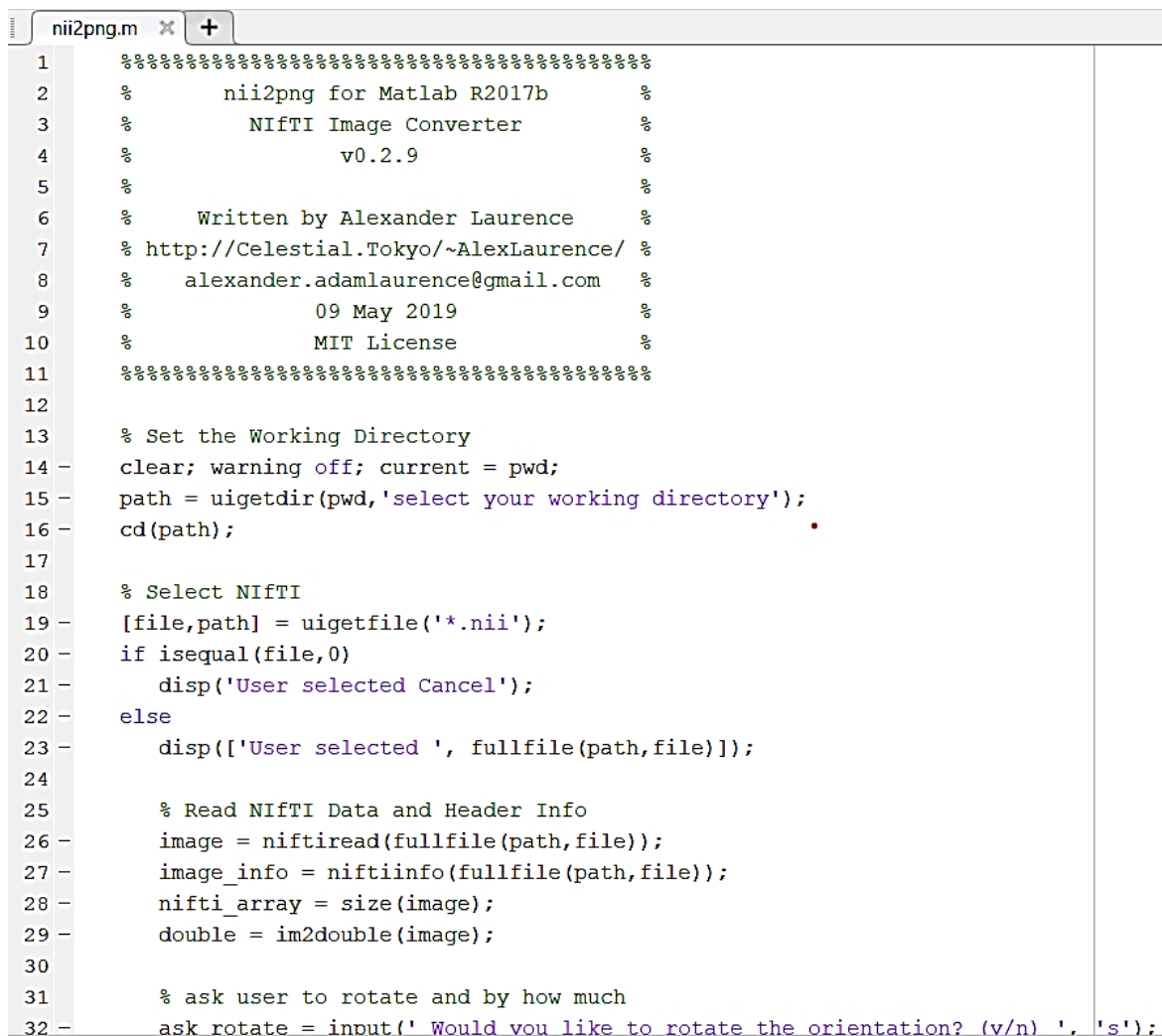
Zhou, S. J., Wang, L. L., Yang, R., Yang, X. J., Zhang, L. G., Guo, Z. C., ... & Chen, J. X. (2020a). Sleep problems among Chinese adolescents and young adults during the coronavirus-2019 pandemic. *Sleep Medicine*, 74, 39-47. 10.1016/j.sleep.2020.06.001

Zhou, Q., Shi, Y., Xu, Z., Qu, R., & Xu, G. (2020b). Classifying melanoma skin lesions using convolutional spiking neural networks with unsupervised stdp learning rule. *IEEE Access*, 8, 101309-101319. 10.1109/ACCESS.2020.2998098

Zissi, A. (2022). Social stigma in mental illness: A review of concepts, methods and empirical evidence. *Psychiatrike= Psychiatriki*, 33(2), 149-156.
10.22365/jpsych.2021.039

APPENDICES

Appendix A: Matlab code for image format conversion



```
1  %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
2  %      nii2png for Matlab R2017b      %
3  %      NIfTI Image Converter          %
4  %      v0.2.9                        %
5  %                                     %
6  %      Written by Alexander Laurence  %
7  % http://Celestial.Tokyo/~AlexLaurence/ %
8  %      alexander.adamlaurence@gmail.com %
9  %      09 May 2019                    %
10 %      MIT License                     %
11 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
12
13 % Set the Working Directory
14 - clear; warning off; current = pwd;
15 - path = uigetdir(pwd,'select your working directory');
16 - cd(path);
17
18 % Select NIfTI
19 - [file,path] = uigetfile('*.nii');
20 - if isequal(file,0)
21 -     disp('User selected Cancel');
22 - else
23 -     disp(['User selected ', fullfile(path,file)]);
24
25     % Read NIfTI Data and Header Info
26 -     image = niftiread(fullfile(path,file));
27 -     image_info = niftiinfo(fullfile(path,file));
28 -     nifti_array = size(image);
29 -     double = im2double(image);
30
31     % ask user to rotate and by how much
32 -     ask_rotate = input(' Would you like to rotate the orientation? (y/n) ', 's');
```

Figure 1: Matlab code snippets for image conversion (Laurence, 2020).

Appendix B: Brain slices data

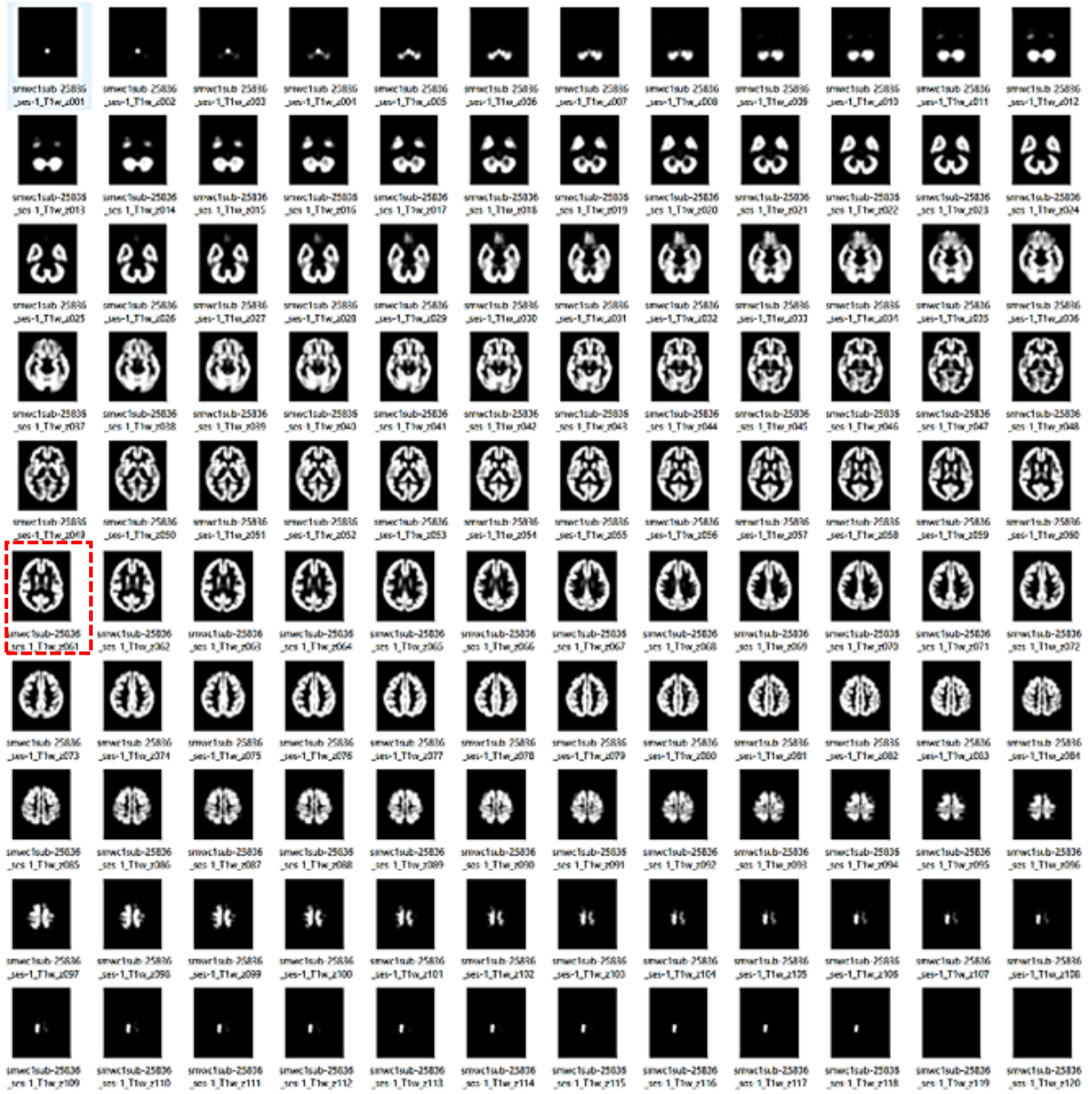


Figure 2: Conversion of NIFTI image to PNG, highlighting the 61st brain slice image with a red outline