



Faculty of Cognitive Sciences and Human Development

**Development of Hybrid Convolutional Neural Network and Radial Basis
Function for Autism Spectrum Disorder Classification**

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Development of Hybrid Convolutional Neural Network and Radial Basis Function for Autism Spectrum Disorder Classification

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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.



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ABSTRACT

Autism spectrum disorder (ASD) has become a common topic. The symptoms and heterogeneity of individuals with ASD change over time. In addition, the assessment using rs-fMRI data to classify ASD fails to attain the biomarker standards, and the obstacle still does not settle in the previous study. According to the Centers for Disease Control and Prevention (CDC) report, in 2021, the prevalence rate of ASD will increase to 1 in 44 children. Therefore, further methods for higher classification performance must be investigated. Deep learning has recently dramatically improved the cutting edge in a wide range of artificial intelligence jobs. Hence, this study proposed hybrid deep learning algorithms for ASD classification. Two algorithms merged: U-net neural network and Radial Basis Function (RBF) for medical image segmentation. Besides, the convolutional neural network (CNN) was implemented and combined with the RBF algorithm for the ASD classification. In this research, the classification of ASD achieved 94.79% accuracy, a better result compared with previous research. This study also illustrates the applicability of deep learning methods in neuroscience research projects. Future research should explore diverse algorithms, validating them across varied datasets with different hyperparameters to enhance ASD classification efficiency.

Keywords: Autism spectrum disorder, deep learning, UNet, radial basis function

Pembangunan Rangkaian Neural Konvolusi Hibrid dan Fungsi Asas Radial untuk Klasifikasi Gangguan Spektrum Autisme.

ABSTRAK

Gangguan spektrum autisme (ASD) telah menjadi topik biasa. Gejala dan heterogeniti individu dengan ASD berubah dari semasa ke semasa. Di samping itu, penilaian menggunakan data rs-fMRI untuk mengklasifikasikan ASD gagal mencapai piawaian biomarker, dan halangan masih tidak diselesaikan dalam kajian terdahulu. Menurut laporan Pusat Kawalan dan Pencegahan Penyakit (CDC), pada tahun 2021, kadar prevalens ASD akan meningkat kepada 1 dalam 44 kanak-kanak. Oleh itu, kaedah selanjutnya untuk prestasi pengelasan yang lebih tinggi mesti disiasat. Pembelajaran mendalam baru-baru ini telah meningkatkan secara dramatik kecanggihan dalam pelbagai jenis pekerjaan kecerdasan buatan. Oleh itu, kajian ini mencadangkan algoritma pembelajaran mendalam hibrid untuk klasifikasi ASD. Dua algoritma digabungkan: rangkaian neural U-net dan Radial Basis Function (RBF) untuk pembahagian imej perubatan. Selain itu, rangkaian neural convolutional (CNN) telah dilaksanakan dan digabungkan dengan algoritma RBF untuk klasifikasi ASD. Dalam penyelidikan ini, klasifikasi ASD mencapai ketepatan 94.79%, hasil yang lebih baik berbanding dengan penyelidikan terdahulu. Kajian ini juga menggambarkan kebolegunaan kaedah pembelajaran mendalam dalam projek penyelidikan neurosains. Penyelidikan masa depan harus meneroka algoritma yang pelbagai, mengesahkannya merentas set data yang berbeza dengan hiperparameter berbeza untuk meningkatkan kecekapan pengelasan ASD.

Kata kunci: Gangguan spektrum autisme, pembelajaran mendalam, UNet, fungsi asas radial

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LIST OF ABBREVIATIONS

ABIDE	Autism Brain Imaging Data Exchange
ADHD	Attention-Deficit/Hyperactivity Disorder
ASD	Autism Spectrum Disorder
AUC	Area Under the Curve
BOLD	Blood oxygen level-dependent
CDC	Centers for Disease Control and Prevention
CNN	Convolution Neural Network
DBN	Deep Belief Network
DBM	Deep Boltzmann Machines
DNN	Deep Neural Networks
FCN	Fully Convolutional Network
FXS	Fragile X Syndrome
GI	Gastrointestinal problems
GNB	Gaussian Naive Bayes
IOU	Intersection Over Union
MLP	Multi-Layer Perceptron
MRI	Magnetic resonance imaging
NITRC	NeuroImaging Tools and Resources Collaboratory

OCD	Obsessive-Compulsive Disorder
PA	Pixel Accuracy
RBM	Restricted Boltzmann Machine
RBF	Radial Basis Function
RL	Reinforcement Learning
RNN	Recurrent neural network
ROC	Receiver Operating Characteristics
SOM	Self-Organizing Map
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 Study Background

Autism Spectrum Disorder (ASD) is a complex brain disease, that is not easy to diagnose and detect (Eslami et al., 2019). People with ASD have difficulties in speaking, social interaction problems, undesirable repetitive habits, and motor skill impairments, all of which stem from the neurological system dysfunction (Kang et al., 2020). Current diagnostic techniques often distinguish this condition in children from the age of three years onwards (Khodatars et al., 2021). Generally, boys are about 4 or 5 times more likely than girls to be diagnosed with ASD (Giarelli et al., 2010). The incidence of ASD grew from 2004 to 2021, as reported by the Centers for Disease Control and Prevention (CDC). Based on prevalence and case estimates, ascertaining the number of adults with ASD, both diagnosed and undiagnosed, may be feasible for states (Dietz et al., 2020). Figure 1 shows the prevalence of ASD from the year 2004 to 2021:

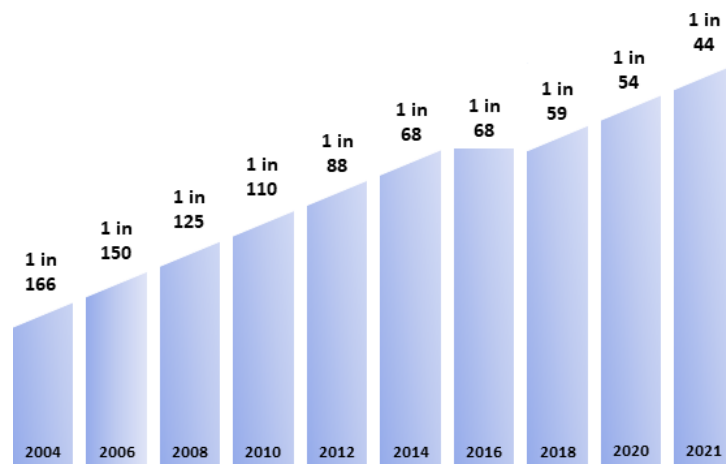


Figure 1.1: ASD prevalence rate from 2004 to 2021 (CDC, 2021)

From Figure 1.1, the prevalence in 2004 was 1 in 166 children, which constantly increased until 2014 to 1 in 68 children. Then it remained the same in 2016. After that, it expanded to 1 in 44 children in 2021. In 2021, the prevalence rate of ASD will increase to 1 in 44 children (Daniolou et al., 2022). Many children were diagnosed beyond the age of four, even though autism may reliably be identified as early as two (Maenner et al., 2021).

Based on the Centers for Disease Control and Prevention (CDC) report in 1996, about 34 per 10,000 children have autism or related diseases, and the ratio between boys and girls is 4:1 (Yeargin-Allsopp et al., 2003). In recent years, the prevalence has increased to 185 per 10,000 children, of which 1 out of 54 has been diagnosed with autism (Maenner et al., 2020a). Rachel Looome's research shows that the current ratio between boys and girls with autism is closer to 3:1 (Loomes et al., 2017). This illustrates that the prevalence of ASD has been on the rise since the year 1996.

Diagnosing ASD is a daunting task because no medical test, such as cellular analysis, blood test, and other medical procedures can produce conclusive results. According to Woodbury-Smith's research, both common and rare variants may lead to risk, and significant strides in understanding the genetic architecture of ASD (Woodbury-Smith & Scherer, 2018). Integrating genetics with clinical phenotypes and other practical genomic approaches like transcriptomics and epigenomics can contribute to a greater understanding of the molecular pathways underlying ASD and, in turn, provide guidance for clinical treatment (Ramaswami & Geschwind, 2018). The process is time consuming, and it is quite subjective, which makes misdiagnosis very likely. As a result, the creation of fully automatic ASD diagnosis technologies will have these benefits and advantages: ease the burden of medical professionals in carrying out proper diagnosing, and as well as facilitating the detection of symptoms, and subsequent early intervention and treatment of

affected children. Artificial intelligence methods, for example, Convolutional Neural Network (CNN), may help diagnose ASD more effectively and get better results in screening rare and common variants of ASD. Deep learning, a kind of machine learning, is a popular artificial intelligence technique.

Deep learning, also called a subset of artificial intelligence, represents a subfield of machine learning. Deep learning is a type of machine learning an expanded version of traditional machine learning by adding more sophisticated algorithms to the model (Kamilaris & Prenafeta-Boldú, 2018). Deep learning mimics how individuals acquire certain types of information and is an essential component of data science, which includes statistics and predictive modeling (Rusk, 2016). Deep learning has demonstrated superhuman performance in specific applications within confined contexts, surpassing human abilities in tasks such as image and speech recognition, and strategic games. Notable achievements include outperforming human experts in image classification, as evidenced by deep convolutional neural networks (CNN) achieving accuracy rates higher than those of trained radiologists in detecting certain medical conditions from imaging data (Esteva et al., 2017). Similarly, in natural language processing, models like OpenAI's GPT-3 have showcased superior performance in language understanding and generation tasks (Brown et al., 2020). In the realm of games, Google's AlphaGo defeated world champion Go players, a milestone demonstrating the strategic and decision-making capabilities of deep learning algorithms in highly complex environments (Silver et al., 2016). These examples highlight the potential of deep learning to exceed human performance in well-defined tasks and specialized domains.

In addition, deep learning algorithms improved the latest artificial intelligence tasks such as object detection, speech recognition and machine translation (Al-Fraihat et al.,

2024). Deep learning also uses deep architectures to handle many complex artificial intelligence procedures. Deep learning excels in detecting complicated structures in large volumes of data. It enables computer models composed of different preparation layers to learn information representations with various reflection dimensions. Deep learning could also be employed for image segmentation. Deep learning extracts boundaries and measures tissue volumes in medical image analyses (Chahal & Gulia, 2019). The deep learning method can segment the ASD patient's brain tissue volumes as features for classifying ASD and non-ASD (Heinsfeldt et al., 2018).

The proposed hybrid deep learning methods in this study are intended for medical image segmentation and ASD classification. The neuroimaging data are collected from the NeuroImaging Tools and Resources Collaboratory (NITRC) websites. In addition, this study aims to preprocess ASD medical data, demonstrate the combination of deep learning algorithms and evaluate the algorithm's effectiveness based on accuracy. This research also provides a connection between ASD and deep learning to fill the research gap for further understanding.

1.1.2 Autism Spectrum Disorder Diagnosis using Artificial Intelligence (AI)

In past years, people in rural areas with low socioeconomic status have faced significantly longer wait times for diagnoses compared to the rest of the nation. Additionally, the cost of healthcare for individuals with autism has been prohibitively high. These pressing issues underscore the urgent need for new applications that can collect more relevant data (Allison et al., 2012).

The human brain, with its complex network of neuronal assemblies, forms valuable

connections that contribute to various systems. These systems exhibit characteristics akin to other biological and physical frameworks, classifying the brain as a complex system. Leveraging prior investigations by numerous researchers, distinctions between ASD and non- ASD individuals have been identified using 128-channel EEG signals. The most severe synchronicity situations yield the finest perceptible data, and the rated quality list can serve as an effective biomarker for diagnosing chemical imbalances (Jamal et al., 2014). Moreover, multisite functional connectivity MRI classification of autism has been explored, revealing that classification across multiple sites must consider additional sources of variability in individuals, unlike single-site datasets (Nielsen et al., 2013). The NITRC dataset has been employed to differentiate between autism and non-autism patients based on brain connectivity measures. Functional magnetic resonance imaging (fMRI) is utilized to study the brain and its components, monitoring changes in blood oxygen level-dependent (BOLD) signals for better understanding (Sherkatghanad et al., 2020).

The Autism Brain Imaging Data Exchange (ABIDE) is a collaborative effort that includes neuroimaging and phenotypic data from 1,112 individuals. It is the most frequently used data-driven technique for autism diagnosis and biomarker discovery (Di Martino et al., 2014). Additionally, Koyamada uses Deep Neural Networks (DNN) to study brain states from quantifiable brain activities. DNN models have outperformed supervised learning techniques like Linear Regression and Support Vector Machines, with a mean accuracy of 50.74 percent, indicating the superiority of deep learning over traditional methods (Koyamada et al., 2015).

Conventional ASD classification by doctors presents several challenges. Diagnosing ASD typically involves lengthy clinical assessments based on behavioral observations, which are inherently subjective and can lead to variability in diagnoses (Lord

et al., 2004). This process is not only time-consuming but also resource-intensive, often resulting in delayed diagnoses and limiting early intervention opportunities (Daniels & Mandell, 2013). Moreover, access to specialized clinicians is limited in rural and economically disadvantaged areas, exacerbating healthcare disparities and hindering timely diagnosis and treatment (Zuckerman et al., 2015).

While machine learning (ML) and deep learning (DL) have shown promise in automating and improving the accuracy of ASD classification, several challenges persist. High-quality, annotated datasets necessary for training these models are often scarce and imbalanced, complicating effective model development (Bone et al., 2014). Additionally, the "black box" nature of DL models raises concerns about interpretability and trust among clinicians (Doshi-Velez & Kim, 2017). Models trained on single-site data often fail to generalize across different sites due to variations in imaging protocols and demographic differences, further complicating their applicability (Nielsen et al., 2013). The computational complexity and risk of overfitting with limited datasets also pose significant hurdles (Abraham et al., 2017). Integrating these advanced tools into clinical workflows remains a critical challenge, requiring user-friendly interfaces and seamless interoperability with existing health systems (Esteva et al., 2017).

According to previous research, Convolutional Neural Network (CNN) is a common deep learning approach for classification, detection, and identification of ASD (Alzubaidi et al., 2021). CNN has shown excellent results in solving various computer vision and machine learning problems (Wu, 2017). However, CNN has limitations in medical imaging, such as the challenge and cost of obtaining training data that matches the feature space and data distribution characteristics of test data. In biomedical image processing, CNN lacks localization from the desired output, and many training images are

typically unavailable for biomedical tasks (Ronneberger et al., 2015). Consequently, transfer learning, which involves training a high-performance learner for a target domain from a similar source domain, becomes essential (Weiss et al., 2016). Transfer learning reduces training time and improves accuracy by reusing pre-trained models that have already learned to identify lower-level features such as edges, lines, and curves (Liawatimena, 2018). Figure 1.2 illustrates the CNN architecture for autism classification.

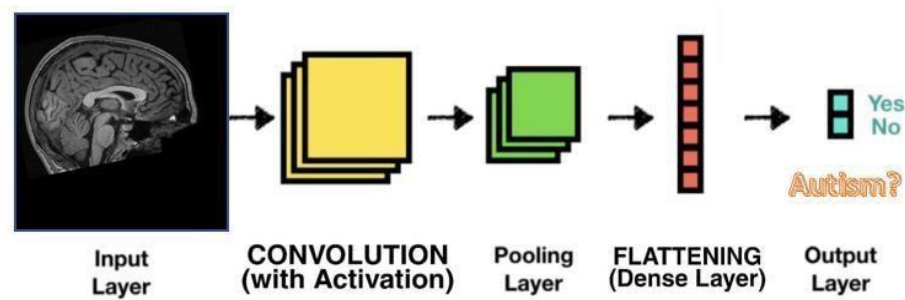


Figure 1.2: CNN for ASD classification (Li et al., 2018).

In Figure 1.2, brain imaging data are input into the input layer and then processed through the convolution layer, pooling layer, flattening layer, and dense layer to classify ASD and non- ASD in the output layer. To diagnose early biomarkers of ASD, Li et al. (2018) developed a multichannel CNN based on a patch-level data-expanding approach.

It is advisable to integrate deep learning with other algorithms for improved problem classification in medical imaging (Lundervold & Lundervold, 2019). This method involves preparing and adjusting the images, using deep learning to identify complex patterns, and applying traditional algorithms for detailed classification. These fusion leverages deep learning's ability to detect broad patterns and traditional methods' precision in classification, thereby enhancing accuracy in medical diagnoses. Consequently, this research utilizes hybrid deep learning algorithms, merging UNet and Radial Basis Function (RBF) for image segmentation, and CNN and RBF for ASD

classification.

1.2 Problem Statement

The rising prevalence of ASD presents significant challenges in diagnosis and management. According to the Centers for Disease Control and Prevention (CDC), the incidence of ASD is increasing, with more severe manifestations being reported (Maenner et al., 2020). The complexity of ASD diagnosis arises primarily from the absence of a definitive pathophysiological marker, necessitating reliance on psychological assessments alone (Yazdani et al., 2020). This study aims to address these diagnostic challenges by exploring advanced imaging and deep learning techniques to enhance the accuracy and efficiency of ASD detection. By integrating innovative methods, this research seeks to mitigate the limitations of current psychological diagnostic criteria, thereby improving early detection and intervention strategies.

ASD is often accompanied by comorbid conditions such as seizures, gastrointestinal issues, and sleep disorders, which exacerbate the overall health burden on affected individuals (Mannion & Leader, 2014). Understanding the broader impact of these comorbidities is crucial as they influence the overall treatment and management strategies for ASD. This research integrates knowledge of these associated conditions to develop a more holistic diagnostic approach, which in turn can lead to more comprehensive care plans for individuals with ASD. By addressing the interplay between ASD and its comorbidities, this study aims to improve diagnostic accuracy and patient outcomes. Given the chronic nature of ASD and its heterogeneous presentation, continuous and extensive care is necessary, with symptoms varying significantly over time (Lord et al., 2018).

Traditional diagnostic methods using resting-state functional MRI (rs-fMRI) have

not yet succeeded in establishing reliable biomarkers for ASD (Plitt et al., 2015). This study highlights the limitations of current diagnostic techniques, such as the heavy reliance on labor-intensive behavioral assessments, and emphasizes the need for innovative imaging methods. These advanced techniques can facilitate early and accurate diagnosis, ultimately reducing the burden on healthcare providers and improving patient care.

Existing artificial intelligence (AI) approaches to classify ASD, particularly those employing deep learning techniques, have yielded inconsistent and suboptimal results. For instance, Deep Neural Networks (DNN) have achieved an accuracy of 70% in classifying ASD (Heinsfeld et al., 2018). Another study utilizing the Convolutional Neural Network (CNN) model attained a 70.22% accuracy (Ruuska et al., 2018). The Deep Belief Network (DBN) presented by Akhavan achieved 65.56% accuracy in ASD classification (Akhavan Aghdam et al., 2018). The Deep Multimodal Learning model developed by Tang et al. managed to hit 74% accuracy (Tang et al., 2020). Surprisingly, the CNN employed by Rabbi et al. scored a higher accuracy of 92.31% (Rabbi et al., 2021). These inconsistencies underscore the inadequacy of current AI models in providing reliable ASD classification.

To address these limitations, recent research suggests combining deep learning with other algorithms to enhance performance in medical imaging tasks. For instance, Convolutional Neural Networks coupled with Gated Recurrent Units (CNN-GRU) recorded 72.46% accuracy (Jiang et al., 2022). Hybrid models, such as the hybrid autoencoder combined with convolution networks, yielded improved performance by registering 84.05% accuracy (Sewani & Kashef, 2020). Building on these insights, this study proposes the development of novel models, specifically UNet-RBF and CNN-RBF, aiming to achieve higher accuracy and reliability in ASD detection. By integrating advanced deep learning techniques with robust feature extraction methods, this

research aspires to overcome the current limitations in ASD diagnosis and deliver better clinical outcomes and improved quality of life for individuals with ASD.

1.3 Objectives

The research objectives of this research is as follows:

- i. To pre-process the fMRI data of ASD using Autism Brain Imaging Data Exchange(ABIDE) dataset.
- ii. To develop a hybrid algorithm, UNet-RBF for segmentation.
- iii. To develop a hybrid algorithm, CNN-RBF for ASD classification.
- iv. To analyze the performance of the proposed algorithm with a custom CNN architecture.

1.4 Scope of Study

The scope of this research project encompasses specific parameters for conducting the study, aiming to raise the effectiveness and performance of ASD classification through the utilization of a hybrid algorithm to achieve improved performance. Brain imaging data are collected from the NeuroImaging Tools and Resources Collaboratory (NITRC) website, a globally accessible multi-site database that provides image data of resting-state functional magnetic resonance imaging (rs-fMRI) image data.

Data preprocessing forms an integral part of this study. The segmentation model has been employed for data segmentation, and the UNet-RBF model for effectively isolating the cerebellum from the rest of the brain. Subsequently, ASD and non-ASD classification is performed using the CNN-RBF model. The research resorts to the Jupyter notebook in the Python programming language, with additional libraries such as Keras and

TensorFlow to support the implementation. The results of the ASD classification are presented in a statistical graph, along with a detailed confusion matrix. The confusion matrix records the essential metrics and provides a comprehensive evaluation of the model's performance.

1.5 Research Significance

The prevalence rate of ASD is increasing, and the ASD issues are getting worse daily. This research centralizes the brain, its neuronal patterns of functional connectivity, and the approach employed in the hybrid deep learning algorithms. The results from this research fill the research gaps, which would benefit the neuroscience and artificial intelligence fraternity. By providing a more accurate and efficient method for ASD classification, this hybrid model can enhance early diagnosis and intervention strategies, leading to improved outcomes for individuals with ASD and advancing the field of AI in medical applications. In addition, this research puts forward a new hybrid deep learning model, UNet-RBF coupled with CNN-RBF for ASD classification, which is capable of producing better performance. Furthermore, the study demonstrates the utilizing of deep learning approaches in neuroscience research initiatives.

1.6 Organization of Study

This research consists of five chapters. Chapter 1 briefly explains some background of ASD and deep learning. This chapter provides some knowledge on ASD classification using deep learning algorithms. In addition, the problem statement, research objectives, research contribution and the scope of study are also included in this chapter.

Chapter 2 reviews the previous studies related to ASD classification using deep

learning algorithms. Besides, this chapter illustrates the linkage between deep learning and ASD based on the discussion of previous work.

Chapter 3 represents the research methodology. This chapter provides the method for conducting the research. The research design shows the process of ASD classification using hybrid deep learning algorithm. This chapter explores the development of a novel hybrid algorithm that combines Convolutional Neural Networks (CNN) with Radial Basis Functions (RBF) after data preprocessing. Additionally, various methods for evaluating the algorithm's performance are outlined in this chapter.

Chapter 4 describes some discussion and results. This chapter presents the findings and results from the research following the methodology. ASD classification is addressed through the proposed of the UNet-RBF and CNN-RBF models. The results then compared with other algorithms and the accuracy based on the confusion matrix.

Chapter 5 is a research conclusion which summarizes all the work in this research. This chapter also includes a summary of research, recommendation, and contribution.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter interprets autism spectrum disorder (ASD) and deep learning. Besides, it also reviews the applications of deep learning for classification of ASD. Figure 2.1 shows the organization of Chapter 2.

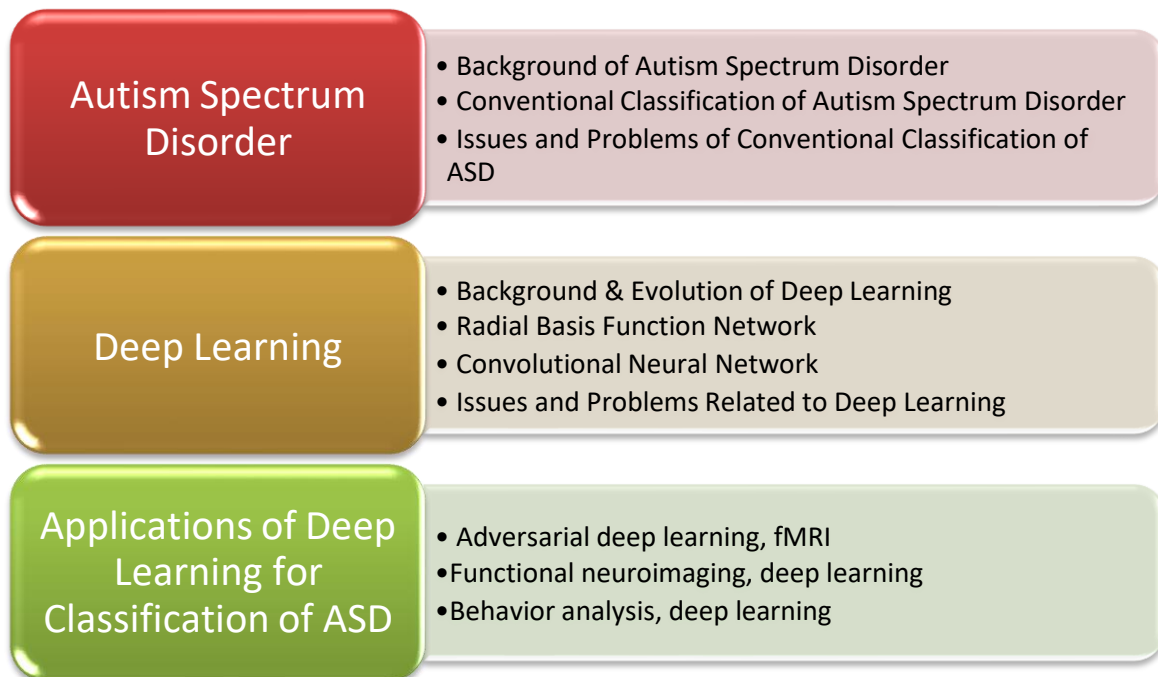


Figure 2.1: Organization of Chapter 2.

This chapter begins with an explanation of ASD, and then, briefly comments on deep learning. Next is a discussion on the applications of deep learning for classification of ASD. Some previous works about how deep learning helps in ASD classification is also mentioned. Then, the chapter delves into the connection and relationship between artificial intelligence and neuroscience. The last portion of the chapter is a summary.

2.2 Autism Spectrum Disorder

ASD is a common neurodevelopmental condition marked by poor social interaction and repetitive behavioral activities (Ramaswami & Geschwind, 2018). According to a recent study of global occurrence, the average age at which ASD is diagnosed ranges between 38 and 120 months, though it can be recognized as early as 18 months of age. (Hyman et al., 2020). ASD is a term used interchangeably with autism, but the former refers to a wider group of conditions, namely autistic disorder, pervasive developmental disorders, and Asperger's syndrome.

ASD is classified into three levels: Level 1 (needing assistance), Level 2 (requiring much assistance), and Level 3 (necessitating very substantial support). Clinicians can establish a definite diagnosis basing on the three different levels of autism and provide caregivers with explicit knowledge of an affected person's strengths and limits (Weitlauf et al., 2014). A patient with Level 1 ASD typically can talk and communicate fairly fluently but has difficulties in holding back-and-forth discussions with others. They do not seem to have the social skills of making friends. They may also be rigid in certain respects and struggle with transitioning from one task to another.

Furthermore, ASD patients find planning and organizing burdensome, the consequence of which is deprivation of independence in their daily life (Masi et al., 2017). People with Level 2 ASD are even more inhibited than those with Level 1 ASD in handling verbal and social communication. They have another hurdle in changing their focus. For example, if they have to shift from one activity to the next, such as leaving school at the end of the day, they will become quite unhappy. Level 3 autism is the most severe condition because patients exhibit many of the same behaviors as those in Level 1 and 2 ASD, but to a greater extent. Patients with Level 3 ASD have minimal capacity to

communicate intelligibly. Another characteristic of Level 3 ASD is repeated behavioral activities (Khalifeh et al., 2016). These behaviors can include repetitive motions, such as hand-flapping or rocking, and a strong adherence to specific routines or rituals, which can significantly interfere with daily functioning.

Certain methods and tests can be used to identify ASD; for example, Autism Quotient (AQ), Social Responsiveness Scale (SRS), and Vineland. AQ is used to determine whether individuals with average intelligence exhibit signs of autism or another autism spectrum disorder; SRS is used to measure the social ability of children; while Vineland is used to measure the adaptive behavior of individuals from birth to age 9 (Baron-Cohen et al., 2001).

ASD has several symptoms; the core of which are deficit in communication skills, repetitive behaviors, and awkwardness in social interaction. There are many other signs of ASD, such as poor eye contact, learning disability, spinning objects, problems in understanding, short attention span, and preferring to play alone. Besides, ASD comorbidities are not uncommon, which may include attention-deficit/hyperactivity disorder (ADHD), Epilepsy, Gastrointestinal (GI) problems, obsessive-compulsive disorder (OCD), and sleep disorder.

2.2.1 Background of Autism Spectrum Disorder

Autism spectrum disorder (ASD) is often accompanied by an array of medical comorbidities, the clinical diagnoses of which are tedious and complex. A study conducted in Manitoba on children diagnosed with ASD highlighted that 29.0% had one or more medical comorbidities, and the most prevalent of which was global developmental delay, detected in 23.0% of the children (Mathew et al., 2022). Neurological comorbidities,

including cerebral palsy, seizures, and hypotonia, were also notably common. The study underscored the significance of considering these comorbidities for prognosis and service allocation. Medical comorbidities are more prevalent in children with ASD than in the general population, especially genetic disorders such as Fragile X syndrome, Down syndrome, and tuberous sclerosis complex. Neurological disorders like epilepsy, migraine, and hydrocephalus, as well as gastrointestinal disorders, are observed to have higher rates of occurrence among ASD children. The prevalence of sleep disorders in individuals with ASD is around 80%, and allergic disorders are also significantly more common (Musken et al., 2017).

Autism Spectrum Disorder (ASD) is attributed to early aberrant brain development and neuronal remodeling (Bauman & Kemper, 2005). Genetic influences are significant, prompting linkage and association studies to identify susceptibility genes. While certain regions on chromosomes 2, 7, and 13 have been implicated, definitive gene identification remains elusive. Environmental factors, including air pollution and prenatal disorders, are linked to autism risk (Altevogt et al., 2008). Proximity to freeways and exposure to traffic-related air pollution increase the risk of autism in children (Gong et al., 2014). Maternal factors such as antibodies affecting fetal mental health and gestational diabetes also contribute to autism risk.

Children with Fragile X Syndrome (FXS) exhibit distinct brain differences compared to idiopathic ASD, including larger caudate volume and smaller amygdala volume (Wolff et al., 2013). In individuals with Tuberous Sclerosis Complex (TSC) and ASD, the corpus callosum and arcuate fasciculus show smaller volumes, indicating altered neural network architecture (Benvenuto et al., 2017). ASD, whether idiopathic or associated with TSC, is characterized by decreased long-term availability, increased short-

term availability, and evidence of decreased functional specialization.

The COVID-19 pandemic has disproportionately impacted individuals with ASD, causing disruptions in education, employment, personal routines, limited access to behavioral health services, and changes in healthcare delivery (Baweja et al., 2022). Individuals with ASD face heightened vulnerability during the pandemic due to challenges in communication, socialization, and executive functioning, emphasizing the need to address their unique needs in crisis situations according to the World Health Organization.

2.2.2 Conventional Classification of Autism Spectrum Disorder

The conventional classification of ASD has faced various issues and challenges. ASD is highly heterogeneous, with individuals exhibiting a wide range of symptoms and severities. This diversity complicates the conventional classification, which may not capture the full spectrum of ASD manifestations. A study by Hirata et al. (2023) explored differences in network connectivity related to attention-deficit/hyperactivity and autistic traits, emphasizing the complexity and variability in ASD presentations.

In addition, traditional diagnostic criteria may not adequately account for the nuanced presentations of ASD. Recent advances, such as using urine FTIR spectra for screening, suggest a move towards more precise and individualized diagnostic methods, highlighting the limitations of current classification systems (Sarigul et al., 2023).

Conventional classifications often overlook the detailed genetic and neurobiological underpinnings of ASD. (Birtele et al. 2023) discussed the non-synaptic functions of the SYNGAP1 gene in cortical neurogenesis associated with ASD, pointing towards a more complex etiological understanding than what current classifications provide.

The presence of comorbid conditions in individuals with ASD, such as gastrointestinal issues, often complicates classification. Wang et al., (2023) investigated altered gut microbiota in children with constipated ASD, indicating the need for a more integrative approach in classification that considers comorbid health issues.

The search for reliable biomarkers related to ASD is ongoing and hopefully will be superior to those of the existing classification system. Research like that of (Qin et al., 2022), which studied the downregulation of mGluR1-mediated signaling in ASD, underscores the importance of incorporating biomarkers into future classification framework.

There are three domains from which ASD diagnostic criteria may be derived. The first is difficulty in social contact and interaction, the second is poor in communication abilities, and the third is displaying limited and repetitive behaviors. These are the three major problems. A person must have at least six traits from the three domains to be diagnosed with autism, with at least two items from the first domain and 1 item from each of the second and third domains (Brentani et al., 2013). The diagnostic criteria require a departure from the anticipated formative examples of their age to value delays or irregular working in social collaboration, dialect, or creative play throughout their first three years of life (Klin, 2006). The discovery of autism in children as young as two years old has remained consistent across long follow-up periods. However, these longitudinal studies have shown that newborns with other, more non-explicit signals not associated with friendliness, may be differentiated much sooner than those with the adverse effects portrayed in the text. Instead of recommending delayed testing, clinicians are strongly encouraged to identify and address early concerns and abnormalities.

The diagnostic criteria call for recognizing delays or aberrant functioning in social

interaction, language usage, and creative play throughout the first three years of life, leading to a divergence from the predicted developmental pattern for their age of affected children. As a result, identifying early indicators of ASD and initiating therapies as soon as feasible is a priority, as it is well acknowledged that early intervention leads to a better prognosis.

Traditionally, diagnosing ASD relies on observing a child's behavior and developmental history due to the absence of medical tests. However, advancements in non-invasive brain imaging methods, particularly functional magnetic resonance imaging (fMRI), have facilitated the understanding of neuronal circuitry in disorders like ASD (Tang et al., 2020). fMRI allows visual assessment of a brain's functional features, aiding in the collection of crucial data on neurological diseases (Glover, 2011). Recent applications of artificial intelligence (AI) in conjunction with fMRI have improved the accuracy of ASD identification, leveraging the slight structural differences in the brains of ASD patients as features for deep learning classification (Bi et al., 2018). The use of deep learning offers efficiency and accuracy, assisting physicians in saving time during ASD diagnosis.

2.2.3 Issues and Problems for Conventional Classification of Autism Spectrum Disorder

The conventional classification of ASD grapples with several intricate challenges that hinder accurate diagnosis and comprehensive understanding. One of the foremost issues stems from the heterogeneous nature of ASD, where individuals exhibit a diverse array of symptoms and severity levels (Hirata et al., 2023). This variability poses a significant obstacle to conventional classification systems, which may struggle to encapsulate the full spectrum of ASD manifestations, leading to potential misdiagnosis or

underdiagnosis.

Traditional diagnostic criteria for ASD may also fall short in capturing the nuanced presentations of the disorder, necessitating a more refined and individualized approach to diagnosis (Sarigul et al., 2023). Recent advancements, such as utilizing urine Fourier-transform infrared (FTIR) spectra for screening, signify a shift towards more precise diagnostic methods that acknowledge the limitations of current classification systems. However, the integration of such methods into clinical practice requires further validation and standardization.

Furthermore, conventional classifications often overlook the intricate genetic and neurobiological underpinnings of ASD, resulting in a superficial understanding of the disorder's etiology (Birtele et al., 2023). Studies exploring the non-synaptic functions of genes like SYNGAP1 in cortical neurogenesis have underscored the need for a more comprehensive and nuanced approach to classification.

Comorbid conditions, such as gastrointestinal issues, frequently co-occur with ASD and can complicate classification efforts (Wang et al., 2023). Understanding the interplay between ASD and these comorbidities requires an integrative approach that considers both the neurological and physiological aspects of the disorder.

Moreover, the reliance on behavioral observation and developmental history for ASD diagnosis poses challenges, particularly in identifying early indicators of the disorder (Brentani et al., 2013). Although ASD can be detected in children as young as two years old, the diagnostic criteria necessitate a departure from anticipated developmental patterns, emphasizing the importance of early intervention to improve long-term outcomes.

Advancements in non-invasive brain imaging techniques, such as functional magnetic resonance imaging (fMRI), hold promise for enhancing ASD diagnosis. fMRI

allows for the visualization of brain functional features, aiding in the collection of crucial data on neurological disorders like ASD (Glover, 2011). Recent studies have leveraged artificial intelligence (AI) algorithms in conjunction with fMRI to improve the accuracy of ASD identification by detecting subtle structural differences in the brains of individuals with ASD (Bi et al., 2018).

In conclusion, the conventional classification of ASD faces multifaceted challenges that necessitate a holistic and multidisciplinary approach to diagnosis and understanding. Addressing these issues requires ongoing research efforts, collaboration among diverse fields, and the integration of novel diagnostic methodologies to ensure accurate and comprehensive classification of ASD.

2.3 Deep Learning

Deep learning is a subfield of machine learning that utilizes artificial neural networks. It involves the use of large neural networks that utilize complex models with multiple nonlinear transformations. According to LeCun et al. (2015), deep learning algorithms have significantly improved the latest versions of various artificial intelligence tasks, including object identification, speech recognition, and machine translation. With deep learning, computational models may learn multi-layered representations of data, enabling more complex and nuanced analysis (Dong et al., 2021). In addition, deep learning can address many complex artificial intelligence tasks due to its deep architecture.

Deep learning is good at discovering complex structures in high-dimensional data. As a result, deep learning has transformative applications across numerous domains, including science, business, and government. In science, it aids in medical image analysis, genomics, and climate modeling; in business, it enhances finance, marketing, and

supply chain management; and in government, it improves security, public administration, and policy making. For deep learning to be effective, large datasets are essential, as they enable the optimization of millions of internal parameters, ensure robust generalization to new data, and facilitate learning complex patterns, ultimately driving the accuracy and reliability of the models. Figure 2.2 shows that deep learning and machine learning indicate the field of artificial intelligence.

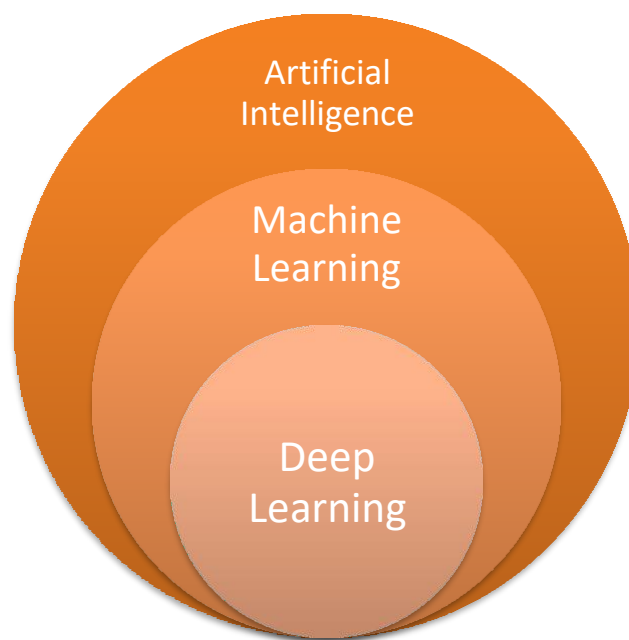


Figure 2.2: The Artificial Intelligence with ML and DL

Machine learning comprises three primary types of learning: supervised and unsupervised learning, and reinforcement learning. These three learnings help to generate output from data in some different ways.

Supervised learning is essentially a formalization of the concept of learning by doing. In supervised learning, there are two sets of data, training and testing set. The

objective is to enable the machine to learn from labelled examples in the training data set. After that, it can identify unlabeled examples in the test set with the highest possible accuracy (Learned miller, 2014). The standard algorithms in supervised learning are the artificial neural network, backpropagation, decision tree learning, support vector machines, random forests, ensembles of classifiers, Naive Bayes classifier, and nearest neighbor algorithm. Supervised learning also can help in classification and regression. Previous studies have demonstrated various outcomes and limitations of these algorithms across different domains. Artificial neural networks and backpropagation have been successful in complex pattern recognition tasks but can suffer from overfitting with small datasets (LeCun et al., 2015). Decision tree learning and random forests offer interpretability and robustness but may struggle with very large feature spaces (Breiman, 2001). Support vector machines excel in high-dimensional spaces but require careful parameter tuning (Cortes & Vapnik, 1995). Besides that, some applications for supervised learning are pattern recognition, speech recognition, object recognition in computer vision, spam detection, handwriting recognition and so on (Sabharwal & Selman, 2011).

Unsupervised learning teaches systems to detect patterns in data without labeled examples, identifying underlying structures through self-organization (Ghahramani, 2003). Previous studies have demonstrated various applications and limitations of these algorithms. For example, clustering algorithms like k-means and hierarchical clustering have been used extensively in customer segmentation, revealing distinct customer groups for targeted marketing strategies but often requiring prior knowledge of the number of clusters (Jain, 2010). Dimensionality reduction techniques such as principal component analysis (PCA) have been applied in image compression and feature extraction, effectively reducing data complexity while sometimes losing interpretability of the reduced

dimensions (Wold et al., 1987). Despite lacking feedback, unsupervised learning creates useful representations for decision-making and prediction, as seen in anomaly detection in network security where it identifies unusual patterns without predefined labels (Chandola et al., 2009). However, it can be sensitive to noise and outliers, which may affect the quality of the learned patterns. Unsupervised learning also aims to uncover meaningful patterns beyond random noise, enhancing understanding and utility across various domains.

Reinforcement Learning (RL) is a pivotal branch of machine learning focused on sequential decision-making, where an agent learns to make a series of decisions by interacting with an environment. This learning process is characterized by the agent's ability to develop new skills and habits over time, a concept central to RL's unique approach to problem-solving. According to Deng research, causal reinforcement learning is an emerging area in this field, exploring the causal relationships within the learning environment (Deng et al., 2023).

A key feature of RL is its reliance on trial and error, as highlighted by François. This approach allows the RL agent to learn optimal behaviors through continuous interaction with the environment, without needing complete knowledge or control over it (François-lavet et al., 2018). Zhang discusses the application of RL in multi-agent systems, emphasizing the importance of sequential decision-making in inducing Stackelberg Equilibrium in such environments (Zhang, 2023).

2.3.1 Background of Deep Learning

Deep learning is a form of machine learning that operates in a similar manner to traditional machine learning. Machine learning represents the computer program that can

learn the programmed by humans. Machine learning is used for big data analytics and data mining. Supervised learning in machine learning includes classification, regression, random forests, decision trees, support vector machines, and unsupervised learning, including clustering algorithms (Wehle, 2017). The term "deep" comes from deep learning models with many layers called neural networks. The difference between deep learning and machine learning is that deep learning requires extensive data because it can detect the wrong prediction on its own and has more layers than machine learning. Besides, deep learning provides high accuracy compared with machine learning. In addition, deep learning automatically learns the best features that represent the data through its multiple layers of abstraction, eliminating the need for manual feature engineering. This capability allows deep learning models to identify and leverage complex patterns directly from raw data, which significantly enhances their performance on tasks such as image and speech recognition. Deep Learning systems extract more information from data. As a result, the time spent building a new feature extractor for each challenge is reduced. However, for machine learning, the data characteristics must be detected by an expert, and the coding must be done manually according to the data type and domain. Figure 2.3 illustrates the difference between deep learning and machine learning.

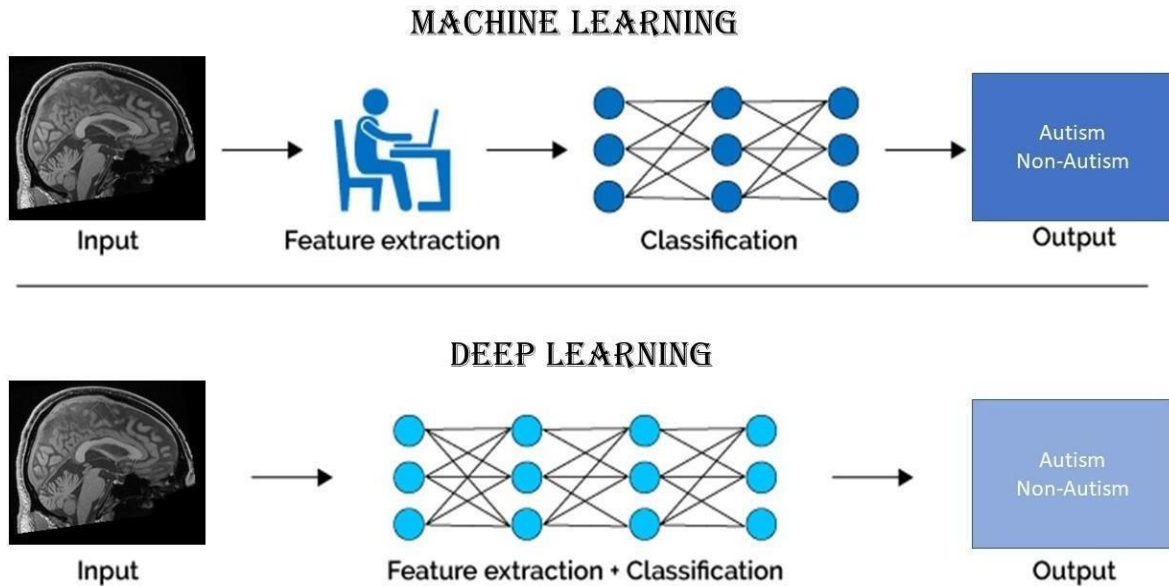


Figure 2.3: Deep Learning vs. Machine Learning

From Figure 2.3, machine learning separates the classification task and the feature extraction into two steps, while deep learning merges these steps. The primary purpose is to train deep learning with extensive data compared with machine learning. Better performance generates extensive data.

These networks consist of interconnected nodes, or neurons, organized into layers, and they have the capability to learn from data by adjusting the strengths of connections, known as weights. The concept of the perceptron, introduced by Frank R in 1957, provided an initial glimpse into artificial neurons, even though it was limited to solving linear problems (Kanal, 2003). The development of the backpropagation algorithm by Paul Werbos in 1974 was a pivotal moment, allowing for the training of multi-layer neural networks by minimizing errors (Smolensky, 1986). Over time, the field of deep learning saw the introduction of various neural network architectures, such as Convolutional Neural Networks (CNNs) by Yann LeCun in 1989, which revolutionized computer vision, and Long Short-Term Memory (LSTM) networks by Sepp Hochreiter and Jürgen Schmidhuber in 1997, designed to handle sequential data effectively

(LeCun et al., 2015). While early progress in neural networks faced challenges during the "AI Winter" of the 1970s and 1980s due to limited computational resources, the late 1980s witnessed a resurgence driven by researchers like Geoffrey Hinton and Yann LeCun. This resurgence laid the foundation for the deep learning revolution in the 2000s, fueled by advances in GPUs, large datasets, and improved algorithms. In 2012, the ImageNet Large Scale Visual Recognition Challenge marked a turning point when Alex Krizhevsky's deep neural network, AlexNet, outperformed traditional machine learning methods in image classification. Since then, deep learning has achieved remarkable success across diverse domains, from image and speech recognition to natural language processing, autonomous vehicles, and healthcare. This ongoing evolution of deep learning continues to address challenges, including model interpretability, adversarial attacks, ethical considerations, and the development of more efficient hardware.

2.3.2 Evolution of Deep Learning

In the historical development of understanding of the brain and the field of artificial intelligence, there were several pivotal moments. In 300 BC, Aristotle's concept of Associationism marked the early attempts to comprehend the mind's workings through the relationships between its components (Wang, 2017). These components encompassed ideas, memories, and experiences, linked through principles like similarity, contrast, and contiguity. Teuvo Kohonen's Self- Organizing Map (SOM) was introduced in his seminal work in 1982 (Kohonen, 1982), presenting a method for reducing data dimensionality while preserving topological relationships. However, criticisms emerged regarding its scalability, computational complexity, and sensitivity to parameter settings (Vesanto & Alhoniemi, 2000). Concurrently, Kunihiko Fukushima's Neocognitron laid the groundwork

for CNN (Fukushima & Miyake, 1982), inspiring their hierarchical architecture, which mimics visual cortex functionality. While SOM and CNN share goals in pattern recognition and data representation, the emergence of CNN cannot be solely attributed to the weaknesses of SOM; rather, CNN represent a distinct approach to addressing challenges in image classification and feature extraction, as evidenced by LeCun et al. in 1998.

The 1980s and 1990s marked significant progress in neural networks. Paul Smolensky introduced Harmonium in 1986, later known as the Restricted Boltzmann Machine (RBM), which introduced a modified version of the Boltzmann Machine (Smolensky, 1986). Michael I. Jordan is credited with defining the Recurrent Neural Network (RNN), which paved the way for modeling sequential data. In 1997, Schuster & Paliwal introduced the Bidirectional RNN, allowing information to be processed in both forward and backward directions (Schuster & Paliwal, 1997). Hochreiter & Schmidhuber's Long-Short Term Memory (LSTM) models addressed the vanishing gradient problem in RNNs, making them suitable for time-series data analysis (Hochreiter, 1997).

The turning point in deep learning came in 2006 when Geoffrey Hinton introduced Deep Belief Networks (DBN) and layer-wise pre-training techniques, ushering in the modern era of deep learning (Hinton et al., 2006). Salakhutdinov & Hinton, (2009) presented Deep Boltzmann Machines (DBM), representing an improvement over DBN. Then, in 2015, Ronneberger introduced U-Net, a specialized neural network architecture for tasks like semantic segmentation, instance segmentation, and object detection (Ronneberger et al., 2015). U-Net expanded upon the concepts of CNN and Fully Convolutional Networks, becoming a widely used tool in computer vision tasks (Jha et al., 2020).

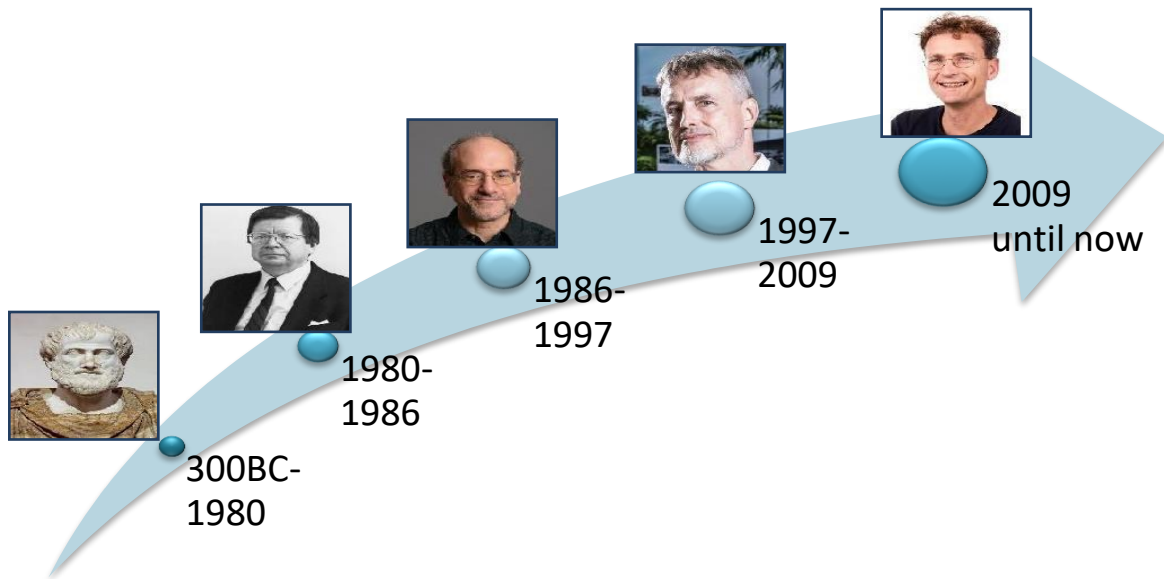


Figure 2.4: Brief history of deep learning.

Figure 2.4 briefly shows the history of deep learning evolution. With the evolution, deep learning is able to improve accuracy, automation efficiency, and have better personalization.

2.3.3 Radial Basis Function Network

Radial Basis Function (RBF) networks are a significant aspect of neural network research, particularly known for their application in function approximation, pattern recognition, and solving partial differential equations. RBF networks are characterized by their use of radial basis functions as activation functions in the hidden layer. These networks have a simple structure, typically consisting of an input layer, a single hidden layer with a non-linear RBF activation function, and a linear output layer (Arora et al., 2023).

The effectiveness of RBF networks lies in their ability to approximate any continuous function with arbitrary accuracy, given enough neurons in the hidden layer (Fasshauer & Zhang, 2007). The most used radial basis function is the Gaussian function,

which provides a good balance between computational efficiency and the ability to approximate complex functions (Wurzberger & Schwenker, 2024). Other types of radial basis functions include multiquadric, inverse multiquadric, and polyharmonic spline.

Training RBF networks involves two main steps: selecting the centers and widths of the radial basis functions and determining the weights of the output layer. The centers and widths can be chosen using unsupervised methods like k-means clustering, while the weights are typically calculated using a supervised method like least squares regression (Liu et al., 2022). This two-step training process is generally simpler and faster than the backpropagation algorithm used in other types of neural networks.

Despite their simplicity, RBF networks face challenges in terms of scalability and the curse of dimensionality. As the dimensionality of the input space increases, the number of RBF centers required to effectively cover the space can grow exponentially. This can lead to overfitting and increased computational costs. Recent research has focused on developing methods to select optimal RBF centers and to regularize the network to prevent overfitting (Cui et al., 2021). Figure 2.5 below shows simple RBF network architecture.

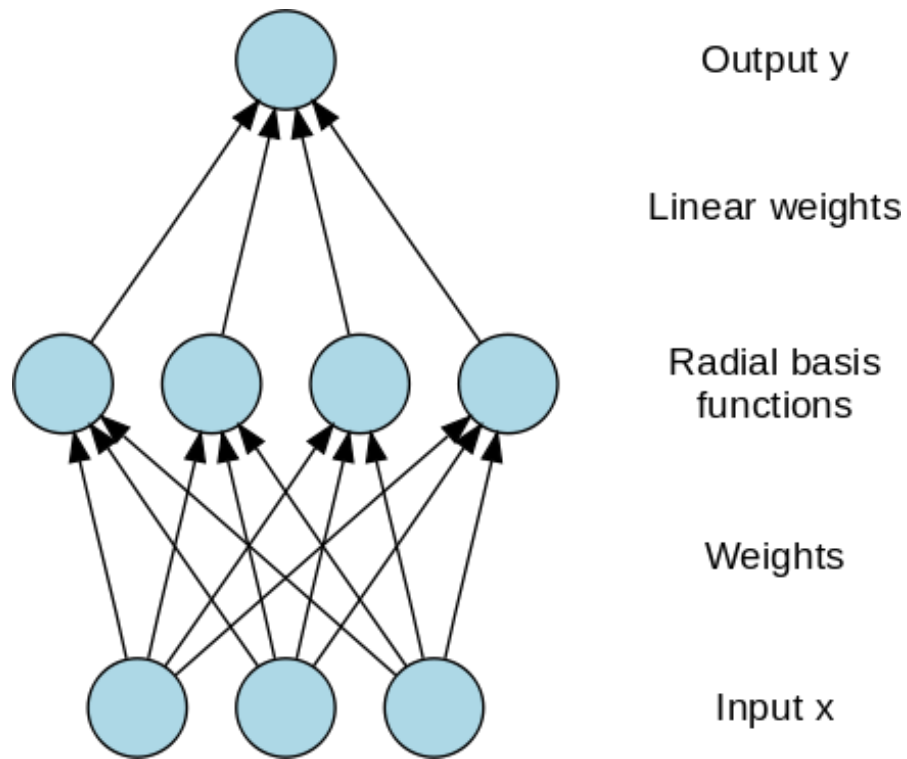


Figure 2.5: RBF network architecture

Based on figure 2.5, there are typically three layers. The input layer receives raw data, where each input neuron corresponds to a specific feature or pattern in the input data. The hidden layer consists of neurons, each associated with a radial basis function, often Gaussian, acting as prototypes to capture different patterns or clusters in the input data. These hidden neurons compute the similarity between input data and their center points using these radial basis functions. Finally, the output layer, typically linear, combines the activations of the hidden layer neurons to produce the network's final output. This output can be a single value for regression tasks or a set of values representing class probabilities in classification tasks. Overall, the RBF architecture effectively transforms and processes input data to make predictions or classifications based on learned patterns and clusters.

RBF is very similar to Multilayer Perceptron (MLP). Both networks are capable of learning to approximate function. The difference is MLP has multiple layers of

interconnected neurons with nonlinear activation functions, while RBF networks typically have just two layers and use radial basis functions as activation functions.

Furthermore, RBF networks have evolved through integration with other machine learning techniques to improve performance. For example, combining RBF networks with deep learning architectures or reinforcement learning algorithms has shown promise in tasks like image classification and dynamic system control (Amirian & Schwenker, 2020).

2.3.4 Convolutional Neural Network

Convolution neural network, CNN, is an artificial neural network algorithm; and it was first developed by Yan LeCun, a researcher in computer science. Compared with other classification algorithms, CNN requires minimal pre-processing. Instead of hand-engineered filters in traditional methods, CNN can learn filters or features with sufficient training. Figure 2.6 show convolution neural network architecture.

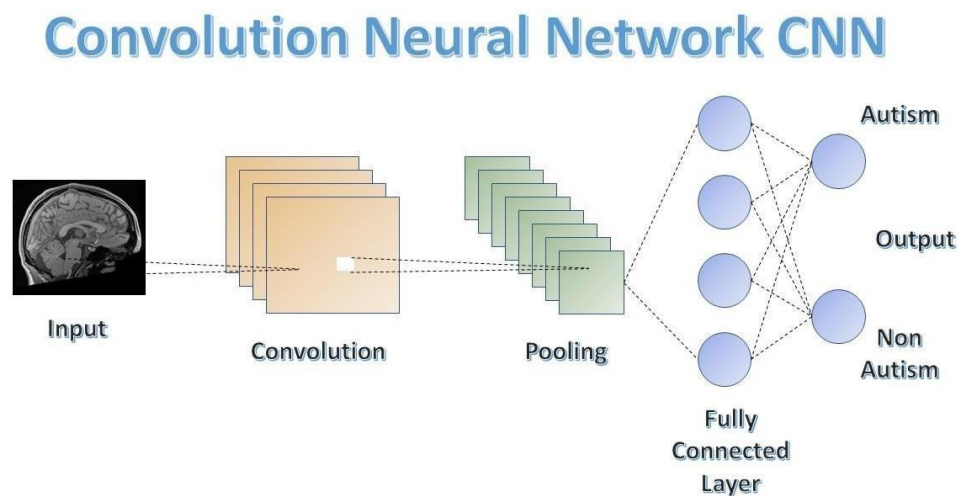


Figure 2.6: Convolution neural network architecture.

Based on Figure 2.6, the input data convolutions to a few layers feature maps and are fully connected to generate the output. Convolutional Neural Networks (CNN) is practically equivalent to customary ANN in that they are contained neurons that self-

improve through learning. Each neuron continues to receive input and perform a task, forming the foundation of numerous ANNs. Despite processing input images into class scores, the entire system still generates a single comprehensive score function. The last layer contains a loss function related to the classes, and most of the common tips and tricks used for traditional ANNs remain applicable (Shea, 2015).

2.3.4.1 Conventional Convolutional Neural Network

Convolutional Neural Networks (CNN) have become indispensable tools in computer vision tasks such as image classification, object detection, and facial recognition due to their remarkable success, particularly when applied to large datasets. Over the years, CNN architectures have undergone numerous variations and enhancements, resulting in state-of-the-art models like AlexNet (Krizhevsky et al., 2012a), VGGNet (Simonyan & Zisserman, 2014), and ResNet (He et al., 2016), each offering unique architectural features and performance advantages.

In CNN, convolutional layers are structured as rectangular grids of neurons, with each neuron taking inputs from corresponding regions in the previous layer (LeCun et al., 2015). The weights are shared across neurons, allowing for image convolution through the previous layer using predefined convolution filters.

Following the convolutional layers, the pooling layer down-samples the input by conveying small rectangular blocks from the convolutional layer to produce a single output. Two common types of pooling are average pooling and max pooling, with the latter being utilized in this study (Boureau et al., 2010).

The max pooling layer aggregates information by examining a specific region of the input and selecting the maximum value within that region, effectively down sampling the data (Scherer et al., 2010). This down sampling process simplifies the representation of

features, making subsequent processing more efficient.

Following the max pooling layer, the flattened layer transforms the multi-dimensional output of the convolutional layer into a one-dimensional array. This transformation facilitates the input into subsequent layers by converting the spatial information of feature maps into a linear format.

Finally, the last layer in a typical CNN architecture is the dense layer, which consists of a set of neurons that receive input from all the neurons in the preceding layer, hence the name "dense." The dense layer is responsible for making the final classification decision based on the features extracted by the convolutional layers. It is commonly used in image recognition tasks.

Based on previous research (Sherkatghanad et al., 2020), ASD patients and control participants may be recognized and classified using CNN architecture. The training period can be significantly reduced when using CNN designs due to their ability to achieve superior classification performance with fewer parameters. This efficiency stems from CNN architectures that leverage shared weights and local connectivity, optimizing computational resources while preserving or improving accuracy. By efficiently extracting relevant features from input data through convolutional layers, CNN reduces the overall complexity of model training, making them particularly advantageous in resource-constrained environments or when dealing with large datasets (Krizhevsky et al., 2012). In addition, it also achieves highest accuracy as 70.22% by using less complex and faster models. For instance, the CNN models utilized reduced convolutional layers and optimized pooling strategies, which sped up the classification process and maintained high accuracy levels. This approach illustrates how prioritizing simplicity and efficiency in model design can lead to significant advancements in medical image analysis, particularly in diagnosing

ASD. Based on CNN, ASD may be identified, especially in children.

2.3.4.2 Pre-Trained Convolutional Neural Network

Pre-trained Convolutional Neural Networks (CNNs) have revolutionized the field of deep learning and artificial intelligence by offering a powerful way to leverage the knowledge and feature representations learned from vast datasets. These pre-trained networks serve as invaluable starting points for tackling new computer vision tasks, such as image classification, object detection, and segmentation, among others (Alzubaidi et al., 2021).

The key principle behind pre-trained CNNs is that they are initially trained on a massive dataset, often consisting of millions of images, to excel at a specific task, such as image classification. During this training, the network learns to recognize a multitude of features, ranging from simple edges and textures to complex visual patterns and object categories. These features, extracted by the network's convolutional layers, form a rich hierarchical representation of visual information.

When a new, related task arises, rather than training a CNN from scratch, a pre-trained model can be adopted as a foundation (He et al., 2016). Typically, the lower convolutional layers, which have captured general features applicable to various problems, are retained, while the top layers, including the fully connected layers, are adjusted or replaced to adapt to the specifics of the new task. This process of fine-tuning enables the network to generalize the learned features to the new problem, often resulting in improved performance. Moreover, the use of pre-trained models drastically reduces the time and computational resources required for training, which is particularly valuable when working with limited data.

The benefits of pre-trained CNNs extend to a wide range of applications, spanning from image recognition in healthcare and self-driving cars to sentiment analysis in natural language processing. Researchers and developers can choose pre-trained models based on architectures like ResNet, VGG, or Inception, and fine-tune them for their specific domains, leading to faster, more accurate, and state-of-the-art AI models. This approach has democratized access to sophisticated deep learning capabilities, enabling individuals and organizations to harness the power of AI for diverse real-world problems.

2.3.5 Transfer Learning

Transfer learning as shown in Figure 2.7, in machine learning, represents a method that reuses a pre-train model for training. Transfer learning aims to improve target learners' performance in target domains through information transfer (Zhuang et al., 2021). Transfer learning brings many benefits that save time, offer a high learning rate, and so on because some similar tasks have been trained. Besides, transfer learning is a helpful machine learning method for dealing with the fundamental issue of inadequate training data (Tan et al., 2018).

TRANSFER LEARNING

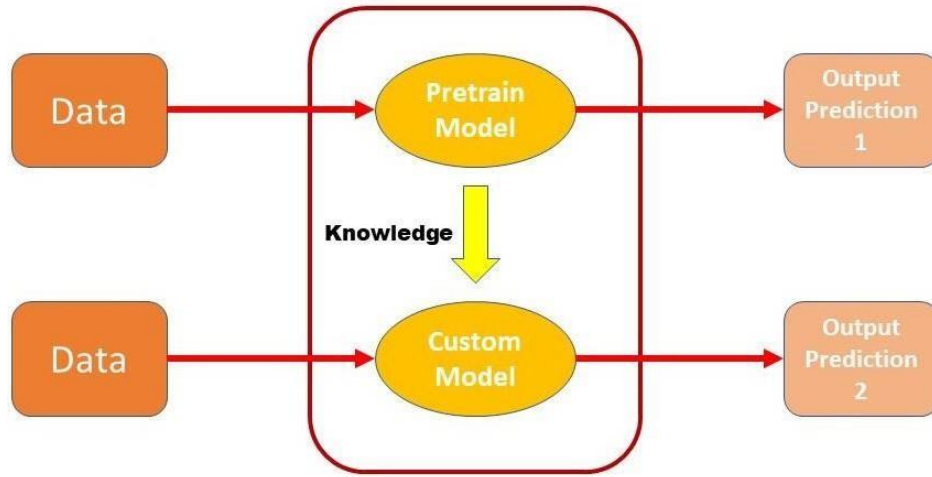


Figure 2.7: Transfer Learning

The study by Weiss et al., (2016) provides an insightful exploration into the diverse practical applications of transfer learning, particularly in the realm of natural language processing (NLP). Their research highlights various tasks, including sentiment classification, text classification, spam email detection, and multiple language text classification, as just a subset of the wide array of applications within NLP. Moreover, transfer learning in CNN involves leveraging a pre-trained model's learned features and architecture for similar tasks. Specifically, in the context of image segmentation using a UNet architecture, transfer learning entails initializing the UNet model with weights learned from a pre-trained model, often on a large-scale dataset like ImageNet. By fine-tuning the upper layers of the UNet while freezing the lower layers, the model can adapt its feature extraction capabilities to the specific segmentation task at hand. This approach allows the UNet model to leverage the learned representations from the pre-trained model, thereby enhancing its performance on the segmentation task, especially when labeled data is limited.

2.3.6 Issues and Problems Related to Deep Learning

Based on previous studies, deep learning algorithms have been used to identify ASD. The researchers used the ABIDE dataset from the ABIDE website (Autism Brain Imaging Data Exchange) and achieved about 70% accuracy in identifying autism (Heinsfeld et al., 2018). Neuroscientific research can help bridge the gap between accurately mapping the complexity of the range of changes in autism spectrum disorder behavior and their corresponding neural patterns. By identifying the patterns of activation in ASD and their relationship with neural and psychological aspects, we can gain a better understanding of the disorder's etiology (Just & Keller, 2013).

According to Heinsfeld et al. (2018), deep learning techniques may dependably arrange massive multi-site datasets. Classification over various destinations must oblige extra wellsprings of difference in subjects, filtering systems, and gear in contrast with single-site datasets (Nielsen et al., 2013). Such variety adds commotion to the mind imaging information that challenges the capacity to draw marks from the cerebrum enactment that can arrange sickness states. Indeed, the ability of machine learning models to achieve high accuracy even in the presence of noise generated from various sources, including different types of equipment and demographics, demonstrates promise for their application in clinical datasets. This success paves the way for future utilization of machine learning in aiding the diagnosis and characterization of mental disorders.

Based on Plitt et al. (2015), the use of rs-fMRI data for ASD classification has not yet reached the standards required for reliable biomarkers. This limitation persists despite various advancements in neuroimaging techniques and analytical methods. The primary challenges include high inter-individual variability, differences in scanning protocols across studies, and the inherent complexity of brain connectivity patterns (Yahata et al.,

2016). However, the integration of deep learning techniques has shown promise in overcoming some of these obstacles. For example, Plitt et al. (2015) demonstrated that a deep learning model could achieve a classification accuracy of 76.67% in a study involving 178 participants, including both individuals with ASD and typically developing controls matched for IQ. This significant improvement suggests that deep learning algorithms, which can automatically learn and extract relevant features from complex datasets, might offer a more effective approach for ASD classification compared to traditional rs-fMRI analysis methods (Heinsfeld et al., 2018). Despite these advancements, further research is needed to enhance the robustness and generalizability of these models to meet clinical biomarker standards.

According to Nielsen et al. (2013), classification precision decreases in larger population tests and when the data comes from diverse geographic regions. Supervised learning techniques, such as support vector machine (SVM) or Gaussian Naive Bayes (GNB) classifiers, have been utilized in machine learning to analyze brain imaging data. These methods involve assigning class labels to a training dataset and then using the patterns found in the training data to classify a test dataset (Heinsfeld et al., 2018).

Based on Bi et al. (2018), the SVM method achieved a performance accuracy of 96.15% in classifying ASD, but it only used brain-related features as input. For a long time, medical imaging has been used as a screening technique in hospitals. The field of medical imaging has gained significantly from recent developments in hardware design, safety protocols, computing resources, and data storage capabilities. According to previous research, medical image analysis with segmentation, classification, and abnormality detection in images are currently the most common applications (Anwar et al., 2018). A meta-analysis of 17 imaging studies revealed that individuals with autism have reduced

brain tissue in regions of the cerebellum, which is a brain structure located near the base of the skull (Stoodley, 2014). Besides that, the amygdala and hippocampus volume also detect ASD. People with ASD will have a smaller amygdala and hippocampus volume than those without ASD (Nordahl et al., 2020). Scientists previously thought the cerebellum was just coordinated movements, but they now know it also plays a role in cognitive and social interaction. Magnetic resonance imaging (MRI) studies have contributed significantly to the understanding of the neurodevelopmental characteristics that underlie ASD. Neuroimaging is one of the few methods that enables the direct observation of the brain in vivo and has thus provided valuable insights into the disorder (Ha et al., 2015).

From LeCun's seminal study in 1998, CNN emerged as a quintessential deep learning algorithm for a multitude of tasks, including classification, detection, and recognition. In several computer vision and machine learning problems, CNN has demonstrated excellent results (Wu, 2017). In some cases, obtaining training data that suited the test data's feature space and expected data distribution characteristics can be challenging and costly. However, CNN lacks localization from the desired output for biomedical image processing. Furthermore, many preparing pictures are typically inaccessible in biomedical assignments (Ronneberger et al., 2015).

Some robust neural networks have been proposed for medical image segmentation, such as R2U-net, Attention U-net, full-scale connected UNet, FANet, DC-Unet, and TransUnet. These segmentation neural networks show better performance during medical image segmentation than previous neural networks like CNN. These neural networks use a u-shaped hybrid architecture to encode clear global meaning by treating image features as sequences to improve the efficiency of diagnosis.

2.3.6.1 Image Pre-processing

The similarity between distinct brain areas based on their activity throughout the scanning time is quantified in current modelling and analytic methodologies of resting-state functional brain networks. If the similarity value between two areas is greater than or equal to a predefined threshold, the two regions are deemed to be linked in the resultant functional brain network. Otherwise, the two areas are not linked (Kaveh et al., 2022).

According to Arslan (2017), fMRI signals are prone to be affected by noises from various causes, including head movement, cardiac/respiratory pulsation, and scanner-induced abnormalities. This creates substantial difficulties in using and interpreting MRI data. Because retrieved brain network properties, such as nodes and edges, are reliant on MRI data processing, additional pre-processing processes are necessary to mitigate the effects of noises in MRI signals.

There are some famous tools and pipelines to pre-processing fMRI data. Famous tools such as Forensic Science Laboratory Division (FSL) (Smith et al., 2004), Analysis of Functional NeuroImages (AFNI) (Cox, 1996), Statistical parametric mapping (SPM) (Friston et al., 1991), and Advanced Normalization Tools (ANTS) (Avants et al., 2011) provide completely automated GUI-based preparation workflows. They are appropriate for processing extensive data (Strother et al., 2004). According to Millman & Brett (2007), the implementation of SPM is in Matlab, a programming language while FSL and AFNI are implemented in C and C++. The outcomes of various data preparation techniques across various software programs could be inconsistent, which might make neuroimaging research less repeatable.

2.3.6.2 Image Segmentation

Image segmentation is a process of dividing an image into multiple segments or regions to extract useful information and make the representation of an image more meaningful and interpretable. Various algorithms and methods have been developed for image segmentation (Chakraborty et al., 2012). There are several types of image segmentation techniques available, including threshold-based segmentation, edge-based segmentation, region-based segmentation, clustering-based segmentation, and artificial neural network- based segmentation. In diagnosing and classifying ASD, the common method is Artificial Neural Network Based Segmentation.

Edge-based segmentation is a technique used to identify the edges in an image, which can then be used to separate regions of the image. Various edge detection operators are used in this technique to locate edges based on differences in color, texture, or other characteristics. The edges detected in the image can be used to define regions of interest or boundaries between different objects in the image (Priyadharsini & Sharmila, 2019). In addition, in the region-based segmentation technique, nearby pixels are compared for similarity. In other words, pixels with comparable characteristics are categorized into separate zones. Similarity is often determined using gray-level intensity, as is the case with all segmentation approaches, but there are additional options, including variance, color, and multispectral characteristics (Gould et al., 2009). Systems that use region-based segmentation attempt to classify pixels into areas based on similar characteristics, such as estimated grey level quality. In comparison with other procedures, this segmentation method is relatively simple, effective, and noise resistant (Dubey & Vijay, 2018). Furthermore, a two-layer, back-propagated network of perceptron neurons serves as the artificial neural network utilized for segmentation. (BPNN), which determines a binary

outcome for each introduced pixel (defected-healthy).

The table 2.1 shows the comparison of different used methods based on the best performance in image segmentation.

Table 2.1: Comparison of Different Used Methods Based on the Best Performance in Image Segmentation

Segmentation Technique	Author	Accuracy Results	Advantages	Disadvantage
Threshold Based Segmentation	(Vijayan, 2019)	88.5%	To obtain the intensity value, transform the grayscale picture to binary.	The time and resources required to calculate the new data collection
Region-Based Segmentation	(Nagashree et al., 2019)	-	Provide a distinct and clear perspective of the original image	When there are no substantial changes in the pixel values of the object and the background, it did not generate many reliable segmentation results.
Clustering Based Segmentation	(Aruna Kumar et al., 2022)	56.84%	Capable of processing complicated, mainly unknown, and inaccurate brain images.	Suffers from the inherent noise and intensity inhomogeneity (IIH) that the collecting method has caused in the data.
ANN Based Segmentation	(Khadem-Reza & Zare, 2022)	88.46%	Suggested a method for diagnosing autism that examines local brain regions and could help understand the ASD. In addition, less time-consuming compared with clinical evaluations for ASD.	Due to the tremendous heterogeneity of ASD, any of the chosen individuals experienced comorbidities. These comorbidities may have an impact on volume and surface of the brain, which may have impact on the diagnosis' specificity.

The study by Vijayan (2019) addresses the challenge of transforming grayscale images into binary format for enhanced image segmentation. The primary objective was to develop a segmentation technique that leverages intensity values to convert grayscale images into a binary format, simplifying subsequent image processing. The methodology involved calculating the intensity value of each pixel and applying a threshold to distinguish between different regions in the image. This technique achieved an accuracy rate of 88.5%, indicating its reliability in differentiating image regions. One significant advantage of this method is its ability to simplify image analysis by converting it into a binary format. However, the major disadvantage is the substantial time and resources required to calculate the necessary data for each image, which can be a limiting factor for its practical application.

Nagashree et al. (2019) focused on developing a segmentation technique that provides a clear and distinct perspective of the original image. The problem addressed was the need for reliable segmentation methods that can effectively distinguish different regions within an image. The region-based segmentation method involves analyzing pixel values within a region and comparing them to neighboring regions to identify boundaries. While specific accuracy results were not provided, the technique is noted for its ability to offer a clear perspective of the image, enhancing the visibility of different regions. The primary advantage of this method is its effectiveness in providing distinct segmentation results. However, it struggles when there are minimal changes in pixel values between the object and the background, leading to less reliable outcomes.

Aruna Kumar et al. (2022) aimed to tackle the complexity of processing brain images that are often complicated, unknown, and inaccurate. Their objective was to develop a clustering-based segmentation technique capable of handling these complexities.

The methodology employed clustering algorithms to group similar pixels, thus segmenting the image based on these clusters. The study achieved an accuracy rate of 56.84%, demonstrating the method's potential in processing complex images. One of the main advantages of this approach is its capability to handle complicated and inaccurate images, making it particularly useful for brain imaging applications. However, the technique suffers from the inherent noise and intensity inhomogeneity (IIH) in the data, which can negatively impact segmentation accuracy.

The research conducted by Khadem-Reza & Zare (2022) focused on using artificial neural networks (ANN) for diagnosing autism spectrum disorder (ASD) through brain imaging. The problem statement highlighted the need for reliable and efficient methods to diagnose ASD by examining local brain regions. The objective was to propose an ANN-based segmentation method that could identify patterns associated with ASD. This technique achieved an accuracy of 88.46%, indicating its effectiveness in diagnosing ASD. A significant advantage of this method is its time efficiency compared to traditional clinical evaluations, as well as its potential to enhance understanding of brain regions related to ASD. However, the heterogeneity of ASD and the presence of comorbidities among individuals can affect brain volume and surface measurements, impacting the specificity and reliability of the diagnosis.

2.3.6.3 Image Classification

Image classification is the process of identifying and categorizing the features present in an image based on the object, usually represented by a distinct grey level or color. Image classification is a critical component of digital image analysis. In the case of ASD classification, various performance measures such as accuracy, specificity, sensitivity, precision, F1-score, and AUC are calculated based on the classifier used.

In the literature, several traditional classifier approaches based on machine learning are explored, depending on the descriptor used to select the function to fulfil the classification task. For ASD classification using fMRI data, the famous classifier used is SVM for machine learning (Santana et al., 2022). This is because it offers fast and efficient training. Besides, it also achieves 76% accuracy, which is a high accuracy for machine learning to classify fMRI image data.

Table 2.2 shows the summary of AI classifier used for ASD detection.

Table 2.2: Summary of AI Classifier Used for Autism Spectrum Disorder Detection

Method	Author	Classifier	Accuracy	Advantages	Disadvantages
Machine Learning	(Santana et al., 2022)	Support Vector Machine (SVM)	76%	Fast and efficiency when training.	Unable dealing with larger samples. More well-designed research are needed to investigate the possible application of those categorization systems in clinical contexts.
	(Chaitra et al., 2020)	Recursive cluster elimination (RCE)	70.1%	Iterative approach for selecting relevant characteristics from a big feature collection that is simple and effective.	Cannot be sure of the absolute precision it would have attained if such causes of machine variability did not exist.
Deep Learning	(Yousedia net al., 2022)	Principal Component	80%	Subject groups can be classified based on connection fingerprints of brain areas. Besides, embedded factors concerning the structure of the functional connections of the brain may make ASD identification easier.	Could not identify ROIs that alter connectivity strength values.

Table 2.2 continued

Method	Author	Classifier	Accuracy	Advantages	Disadvantages
Deep Learning	(Almuqhim & Saeed, 2021)	ASD-SAENet (sparse autoencoder)	79.1%	Improved specificity overcomes the little drop in sensitivity. Besides, it demonstrates that the number of true-negative rates is lower than in other state-of-the-art approaches.	Exhibits greater generalizability across numerous data gathering locations, however the characteristics that may be most useful in classification cannot be established due to the deep-learning model's non-interpretability.
	(Kong et al., 2019)	Deep neural network (DNN)	90.39%	To achieve the highest classification accuracy, the top-ranked features are fed into the DNN classifier. The experimental findings show that our proposed technique is a useful adjunct diagnostic tool for ASD/TC categorization.	-

Based on Table 2.2, Santana et al. (2022) aimed to address the problem of efficiently classifying autism spectrum disorder (ASD) using machine learning techniques, specifically focusing on the Support Vector Machine (SVM) classifier. The research objective was to evaluate the SVM's effectiveness in terms of accuracy and training efficiency. The methodology involved applying the SVM classifier to a relevant dataset, achieving an accuracy of 76%. The significant results highlighted that the SVM classifier provided fast and efficient training processes. However, the study also noted that handling larger sample sizes posed a challenge and emphasized the need for more comprehensive research to explore the potential applications of these categorization systems in clinical contexts. The primary advantage of the SVM approach was its rapid training capability, while the main disadvantage was its limited scalability to larger datasets and the requirement for further validation in clinical settings.

Chaitra et al. (2020) focused on improving the precision of ASD classification by addressing the issue of feature selection variability. Their research objective was to assess the effectiveness of Recursive Cluster Elimination (RCE) in selecting relevant features from a large collection. The methodology involved using RCE to iteratively eliminate irrelevant features, resulting in an accuracy of 70.1%. The significant results demonstrated that RCE could effectively streamline the feature selection process, making it both simple and effective. Despite its strengths, the study acknowledged potential issues with machine variability that could affect the absolute precision of the classification results. The advantage of this approach was its iterative and systematic feature selection process, while the disadvantage lay in the potential for variability-related precision issues.

Yousedian et al. (2022) aimed to tackle the challenge of classifying ASD using deep learning techniques, with a specific focus on understanding the connectivity patterns

in the brain. The research objective was to utilize Principal Component Analysis (PCA) within a deep learning framework to classify subject groups based on the connection fingerprints of brain areas. The methodology involved applying PCA to the dataset, achieving an accuracy of 80%. Significant results indicated that the approach was effective in classifying subjects and embedding factors related to brain connectivity, which aided in ASD identification. However, the study noted a significant disadvantage in the difficulty of identifying regions of interest (ROIs) that affect connectivity strength values. The primary advantage was the detailed classification based on brain connectivity patterns, while the main drawback was the challenge in pinpointing specific ROIs that alter connectivity strength.

Almuqhim & Saeed (2021) addressed the problem of enhancing specificity in ASD classification through deep learning models. The research objective was to evaluate the effectiveness of the ASD-SAENet (sparse autoencoder) in improving specificity and accuracy. The methodology involved applying the ASD-SAENet, which achieved an accuracy of 79.1%. Significant results showed that this approach improved specificity and demonstrated lower true-negative rates compared to other methods. Nonetheless, the study highlighted the non-interpretability of the deep learning model as a significant disadvantage, making it difficult to establish useful classification characteristics. The main advantage was the improved specificity and reduction in true-negative rates, while the primary disadvantage was the model's non-interpretability, limiting its practical applicability.

Kong et al. (2019) aimed to achieve high classification accuracy for ASD using deep learning techniques. The research objective was to implement a Deep Neural Network (DNN) classifier to enhance the diagnostic tool's accuracy. The methodology

involved feeding top- ranked features into the DNN classifier, which achieved a high accuracy of 90.39%. Significant results demonstrated the DNN's effectiveness as an adjunct diagnostic tool for ASD/TC categorization, achieving the highest classification accuracy among the studies discussed. The study reported high classification accuracy but did not elaborate on specific disadvantages, suggesting a need for further exploration of potential limitations. The main advantage was the high accuracy rate, while the lack of discussion on specific disadvantages indicates areas for future research to identify and address any limitations.

Previous research on ASD classification has limitations including issues with scalability to larger datasets, precision affected by machine variability, and the non-interpretability of deep learning models. Additionally, identifying critical brain regions and comprehensively evaluating potential limitations remain significant challenges. These gaps highlight the need for more robust,scalable, and interpretable models.

2.4 Applications of Deep Learning for Classification of Autism Spectrum Disorder

Deep learning has emerged as a powerful tool in the classification of ASD, offering new insights and approaches to understanding this complex condition. A recent study by Tang demonstrates the use of adversarial deep learning on resting-state fMRI for multi-site diagnostic classification of ASD, highlighting the potential of deep learning in handling complex neuroimaging data (Tang et al., 2020). In 2016, Ryali further explored this potential by using functional neuroimaging data to classify ASD, underscoring the capability of deep learning algorithms to analyze brain imaging effectively (Ryali et al., 2016).

Another facet of deep learning in ASD classification involves behavior analysis. A

study on the design of a behavior classification system for monitoring ASD using deep learning showcases how behavioral data, when combined with deep learning techniques, can be instrumental in identifying ASD characteristics (Dcoutho et al., 2024). Additionally, Pavithra et al., (2023) emphasizes the identification of ASD from functional MRI data using deep learning, indicating how neuroimaging combined with advanced computational methods can aid in more accurate ASD diagnosis.

Moreover, recent advancements in optimization algorithms, like the Jellyfish Search Optimization, have been integrated with deep learning for enhanced ASD classification. This approach not only improves the accuracy of ASD detection but also paves the way for more sophisticated analysis techniques in the field. Finally, the application of deep learning in skull stripping and classification of ASD further illustrates the versatility of these methods in different aspects of ASD research, from preprocessing of neuroimaging data to the final classification task (Brundha et al., 2022).

Furthermore, the detection of ASD using deep learning approaches has been a focus of research as well. For instance, the application of deep learning in detecting ASD sheds light on the capabilities of these technologies in accurately identifying the disorder (Ramanjot et al., 2022).

In addition, the work of Mittal on a deep learning approach for ASD, titled "DL-ASD," presents a novel method in the classification and interpretation of ASD, showcasing the versatility of deep learning in various aspects of ASD research (Mittal et al., 2022). Lastly, a study on deep learning approaches for the classification and interpretation of ASD discusses new methods for analyzing and understanding the disorder, thereby contributing to the growing body of knowledge in this field.

2.5 Summary

In this chapter, the exploration of ASD and its classification using Deep Learning is presented. The chapter begins with an introduction and proceeds to discuss the background of ASD, conventional classification methods, and the associated issues.

The focus then shifts to Deep Learning, with an overview of its evolution, including the Radial Basis Function Network and the Convolutional Neural Network (CNN). The various types of CNN, such as conventional and pre-trained models, are also examined, along with the challenges and problems inherent in Deep Learning.

The core emphasis of this chapter is the application of Deep Learning for ASD classification. This application holds significant potential for improving the accuracy and efficiency of diagnosis and understanding of this complex disorder.

In summary, this chapter provides a foundational understanding of how Deep Learning techniques can be applied to advance the classification and comprehension of ASD. This has the potential to yield innovative applications in the field of healthcare and the study of neurodevelopmental disorders.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The chapter outlines the approaches and techniques employed to conduct the study. These methodologies can aid in identifying, evaluating, and analyzing the research topic. It also elucidates the classification of ASD through a hybrid deep learning algorithm, encompassing the conceptual framework, data preparation, and a synopsis of the research.

3.2 Overall Flow of Proposed Autism Spectrum Disorder Classification

The proposed workflow for classifying ASD begins with the ABIDE dataset, which is subjected to a series of processing steps starting with image pre-processing. This is followed by a segmentation phase using a UNet-RBF model to delineate relevant features. To expand and vary the dataset, image augmentation techniques are applied. For classification, two methods are employed: a custom Convolutional Neural Network (CNN) and a hybrid approach combining CNN with Radial Basis Function (RBF) networks. The performance of these methods is evaluated, and the process iterated until the classification objectives are met. Figure 3.1 shows the research design process flow in this study.

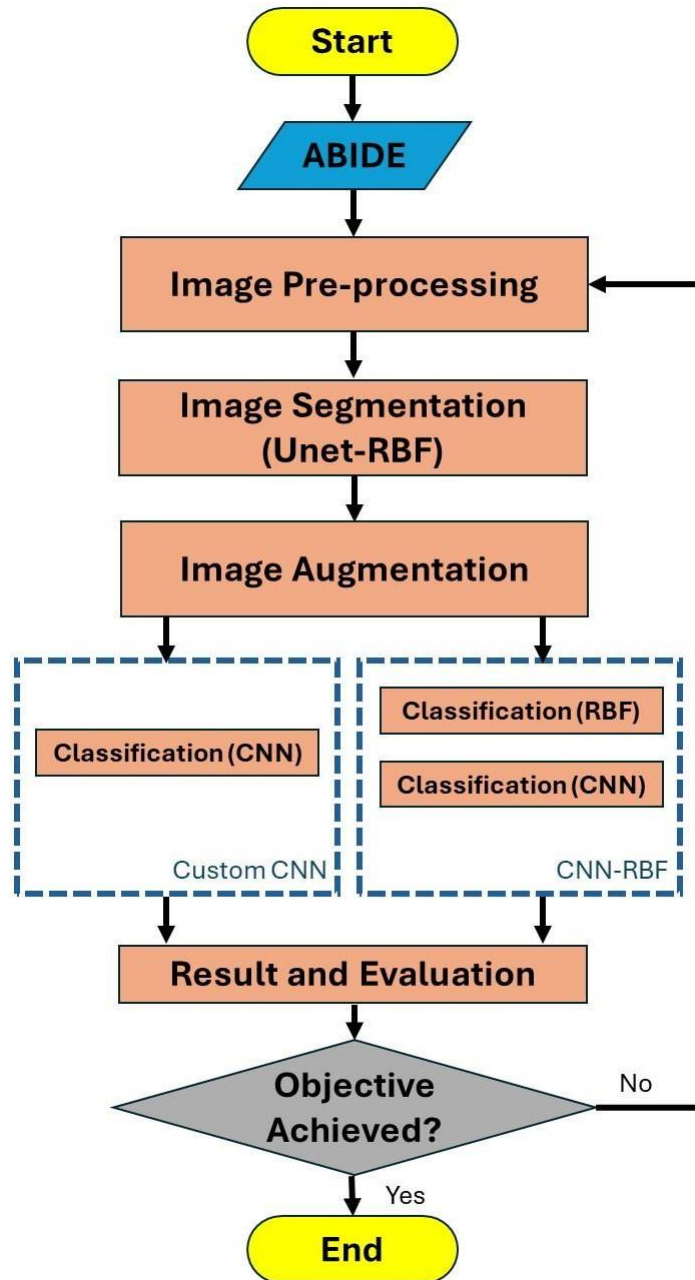


Figure 3.1: Research design process flow

From Figure 3.1, the first step is to collect fMRI data. In this research, the data collected form Autism Brain Imaging Data Exchange (ABIDE). It represents the worldwide multi-site database which provides aggregated functional and structural brain imaging data collected. Data collection indicates the process of collecting the desired

information with a minor deformation; therefore, analysis can provide credible and logical answers (Parveen & Showkat, 2017). After that, preprocessing data is carried out. This includes image segmentation and augmentation. Preprocessing data may help to make the data trainable in the model because including techniques like data cleaning, transformation, feature engineering, and data augmentation, is crucial for enhancing the accuracy and performance of machine learning models. Properly prepared data ensures robust, efficient, and effective model training (Guyon & Elisseeff, 2003). The next step is to propose a deep learning algorithm for training data. The custom CNN model and CNN-RBF is applied for classification. After that, the result and evaluation. The ASD may classify based on the result. This research recorded the accuracy and loss performance as the results. Besides, the evaluation method used to evaluate the results is the confusion matrix. If the research objective is not achieved, the experiment repeats again from image preprocessing.

3.3 Data Acquisition and Data Preparation

In this research, brain imaging data of the resting-state functional magnetic resonance imaging (rs-fMRI) acquired from NeuroImaging Tools and Resources Collaboratory (NITRC) website (<https://www.nitrc.org/projects/nitrcir>). NITRC is a free web-based resource that provides in-depth information on a growing range of neuroinformatic data and tools. Since its inception in 2007, NITRC has been supplying software and data generated from previously lost or ignored research, which are utilized by the neuroscience community in making discoveries. Thus far, 700 images related to brain imaging data are accessible: 350 for ASD; and another 350 for non-ASD. Figure 3.2 illustrates an example of ASD and non-ASD image data.

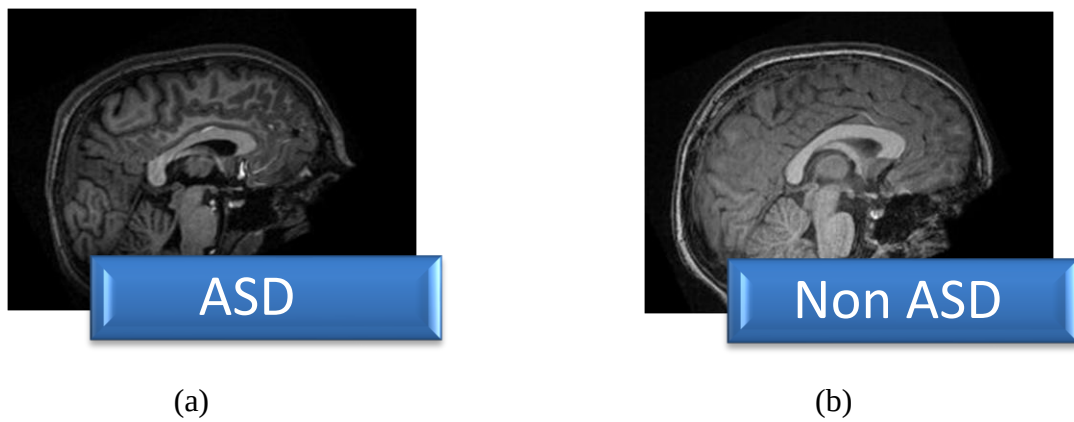


Figure 3.2: Example of (a) ASD and (b) non-ASD data.

Functional magnetic resonance imaging (fMRI) data reveal significant differences in brain connectivity and activation patterns between individuals with ASD and those non-ASD. In ASD, there is often reduced connectivity within the default mode network (DMN), a brain network associated with self-referential and social cognitive processes, and increased connectivity in sensory and subcortical networks, which may be related to the heightened sensory sensitivity observed in ASD (Uddin et al., 2013). Additionally, individuals with ASD show atypical activation in brain regions involved in social processing, such as the fusiform gyrus and the amygdala, leading to differences in social and emotional processing (Di Martino et al., 2009). In contrast, non-ASD individuals typically exhibit more balanced and efficient connectivity and activation patterns across these networks, supporting more typical social interactions and sensory processing (Buckner et al., 2008). These differences in fMRI data highlight the distinct neural mechanisms underlying ASD.

Data pre-processing, also called data preparation, the initial process in machine learning or deep learning. In data pre-processing, raw data are prepared to a level acceptable for training. Proper data preparation is crucial as it may substantially influence

machine learning algorithm's generalization performance (Astorino et al., 2011). In addition, to resolve issues of learning from massive datasets, an appropriate approach is to select a representative sample from the datasets.

Another common concern in data preparation is handling of missing data. Pre-processing data has a higher probability of yielding high-quality mining results. Data preparation, cleaning, and transformation make up most of the work in a data mining application.

In data preparation, the image data must all be read from the path at the start of image data pre- processing. A function is created to load the folders containing images into arrays. There are three main types of images. First is the intensity image. This image seems to be a data matrix with scaled values that indicate intensities. In digital imaging, the representation and scaling of pixel intensity values depend on the data type used. For images stored as 8-bit unsigned integers (uint8), pixel values range from 0 to 255, while for 16-bit unsigned integers (uint16), the range extends from 0 to 65,535. When using 32-bit single-precision floating- point numbers (float32), pixel values are typically normalized to the range [0, 1], although using the range [0, 255] for float32 is uncommon. This normalization is beneficial for mathematical operations and algorithms that assume standardized input ranges (King, 2012). A binary image, on the other hand, is a black and white image where each pixel has only one logical value, either 0 or 1. Finally, a color image is similar to an intensity image, but with three channels representing red, green, and blue (RGB) intensities at each pixel location.

Once the images are read, it is necessary to resize them. To visualize the changes made in the images during the resizing process, two functions are created: one for displaying a single image and another for displaying two images side by side. Afterward, a

processing function is created that takes the images as a parameter. Resizing the images is crucial because the size of the images captured by the camera and fed into the AI algorithm may vary. Therefore, a standard size for all images fed into the AI algorithm should be established. Figure 3.3 below demonstrate the fMRI data after resizing:

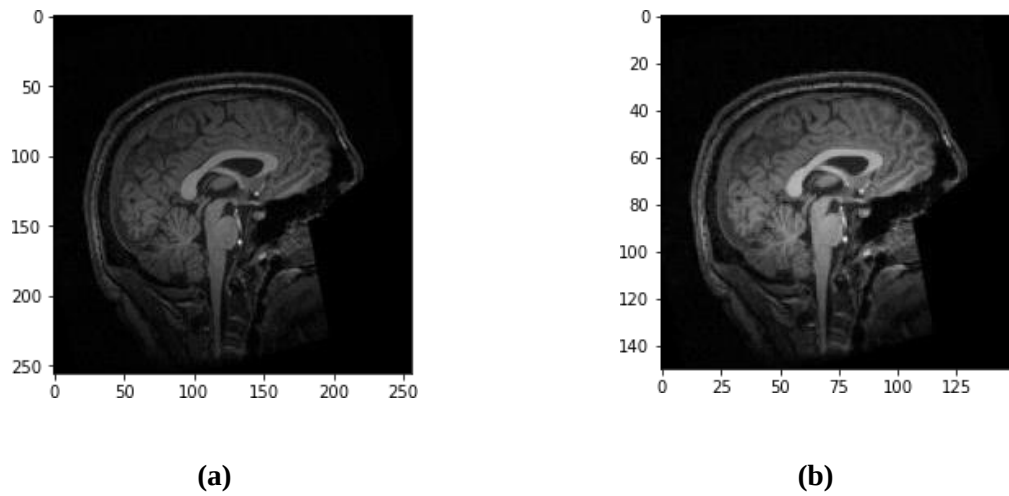


Figure 3.3 Example of Resize: (a) Before Resize and (b) After Resize

From Figure 3.3, Resizing fMRI data from 256x256 to 150x150 pixels is often necessary to reduce computational load and memory usage during data processing and analysis, particularly when working with large datasets or performing complex machine learning tasks. Smaller image dimensions help accelerate processing times and allow the use of more efficient algorithms without significantly compromising the spatial resolution needed for accurate analysis (Eklund et al., 2016). This resizing process ensures that computational resources are utilized effectively while maintaining the essential features of the brain images required for analysis (Plis et al., 2014).

After that, the images are converted to ground truth data using CVAT (Computer Vision Annotation Tool) which is an open-source, web-based application. CVAT offers a user-friendly interface that supports a variety of annotation types such as bounding boxes, polygons, and masks. Additionally, CVAT supports collaboration, allowing multiple users

to work on annotations simultaneously, which is crucial for large-scale projects.

Generating ground truth data with CVAT involves several essential steps. Initially, users upload images to the platform, which supports a wide range of file formats. Annotators then proceed to label objects within these files utilizing CVAT's extensive annotation tools. To enhance efficiency, CVAT integrates machine learning models that automate certain aspects of the annotation process. Upon completion of the annotations, a review process ensures accuracy and quality. Finally, the annotated data is exported in various formats compatible with leading machine learning frameworks, such as TensorFlow and PyTorch. This streamlined workflow facilitates the efficient creation of high-quality ground truth data, which is crucial for training and validating machine learning model (Cakic et al., 2023).

3.4 Image Segmentation Using Proposed Integrated UNet and Radial Basis Function

Segmentation is a crucial process that decomposes images into objects and backgrounds using various methods. The edges of an image are rich in information, indicating the location, shape, size, and texture of the objects. Edge detection, closely related to image processing and pre-processing, assigns a value to each point in the input image, determining whether it is the edge of an element or the background. Edge detectors seek to find sharp changes in the intensity of the image function, forming edges at points where brightness changes abruptly. Edge detectors fall into two categories: one that detects known objects and the other that detects objects without previous knowledge of the scene being processed. The latter category is advantageous for its independence from the image being processed, and this article will focus on it. A comparison of detectors of authentic images can be found.

3.4.1 Proposed UNet and RBF model

The UNet-RBF is a segmentation model and mainly segments the cerebellum from the original image data. The cerebellum is a central brain structure called the 'small brain'. The function of the cerebellum is to balance motor activities, regulate muscle activation and speech, and organize eye movements, which significantly influence human eyesight (Tunali, 2020). In ASD classification, the volume of the cerebellum represents a characteristic. According to a meta-analysis of 17 imaging studies, autistic patients have less brain tissue in areas of the cerebellum, the brain structure near the base of the skull (Stoodley, 2014). After segmentation, ASD may classify more accurately.

UNet is a convolutional neural network (CNN) and is mainly for medical image segmentation. Ronneberger first proposed UNet in 2015 (Ronneberger et al., 2015). In UNet, the connection skips and supports restoring the whole spatial goal at the output of the network, the fully convolutional network (FCN). In the previous study, CNN revealed excellent results in image classification, recognition, object detection, etc. but lacked localization from the desired output in biomedical image processing. In convolutional networks, the output to an image has only a single class mark, but in biomedical image processing, each pixel should have a class mark. Figure 3.4 show UNet architecture:

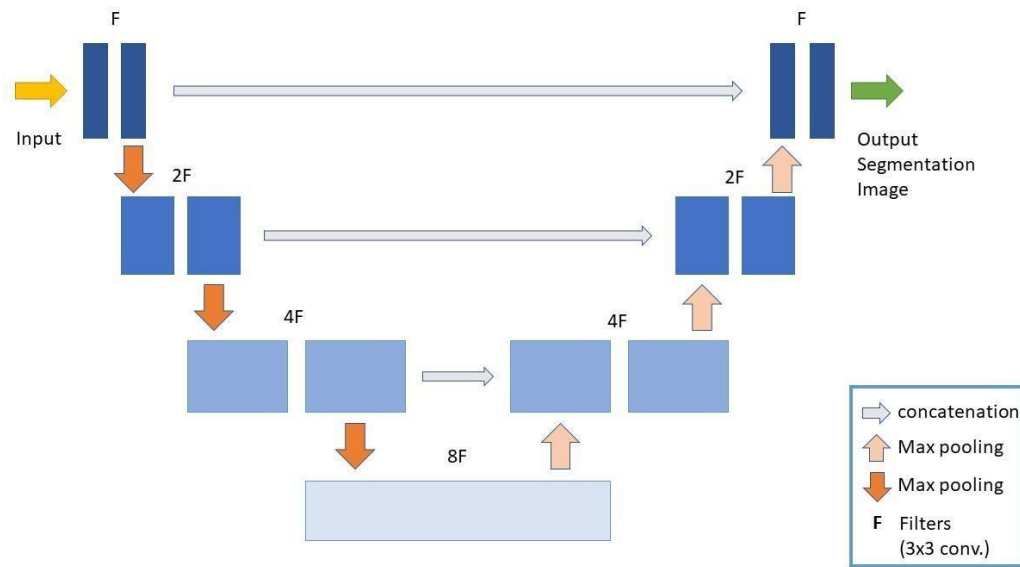


Figure 3.4: UNet architecture.

U-net is an extraordinary neural network architecture specially used for semantic segmentation, instance segmentation, and object detection. From a traditional CNN, UNet expanded with some changes and improved. A Fully Convolutional Network (FCN) represents an early Deep Learning (DL) architecture equipped end-to-end for pixel-wise prediction for semantic segmentation tasks (Jha et al., 2020). UNet is the same as FCN because the content is a down-sampling layer and an up-sampling layer (Weng et al., 2019). It is called U-net because it has the shape of "U" architecture. From figure 3.5, the left side is named the contracting path, and the right side is named the expansive path. In the contracting path, regular convolutions and max-pooling layers have been applied. However, transposed and regular convolutions have been applied in an expansive path. UNet accepts all image sizes because it does not consist of a dense layer.

Another approach to combine with U-net is to use the radial basis function, RBF. Radial functions are a type of function that can be applied to any model, be it linear or nonlinear, and any network, be it single-layer or multi-layer. The RBF is used in previous

research for interpolating and approximating dispersed data (Smolik et al., 2018). Radial basis networks represent fully connected feedforward neural networks that use a radial basis function as their activation on their hidden layers. In addition, RBF is attractive for functional approximation because it can be solved using a generalization of least squares regression. RBF is the most potent kernel available for support vector machines. The most common activation function in RBF is the Gaussian. The Gaussian function is normalized by summing all of the Gaussian components, similar to Gaussian mixture estimation (Tominec et al., 2021). The equation of RBF with Gaussian function is shown at (3.1) below.

$$\phi(r) = e^{-(sr)^2} \quad \text{Equation 3.1}$$

From the equation in (3.1), $\phi(r)$ represents a function with respect to the origin or a certain point c , i.e., $\phi(r)=f(\|r-c\|)$ where the norm is usually the Euclidean norm but can be another type of measure. Euclidean norm but can be another type of measure. "Euclidean space" refers to a mathematical space that can be described using Euclidean geometry, which is a system of geometry based on a set of axioms involving points, lines, and planes. It is an n -dimensional space that has a fixed number of dimensions and can be visualized in three-dimensional space. In this space, an n -dimensional vector represents a point, and the Euclidean norm is used to measure the length of a vector.

RBFs can be viewed as a method of approximating a function by summing a sequence of functions that are precise in a local region, but imprecise elsewhere, and that when combined, closely approximate the original function. This is because RBFs are defined as functions centered around specific points in the input space. RBF's have desirable properties such as localization, functional approximation, interpolation, cluster

modelling, and quasi- orthogonality.

In addition, RBF also represents the multivariable function which can improve the artificial neural network. RBF was presented and proposed in 1988 by Broomhead and Lowe. Radial basis function networks are feedforward networks with a long history in machine learning. However, there is little literature on how to train the network for higher accuracy (Frank, 2014). According to Dietrich Wettschereck, the supervised training of hidden layer parameters in RBF can improve predictive performance.

In this research, RBF merges with UNet in the fully connected layer to become a new model for segmentation. The UNet-RBF model is better than other methods due to its enhanced feature extraction and generalization capabilities. Specifically, it integrates the RBF kernel function into the UNet architecture, which helps capture more complex patterns and relationships in the data. This integration improves segmentation accuracy, particularly in medical imaging, where the precise delineation of anatomical structures or pathological regions is crucial. The RBF kernel's ability to handle non-linear data makes the UNet-RBF method more robust and effective in dealing with the variability and complexity of medical images compared to standard UNet or other convolutional neural network-based methods.

Figure 3.5 shows the UNet-RBF model architecture.

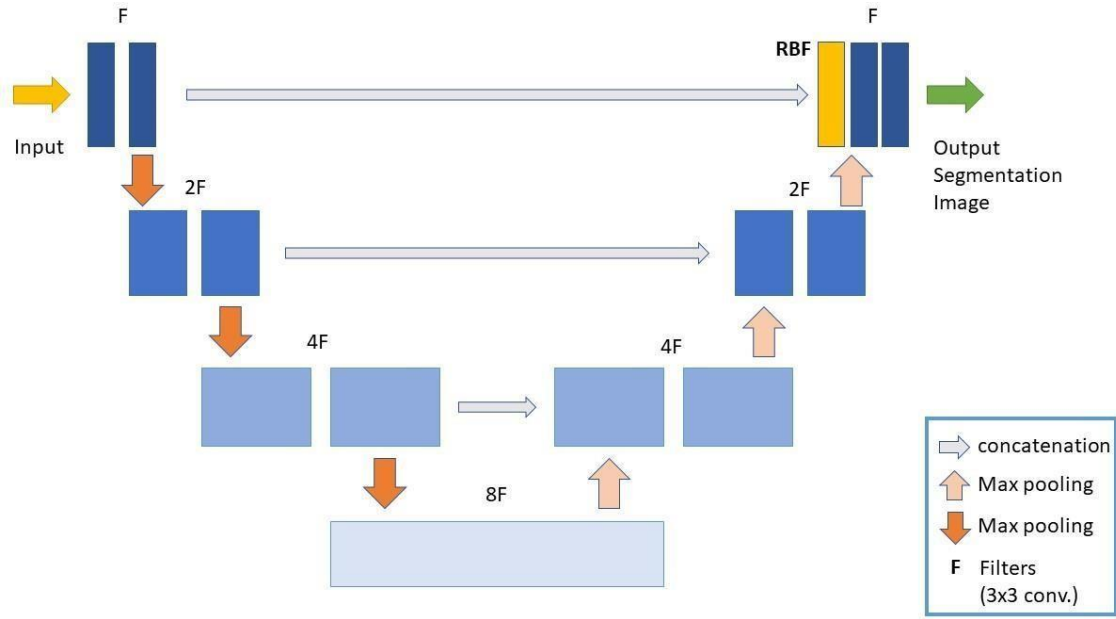


Figure 3.5: The UNet-RBF model architecture.

During the training process, the UNet-RBF model learns to map input images to their respective segmentations by minimizing the error between its predicted outputs and the ground truth annotations. This is achieved through backpropagation and optimization algorithms that adjust the model's parameters to reduce the loss function, which measures the discrepancy between the predicted segmentations and the ground truth. As the model iteratively processes the training data, it gradually improves its ability to accurately segment new, unseen images, leveraging the patterns and features it has learned from the ground truth data. This supervised learning approach ensures that the UNet-RBF model can perform precise and reliable image segmentation tasks in practical applications. After training, the segmented data displays in Figure 3.6. This segmented data will be used for ASD and non-ASD classification.



Figure 3.6: Segmented Data for (a) ASD and (b) non-ASD

According to Figure 3.6, the cerebellum from the human brain is segmented for feature extraction. Although the cerebellum is well known for its role in motor control, it also affects cognition, including the ability to communicate verbally. It has long been regarded as part of the motor system like the basal ganglia, but its activities extend beyond motor control in ways that are still a mystery.

3.5 Proposed Autism Spectrum Disorder Classification

This study proposes using the data augmentation method and CNN-RBF model to classify ASD.

3.5.1 Data Augmentation

The existing image augmentation techniques can be classified into two broad categories: traditional white-box methods and black-box methods based on deep neural networks. This section introduces some of the most impactful methods in the field of image synthesis and augmentation. The first category is traditional transformations, which include affine image transformations and color modification. The most used affine transformations are rotation, reflection, scaling, and shearing.

Geometric distortions or deformations are commonly used to augment training datasets for deep neural models. This is done to balance the size of datasets and improve their efficiency. Affine transformations such as rotation, reflection, scaling, and shearing are frequently used as geometric distortions for data augmentation. Additionally, methods like histogram equalization, contrast or brightness enhancement, white balancing, sharpening, and blurring are also popular. These easy-to-understand methods are fast, reproducible, and reliable. Furthermore, their implementation code is readily available to download for most deep learning frameworks, making them even more accessible. Nonetheless, their efficiency improvement is still the subject of ongoing research.

Python, a programming language, is used for data augmentation in this study. Image data generator imported from TensorFlow, Keras is utilized to set up the parameters. The total data increases to 22,980 images after data augmentation. The parameters of data augmentation are shown in Table 3.1 below:

Table 3.1: Parameters of data augmentation

Rotation range	Width shift range	Height shift range	Shear range	Zoom range
45	0.2	0.2	0.2	0.2

Selecting specific data augmentation parameters, such as a rotation range of 45 degrees, is influenced by the requirements of the image recognition task and the nature of the dataset being used. For instance, in the context of medical imaging, where datasets are limited and class imbalance is prevalent, augmentation techniques like rotation, shifting, and zooming are employed to simulate various real-world conditions and improve the robustness of the models (Esteva et al., 2017). These parameters are chosen to reflect realistic variations that an object might undergo in the real world, such as different

orientations and sizes. The 45-degree rotation range, for example, can help the model learn to recognize objects that are not perfectly aligned with the camera, which is a common scenario in natural images.

Moreover, the choice of data augmentation parameters is often guided by empirical studies and the specific challenges of the domain. For instance, Krizhevsky et al. (2012) demonstrated the effectiveness of various augmentation techniques, including rotation and shifting, in reducing overfitting and improving model performance on large datasets like ImageNet. In addition to improving generalization, these techniques help in addressing issues like viewpoint, lighting, and scale variability, which are critical for accurate image recognition (Leevy et al., 2018).

The width shift range and height shift range parameters define the fraction of the total width or height by which the image can be randomly shifted either horizontally or vertically. A range of 0.2 means the image can be shifted up to 20% of its total width or height. This type of augmentation simulates the effect of objects being located at different positions within the image frame, which is a common real-world scenario. It helps the model learn to recognize objects regardless of their specific position in the image, thereby improving its robustness and ability to generalize (Awaluddin et al., 2023).

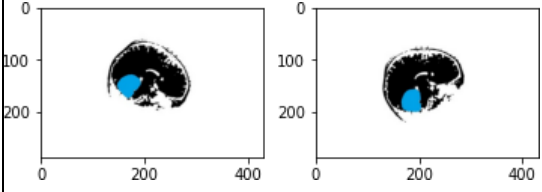
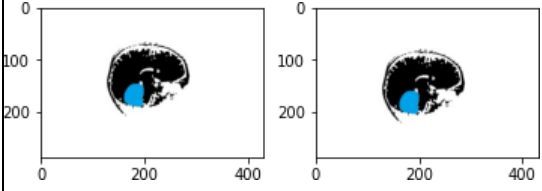
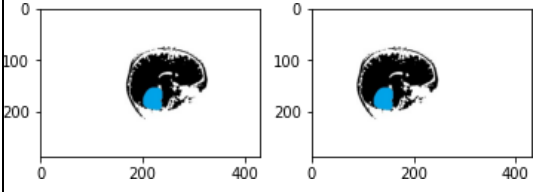
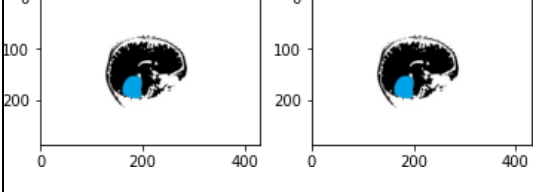
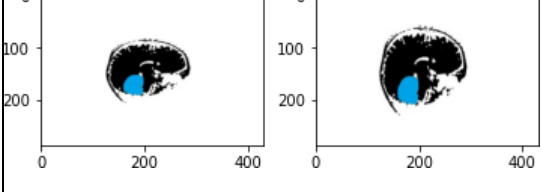
Shear transformations simulate the effect of the object being viewed from a different angle. In this context, a shear range of 0.2 indicates that the images will be sheared by a random factor within this range, introducing a moderate level of geometric transformation. This is particularly useful for teaching the model to recognize objects in images that have been captured from various angles, enhancing its ability to understand perspective and dimensionality (Awaluddin et al., 2023).

The zoom range parameter allows the images to be randomly zoomed in or out by a

specified factor. A zoom range of 0.2 implies that the image will be zoomed in or out by up to 20%. This kind of augmentation is useful for modeling scenarios where objects might appear at varying distances from the camera, thus appearing larger or smaller in the frame. It helps in training the model to recognize objects irrespective of their size in the image, which is a common challenge in real-world applications (Shorten & Khoshgoftaar, 2019).

Table 3.2 shows the images after augmentation.

Table 3.2: Data augmentation rotation examples

Original Image	Parameters	Images after Augmentation
	Rotation range	
	Width shift range	
	Height shift range	
	Shear range	
	Zoom range	

Based on Table 3.2, the width and height shift range are 0.2, and they adjust the horizontal and vertical shift parameters. Alternatively, these inputs may give a floating-point number representing the percentage (between 0 and 1) of the image's width or height that should be shifted. Besides, it is also possible to provide a specific number of pixels that will be used to move the picture. In addition, shearing is an additional bounding box transformation that may be performed with the assistance of the transformation matrix. Shearing seems to have an impact. In addition, zoom augmentation enlarges the picture by increasing the zoom factor and adding additional pixel values surrounding the image or interpolating pixel values, depending on the situation. After data augmentation, the images data increase.

3.5.2 Autism Spectrum Disorder Classification Using Proposed Integrated Convolutional Neural Network and Radial Basis Function

A convolution neural network (CNN) is mainly used for image classification. This research combines CNN and RBF algorithms to propose a new hybrid deep learning algorithm for obtaining better results. In this way, the RBF algorithms may help to solve the function approximation, especially in classifying ASD and non-ASD through the cerebrum in the human brain. After getting the segmented data, the model of CNN-RBF is created through python. CNN consists of several layers: the convolutional layers, the pooling layers, and the fully connected layers. The RBF layer is added to the fully connected layer.

The data input shape of this implementation is (64,64,1). The parameter in CNN represents the weights and biases. In every layer, the sum of weight and biases are shown in Table 3.2. The convolutional layers and the dense layer in the fully connected layer are

computed, but the pooling layer, flatten layer, and dropout layer parameters are not computed since these layers lack trainable parameters. In addition, since the output layer simply includes the categorized data, it lacks any parameters that may be learned. The total number of parameters in this model is 297,938. Based on Table 3.2, the "None" values in the Output column refer to the batch size, which is not fixed and can vary depending on the input data during training or inference. This flexibility is crucial for handling varying amounts of input data without modifying the network architecture.

The model summary is shown in Table 3.3 below:

Table 3.3: CNN-RBF model

Layer	Output	Parameter
Convolution layer	(None, 60, 60, 64)	1664
Convolution layer1	(None, 56, 56, 64)	102464
Convolution layer2	(None, 52, 52, 64)	102464
Max pooling layer	(None, 26, 26, 64)	0
Batch normalization	(None, 26, 26, 64)	256
Convolution layer3	(None, 24, 24, 32)	18464
Convolution layer4	(None, 22, 22, 32)	9248
Convolution layer5	(None, 18, 18, 32)	25632
Max pooling layer1	(None, 9, 9, 32)	0
Batch normalization1	(None, 9, 9, 32)	128
Convolution layer6	(None, 9, 9, 16)	528
Convolution layer7	(None, 9, 9, 16)	272
Convolution layer8	(None, 5, 5, 16)	6416
Max pooling layer2	(None, 2, 2, 16)	0
Batch normalization2	(None, 2, 2, 16)	64
Flatten layer	(None, 64)	0
RBF layer	(None, 50)	3200
Dense layer	(None, 512)	26112
Dropout	(None, 512)	0
Dense layer1	(None, 2)	1026
Total Parameters		297,938

Integrating RBF offers advantages such as improved function approximation and flexibility. By combining RBF with CNN, the model can effectively discern autism and non-autism cases with higher accuracy. The hybrid architecture addresses the limitations of individual models and capitalises on their complementary strengths. This combination enhances the model's ability to capture intricate relationships in the data and improves its overall performance.

Mathematically, the CNN-RBF model incorporates convolutional neural networks (CNN) and radial basis function networks (RBF) for medical image classification. Firstly, the CNN extracts hierarchical features from input images through convolutional layers, represented as

$$f(\mathbf{X}) = \sigma(\mathbf{W}i * \mathbf{X} + \mathbf{b}i) \quad \text{Equation 3.2}$$

where σ denotes the activation function, $\mathbf{W}i$ and $\mathbf{b}i$ are learned filters and biases, and $\mathbf{X}$ represent the input image. Secondly, the RBF layer computes activations a_k using Gaussian radial basis functions, incorporating outputs from the CNN, expressed as

$$a_k = \sum_{i=1}^N w_{ki} \exp\left(-\frac{|\mathbf{F} - \mathbf{C}_i|^2}{2\sigma_k^2}\right) \quad \text{Equation 3.3}$$

where $\mathbf{F}$ is the CNN's output feature map, $\mathbf{C}_i$ represents learned prototypes, w_{ki} denotes weights, σ_k^2 and N is the total number of prototypes. Finally, concatenated RBF layer outputs are processed by fully connected layers for classification, where

$$\mathbf{z} = \mathbf{W}_d \cdot \mathbf{a} + \mathbf{b}_d \quad \text{Equation 3.4}$$

and

$$\mathbf{y} = \text{softmax}(\mathbf{z}) \quad \text{Equation 3.5}$$

yield predicted probabilities for autism and non-autism classes. This integration enables the model to classify medical images effectively, leveraging learned features and prototype distances from both CNN and RBF. The CNN-RBF model is shown in Figure 3.7.

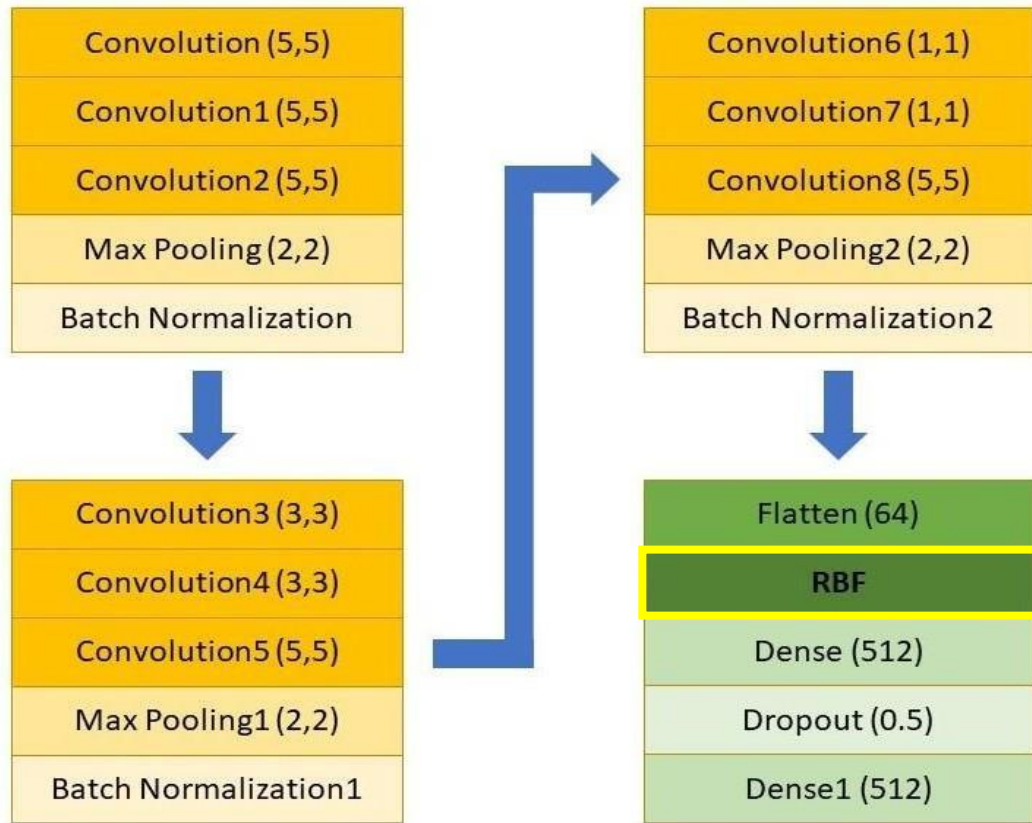


Figure 3.7: CNN-RBF model

From Figure 3.7, the CNN-RBF model contains four stages. There are three convolution layers, one max pooling layer, and one batch normalization in each of the first three stages. Stage 4 is a fully connected layer containing one flatten layer, an RBF layer, two dense layers, and one dropout layer. In convolutional layers, neurons can be seen as rectangular grids. In the previous layer, each neuron takes inputs from the previous layer arranged in a rectangular grid, and the weights for each neuron are identical. When performing image convolution through this layer, the weights are determined by the convolution filter.

The pooling layer conveys the small rectangular blocks from the convolutional layer as input to produce a single output through the subsamples process. This layer consists of 2 types of pooling: average pooling and max pooling. This research uses the max pooling layer for the subsamples process. The parameters in all stages are different, from more to less.

3.6 Measurement Metrics

Measurement metrics are essential for evaluating the performance of machine learning models. Common metrics include accuracy, precision, recall, and F1-score, which provide insights into the model's predictive capabilities and its balance between false positives and false negatives. These metrics help in understanding the strengths and weaknesses of the model in various scenarios and guide improvements and optimizations.

3.6.1 Measurement Metrics for Autism Spectrum Disorder Image Segmentation

In this research, the output is accuracy and loss performance after training with the proposed model. The accuracy and loss are demonstrated in the statistical graph using python programming. "Matplotlib" is used as a plotting library in python for plotting the graph. Besides, for UNet-RBF, the output is evaluated based on metrics. Pixel Accuracy (PA) and IOU (intersection over union) are famous evaluation metrics for the segmentation model. PA is an elective measurement to assess semantic segmentation and is used to report the percent of pixels in the picture which are effectively characterized. The equation is defined as follows:

$$PA = \frac{\text{True Predicted Pixels}}{\text{Total number of Image Pixels}} = \frac{TP + TN}{TN + FN + TP + FP} \quad \text{Equation 3.6}$$

From the equation, TP represents True Positive, and TN means True Negative. While FP is a False Positive, and FN represents a False Negative. The IOU metric is commonly used to evaluate the performance of object detection models on a given dataset. This metric calculates the ratio of the area of intersection to the area of union between the predicted bounding box and the ground-truth bounding box. In other words, it measures the degree of overlap between the predicted and actual object locations in the image. The equation for IOU is shown below:

$$IOU = \frac{TP}{TP + FN + FP} \quad \text{Equation 3.7}$$

However, for medical image segmentation, the Dice coefficient and Jaccard index are the most common performance metrics (Bertels et al., 2019). The dice coefficient is calculated as twice the intersection area of two images divided by the total number of pixels in both images. The coefficient is positively correlated, indicating that if one model performs better than another in segmenting an image, the other will also agree with the result. The Jaccard Index is a mathematical tool that is commonly used to measure the similarity and diversity of sample sets. The Jaccard coefficient has broad applications in various fields, including computer science, ecology, and genomics, where binary or binarized data are utilized. The equation for Dice coefficient and Jaccard efficiency shown as below:

$$\text{Dice coefficient} = \frac{2TP}{2TP + FP + FN} \quad \text{Equation 3.8}$$

$$\text{Jaccard coefficient} = \frac{|A \cap B|}{|A \cup B|} \quad \text{Equation 3.9}$$

According to the Jaccard coefficient, A and B represent the two sets. It illustrates

that the number in either set is divided by the number in both sets. The Jaccard coefficient may be used to locate similarities between two asymmetric binary vectors or between two sets.

3.6.2 Measurement Metrics for Autism Spectrum Disorder Classification

In addition, the confusion matrix of binary classification is used in this research for evaluation in CNN-RBF. Figure 3.8 shows the confusion matrix for binary classification.

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Figure 3.8: Confusion matrix for binary classification

In the confusion matrix, the letters TP, FP, TN, and FN represent true positive, false positive, true negative, and false negative respectively. These frequencies may be used to construct classification performance indicators, which show how well the classifier detects the given class. Precision, sensitivity, specificity, and accuracy are the most prevalent of these metrics. The equation for precision, sensitivity, specificity and accuracy

are shown as below:

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{Equation 3.10}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad \text{Equation 3.11}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad \text{Equation 3.12}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad \text{Equation 3.13}$$

Sensitivity refers to the ability of a test to correctly identify a person as positive if they have a disease. Specificity, on the other hand, it measures a test's ability to accurately identify a person as negative if the person does not have the illness. Precision is the proportion of relevant results among all the search results returned. These terms are commonly used in various fields such as medical diagnostics, information retrieval, and machine learning evaluation.

3.7 Summary

This chapter explains the methodology of the research. The general framework and specific framework help conduct the research experiment. Data preprocessing is described clearly with several steps. After that, the UNet-RBF and CNN-RBF model is applied as a hybrid deep learning model to detect ASD and non-ASD. Lastly, the performance of the output is assessed through some evaluation methods.

CHAPTER 4

RESULTS, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the findings and results drawn from the research conducted following the methodology described in Chapter 3. The UNet-RBF and CNN-RBF model proposed to classify ASD. The results are then compared with other algorithms, and the accuracy performs based on the confusion matrix.

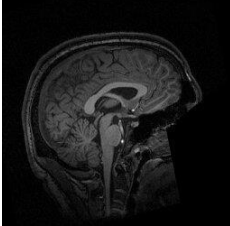
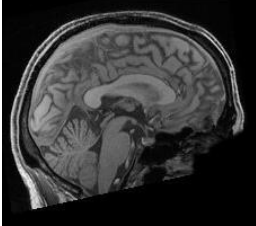
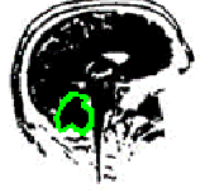
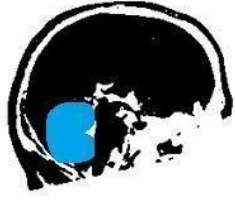
4.2 Results of Cerebellum Segmentation

The brain imaging data are collected from NeuroImaging Tools and Resources Collaboratory (NITRC) website. The original brain imaging data is clear and with a black background. The data is in jpg format. JPG is a digital picture format that stores image data in compressed form.

After that, the images are saved in 2 folders, which are ASD and non-ASD folders, and each folder contains 350 images. Then, the UNet-RBF model was applied in the jupyter notebook. The data split is 0.2. This means that the training dataset contains 80% of the data, and the test dataset contains 20% of the data. After splitting the dataset, the images resize into 150 x 150. Before using the UNet-RBF model, the data is first transformed into ground truth data. The cerebellum can easily segment from the ground truth data through the UNet- RBF segmentation model.

Table 4.1 below shows the process of the image after applying the UNet-RBF model.

Table 4.1: The process of the image.

Data Type	Techniques Applied	Example of brain imaging data	
		Autism	Non-Autism
Original data	-		
Grayscale data	Convert a 2D grayscale array from a 3D colourimage array.		
Ground truth data	Using Computer Vision Annotation Tool (CVAT) to create ground truth data.		
Segmented data	Artificial Neural Network based segmentation (UNet-RBF model)		

According to Table 4.1, UNet-RBF model successfully segmented the cerebellum from brain imaging data after transforming the original data to grayscale data. Grayscale images reduce the complexity of the data, as they only contain intensity values instead of multiple color channels. This simplification can make the segmentation process more efficient and focused, allowing the model to better detect and segment structures like the cerebellum. After that, the ground truth data is generated from CVAT for training. For the UNet-RBF model, the IoU results show in the Figure 4.1 below:

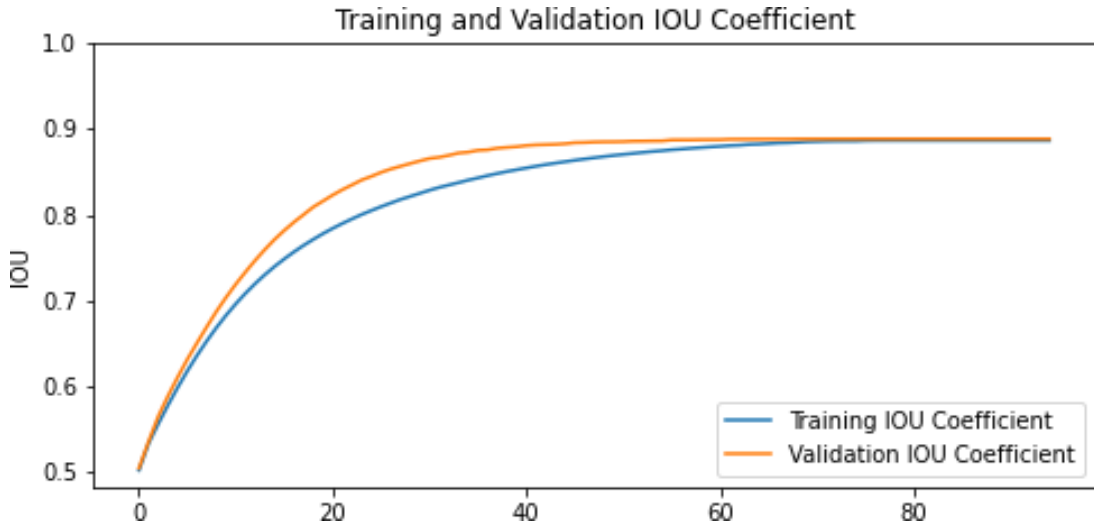


Figure 4.1: IoU Coefficient of UNet-RBF model

The graph presents the progression of Intersection over Union (IoU) coefficients for a particular model during the training phase. The IoU is a measure used in computer vision to quantify the percent overlap between the target mask and the prediction output by the model. It is particularly prevalent in tasks like object detection and semantic segmentation (Everingham et al., 2014).

From Figure 4.1, the training stops at epoch 95 with the increasing IoU score from 49.65 to 88.71, and for the test dataset, the result is 89.25. As the training progresses, both the training and validation IoU coefficients are observed to increase and plateau, which implies that the model is effectively learning and generalizing the task it has been trained for. Notably, the validation IoU closely tracks the training IoU, suggesting that the model is not overfitting, as it performs similarly on unseen data (Rahman & Wang, 2016).

The convergence of the curves at a high IoU value indicates a successful training outcome, meaning the model predictions are aligning well with the ground truth data. However, since the curves do not completely flatten out, there might be some benefit to continued training, or possibly, the model might achieve marginal gains with additional

epochs (Zhao et al., 2022). The Dice Coefficient is widely used in the medical image segmentation domain to evaluate the performance of segmentation tasks. The result of dice coefficient in UNet-RBF shows in Figure 4.2 below:

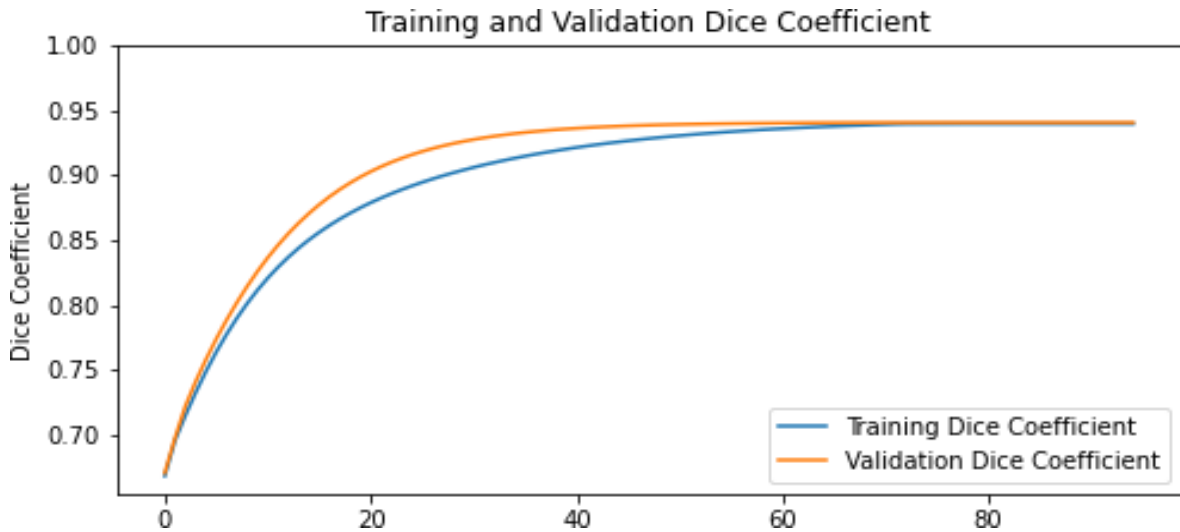


Figure 4.2: Dice Coefficient for UNet-RBF model

The graph shows that both the training and validation dice coefficients increase over time and begin to plateau, suggesting that the model is learning and is close to converging to its optimal state. The close proximity of the validation dice coefficient to the training dice coefficient indicates good model generalization without significant overfitting.

The plateau observed in both the training and validation curves suggests that most of the learning has been achieved. If the curve were to level off entirely, it would suggest that further training would not significantly change the model's performance, unless other changes are made.

Depending on the context and the specific application, it might be worth considering further training until the performance improvement is negligible. Early stopping could be employed to prevent overfitting, ending the training process when the

validation score starts toworsen.

Based on the results presented in Figure 4.2, the training process for UNet-RBF shows a notable increase in the dice coefficient, rising steadily from 66.34% initially to 94.01% by epoch 95. Furthermore, the segmentation performance on the test dataset yields a dice coefficient of 94.32%. This performance compares favorably with existing literature on cerebellum segmentation methods. For instance, while multi-atlas segmentation methods typically achieve dice coefficients ranging from 0.85 to 0.92 (Iglesias & Sabuncu, 2015), UNet- RBF method surpasses these benchmarks, indicating superior accuracy in delineating cerebellar structures. Moreover, compared to deep learning methods such as DeepMedic and V-Net, which generally report dice coefficients between 0.88 to 0.94 (Kamnitsas et al., 2017), UNet-RBF demonstrates comparable or even higher segmentation accuracy, underscoring its effectiveness in clinical applications requiring precise anatomical delineation.

This comparison highlights the robust performance of our proposed method in achieving high dice coefficients both during training and on unseen test data, positioning it asa promising advancement in cerebellum segmentation research.

4.3 Result of Autism Spectrum Disorder Classification

In this study's dataset, the data is divided into three sets: training, validation, and testing. The validation set is a portion of the data that is used to assess a model's suitability to the training data objectively while adjusting model hyper-parameters. Table 4.2 below shows the different dataset splits.

Table 4.2: Dataset split

Dataset split	Training	Validation	Test	Total
0.2	14707 images	4596 images	3677 images	22980 images
0.3	11260 images	6894 images	4826 images	22980 images
0.4	8272 images	9192 images	5516 images	22980 images

Based on Table 4.2, the dataset split of 0.2 means 20% of the dataset as a test set, and the remaining dataset is split into 80% as a training set and 20% as the validation set. For dataset 0.3, there is 30% of the dataset as a test set, and the remaining dataset is split into 70% as training set and 30% as the validation set. While for dataset 0.4, 40% of the dataset is test set, the remaining dataset is split into 60% as a training set and 40% as the validation set.

In addition, the learning rate is a crucial hyper-parameter that controls the magnitude of weight updates during the training of a machine learning model. If the learning rate is set too low, the training process may take a long time to converge or get stuck in a local minimum.

A common default setting for the learning rate is 0.1 or 0.01, which may be a reasonable starting point for the task (Bengio, 2009). In this research, the configuration of learning rate value for training is 0.1, 0.01, 0.001, 0.0001, 0.00001, 0.000001.

4.3.1 Comparison of learning rate and dataset split

Table 4.3, Table 4.4 and Table 4.5 display the classification accuracy performance of the CNN-RBF, custom CNN and RBN model for various dataset splits and different learning rates.

Table 4.3: Results of different learning rates and dataset split for CNN-RBF model.

Accuracy of CNN-RBF model (%)			
Learning Rate	20% of dataset as test set and remaining split into 80% as training set and 20% as validation set. (0.2)	30% of dataset as test set and remaining split into 70% as training set and 30% as validation set (0.3)	40% of dataset as test set and remaining split into 60% as training set and 40% as validation set (0.4)
0.1	49.92	50.06	49.27
0.01	49.93	50.07	50.72
0.001	50.12	49.62	50.73
0.0001	88.42	77.39	86.87
0.00001	94.79	92.36	92.07
0.000001	89.26	90.32	90.81

According to Table 4.3, the best classification accuracy for the 0.2 dataset split was 94.79% at a learning rate of 0.00001. The best classification accuracy obtained for the 0.3 and 0.4 dataset split was 92.36% and 92.36%, respectively, at the learning rate of 0.00001.

Table 4.4: Results of different learning rates and dataset split for CNN model.

Accuracy of CNN model (%)			
Learning Rate	Dataset split (0.2)	Dataset split (0.3)	Dataset split (0.4)
0.1	48.79	49.71	49.35
0.01	49.52	49.84	49.47
0.001	49.97	50.15	49.53
0.0001	84.83	86.74	79.43
0.00001	89.25	87.72	87.51
0.000001	84.98	86.03	82.66

Based on Table 4.4, the highest accuracy of CNN model for the 0.2 dataset split was 89.25%, also same at learning rate of 0.00001. For 0.3 and 0.4 dataset split, 87.72% and 87.51% at the learning rate of 0.00001 represent the best accuracy. In CNN model, the learning rate of 0.00001 also gives the highest classification accuracy.

Table 4.5: Results of different learning rates and dataset split for RBN model.

Accuracy of RBN model (%)			
Learning Rate	Dataset split (0.2)	Dataset split (0.3)	Dataset split (0.4)
0.1	49.97	49.84	50.46
0.01	56.61	50.15	49.53
0.001	55.91	53.29	57.65
0.0001	57.15	65.10	60.63
0.00001	57.31	57.90	56.77
0.000001	56.76	57.86	56.24

In relation to Table 4.5, the highest accuracy was 61.85% which is in 0.3 dataset split at a learning rate of 0.0001. However, for the 0.2 and 0.4 dataset split, the accuracy was 57.15% and 60.63%, respectively, at the learning rate of 0.0001. The learning rate of 0.0001 gives the highest classification accuracy for the RBN model.

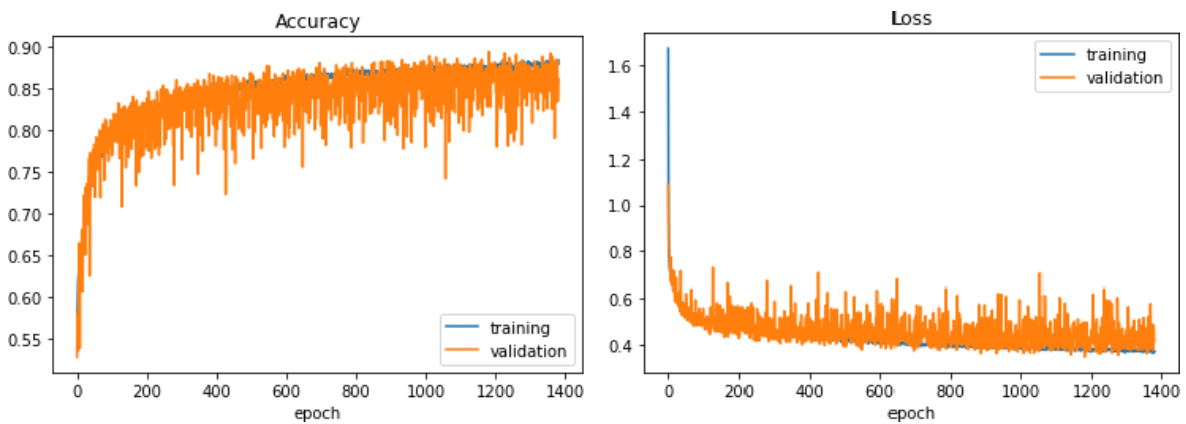
4.3.2 Result of custom CNN model

The custom CNN model remains the same as the original CNN principle. Table 4.6 below shows the accuracy and loss performance for custom CNN model.

Table 4.6 Accuracy performance of custom CNN model

Epoch	Accuracy (%)	Validation Accuracy (%)	Loss	Validation Loss
200	87.35	78.43	0.6287	0.8618
400	93.44	86.97	0.3905	0.5827
600	95.81	85.23	0.2900	0.6900
800	96.82	92.93	0.2422	0.3688
1000	97.47	88.50	0.2074	0.5397
1192	97.89	88.96	0.1872	0.2961

From Table 4.6, the training accuracy increases to 97.89%, while the loss decreases from 0.62 to 0.18. Besides, the validation accuracy also increased to 88.96%, while the validation loss decreased from 0.86 to 0.29. The epoch stops at 1192 epochs since it reaches the maximum accuracy. Figure 4.3 shows a statistical graph to demonstrate accuracy and loss.

**Figure 4.3:** Statistical graph of accuracy and loss performance for custom CNN model

From figure 4.3, the training and validation accuracy increases sharply until epoch 500 and after that increases slowly. Besides, the loss shows decreasing. The training performance metric increases sharply initially and then plateaus, suggesting that the model

is learning effectively from the training data. The validation performance closely follows the training curve but with greater variance, indicating that while the model is generalizing well, there might be some epochs where the validation performance fluctuates. This fluctuation can be due to a variety of factors, such as the diversity of the validation dataset or the learning rate.

The training loss decreases rapidly, which is typical at the beginning of training as the model's weights adjust to minimize the error. However, the validation loss, while decreasing, exhibits a lot of variances, suggesting that the model may be sensitive to the validation dataset. The significant variance in the validation loss could also point to the potential for improvements in model regularization or training stability.

The graphs indicate that the custom CNN model is generalizing well, as the validation curves for both the performance metric and loss do not diverge significantly from the training curves. This is a good sign that the model is not overfitting to the training data.

4.3.3 Results of CNN-RBF model

The results of the CNN-RBF model are accuracy performance and loss performance for ASD classification. The accuracy of a classification model is a way of evaluating its overall performance. It is most often represented as a percentage of the total. A prediction's accuracy may be expressed as the number of times a prediction's value equals the actual value. It is binary (either true or false) for a specific sample. During the training phase, accuracy is often graphed and monitored. However, the value is frequently related to the total or final model accuracy. Loss is more challenging to understand than accuracy.

When calculating the loss function (also known as the cost function), consider how much a forecast deviates from the actual value. The model's performance can now be seen in greater detail. While accuracy measures the number of false positives, loss measures the total number of false negatives in training and validation sets. People often employ loss in the training method to determine the model's "best" parameter values (e.g., weights in a neural network). The objective is to reduce this number as much as possible throughout the training.

For the CNN-RBF model, the results are shown in Table 4.7 below:

Table 4.7: Accuracy performance of CNN-RBF model

Epoch	Accuracy (%)	Validation Accuracy (%)	Loss	Validation Loss
200	86.29	75.41	0.6632	0.8629
400	92.68	88.99	0.3969	0.5287
600	95.80	87.00	0.2798	0.6258
800	96.96	93.96	0.2299	0.3266
1000	97.55	94.91	0.1981	0.2865
1200	97.87	94.51	0.1747	0.2933
1302	98.07	95.42	0.1704	0.2702

From table 4.7, the training accuracy increases from 86.29% to 98.07%, while the loss decreases from 0.626 to 0.17. Besides, the validation accuracy also increased from 75.41% to 95.42%, while the validation loss decreased from 0.86 to 0.27. The epoch stops at 1192 epochs because it reaches maximum accuracy. Figure 4.4 shows statistical graph to demonstrate train accuracy and loss.

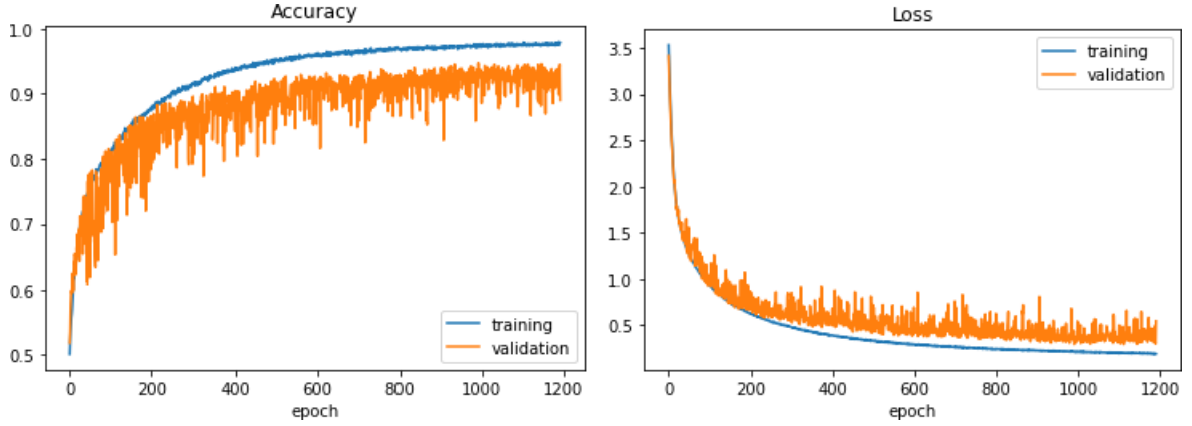


Figure 4.4: Statistical graph of accuracy and loss performance

According to Figure 4.4, the trend of the graph grows absolutely for the training and validation accuracy, yet the training and validation loss decreases continuously. The left graph depicts an upward trend for both the training and validation performance over time, which is typical for a metric like accuracy. The CNN-RBF model's training performance improves rapidly initially, showing the effectiveness of the model in learning from the training data. The validation performance also increases but with some variability, indicative of the model's ability to generalize to new data, though with some epochs demonstrating fluctuations, possibly due to the diversity of the validation set or the model's sensitivity to certain data features.

The right graph shows the model's loss over time. Both decreasing and validation loss decrease sharply at the beginning and then level off, which is a common pattern as the model begins to fit the data. The loss minimization is a direct objective of the training process, and the sharp initial decrease is indicative of rapid learning. However, the significant variability in the validation loss suggests that the model may benefit from improved training stability (Lecun et al., 1998).

Both graphs suggest the model is converging, evidenced by the leveling off of both the performance and loss metrics. In the context of CNN-RBF models, this implies that

the balance between feature extraction from the CNN layers and the interpolation from the RBF layer is functioning effectively.

4.3.4 Results of RBN model

Radial basis networks are an uncommon subtype of neural networks that uses radial basis functions as the activation function. RBNs can be used for function approximation. Table 4.8 below shows the accuracy and loss performance for RBN model.

Table 4.8: Accuracy performance of RBN.

Epoch	Accuracy (%)	Validation Accuracy (%)	Loss	Validation Loss
200	58.94	62.33	0.6693	0.6589
400	60.32	61.94	0.6605	0.6536
600	62.42	62.43	0.6411	0.6411
800	64.04	57.38	0.6277	0.7232
908	65.10	52.98	0.6232	0.7654

According to table 4.8, the training accuracy is increasing from 58.94% to 65.10% while the loss is decreasing from 0.6693 to 0.6232. Besides, the validation accuracy decreases from 62.33% to 52.98% while the validation loss increase from 0.6589 to 0.7654. The epoch stops at 908 epochs because it reaches the maximum accuracy. Figure 4.5 displays the statistical graph of accuracy and loss performance.

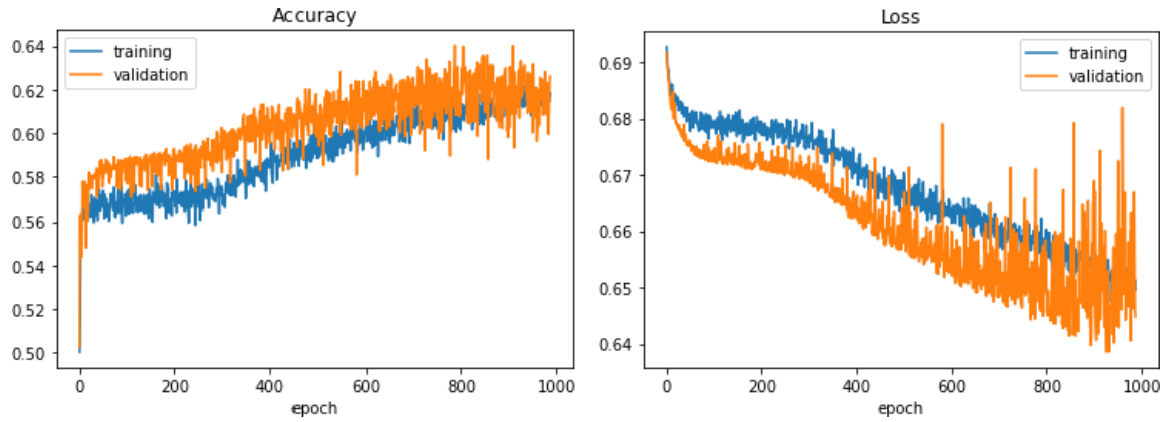


Figure 4.5: Statistical graph of accuracy and loss performance of RBN

Based on Figure 4.5, the epoch 0 until epoch 50 shows the training accuracy increase dramatically and after that increases slowly while the loss decreases constantly from 0.6693 to 0.6232. The left graph displays an upward trend in both the training and validation metrics, which typically represent accuracy or some other measure of predictive performance.

4.3.5 Evaluation Results

In this study, the evaluation method that have been chosen is binary classification confusion matrix. Figure 4.6 below shows confusion matrix of custom CNN model and CNN- RBF model.

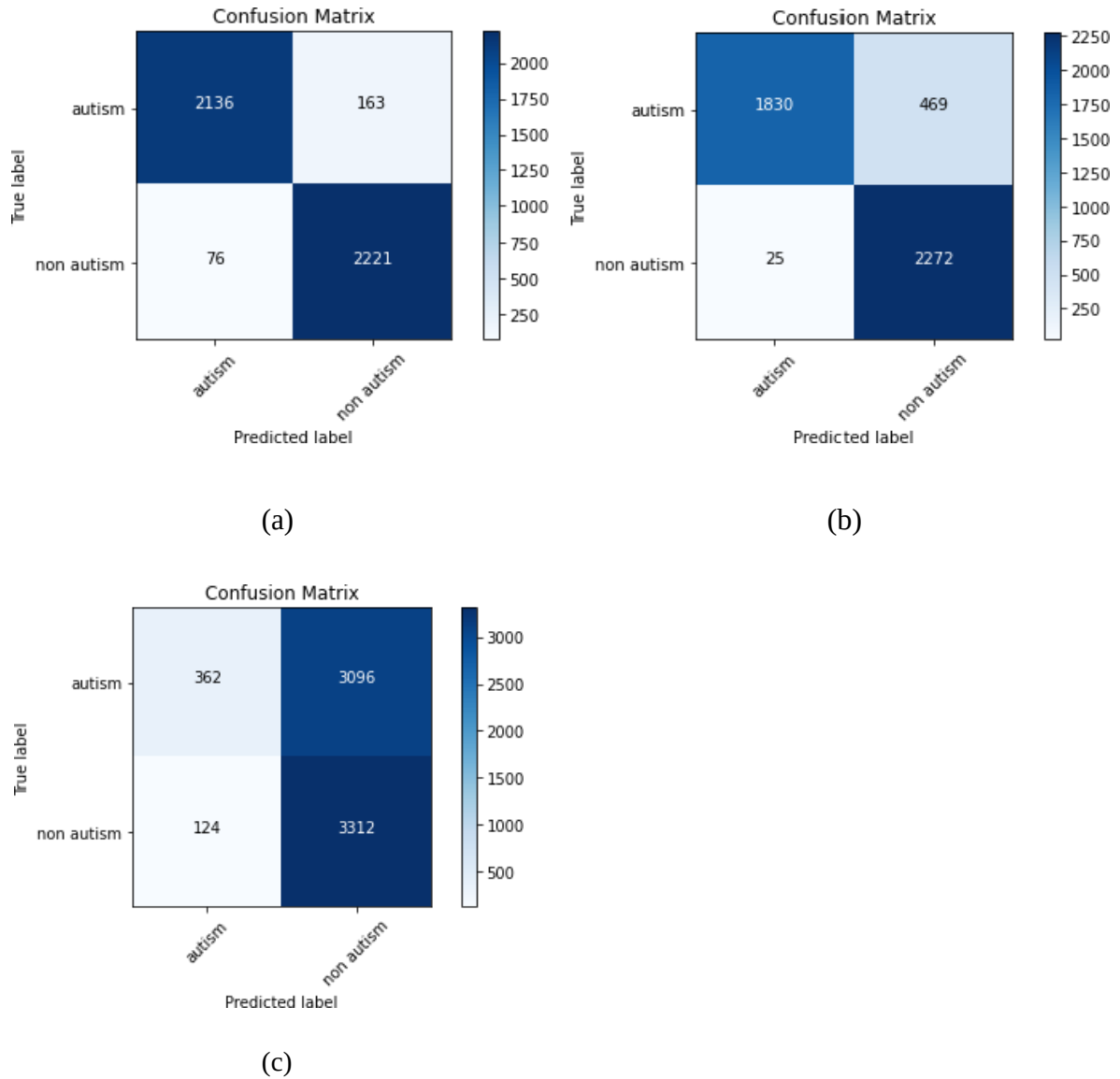


Figure 4.6: Confusion Matrix for (a) CNN-RBF model, (b) CNN model, (c) RBN

To explain the performance of a classification model on known-true test data, a confusion matrix is often utilized. The confusion matrix is not difficult to grasp, but some terms are impenetrable to certain people. In figure 4.6, for the CNN-RBF model, the true positive is 2136, and the true negative is 2221; however, the false positive is 76, and the falsenegative is 163. Besides, for the custom CNN model, the true positive is 1784, and the true negative is 2177 however, the false positive is 120, and the false negative is 515. Furthermore, for RBN model, the true positive is 362, and true negative is 3312, while the

false positive is 124 and the false negative is 3096. Table 4.9 below shows the results from the confusion matrix.

Table 4.9: Results from confusion matrix

	CNN-RBF model	Custom CNN-model	RBN
Accuracy (%)	94.79	86.18	53.29
Sensitivity (%)	92.90	77.59	10.46
Specificity (%)	96.69	94.77	96.39
Precision (%)	96.56	93.69	74.48

Based on Table 4.9, for the CNN-RBF model, the test accuracy from the confusion matrix is 94.79%. In addition, other results like sensitivity with 92.90%, specificity with 96.69%, and precision with 96.56% have been calculated based on the confusion matrix. Besides, for the custom CNN model, the test accuracy from the confusion matrix is 86.18%. In comparison, other results like sensitivity with 77.59%, specificity with 94.77%, and precision with 93.69% have been calculated based on the confusion matrix. Moreover, for RBN, the test accuracy from the confusion matrix is 53.29%, sensitivity is 10.46%, specificity is 96.39%, and precision is 74.48% based on the confusion matrix.

These results indicate that the CNN-RBF model effectively balances feature extraction from the CNN layers and interpolation from the RBF layer, resulting in robust classification performance across multiple metrics. Therefore, based on the provided data, the CNN-RBF model emerges as the preferred choice for the given classification task due to its superior accuracy and comprehensive performance across sensitivity, specificity, and precision metrics.

4.4 AUC and ROC curve

Performance assessment is critical in machine learning and deep learning. Thus, the AUC-ROC Curve may be used while dealing with a classification issue. The AUC-ROC (Area Under the Curve - Receiver Operating Characteristics) curve is an essential evaluation tool for multi-class classification problems. It assesses the performance of classification models based on various threshold values. The ROC curve indicates the degree of separability between classes, while the AUC represents the measure of this separability. In other words, it shows how well the model can distinguish between classes. The higher the AUC value, the more accurately the model predicts 0 class as 0 and 1 class as 1. Therefore, the AUC-ROC curve is a critical statistic for assessing the success of any classification model. For example, the greater the AUC, the more accurate the model discriminates between patients with and without autism. Figure 4.7 to Figure 4.9 show the ROC performance for the CNN- RBF model, custom CNN model, and RBN.

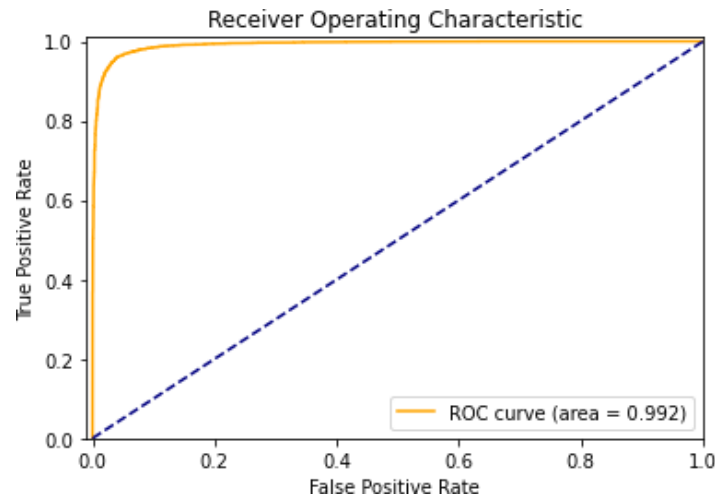


Figure 4.7: AUC and ROC performance for CNN-RBF model

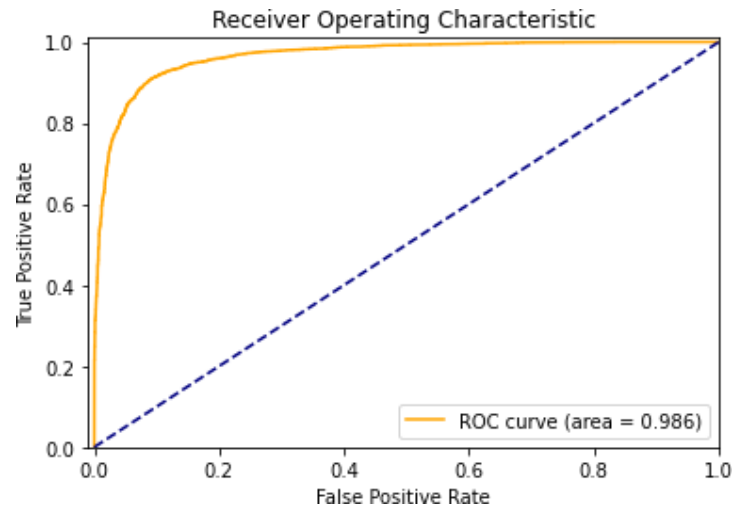


Figure 4.8: AUC and ROC performance for custom CNN model

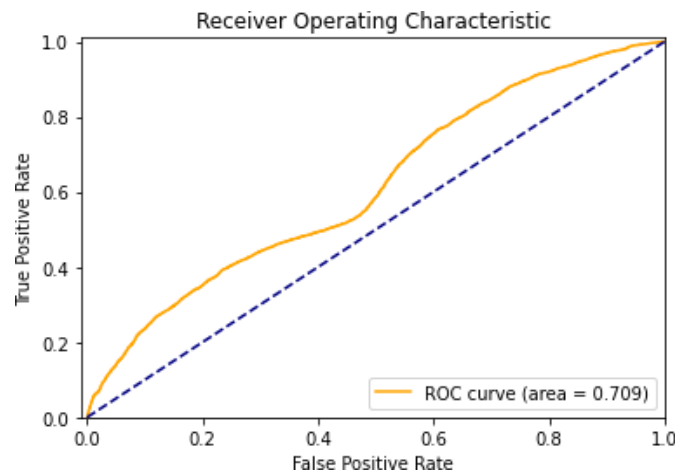


Figure 4.9: AUC and ROC performance for RBN

Based on figures, the ROC curve in the first graph is almost perfect, with an AUC of 0.992. This indicates that the classifier has an excellent performance in distinguishing between the positive and negative classes. Similarly, the second graph shows an AUC of 0.986, which is also indicative of outstanding classifier performance. Although slightly lower than the first, this value still suggests that the classifier has a strong discriminative ability.

The third graph shows a classifier with an AUC of 0.709, which is considerably

lower than the first two. This value points to a moderate classification performance. The ROC curve is closer to the diagonal line of no-discrimination than the other two curves, indicating a higher rate of false positives and a lower true positive rate.

Comparing the three graphs, the first two models would be preferable for most applications due to their high AUC values. However, the selection of the model might also depend on the specific cost of false positives and false negatives in the application domain. For example, in medical diagnostics, a high true positive rate might be prioritized even if it results in a higher false positive rate (Fawcett, 2006).

These ROC performances show that the proposed CNN-RBF model has outstanding discrimination between the different classes as compared to the classification performance of custom CNN model.

4.5 Summary

The chapter delves into the architecture and efficacy of various models for ASD classification, highlighting a Radial Basis Network (RBN) model, a custom Convolutional Neural Network (CNN), and a proposed CNN-RBF hybrid model. Comparisons drawn from the confusion matrix and performance metrics reveal the CNN-RBF model's enhanced accuracy in ASD classification over its RBN and custom CNN counterparts.

Further scrutiny using the Receiver Operating Characteristic (ROC) curve performance corroborates the superiority of the CNN-RBF model. Its ROC curve boasts a higher Area Under the Curve (AUC), signifying a robust discriminative capacity for ASD presence. The hybrid model merges CNN's feature extraction prowess with RBF's pattern classification efficiency, culminating in a sophisticated framework adept at handling the diagnostic complexities of ASD.

This analysis affirms the hybrid CNN-RBF model's potential in refining ASD

diagnostic methods. The architecture's advanced integration suggests significant contributions to medical diagnostics, particularly within the nuanced scope of ASD, where precision and reliability are paramount.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In conclusion, this study demonstrates the significant potential of hybrid deep learning algorithms, specifically the UNet-RBF and CNN-RBF models, in accurately classifying ASD. Achieving a remarkable accuracy rate of 94.79%, these models represent a substantial advancement in the application of artificial intelligence for medical diagnostics, particularly in the nuanced field of ASD identification. The research not only meets its objectives by effectively preprocessing fMRI data and evaluating the proposed algorithms through rigorous binary classification metrics but also sets a new benchmark for future studies in this area. The implications of this work extend beyond ASD classification, offering a blueprint for integrating advanced AI methodologies into existing diagnostic and treatment frameworks across a range of neurological disorders. This study not only contributes to the ongoing development of AI in healthcare but also opens up new avenues for research, promising to enhance the precision, efficiency, and personalization of future medical interventions.

Moving forward, optimizing the UNet-RBF and CNN-RBF models for superior performance will require innovative approaches, including refining model architectures and employing advanced optimization techniques. The integration of these models into larger and more heterogeneous datasets will necessitate addressing challenges such as computational efficiency and the robustness of data preprocessing methods to ensure the models' applicability across diverse populations. Integrating this research into existing ASD diagnostic and treatment frameworks could significantly enhance the precision and speed of diagnoses, facilitating earlier and more targeted interventions. The success of

these models in classifying ASD opens promising pathways for AI research in healthcare, suggesting a broad applicability of these methodologies to other neurological disorders. This adaptability underscores the potential for AI-driven tools to revolutionize diagnostics and treatment planning across a spectrum of conditions, marking a pivotal step towards more personalized and effective healthcare solutions.

5.2 Recommendations for Future Work

This research aims to use a deep learning system to classify ASD. According to the findings of this study, further research should be done on using deep learning to diagnose ASD. This study only proposed the UNet-RBF model for segmentation and the CNN-RBF model for classification. The other hybrid model does not propose to compare the accuracy performance in this study. In the future, some different types of hybrid deep learning algorithms need to be proposed to classify ASD for comparison. Besides, some other algorithms like K-Nearest Neighbors, Gradient Boosting Machines and so on can also merge to generate a new hybrid model for better performance. In addition, more image data should be added to conduct the study to improve the accuracy so that the accuracy can increase up to 99%. The larger dataset allows the model to encounter more edge cases and rare examples during training, thereby increasing the model's accuracy and its ability to handle new, unseen data effectively.

REFERENCES

- Abraham, A., Milham, M. P., Di Martino, A., Craddock, R. C., Samaras, D., Thirion, B., & Varoquaux, G. (2017). Deriving reproducible biomarkers from multi-site resting-state data: An Autism-based example. *NeuroImage*, 147, 736–745. <https://doi.org/10.1016/j.neuroimage.2016.10.045>
- Akhavan Aghdam, M., Sharifi, A., & Pedram, M. M. (2018). Combination of rs-fMRI and sMRI Data to Discriminate Autism Spectrum Disorders in Young Children Using Deep Belief Network. *Journal of Digital Imaging*, 31(6), 895–903. <https://doi.org/10.1007/s10278-018-0093-8>
- Al-Fraihat, D., Sharrab, Y., Alzyoud, F., Qahmash, A., Tarawneh, M., & Maaita, A. (2024). Speech recognition utilizing deep learning: A systematic review of the latest developments. *Human-centric Computing and Information Sciences*, 14. <https://doi.org/10.22967/HCIS.2024.14.015>
- Allison, C., Auyeung, B., & Baron-Cohen, S. (2012). Toward brief “Red Flags” for autism screening: The Short Autism Spectrum Quotient and the Short Quantitative Checklist for Autism in toddlers in 1,000 cases and 3,000 controls [corrected]. *Journal of the American Academy of Child and Adolescent Psychiatry*, 51(2), 202–212.e7. <https://doi.org/10.1016/j.jaac.2011.11.003>
- Almuqhim, F., & Saeed, F. (2021). ASD-SAEtNet: a sparse autoencoder, and deep-neural network model for detecting autism spectrum disorder (ASD) using fMRI data. *Frontiers in Computational Neuroscience*, 15, 654315.
- Altevogt, B. M., Hanson, S. L., & Leshner, A. I. (2008). Autism and the Environment: Challenges and Opportunities for Research. *Pediatrics*, 121(6), 1225–1229. <https://doi.org/10.1542/peds.2007-3000>

- Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, 8(1), 53. <https://doi.org/10.1186/s40537-021-00444-8>
- Amirian, M., & Schwenker, F. (2020). Radial Basis Function Networks for Convolutional Neural Networks to Learn Similarity Distance Metric and Improve Interpretability. *IEEE Access*, PP, 1. <https://doi.org/10.1109/ACCESS.2020.3007337>
- Anwar, S. M., Majid, M., Qayyum, A., Awais, M., Alnowami, M., & Khan, M. K. (2018). Medical Image Analysis using Convolutional Neural Networks: A Review. *Journal of Medical Systems*, 42(11), 226. <https://doi.org/10.1007/s10916-018-1088-1>
- Arora, G., KiranBala, Emadifar, H., & Khademi, M. (2023). A review of radial basis function with applications explored. *Journal of the Egyptian Mathematical Society*, 31(1), 6. <https://doi.org/10.1186/s42787-023-00164-3>
- Arslan, S. (2017). *Connectivity-driven parcellation methods for the human cerebral cortex*. SalimArslan.
- Aruna Kumar, S. V, Yaghoubi, E., & Proença, H. (2022). A Fuzzy Consensus Clustering Algorithm for MRI Brain Tissue Segmentation. *Applied Sciences*, 12(15), 7385.
- Astorino, A., Gorgone, E., Gaudioso, M., & Pallaschke, D. (2011). Data preprocessing in semi-supervised SVM classification. *Optimization*, 60(1–2), 143–151. <https://doi.org/10.1080/02331931003692557>
- Avants, B., Tustison, N., Wu, J., Cook, P., & Gee, J. (2011). An Open Source Multivariate Framework for n-Tissue Segmentation with Evaluation on Public Data. *Neuroinformatics*, 9,381–400. <https://doi.org/10.1007/s12021-011-9109-y>

- Awaluddin, B.-A., Chao, C.-T., & Chiou, J.-S. (2023). Investigating Effective Geometric Transformation for Image Augmentation to Improve Static Hand Gestures with a Pre- Trained Convolutional Neural Network. *Mathematics*, 11, 4783. <https://doi.org/10.3390/math11234783>
- B J, B., & Vijayan, N. (2019). Employing thresholding and sobel technique to detect autism from MRI. *International Journal of Recent Technology and Engineering*, 7, 99–103.
- Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The Autism- Spectrum Quotient (AQ): Evidence from Asperger Syndrome/High-Functioning Autism, Males and Females, Scientists and Mathematicians. *Journal of Autism and Developmental Disorders*, 31(1), 5–17. <https://doi.org/10.1023/A:1005653411471>
- Bauman, M. L., & Kemper, T. L. (2005). Neuroanatomic observations of the brain in autism: a review and future directions. *International Journal of Developmental Neuroscience*, 23(2– 3), 183–187. <https://doi.org/10.1016/j.ijdevneu.2004.09.006>
- Baweja, R., Brown, S. L., Edwards, E. M., & Murray, M. J. (2022). COVID-19 Pandemic and Impact on Patients with Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders*, 52(1), 473–482. <https://doi.org/10.1007/s10803-021-04950-9>
- Bengio, Y. (2009). Learning deep architectures for AI. In *Foundations and Trends in Machine Learning* (Vol. 2, Issue 1). <https://doi.org/10.1561/22000000006>
- Benvenuto, A., Siracusano, M., Graziola, F., Marciano, S., Gialloreti, L. E., Mazzone, L., Moavero, R., & Curatolo, P. (2017). Autism Spectrum Disorder in Tuberous Sclerosis: The preventive value of early detection. *Biomed Prevent.*

- Bertels, J., Eelbode, T., Berman, M., Vandermeulen, D., Maes, F., Bisschops, R., & Blaschko, M. B. (2019). Optimizing the Dice Score and Jaccard Index for Medical Image Segmentation: Theory and Practice. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11765 LNCS, 92–100. https://doi.org/10.1007/978-3-030-32245-8_11
- Bi, X., Wang, Y., Shu, Q., Sun, Q., & Xu, Q. (2018a). Classification of Autism Spectrum Disorder Using Random Support Vector Machine Cluster. *Frontiers in Genetics*, 9. <https://doi.org/10.3389/fgene.2018.00018>
- Bi, X. A., Wang, Y., Shu, Q., Sun, Q., & Xu, Q. (2018b). Classification of autism spectrum disorder using random support vector machine cluster. *Frontiers in genetics*, 9, 18. <https://doi.org/10.3389/fgene.2018.00018>
- Birtele, M., Del Dosso, A., Xu, T., Nguyen, T., Wilkinson, B., Hosseini, N., Nguyen, S., Urenda, J.-P., Knight, G., Rojas, C., Flores, I., Atamian, A., Moore, R., Sharma, R., Pirrotte, P.,
- Ashton, R. S., Huang, E. J., Rumbaugh, G., Coba, M. P., & Quadrato, G. (2023). Non-synaptic function of the autism spectrum disorder-associated gene SYNGAP1 in cortical neurogenesis. *Nature Neuroscience*, 26(12), 2090–2103. <https://doi.org/10.1038/s41593-023-01477-3>
- Bone, D., Goodwin, M., Black, M., Lee, C.-C., Audhkhasi, K., & Narayanan, S. (2014). Applying Machine Learning to Facilitate Autism Diagnostics: Pitfalls and Promises. *Journal of Autism and Developmental Disorders*, 45. <https://doi.org/10.1007/s10803-014-2268-6>

- Boureau, Y.-L., Ponce, J., & Lecun, Y. (2010). A Theoretical Analysis of Feature Pooling in Visual Recognition. In *ICML 2010 - Proceedings, 27th International Conference on Machine Learning*.
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32.
<https://doi.org/10.1023/A:1010933404324>
- Brentani, H., de Paula, C. S., Bordini, D., Rolim, D., Sato, F., Portolese, J., Pacifico, M. C., & McCracken, J. T. (2013). Autism spectrum disorders: An overview on diagnosis and treatment. *Revista Brasileira de Psiquiatria*, 35(SUPPL. 1), 62–72.
<https://doi.org/10.1590/1516-4446-2013-S104>
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., & Amodei, D. (2020). *Language Models are Few-Shot Learners*.
- Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The Brain's Default Network. *Annals of the New York Academy of Sciences*, 1124(1), 1–38.
<https://doi.org/https://doi.org/10.1196/annals.1440.011>
- Cakic, S., Popovic, T., Krco, S., Nedic, D., Babic, D., & Jovovic, I. (2023). Developing Edge AI Computer Vision for Smart Poultry Farms Using Deep Learning and HPC. *Sensors*, 23, 1–17. <https://doi.org/10.3390/s23063002>
- Chahal, A., & Gulia, P. (2019). Machine learning and deep learning. *International Journal of Innovative Technology and Exploring Engineering*, 8(12), 4910–4914.
<https://doi.org/10.35940/ijitee.L3550.1081219>

- Chaitra, N., Vijaya, P. A., & Deshpande, G. (2020). Diagnostic prediction of autism spectrum disorder using complex network measures in a machine learning framework. *Biomedical Signal Processing and Control*, 62, 102099. <https://doi.org/https://doi.org/10.1016/j.bspc.2020.102099>
- Chakraborty, D., kumar Sen, G., & Hazra, S. (2012). *Image Segmentation Techniques: Methods for Segmenting High Spatial Resolution Images*. LAP LAMBERT Academic Publishing.
- Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly Detection: A Survey. *ACM Comput. Surv.*, 41. <https://doi.org/10.1145/1541880.1541882>
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297. <https://doi.org/10.1007/BF00994018>
- Cox, R. W. (1996). AFNI: Software for Analysis and Visualization of Functional Magnetic Resonance Neuroimages. *Computers and Biomedical Research*, 29(3), 162–173. <https://doi.org/10.1006/cbmr.1996.0014>
- Cui, Y., Wu, D., & Xu, Y. (2021). Curse of dimensionality for TSK fuzzy neural networks: Explanation and solutions. In *2021 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.
- Daniels, A. M., & Mandell, D. S. (2013). Explaining differences in age at autism spectrum disorder diagnosis: A critical review. *Autism*, 18(5), 583–597. <https://doi.org/10.1177/1362361313480277>
- Daniolou, S., Pandis, N., & Znoj, H. (2022). The Efficacy of Early Interventions for Children with Autism Spectrum Disorders: A Systematic Review and Meta-Analysis. *Journal of Clinical Medicine*, 11(17). <https://doi.org/10.3390/jcm11175100>

- Dcoutho, S., & Pradeepkandhasamy, J. (2024). *Multimodal Deep Learning in Early Autism Detection—Recent Advances and Challenges*.
<https://doi.org/10.3390/engproc2023059205>
- Deng, J., Eklund, M., Sierla, S., Savolainen, J., Niemistö, H., Karhela, T., & Vyatkin, V. (2023). *Application of reinforcement learning for energy consumption optimization of district heating system*. <https://doi.org/10.1109/ISIE51358.2023.10228102>
- Di Martino, A., Ross, K., Uddin, L. Q., Sklar, A. B., Castellanos, F. X., & Milham, M. P. (2009). Functional Brain Correlates of Social and Nonsocial Processes in Autism Spectrum Disorders: An Activation Likelihood Estimation Meta-Analysis. *Biological Psychiatry*, 65(1), 63–74.
<https://doi.org/https://doi.org/10.1016/j.biopsych.2008.09.022>
- Di Martino, A., Yan, C.-G., Li, Q., Denio, E., Castellanos, F. X., Alaerts, K., Anderson, J. S., Assaf, M., Bookheimer, S. Y., Dapretto, M., Deen, B., Delmonte, S., Dinstein, I., Ertl- Wagner, B., Fair, D. A., Gallagher, L., Kennedy, D. P., Keown, C. L., Keyser, C., ... Milham, M. P. (2014). The autism brain imaging data exchange: towards a large-scale evaluation of the intrinsic brain architecture in autism. *Molecular Psychiatry*, 19(6), 659– 667. <https://doi.org/10.1038/mp.2013.78>
- Dietz, P. M., Rose, C. E., McArthur, D., & Maenner, M. (2020). National and State Estimates of Adults with Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders*, 50(12), 4258–4266. <https://doi.org/10.1007/s10803-020-04494-4>
- Dong, S., Wang, P., & Abbas, K. (2021). A survey on deep learning and its applications. *Computer Science Review*, 40, 100379.

- Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *ArXiv Preprint ArXiv:1702.08608*.
- Dubey, S. K., & Vijay, S. (2018). A review of image segmentation using clustering methods. *Int. J. Appl. Eng. Res*, 13, 2484–2489.
- Eklund, A., Nichols, T. E., & Knutsson, H. (2016). Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates. *Proceedings of the National Academy of Sciences*, 113(28), 7900–7905. <https://doi.org/10.1073/pnas.1602413113>
- Eslami, T., Mirjalili, V., Fong, A., Laird, A., & Saeed, F. (2019). ASD-Diagnet: A hybrid learning approach for detection of autism spectrum disorder using FMRI data. *ArXiv*, 1–8.
- Esteva, A., Kuprel, B., Novoa, R., Ko, J., Swetter, S., Blau, H., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542. <https://doi.org/10.1038/nature21056>
- Everingham, M., Eslami, S., Van Gool, L., Williams, C., Winn, J., & Zisserman, A. (2014). The Pascal Visual Object Classes Challenge: A Retrospective. *International Journal of Computer Vision*, 111. <https://doi.org/10.1007/s11263-014-0733-5>
- Fasshauer, G. E., & Zhang, J. G. (2007). On choosing “optimal” shape parameters for RBF approximation. *Numerical Algorithms*, 45(1), 345–368. <https://doi.org/10.1007/s11075-007-9072-8>
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861– 874. <https://doi.org/https://doi.org/10.1016/j.patrec.2005.10.010>
- François-lavet, V., Henderson, P., Islam, R., Bellemare, M. G., François-lavet, V., Pineau, J., & Bellemare, M. G. (2018). *An Introduction to Deep Reinforcement Learning*. <https://doi.org/10.1561/22000000071>. Vincent

- Frank, E. (2014). Fully supervised training of Gaussian radial basis function networks in WEKA.
- Friston, K. J., Frith, C. D., Liddle, P. F., & Frackowiak, R. S. J. (1991). Comparing Functional (PET) Images: The Assessment of Significant Change. *Journal of Cerebral Blood Flow & Metabolism*, 11(4), 690–699. <https://doi.org/10.1038/jcbfm.1991.122>
- Fukushima, K., & Miyake, S. (1982). Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. In *Competition and cooperation in neural nets* (pp. 267–285). Springer.
- Ghahramani, Z. (2003). Unsupervised learning. In *Summer school on machine learning* (pp. 72-112). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Giarelli, E., Wiggins, L. D., Rice, C. E., Levy, S. E., Kirby, R. S., Pinto-Martin, J., & Mandell, D. (2010). Sex differences in the evaluation and diagnosis of autism spectrum disorders among children. *Disability and Health Journal*, 3(2), 107–116. <https://doi.org/10.1016/j.dhjo.2009.07.001>
- Glover, G. H. (2011). Overview of Functional Magnetic Resonance Imaging. *Neurosurgery Clinics of North America*, 22(2), 133–139. <https://doi.org/10.1016/j.nec.2010.11.001>
- Gong, T., Almqvist, C., Bölte, S., Lichtenstein, P., Anckarsäter, H., Lind, T., Lundholm, C., & Pershagen, G. (2014). Exposure to Air Pollution From Traffic and Neurodevelopmental Disorders in Swedish Twins. *Twin Research and Human Genetics*, 17(6), 553–562. <https://doi.org/10.1017/thg.2014.58>
- Gould, S., Gao, T., & Koller, D. (2009). Region-based segmentation and object detection. *Advances in Neural Information Processing Systems*, 22.

- Guyon, I., & Elisseeff, A. (2003). An Introduction of Variable and Feature Selection. *J. Machine Learning Research Special Issue on Variable and Feature Selection*, 3, 1157–1182. <https://doi.org/10.1162/153244303322753616>
- Ha, S., Sohn, I.-J., Kim, N., Sim, H. J., & Cheon, K.-A. (2015). Characteristics of Brains in Autism Spectrum Disorder: Structure, Function and Connectivity across the Lifespan. *Experimental Neurobiology*, 24(4), 273–284. <https://doi.org/10.5607/en.2015.24.4.273>
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. <https://doi.org/10.1109/CVPR.2016.90>
- Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., & Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. *NeuroImage: Clinical*, 17(December), 16–23. <https://doi.org/10.1016/j.nicl.2017.08.017>
- Hinton, G. E., Osindero, S., & Teh, Y.-W. (2006). A Fast Learning Algorithm for Deep Belief Nets. *Neural Computation*, 18(7), 1527–1554. <https://doi.org/10.1162/neco.2006.18.7.1527>
- Hirata, R., Yoshimura, S., Kobayashi, K., Aki, M., Shibata, M., Ueno, T., Miyagi, T., Oishi, N., Murai, T., & Fujiwara, H. (2023). Differences between subclinical attention- deficit/hyperactivity and autistic traits in default mode, salience, and frontoparietal network connectivities in young adult Japanese. *Scientific Reports*, 13(1), 19724. <https://doi.org/10.1038/s41598-023-47034-7>
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8), 1735-1780.

- Hyman, S. L., Levy, S. E., & Myers, S. M. (2020). Identification, Evaluation, and Management of Children With Autism Spectrum Disorder. *Pediatrics*, 145(1). <https://doi.org/10.1542/peds.2019-3447>
- Iglesias, J. E., & Sabuncu, M. R. (2015). Multi-atlas segmentation of biomedical images: A survey. *Medical Image Analysis*, 24(1), 205–219. <https://doi.org/10.1016/j.media.2015.06.012>
- J, B., Singh, T., & Duraisamy, P. (2022). Skull Stripping and Classification Of Autism Spectrum Disorder Using Deep Learning. *2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6. <https://doi.org/10.1109/ICCCNT54827.2022.9984484>
- Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, 31(8), 651–666. <https://doi.org/10.1016/j.patrec.2009.09.011>
- Jamal, W., Das, S., Oprescu, I. A., Maharatna, K., Apicella, F., & Sicca, F. (2014). Classification of autism spectrum disorder using supervised learning of brain connectivity measures extracted from synchrostates. *Journal of Neural Engineering*, 11(4). <https://doi.org/10.1088/1741-2560/11/4/046019>
- Jha, D., Riegler, M. A., Johansen, D., Halvorsen, P., & Johansen, H. D. (2020). DoubleU-Net: A deep convolutional neural network for medical image segmentation. *Proceedings - IEEE Symposium on Computer-Based Medical Systems, 2020-July(1)*, 558–564. <https://doi.org/10.1109/CBMS49503.2020.00111>
- Jiang, W., Liu, S., Zhang, H., Sun, X., Wang, S., Zhao, J., & Yan, J. (2022). CNNG: A Convolutional Neural Networks with Gated Recurrent Units for ASD Classification. *Frontiers in Aging Neuroscience*, 723.

- Just, M. A., Keller, T. A., & Kana, R. K. (2013). A theory of autism based on frontal-posterior underconnectivity. In *Development and brain systems in autism* (pp. 35-63). Psychology Press.
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147(February), 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- Kamnitsas, K., Ledig, C., Newcombe, V. F. J., Simpson, J. P., Kane, A. D., Menon, D. K., Rueckert, D., & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. *Medical Image Analysis*, 36, 61–78. <https://doi.org/https://doi.org/10.1016/j.media.2016.10.004>
- Kanal, L. N. (2003). Perceptron. In *Encyclopedia of Computer Science* (pp. 1383-1385).
- Kang, J., Han, X., Song, J., Niu, Z., & Li, X. (2020). The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data. *Computers in Biology and Medicine*, 120(March), 103722. <https://doi.org/10.1016/j.combiomed.2020.103722>
- Kaveh, A., Magnani, M., & Rohner, C. (2022). Uncertainty in fMRI Functional Networks of Autism Brain Imaging Data. *ArXiv Preprint ArXiv:2202.02228*.
- Khadem-Reza, Z. K., & Zare, H. (2022). Automatic detection of autism spectrum disorder (ASD) in children using structural magnetic resonance imaging with machine vision system. *Middle East Current Psychiatry*, 29(1), 54. <https://doi.org/10.1186/s43045-022-00220-1>
- Khalifeh, S., Yassin, W., Kourtian, S., & Boustany, R.-M. (2016). Autism in Review. *Le Journal Médical Libanais. The Lebanese Medical Journal*, 64, 110–115. <https://doi.org/10.12816/0027470>

- Khodatars, M., Shoeibi, A., Sadeghi, D., Ghaasemi, N., Jafari, M., Moridian, P., Khadem, A., Alizadehsani, R., Zare, A., Kong, Y., Khosravi, A., Nahavandi, S., Hussain, S., Acharya, U.
- R., & Berk, M. (2021). Deep learning for neuroimaging-based diagnosis and rehabilitation of Autism Spectrum Disorder: A review. *Computers in Biology and Medicine*, 139, 104949. <https://doi.org/10.1016/j.compbiomed.2021.104949>
- King, P. H. (2012). Digital Image Processing and Analysis: Human and Computer Applications with CVPtools, 2nd Edition (Umbaugh, S.; 2011) [Book Reviews]. *IEEE Pulse*, 3(4), 84– 85. <https://doi.org/10.1109/MPUL.2012.2196843>
- Klin, A. (2006). Autismo e síndrome de Asperger : uma visão geral Autism and Asperger syndrome : an overview. *Autism*, 28(Supl I), 3–11. <https://doi.org/10.1590/S1516-44462006000500002>
- Kohonen, T. (1982). *Self-Organized Formation of Topologically Correct Feature Maps*. 69, 59– 60.
- Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biological cybernetics*, 43(1), 59-69.
- Kong, Y., Gao, J., Xu, Y., Pan, Y., Wang, J., & Liu, J. (2019). Classification of autism spectrum disorder by combining brain connectivity and deep neural network classifier. *Neurocomputing*, 324, 63–68. <https://doi.org/10.1016/j.neucom.2018.04.080>
- Koyamada, S., Shikauchi, Y., Nakae, K., Koyama, M., & Ishii, S. (2015). *Deep learning of fMRI big data: a novel approach to subject-transfer decoding*. <http://arxiv.org/abs/1502.00093>

- Krizhevsky, A., Sutskever, I., & Hinton, G. (2012a). ImageNet Classification with Deep Convolutional Neural Networks. *Neural Information Processing Systems*, 25. <https://doi.org/10.1145/3065386>
- Krizhevsky, A., Sutskever, I., & Hinton, G. (2012b). *Imagenet classification with deep convolutional neural networks*.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278–2324. <https://doi.org/10.1109/5.726791>
- Leevy, J., Khoshgoftaar, T., Bauder, R., & Seliya, N. (2018). A survey on addressing high-class imbalance in big data. *Journal of Big Data*, 5. <https://doi.org/10.1186/s40537-018-0151-6>
- Li, G., Liu, M., Sun, Q., Shen, D., & Wang, L. (2018). Early Diagnosis of Autism Disease by Multi-channel CNNs. *Machine Learning in Medical Imaging. MLMI (Workshop)*, 11046, 303–309. https://doi.org/10.1007/978-3-030-00919-9_35
- Liawatimena, S. (2018). *A Fish Classification on Images using Transfer Learning and Matlab*. September. <https://doi.org/10.1109/INAPR.2018.8627007>
- Liu, Y., Yang, H., Zhao, Y. F., & Zheng, G. (2022). A heterogeneous lattice structure modeling technique supported by multiquadric radial basis function networks. *Journal of Computational Design and Engineering*, 9(1), 68–81. <https://doi.org/10.1093/jcde/qwab069>
- Loomes, R., Hull, L., & Mandy, W. P. L. (2017). What Is the Male-to-Female Ratio in Autism Spectrum Disorder? A Systematic Review and Meta-Analysis. *Journal of*

- the American Academy of Child and Adolescent Psychiatry*, 56(6), 466–474.
<https://doi.org/10.1016/j.jaac.2017.03.013>
- Lord, C., Elsabbagh, M., Baird, G., & Veenstra-Vanderweele, J. (2018). Autism spectrum disorder. *The Lancet*, 392(10146), 508–520. [https://doi.org/10.1016/S0140-6736\(18\)31129-2](https://doi.org/10.1016/S0140-6736(18)31129-2)
- Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. *Zeitschrift Für Medizinische Physik*, 29(2), 102–127.
<https://doi.org/https://doi.org/10.1016/j.zemedi.2018.11.002>
- Maenner, M. J., Shaw, K. A., Baio, J., Washington, A., Patrick, M., DiRienzo, M., Christensen, D. L., Wiggins, L. D., Pettygrove, S., Andrews, J. G., Lopez, M., Hudson, A., Baroud, T., Schwenk, Y., White, T., Rosenberg, C. R., Lee, L. C., Harrington, R. A., Huston, M., ... Dietz, P. M. (2020a). Prevalence of autism spectrum disorder among children aged 8 Years- Autism and developmental disabilities monitoring network, 11 Sites, United States, 2016. *MMWR Surveillance Summaries*, 69(4), 1–12. <https://doi.org/10.15585/MMWR.SS6904A1>
- Maenner, M. J., Shaw, K. A., Baio, J., Washington, A., Patrick, M., DiRienzo, M., Christensen, D. L., Wiggins, L. D., Pettygrove, S., Andrews, J. G., Lopez, M., Hudson, A., Baroud, T., Schwenk, Y., White, T., Rosenberg, C. R., Lee, L. C., Harrington, R. A., Huston, M., ... Dietz, P. M. (2020b). Prevalence of autism spectrum disorder among children aged 8 Years- Autism and developmental disabilities monitoring network, 11 Sites, United States, 2016. *MMWR Surveillance Summaries*, 69(4), 1–12. <https://doi.org/10.15585/MMWR.SS6904A1>
- Maenner, M. J., Shaw, K. A., Bakian, A. V., Bilder, D. A., Durkin, M. S., Esler, A., Furnier, S. M., Hallas, L., Hall-Lande, J., Hudson, A., Hughes, M. M., Patrick, M.,

- Pierce, K., Poynter, J. N., Salinas, A., Shenouda, J., Vehorn, A., Warren, Z., Constantino, J. N., ... Cogswell, M.E. (2021). Prevalence and characteristics of autism spectrum disorder among children aged 8 years — Autism and Developmental Disabilities Monitoring Network, 11 sites, United States, 2018. In N. C. on B. D. and D. D. (centers for D. C. and Prevention), U. of U. S. of Medicine., Madison. University of Wisconsin, U. of Minnesota., L. R. University of Arkansas for Medical Sciences Arkansas, S. Diego. University of California, R. N. J. M. School., V. U. M. Center., W. University., J. H. University., Tucson. University of Arizona, & O. R. I. for R. and Education. (Eds.), *MMWR Surveill Summ.* 70(11):1-16 (Vol. 70, Issue 11). <http://dx.doi.org/10.15585/mmwr.ss7011a1>. <https://stacks.cdc.gov/view/cdc/112533>
- Mannion, A., & Leader, G. (2014). Gastrointestinal Symptoms in Autism Spectrum Disorder: A Literature Review. *Review Journal of Autism and Developmental Disorders*, 1(1), 11–17. <https://doi.org/10.1007/s40489-013-0007-0>
- Masi, A., DeMayo, M. M., Glozier, N., & Guastella, A. J. (2017). An Overview of Autism Spectrum Disorder, Heterogeneity and Treatment Options. *Neuroscience Bulletin*, 33(2), 183–193. <https://doi.org/10.1007/s12264-017-0100-y>
- Mathew, S., Bichenapally, S., Khachatryan, V., Muazzam, A., Hamal, C., Velugoti, L. S. D. R., Tabowei, G., Gaddipati, G. N., Mukhtar, M., Alzubaidee, M. J., Dwarampudi, R. S., & Alfonso, M. (2022). Role of Serotonergic Antidepressants in the Development of Autism Spectrum Disorders: A Systematic Review. *Cureus*, 14. <https://api.semanticscholar.org/CorpusID:251916580>
- Millman, K. J., & Brett, M. (2007). Analysis of functional magnetic resonance imaging in Python. *Computing in Science & Engineering*, 9(3), 52–55.

- Mittal, R., Malik, V., & Rana, A. (2022). DL-ASD: A Deep Learning Approach for Autism Spectrum Disorder. *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)*, 1767–1770. <https://doi.org/10.1109/IC3I56241.2022.10072429>
- Muskens, J. B., Velders, F. P., & Staal, W. G. (2017). Medical comorbidities in children and adolescents with autism spectrum disorders and attention deficit hyperactivity disorders: a systematic review. *European Child & Adolescent Psychiatry*, 26(9), 1093–1103. <https://doi.org/10.1007/s00787-017-1020-0>
- Nagashree, N., Patil, P., Patil, S., & Kokatanur, M. (2019). Performance Metrics for Segmentation Algorithms in Brain MRI for Early Detection of Autism. *International Journal of Innovative Technology and Exploring Engineering*, 9(2S), 561–564. <https://doi.org/10.35940/ijitee.b1401.1292s19>
- Nielsen, J. A., Zielinski, B. A., Fletcher, P. T., Alexander, A. L., Lange, N., Bigler, E. D., Lainhart, J. E., & Anderson, J. S. (2013). Multisite functional connectivity MRI classification of autism: ABIDE results. *Frontiers in Human Neuroscience*, 7(September), 1–12. <https://doi.org/10.3389/fnhum.2013.00599>
- Nordahl, C. W., Iosif, A. M., Young, G. S., Hechtman, A., Heath, B., Lee, J. K., Libero, L., Reinhardt, V. P., Winder-Patel, B., Amaral, D. G., Rogers, S., Solomon, M., & Ozonoff, S. (2020). High Psychopathology Subgroup in Young Children With Autism: Associations With Biological Sex and Amygdala Volume. *Journal of the American Academy of Child and Adolescent Psychiatry*, 59(12), 1353-1363.e2. <https://doi.org/10.1016/j.jaac.2019.11.022>
- O'shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.

- Parveen, H., & Showkat, N. (2017). Data collection. *Research Gate*.
- Pavithra, R., Abirami, S. P., Krithika, S., Sabitha, S., & Tharanidharan, P. (2023). Identification of Autism Spectrum Disorder from Functional MRI Using Deep Learning. In V. Goar, M. Kuri, R. Kumar, & T. Senjyu (Eds.), *Advances in Information Communication Technology and Computing* (pp. 277–284). Springer Nature Singapore.
- Plis, S., Hjelm, R. D., Salakhutdinov, R., Allen, E., Bockholt, H. J., Long, J., Johnson, H., Paulsen, J., Turner, J., & Calhoun, V. (2014). Deep learning for neuroimaging: a validation study. *Frontiers in Neuroscience*, 8, 229. <https://doi.org/10.3389/fnins.2014.00229>
- Plitt, M., Barnes, K. A., & Martin, A. (2015). Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards. *NeuroImage: Clinical*, 7, 359–366. <https://doi.org/10.1016/j.nicl.2014.12.013>
- Priyadharsini, R., & Sharmila, T. S. (2019). Object Detection In Underwater Acoustic Images Using Edge Based Segmentation Method. *Procedia Computer Science*, 165, 759–765. <https://doi.org/https://doi.org/10.1016/j.procs.2020.01.015>
- Qin, Y., Du, Y., Chen, L., Liu, Y., Xu, W., Liu, Y., Li, Y., Leng, J., Wang, Y., Zhang, X.-Y., Feng, J., Zhang, F., Jin, L., Qiu, Z., Gong, X., & Wang, H. (2022). A recurrent SHANK1 mutation implicated in autism spectrum disorder causes autistic-like core behaviors in mice via downregulation of mGluR1-IP3R1-calcium signaling. *Molecular Psychiatry*, 27(7), 2985–2998. <https://doi.org/10.1038/s41380-022-01539-1>

- Rabbi, M. F., Hasan, S. M. M., Champa, A. I., & Zaman, M. A. (2021). A Convolutional Neural Network Model for Early-Stage Detection of Autism Spectrum Disorder. *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, 110–114. <https://doi.org/10.1109/ICICT4SD50815.2021.9397020>
- Rahman, M. A., & Wang, Y. (2016). Optimizing Intersection-Over-Union in Deep Neural Networks for Image Segmentation. In G. Bebis, R. Boyle, B. Parvin, D. Koracin, F. Porikli, S. Skaff, A. Entezari, J. Min, D. Iwai, A. Sadagic, C. Scheidegger, & T. Isenberg (Eds.), *Advances in Visual Computing* (pp. 234–244). Springer International Publishing.
- Ramanjot, Singh, D., Rakhra, M., & Aggarwal, S. (2022). Autism Spectrum Disorder Detection using the Deep Learning Approaches. *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 761–766. <https://doi.org/10.1109/ICTACS56270.2022.9988442>
- Ramaswami, G., & Geschwind, D. H. (2018a). Chapter 21 - Genetics of autism spectrum disorder. In D. H. Geschwind, H. L. Paulson, & C. B. T.-H. of C. N. Klein (Eds.), *Neurogenetics, Part I* (Vol. 147, pp. 321–329). Elsevier. <https://doi.org/https://doi.org/10.1016/B978-0-444-63233-3.00021-X>
- Ramaswami, G., & Geschwind, D. H. (2018b). Genetics of autism spectrum disorder. In *Handbook of Clinical Neurology* (1st ed., Vol. 147). Elsevier B.V. <https://doi.org/10.1016/B978-0-444-63233-3.00021-X>
- Ronneberger, O., Fischer, P., & Brox, T. (2015a). *U-Net: Convolutional Networks for Biomedical Image Segmentation*. 1–8.

- Ronneberger, O., Fischer, P., & Brox, T. (2015b). *U-Net: Convolutional Networks for Biomedical Image Segmentation BT - Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015* (N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi, Eds.; pp. 234–241). Springer International Publishing.
- Rusk, N. (2016). Deep learning. *Nature Methods*, 13(1), 35.
<https://doi.org/10.1038/nmeth.3707>
- Ruuska, S., Hämäläinen, W., Kajava, S., Mughal, M., Matilainen, P., & Mononen, J. (2018).
 Evaluation of the confusion matrix method in the validation of an automated system for measuring feeding behaviour of cattle. *Behavioural Processes*, 148, 56–62.
<https://doi.org/10.1016/j.beproc.2018.01.004>
- Ryali, S., Chen, T., Supekar, K., Tu, T., Kochalka, J., Cai, W., & Menon, V. (2016). Multivariate dynamical systems-based estimation of causal brain interactions in fMRI: Group-level validation using benchmark data, neurophysiological models and human connectome project data. *Journal of Neuroscience Methods*, 268, 142–153.
<https://doi.org/10.1016/j.jneumeth.2016.03.010>
- Sabharwal, A., & Selman, B. (2011). S. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Third Edition. *Artif. Intell.*, 175, 935–937.
<https://doi.org/10.1016/j.artint.2011.01.005>
- Salakhutdinov, R., & Hinton, G. (2009, April). Deep boltzmann machines. In *Artificial intelligence and statistics* (pp. 448–455). PMLR.
- Santana, C. P., de Carvalho, E. A., Rodrigues, I. D., Bastos, G. S., de Souza, A. D., & Brito, L. L. (2022). rs-fMRI and machine learning for ASD diagnosis: a systematic review and meta-analysis. *Scientific Reports*, 12(1), 6030.
<https://doi.org/10.1038/s41598-022-09821-6>

- Sarigul, N., Bozatli, L., Kurultak, I., & Korkmaz, F. (2023). Using urine FTIR spectra to screen autism spectrum disorder. *Scientific Reports*, 13(1), 19466. <https://doi.org/10.1038/s41598-023-46507-z>
- Scherer, D., Müller, A., & Behnke, S. (2010). *Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition*. https://doi.org/10.1007/978-3-642-15825-4_10
- Schuster, M., & Paliwal, K. K. (1997). Bidirectional recurrent neural networks. *IEEE Transactions on Signal Processing*, 45(11), 2673–2681. <https://doi.org/10.1109/78.650093>
- Sewani, H., & Kashef, R. (2020). An autoencoder-based deep learning classifier for efficient diagnosis of autism. *Children*, 7(10), 182.
- Sherkatghanad, Z., Akhondzadeh, M., Salari, S., Zomorodi-Moghadam, M., Abdar, M., Acharya, U. R., Khosrowabadi, R., & Salari, V. (2020). Automated Detection of Autism Spectrum Disorder Using a Convolutional Neural Network. *Frontiers in Neuroscience*, 13. <https://doi.org/10.3389/fnins.2019.01325>
- Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data*, 6(1), 60. <https://doi.org/10.1186/s40537-019-0197-0>
- Silver, D., Huang, A., Maddison, C., Guez, A., Sifre, L., Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529, 484–489. <https://doi.org/10.1038/nature16961>

- Smith, S. M., Jenkinson, M., Woolrich, M. W., Beckmann, C. F., Behrens, T. E. J., Johansen-Berg, H., Bannister, P. R., De Luca, M., Drobnjak, I., Flitney, D. E., Niazy, R. K., Saunders, J., Vickers, J., Zhang, Y., De Stefano, N., Brady, J. M., & Matthews, P. M. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *NeuroImage*, 23, S208–S219.
<https://doi.org/https://doi.org/10.1016/j.neuroimage.2004.07.051>
- Smolensky, P. (1986). *Information Processing in Dynamical Systems: Foundations of Harmony Theory*; CU-CS-321-86.
- Smolik, M., Skala, V., & Majdisova, Z. (2018). Vector field radial basis function approximation. *Advances in Engineering Software*, 123(17), 117–129.
<https://doi.org/10.1016/j.advengsoft.2018.06.013>
- Stoodley, C. J. (2014). Distinct regions of the cerebellum show gray matter decreases in autism, ADHD, and developmental dyslexia . In *Frontiers in Systems Neuroscience* (Vol. 8).<https://www.frontiersin.org/articles/10.3389/fnsys.2014.00092>
- Strother, S., La Conte, S., Hansen, L. K., Anderson, J., Zhang, J., Pulapura, S., & Rottenberg, D. (2004). Optimizing the fMRI data-processing pipeline using prediction and reproducibility performance metrics: I. A preliminary group analysis. *Neuroimage*, 23, S196–S207.
- Tan, C., Sun, F., Kong, T., Zhang, W., Yang, C., & Liu, C. (2018). *A Survey on Deep Transfer Learning BT - Artificial Neural Networks and Machine Learning – ICANN 2018* (V. Kůrková, Y. Manolopoulos, B. Hammer, L. Iliadis, & I. Maglogiannis, Eds.; pp. 270–279). Springer International Publishing.

- Tang, M., Kumar, P., Chen, H., & Shrivastava, A. (2020a). Deep multimodal learning for the diagnosis of autism spectrum disorder. *Journal of Imaging*, 6(6). <https://doi.org/10.3390/jimaging6060047>
- Tang, M., Kumar, P., Chen, H., & Shrivastava, A. (2020b). Deep Multimodal Learning for the Diagnosis of Autism Spectrum Disorder. In *Journal of Imaging* (Vol. 6, Issue 6). <https://doi.org/10.3390/jimaging6060047>
- Tominec, I., Larsson, E., & Heryudono, A. (2021). A least squares radial basis function finite difference method with improved stability properties. *SIAM Journal on Scientific Computing*, 43(2), A1441–A1471.
- Tunali, R. S. E.-N. E. (2020). *Cerebellum: Its Anatomy, Functions and Diseases* (p. Ch. 1). IntechOpen. <https://doi.org/10.5772/intechopen.93064>
- Uddin, L. Q., Supekar, K., Lynch, C. J., Khouzam, A., Phillips, J., Feinstein, C., Ryali, S., & Menon, V. (2013). Salience Network–Based Classification and Prediction of Symptom Severity in Children With Autism. *JAMA Psychiatry*, 70(8), 869–879. <https://doi.org/10.1001/jamapsychiatry.2013.104>
- Vesanto, J., & Alhoniemi, E. (2000). Clustering of the Self-Organizing Map. *IEEE Transactions on Neural Networks / a Publication of the IEEE Neural Networks Council*, 11, 586–600. <https://doi.org/10.1109/72.846731>
- Wang, H. (2017). *On the Origin of Deep Learning*. 1–72. <https://doi.org/10.48550/arXiv.1702.07800>
- Wang, H., Liu, S., Xie, L., & Wang, J. (2023). Gut microbiota signature in children with autism spectrum disorder who suffered from chronic gastrointestinal symptoms. *BMC Pediatrics*, 23(1), 476. <https://doi.org/10.1186/s12887-023-04292-8>

- Wehle, H. D. (2017). Machine learning, deep learning, and ai: What's the difference?. *Data Scientist Innovation Day*, 2-5.
- Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. *Journal of Big Data*, 3(1), 9. <https://doi.org/10.1186/s40537-016-0043-6>
- Weitlauf, A. S., Gotham, K. O., Vehorn, A. C., & Warren, Z. E. (2014). Brief report: DSM-5 “levels of support:” A comment on discrepant conceptualizations of severity in asd. *Journal of Autism and Developmental Disorders*, 44(2), 471–476. <https://doi.org/10.1007/s10803-013-1882-z>
- Weng, Y., Zhou, T., Li, Y., & Qiu, X. (2019). NAS-Unet: Neural architecture search for medical image segmentation. *IEEE Access*, 7(c), 44247–44257. <https://doi.org/10.1109/ACCESS.2019.2908991>
- Wold, S., Esbensen, K., & Geladi, P. (1987). Principal component analysis. *Chemometrics and Intelligent Laboratory Systems*, 2(1), 37–52. [https://doi.org/10.1016/0169-7439\(87\)80084-9](https://doi.org/10.1016/0169-7439(87)80084-9)
- Wolff, J. J., Hazlett, H. C., Lightbody, A. A., Reiss, A. L., & Piven, J. (2013). Repetitive and self-injurious behaviors: associations with caudate volume in autism and fragile X syndrome. *Journal of Neurodevelopmental Disorders*, 5(1), 12. <https://doi.org/10.1186/1866-1955-5-12>
- Woodbury-Smith, M., & Scherer, S. W. (2018). Progress in the genetics of autism spectrum disorder. *Developmental Medicine and Child Neurology*, 60(5), 445–451. <https://doi.org/10.1111/dmcn.13717>
- Wu, J. (2017). Introduction to convolutional neural networks. *National Key Lab for Novel Software Technology. Nanjing University. China*, 5(23), 495.

- Wurzberger, F., & Schwenker, F. (2024). Learning in Deep Radial Basis Function Networks. *Entropy*, 26, 368. <https://doi.org/10.3390/e26050368>
- Yahata, N., Morimoto, J., Hashimoto, R., Lisi, G., Shibata, K., Kawakubo, Y., Kuwabara, H., Kuroda, M., Yamada, T., Megumi, F., Imamizu, H., Náñez Sr, J. E., Takahashi, H., Okamoto, Y., Kasai, K., Kato, N., Sasaki, Y., Watanabe, T., & Kawato, M. (2016). A small number of abnormal brain connections predicts adult autism spectrum disorder. *Nature Communications*, 7(1), 11254. <https://doi.org/10.1038/ncomms11254>
- Yazdani, S., Capuano, A., Ghaziuddin, M., & Colombi, C. (2020). Exclusion criteria used in early behavioral intervention studies for young children with autism spectrum disorder. *Brain Sciences*, 10(2). <https://doi.org/10.3390/brainsci10020099>
- Yeargin-Allsopp, M., Rice, C., Karapurkar, T., Doernberg, N., Boyle, C., & Murphy, C. (2003). Prevalence of autism in a US metropolitan area. *Journal of the American Medical Association*, 289(1), 49–55. <https://doi.org/10.1001/jama.289.1.49>
- Yousedian, A., Shayegh, F., & Maleki, Z. (2022). Detection of Autism Spectrum Disorder Using Graph Representation Learning Algorithms and Deep Neural Network, Based on fMRI Signals. *BioRxiv*.
- Zhang, T. (2023). Reinforcement Learning (pp.373–413). <https://doi.org/10.1017/9781009093057.019>
- Zhang, T. (2023). Reinforcement Learning. In *Mathematical Analysis of Machine Learning Algorithms* (pp. 373–413). chapter, Cambridge: Cambridge University Press.
- Zhao, J., Wu, S., Sun, L., & Li, Q. (2022). IoU-Enhanced Attention for End-to-End Task Specific Object Detection. <https://doi.org/10.48550/arXiv.2209.10391>

- Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., & He, Q. (2021). A Comprehensive Survey on Transfer Learning. *Proceedings of the IEEE*, 109(1), 43–76. <https://doi.org/10.1109/JPROC.2020.3004555>
- Zuckerman, K. E., Lindly, O. J., & Sinche, B. K. (2015). Parental Concerns, Provider Response, and Timeliness of Autism Spectrum Disorder Diagnosis. *The Journal of Pediatrics*, 166(6), 1431-1439.e1. <https://doi.org/10.1016/j.jpeds.2015.03.00>