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THEME:

AI - driven solution for accurate diagnosis and treatement of autism

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Special Thanks

Alhamdulillah for granting me the strength, energy, and courage needed to complete this work.

I would like to express my heartfelt gratitude to my supervisor, Dr. Bennour Akram, for his unwavering support, guidance, and assistance throughout this project. My thanks also go to the jury members for dedicating their time to evaluate this work.

I am grateful to everyone who contributed, both directly and indirectly, to the completion of this project. I extend my appreciation to all my teachers and the professional team of the Mathematics and Computer Science Faculty Department at Tebessa University.

Finally, a special thank you to my family and friends for their encouragement and support during the challenging times of this project.

Dedication

I dedicate this work to my most precious people in the world, my parents, who stayed up nights to cover me with their love.

To my dear father the light of my live: Dr . Salim BAALOUDJ For his constant effort and countless sacrifices in order to devote his life, his money and his fees to serving me, fulfilling my requirements, and staying up for my comfort.

To the one for whom Allah has placed paradise beneath her feet, my mother, the light of my eyes, the hight school Professor Hadhoud Mabrouka. Thank you for your unwavering support, continuous encouragement, and dedication to my success, always striving to see me achieve great heights.

For my brother: Abderraouf el arabi

For all of my friend who help me with informations and motivate me to finish this work .

Abstract

The study of autism spectrum disorder (ASD) is one of the most interesting research topics in recent years because it requires a very rapid and accurate diagnosis. Specialists have relied on children's ability to write, draw, and color, in addition to collecting special pictures of their faces, which has provided many advantages in diagnosis. For example, children with autism may have specific patterns in their drawings and writings, which can indicate certain aspects of their condition. Analyzing these graphic elements can reveal fine motor skill difficulties or repetitive tendencies typical of ASD. Moreover, the facial expressions of children can offer clues about emotional recognition and social responsiveness, two areas often affected by autism.

There are also several other methods of diagnosis, such as studying and analyzing behavior via video, and relying on X-rays of the brain. Behavioral observation can help identify specific behavioral patterns and communication difficulties. Additionally, brain imaging can show abnormalities in brain structure and connectivity, providing biological evidence of autism. For this reason, the diagnostic process remains somewhat complex and difficult. This complexity has encouraged the use of modern artificial intelligence techniques, such as deep learning, to diagnose autism spectrum disorders using coloring, handwriting, and drawing photos and facial images. Artificial intelligence can analyze large amounts of data and identify subtle patterns that humans might miss. To this end, artificial intelligence scientists and researchers have begun to engage in building systems based on deep learning and machine learning. These systems can process images and videos in a sophisticated manner, learn to recognize the features associated with ASD, and improve the accuracy and speed of diagnoses.

In this project, we created three educational models for autism spectrum classification. The first model is an updated CNN model called (Aut-Net) that achieved an accuracy rate of 98% on the coloring dataset. The second model, VGG 16, achieved 98% on the drawing dataset. The third model, Res-Net, is related to the face recognition dataset and achieved 77%. These models and datasets were chosen based on the results of experimenting with different models and selecting the best one, in addition to the available datasets. This rigorous approach ensures that the chosen models are the most effective for the given tasks, enhancing the reliability and accuracy of the diagnostic process.

ملخص

تعد دراسة اضطراب طيف التوحد (ASD) أحد أكثر موضوعات البحث إثارة للاهتمام في السنوات الأخيرة لأنها تتطلب تشخيصًا سريعًا ودقيقًا للغاية. وقد اعتمد المتخصصون على قدرة الأطفال على الكتابة والرسم والتلوين، بالإضافة إلى جمع صور خاصة لوجوههم، مما قدم العديد من المزايا في التشخيص. على سبيل المثال، قد يكون لدى الأطفال المصابين بالتوحد أنماط محددة في رسوماتهم وكتاباتهم، والتي يمكن أن تشير إلى جوانب معينة من حالتهم. يمكن أن يكشف تحليل هذه العناصر الرسومية عن صعوبات في المهارات الحركية الدقيقة أو الميول المتكررة النموذجية لاضطراب طيف التوحد. علاوة على ذلك، يمكن أن تقدم تعبيرات وجه الأطفال أدلة حول التعرف العاطفي والاستجابة الاجتماعية، وهما مجالان غالبًا ما يتأثران بالتوحد.

كما أن هناك عدة طرق أخرى للتشخيص، مثل دراسة وتحليل السلوك عبر الفيديو، والاعتماد على الأشعة السينية للدماغ. يمكن أن تساعد الملاحظة السلوكية في تحديد أنماط سلوكية محددة وصعوبات التواصل. بالإضافة إلى ذلك، يمكن أن يُظهر تصوير الدماغ تشوهات في بنية الدماغ واتصالاته، مما يوفر دليلًا بيولوجيًا على مرض التوحد. ولهذا السبب، تظل عملية التشخيص معقدة وصعبة إلى حد ما. وقد شجع هذا التعقيد على استخدام تقنيات الذكاء الاصطناعي الحديثة، مثل التعلم العميق، لتشخيص اضطرابات طيف التوحد باستخدام التلوين والكتابة اليدوية ورسم الصور وصور الوجه. يمكن للذكاء الاصطناعي تحليل كميات كبيرة من البيانات وتحديد الأنماط الدقيقة التي قد يفوتها البشر.ولتحقيق هذه الغاية، بدأ علماء وباحثو الذكاء الاصطناعي في الانخراط في بناء أنظمة تعتمد على التعلم العميق والتعلم الآلي. يمكن لهذه الأنظمة معالجة الصور ومقاطع الفيديو بطريقة متطورة، وتعلم كيفية التعرف على الميزات المرتبطة باضطراب طيف التوحد، وتحسين دقة وسرعة التشخيص.

في هذا المشروع، قمنا بإنشاء ثلاثة نماذج تعليمية لتصنيف طيف التوحد. النموذج الأول هو نموذج CNN محدث يسمى (Aut-Net) والذي حقق نسبة دقة 98% على مجموعة بيانات التلوين. أما النموذج الثاني، VGG 16، فقد حقق 98% في مجموعة بيانات الرسم. النموذج الثالث، Res-Net، يتعلق بمجموعة بيانات التعرف على الوجوه وحقق 77%. وقد تم اختيار هذه النماذج ومجموعات البيانات بناءً على نتائج تجربة النماذج المختلفة واختيار أفضلها، بالإضافة إلى مجموعات البيانات المتوفرة. ويضمن هذا النهج الصارم أن النماذج المختارة هي الأكثر فعالية للمهام المحددة، مما يعزز موثوقية ودقة عملية التشخيص.

Table of contents

Table of contents

List of figures

List of tables

General Introduction

General Introduction

Autism spectrum disorder (ASD) is a complex neurodevelopmental condition that affects social interaction, communication, and behavior. Despite extensive research efforts, the underlying causes and mechanisms of ASD remain elusive, and accurate diagnosis and effective treatment continue to pose significant challenges. With the prevalence of ASD on the rise, there is an urgent need for innovative approaches that can facilitate early and precise identification, as well as personalized interventions tailored to the unique needs of each individual [1].

This master's thesis aims to propose an AI-driven solution that leverages machine learning techniques to analyze handwriting, coloring, and drawing patterns for accurate diagnosis and treatment of ASD. The primary contributions of this work are as follows:

Developing a CNN architecture called (Aut-Net) specifically used for processing handwriting, coloring, and drawing samples from individuals with ASD.

Employing transfer learning techniques by fine-tuning the pre-trained VGG16 model on ASD-specific datasets.

We also use a second dataset of face recognition contain different children faces with different ages and we applied Res-Net as deep learning model

Conducting a comprehensive study on the state-of-the-art in AI-based approaches for ASD diagnosis and treatment.

The thesis will be organized into four chapters:

Chapter 1: Theoretical Concepts

In this chapter, we will introduce the fundamental concepts and theoretical background relevant to ASD, machine learning, and computer vision techniques used in this work.

Chapter 2: State of the Art

This chapter will provide a comprehensive review of the existing literature and state-of-the-art approaches for AI-driven ASD diagnosis and treatment, highlighting their strengths, limitations, and potential areas for improvement.

Chapter 3: Proposed Approach

In this chapter, we will present the proposed CNN architecture, transfer learning strategies, and Res-Net Additionally, we will describe the datasets used, data preprocessing techniques, and the experimental setup.

Chapter 4: Experimental Study

This chapter will showcase the experimental results obtained from the proposed approach, including performance metrics, visual representations, and insightful observations. We will also compare our results with existing state-of-the-art methods and discuss potential avenues for future research.

We conclude by emphasizing the significance of this study in advancing our understanding of ASD and developing AI-driven solutions that can potentially revolutionize the diagnosis and treatment of this complex disorder. Furthermore, we will summarize the key contributions of this work and outline potential directions for future research.

Chapter 01:

Theoretical concepts

I.1. Introduction

This chapter provides an overview of the basic concepts and diagnostic criteria for autism spectrum disorder (ASD). It begins by explaining the nature of ASD as a neurodevelopmental disorder characterized by deficits in social communication and the presence of repetitive stereotypic behaviors, which are the two hallmarks of ASD. But to understand the diversity in ASD symptoms, cognitive abilities and language skills must also be measured.

It then addresses the diagnostic criteria and assessment methods used to identify and evaluate ASD, including standardized tools, observational measurements, and clinical evaluations by experts.

It also discusses current research on the causative factors and underlying mechanisms that contribute to the development of ASD, including genetic, environmental, and neurobiological influences, along with the latest brain imaging findings and neuropathology studies.

Finally, it discusses the range of evidence-based interventions and support services available to individuals with ASD, emphasizing the importance of early intervention, individualized treatment plans, and multidisciplinary approaches to improve outcomes and quality of life across the lifespan.

I.2. Overview about Autism Spectrum Disorder (ASD)

I.1.1. Definition of Autism Spectrum Disorder (ASD)

It a neurological clutter that seriously disables the communication abilities vital for normal living. Most individuals with extreme introversion have gentle challenges, but often serious ones that require specialized care. As a result of their troubles communicating with others, individuals with A SD regularly battle in social circumstances. Most of the neurophysiological indications of ASD are known to therapeutic experts, but no authoritative biosignature or obsessive method can analyze extreme introvertedness at any time. [1]

I.1.2. Importance of Early Diagnosis of Autism Spectrum Disorder

Despite the nonattendance of a specific treatment convention, getting a determination at an early age can make strides in results altogether. Children with ASD may have distant better a higher; a stronger; an improved and improved chance of progressing their socializing aptitudes in early childhood with legitimate mediation due to greater adaptability in brain advancement at this age. Logical proof proposes that children who get therapeutic care sometime recently at age four have a better normal IQ than those who wait until they are more seasoned. [2]

Despite these endeavors, modern think-about gauges that as it were 34\% of children with ASD are distinguished by the age of three within the Joined together States. In any case, the extent is significantly lower in immature countries. [3]

I.3. Type of AUTISM SPECTRUM DISORDER

I.3.1. Hereditary qualities of ASD

Recent articles (Berg and Geschwind, 2012, Geschwind, 2011, Persico and Napolioni, 2013) provide a comprehensive assessment of the genetics of ASD. In short, there are a number of methods that have been used to study the genetic variation that increases the risk of ASD. These have included common variant association studies, uncommon variant analysis, and gene discovery for classic ASD-associated disorders. Syndromes linked to ASD, include tuberous sclerosis, Rett syndrome, and fragile X syndrome, typically. [4]

I.3.2. ASD Models Including Serotonergic Neurons

One of the first suspected cell types to be disturbed in people with ASD was serotonin (5-HT) neurons. The raphe nuclei of the midbrain and hindbrain contain the cell bodies of 5-HT neurons, however these neurons spread broadly across the neuraxis and are highly neuromodulatory in many different circuits and cell types. 5-HT may be involved in a variety of processes, including the control of typical behaviors like sleep and arousal. [4]

I.3.3. ASD Models Including GABAergic Interneurons

The most fast-acting inhibitory neurotransmitter in the brain is y-aminobutyric acid (GABA). GABAergic interneurons play essential functions in several circuits, such as the cortex, where they regulate information transmission and reduce excessive excitation. Though they only make up 20\% of cortical neurons, GABAergic interneurons are essential for preserving cortical circuit balance and correct function (Markram et al., 2004, Taniguchi et al., 2011). [4]

I.3.4. ASD Models Including the Cerebellum

Cerebellar abnormalities in the brains of autistic people have been identified in a number of clinical trials. For instance, in a voxel-based morphometry analysis, the lower cerebellar gray matter was connected with the Autism Diagnostic Interview-Revised (ADI-R) and the Autism Diagnostic Observation Schedule (ADOS) Generic Scores in autistic participants (Riva et al., 2013). According to imaging studies, autistic people have cerebellar hypoplasia and greater cerebellar activity during a motor task (Allen, Muller, \& Courchesne, 2004). [4]

I.3.5. ASD Models Including the Striatum

According to Middleton and Strick (2000), the striatum is the biggest nucleus of the basal ganglia and receives input from cortical and thalamic regions. In humans, the dorsal striatum consists of the putamen and caudate, whereas in mice, it is a single structure. Composed primarily of GABAergic projection neurons (medium spiny neurons, or MSNs), which synapse onto neurons of the globus pallidus externa (GPe) and substantia nigra pars reticulata (SNPr)/globus pallidus interna (GPi), the output MSNs), which synapse onto neurons of the globus pallidus externa (GPe) and substantia nigra pars reticulata (SNPr)/globus pallidus interna (GPi), the output. [4]

I.3.6. Other Locales and Cell Sorts

Although these are not the only systems that have been theorized to have a function in ASD, we concentrated our review on four systems and cell types that had previously attracted a lot of interest, particularly when utilizing conditional deletion procedures in model organisms. It is, in fact, challenging to pinpoint a cell type or area that hasn't been implicated in ASD before. For some systems, like the hippocampus, the amount of information obtained may be partially explained by the system's experimental tractability. [4]

I.4. Key Characteristics of Autism Spectrum Disorder

One prevalent but sometimes disregarded feature of autism spectrum disorder (ASD) is motor problems. ASD can cause a variety of difficulties for both adults and children with regard to motor abilities, coordination, and mobility. Here are some essential details about physical challenges in autism.

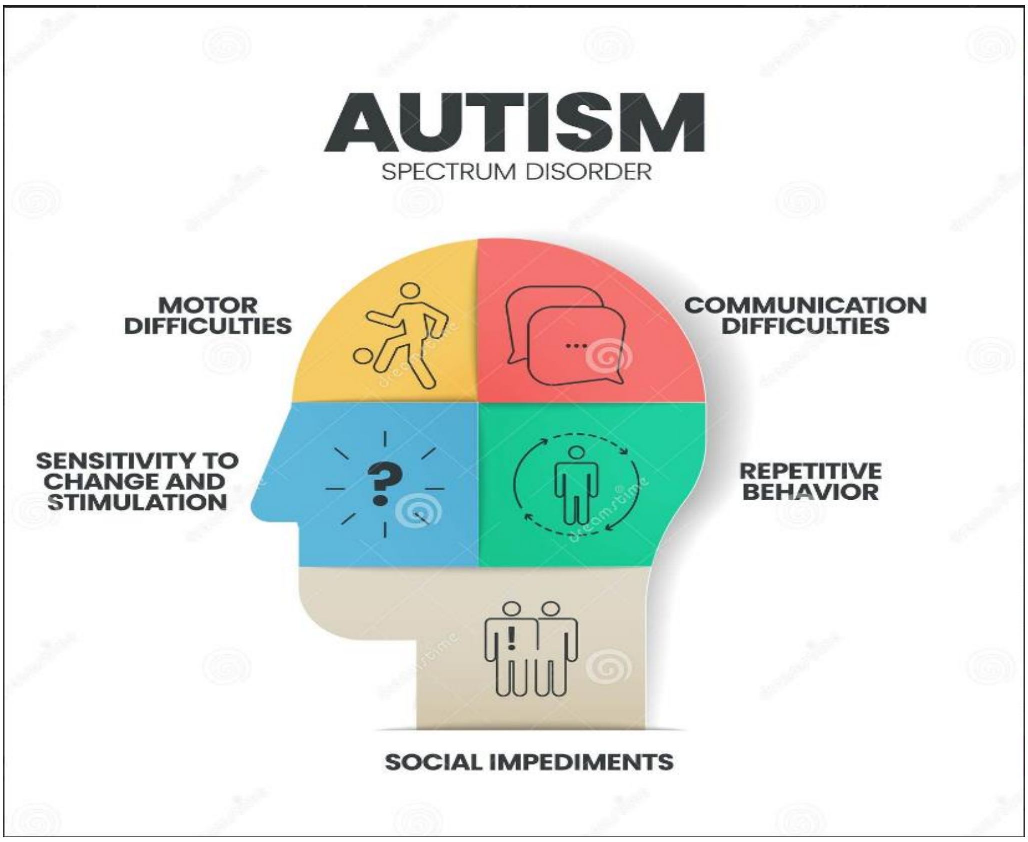

Figure* I. 1*: Key Characteristics of Autism Spectrum Disorder

I.4.1. Deficits in motor skills

According to recent studies, children diagnosed with autism spectrum disorder (ASD) may have some degree of motor impairment, and this may have an impact on their ability to communicate socially. The current study sought to ascertain if individuals with ASD exhibited motor abnormalities particular to their syndrome in contrast to those with "specific language impairment "(SLI). The TD group outperformed the ASD or SLI groups in terms of motor skills, according to our findings.

We draw the conclusion that there is a chance of clinically substantial motor impairments in children with ASD and SLI. [5]

***Figure I. 2** Motor Skills Disorder in Kids with ASD Level 1 [High-Functioning Autism*

I.4.2. Issues with motor coordination

These can include problems with gross motor skills (e.g., walking, running, jumping), fine motor skills (e.g., grasping, manipulating objects), and motor planning and coordination. Some individuals with ASD may also exhibit unusual body movements or postures.

This meta-analysis revealed impairments in motor coordination and movement in individuals with ASD, including difficulties with gait, posture, and object control. [5]

Figure* I. 3 *: Gross Motor Skills - Reduced Motor Skills

I.4.3. Sensory Sensitivities

The study brought to light the over- and under-sensitivity to stimuli including lights, noises, and textures that characterize children with autism. Thirty autistic children and thirty controls completed a questionnaire, and the results showed a substantial disparity in their sensory reactions. Strong reactions, such as avoiding particular textures or covering one's ears to block out noise, might result from these sensitivities. The results highlight the need for specialized therapies and support techniques by indicating that sensory experiences may have an influence on how well children with autism develop their social interaction, attachment, and communication abilities. [5]

Figure* I.4*: sensory hypersensitivity in children with ASD

I.4.4. Communication Challenges

Individuals with ASD may experience delays in language development, echolalia (repeating words or phrases), difficulty understanding non-literal language (e.g., idioms, sarcasm), and challenges with pragmatic language (using language appropriately in social contexts). Individuals with ASD often experience delays or impairments in language development, including difficulties with pragmatic language, speech production, and comprehension. [5]

Figure* I.5*: Communicating With Autistic Children

I.4.5. Difficulty with Flexibility and Adaptability

Resistance to change in routines or environments. Difficulty transitioning between activities or adjusting to unexpected changes. between November 2021 and June 2022, a study involved 218 parents from XX, with half having children with autism and the other half having healthy children. Parents of children with autism reported more concerns and challenges in caregiving, personal time, and daily life maintenance. They also showed higher levels of anxiety, depression, and hostility compared to parents of healthy children, indicating increased emotional strain and the need for additional support for families with children with autism. [5]

Figure* I.6*: problem of communication with ASD children

I.4.6. Strengths and Abilities

It's important to acknowledge the abilities of people with autism. Previous research on exceptional skills has assembled diverse individuals with unique talents. grouping various jobs, like calendar computation and painting, with minimal focus on specialized skills and even less on individual abilities. We analyze the connection between parental-reported abilities and talents and cognitive test scores in 1470 children (4–18 years old) with autism and IQs >70. About half (46%) reported having parental talents, and even those lacking great abilities had a specific strength (23%). Children with strengths in drawing, music, computing, or visuospatial tasks had different cognitive profiles. Those with high memory scores showed balanced verbal and nonverbal ability compared to those whose memory was not addressed. These findings emphasize the need for further study and assessment of capabilities in specific areas. [5]

Figure* I.7*: Strengths and Abilities In children with Autism

I.4.7. Co-occurring Conditions

Employing a population-based cohort, the think about looked for to find out the sorts and rate of mental wellbeing issues related with extreme introvertedness range clutters (ASD) in children matured 10 to 14. Fourteen percent of the eleven2 children within the test had at slightest one comorbid clutter, and eleven percent had two or more. The three most common analyze were social uneasiness clutter (29.2%), attention-deficit/hyperactivity clutter (ADHD) (28.1%), and oppositional insubordinate clutter (28.1%). In expansion to ADHD, 84% of patients detailed another comorbid analyze. There was no prove of a relationship between conceivable hazard components and mental sickness. The creators conclude that as children with ASD habitually have a run of mental wellbeing issues, these disarranges ought to be routinely assessed and the center of medicines. [5]

Figure* I.8 : *Co-occurring Conditions with children with Autism

I.5 Conclusion

In this chapter, we provided an overview of autism spectrum disorder (ASD), its different types, and its key characteristics.. In the next chapter, we reviewed the latest techniques and approaches used in the diagnosis of autism spectrum disorder.

Chapter 2:

State of the art

II.1. Introduction

The of autism spectrum disorder (ASD), a chronic illness that affects social interaction, communication, and behavioral patterns in a variety of groups, has gained more attention in recent years. The development of early intervention techniques and support systems has been stepped up in an attempt to improve the quality of life and results for autistic people. Scientific research has been conducted to improve our knowledge of the fundamental causes of ASD and open the door to new, more efficient therapies.

Prior research aimed at clarifying the characteristics of ASD, the datasets used, the approaches taken, and the main conclusions and outcomes attained will be reviewed and arranged chronologically from oldest to latest contributions

.

II.2. Related works

II.2.1. Autism Spectrum Disorder Detection by Hybrid Convolutional Recurrent Neural Networks from Structural and Resting-State Functional MRI Images

This endeavors to enhance the accuracy of ASD diagnosis by leveraging cognitive and behavioral phenotypes alongside various neuroimaging modalities. (ML) algorithms are applied to differentiate ASD patients from participants using data from structural magnetic resonance imaging (s-MRI) and resting-state functional MRI (rs-f-MRI and f-MRI) sourced from the (ABIDE) multisite repository. The 2D f-MRI images are transformed into 3D s-MRI images, and preprocessing is conducted utilizing the MNI atlas, followed by denoising to eliminate confounding factors. Three fusion strategies, "early fusion, late fusion, and cross fusion," are employed, demonstrating that hybrid convolutional recurrent neural networks outperform standalone convolutional neural networks (CNNs) or recurrent neural networks (RNNs). The proposed model achieves a remarkable 96\% accuracy by integrating s-MRI and f-MRI data, surpassing previous methodologies. [6]

II.2.2. Diagnostic of autism spectrum disorder based on structural brain MRI images using, grid search optimization, and convolutional neural networks

This presents an automated autism diagnostic model leveraging (sMRI). The model comprises two key stages. Firstly, the preprocessing stage involves eliminating unclear images, detecting image edges using the Canny edge detection (CED) algorithm, cropping images to required sizes, and enlarging them by a factor of five through data augmentation. Care is taken to ensure that the data augmentation method does not alter image discrimination, such as coloring, and is applied cautiously to both ASD and typical development (TD) groups to avoid data manipulation. In the second stage, the grid search optimization (GSO) algorithm optimizes the hyperparameters of deep convolutional neural networks (DCNN) employed in the system. Consequently, the proposed ASD diagnostic method based on sMRI achieves an exceptional success rate of 100\%. The reliability of the model is affirmed through five-fold cross-validation, demonstrating its superiority over recent studies and widely-used pre-trained models. [7]

II.2.3. Improving the detection of autism spectrum disorder by combining structural and functional MRI information

In this study, researchers aimed to classify individuals with autism spectrum disorder (ASD) and control subjects using magnetic resonance imaging (MRI) data. They utilized functional connectivity patterns and gray matter volume measurements from cortical parcels as features for functional and structural processing pipelines, respectively. The classification network combined stacked autoencoders and multilayer perceptrons. Using data from the Autism Brain Imaging Data Exchange I (ABIDE I), comprising 817 cases (368 ASD patients and 449 controls), the ensemble classifiers achieved a classification accuracy of 85.06 %, integrating information from both functional and structural MRI sources outperformed individual pipelines. This suggests that combining data from multiple MRI modalities enhances ASD classification accuracy, potentially offering valuable insights for diagnosis and understanding of the disorder. [8]

II.2.4. Identification of autism spectrum disorder using deep learning and the ABIDE dataset

The aim of this was to utilize deep learning algorithms to discern (ASD) patients from extensive brain imaging datasets solely based on their brain activation patterns. We examined ASD patient brain imaging data from a global multi-site database called ABIDE (Autism Brain Imaging Data Exchange). According to recent Centers for Disease Control data, ASD affects one in 68 children in the United States. We explored patterns of functional connectivity that objectively identify ASD participants from functional brain imaging data and sought to uncover the neural patterns emerging from classification. The results advanced the state-of-the-art by achieving 70\% accuracy in identifying ASD versus control patients in the dataset. The emerging patterns indicate an anticorrelation of brain function between anterior and posterior brain areas; this anticorrelation aligns with current empirical evidence of anterior-posterior disruption in brain connectivity in ASD. We present the results and identify the brain regions that contributed most to distinguishing ASD from typically developing controls, according to our deep learning model. [9]

II.2.5. Implementation of Machine Learning and Deep Learning Models Based on Structural MRI for Identification of Autism Spectrum Disorder

This work centers on distinguishing extreme introvertedness range clutters utilizing attractive reverberation imaging (MRI). By comparing MRI pictures of ASD patients with those of people without ASD, different machine learning and profound learning methods were utilized, including irregular woodlands, back vector machines, and convolutional neural systems. The irregular woodland strategy illustrated the most elevated accuracy of 100\%, as decided by a disarray lattice, making it an ideal strategy for ASD recognizable proof through MRI. [10]

II.2.6. Diagnosis of Autism Spectrum Disorder Based on Functional Brain Networks with Deep Learning

This examines the utilization of profound learning strategies to analyze (ASD) useful brain systems derived from fMRI data. By building brain systems and extricating highlights, they achieve a classification accuracy of 76.2\% and an area beneath the bend (AUC) of 79.7\%, employing a profound neural organization (DNN). Comparisons with conventional machine learning calculations appear prevalent. Moreover, combining the DNN with a pre-trained autoencoder helps increase precision to 79.2\% and AUC to 82.4%. These discoveries propose the adequacy of profound learning approaches in ASD. [11]

II.2.7. Handwriting-Based ADHD Detection for Children Having ASD Using Machine Learning Approaches

This explores the use of handwriting patterns to detect ADHD in children with coexisting ASD, employing machine learning (ML) approaches. Handwriting samples from 29 Japanese children (14 with ADHD with coexisting ASD and 15 healthy children) were collected, focusing on two patterns: zigzag lines (ZL) and periodic lines (PL). Thirty statistical features were extracted from the raw datasets and analyzed using sequential forward floating search (SFFS) to identify the best feature subsets. Seven ML-based algorithms were then employed, with classifiers trained using leave-one-out cross-validation. Performance evaluation metrics, including accuracy, recall, precision, f1-score, and area under the curve (AUC), were utilized. The results revealed that the RF-based classifier achieved the highest performance scores for the PL prediction task, with (accuracy = 93.10\%, recall = 90.48\%, precision = 95.00\%, f1-score = 92.68\%, and AUC = 0.930). This indicates the potential for classifying ADHD children with ASD and healthy children based on their handwriting patterns. [12]

II.2.8. CNN-Based Handwriting Analysis for the Prediction of Autism Spectrum Disorder

This aims to leverage handwriting analysis as a potential biomarker for autism spectrum disorder (ASD) identification. With approximately 1 in 44 children worldwide diagnosed with ASD, identifying effective methods for early detection is crucial. ASD is characterized by repetitive sensory-motor behaviors, often accompanied by motor impairments that affect tasks like handwriting.

To assess the viability of handwriting as a diagnostic tool, the compiled a dataset consisting of handwritten texts from children aged 7 to 10. Three pre-trained transfer learning frameworks InceptionV3, VGG19, and Xception—were employed for analysis. After evaluating these models using various quantitative performance metrics, Xception emerged as the most accurate, achieving a remarkable 98\% accuracy rate. This research suggests that handwriting analysis, combined with advanced machine learning techniques, holds promise for improving ASD detection and early intervention strategies. [13]

II.2.9. Handedness in Childhood Autism Shows a Dissociation of Skill and Preference

hand preference and hand skill were examined in 20 children with autism, 20 normal controls, and 12 children with mental retardation. It was found that 90\% of normal controls and 92\% of children with mental retardation exhibited consistency between hand preference and hand skill, whereas only 50\% of children with autism demonstrated this concordance. The remaining 50\% of autistic children favored using the less skilled hand. Additionally, children with autism displayed lower degrees of handedness and consistency compared to the other groups, although this was not linked to the discordance of skill and asymmetry. The proposes a developmental model of handedness, suggesting that the establishment of handedness as preference precedes the development of handedness as skill asymmetry. However, in autism, this causal sequence is disrupted, resulting in established preferences without subsequent consistent skill asymmetry. [14]

II.2.10. Handwriting of Eight-Year-Old Children with Autistic Spectrum Disorder: An Exploration

Informal reports suggest that children with autism spectrum disorder (ASD) may face challenges in handwriting. This aimed to explore handwriting differences in ASD using the Sequential Handwriting Process. Fifty-six 8-year-old Australian children (28 with ASD and 28 without) were evaluated on 13 handwriting process factors and two outcome measures.

While children with ASD showed slower and less legible handwriting, the differences were not statistically significant. However, their accuracy in letter formation was significantly lower ($p = 0.001$). Both groups correlated legibility with oral spelling and letter formation accuracy, but they varied in other correlations. Handwriting process variables didn't significantly correlate with speed in either group. These findings suggest potential cognitive factors influencing handwriting difficulties in ASD. [15]

II.2.11. Writing research involving children with autism spectrum disorder without a co-occurring intellectual disability: A systematic review using language domains and mediational systems framework

This study explores the use of handwriting patterns to detect ADHD in children with coexisting ASD, employing (ML) approaches. Handwriting samples from 29 Japanese children (14 with ADHD with coexisting ASD and 15 healthy children) were collected, focusing on two patterns: zigzag lines (ZL) and periodic lines (PL). Thirty statistical features were extracted from the raw datasets and analyzed using sequential forward floating search (SFFS) to identify the best feature subsets. Seven ML-based algorithms were then employed, with classifiers trained using leave-one-out cross-validation. Performance evaluation metrics including accuracy, recall, precision, f1-score, and area under the curve (AUC) were utilized. The results revealed that the RF-based classifier achieved the highest performance scores for the PL prediction task, with (accuracy = 93.10\%, recall = 90.48\%, precision = 95.00\%, f1-score = 92.68\%, and AUC= 0.930). This study indicates the potential for classifying ADHD children with ASD and healthy children based on their handwriting patterns. [16]

II.2.12. CNN-Based Handwriting Analysis for the Prediction of Autism Spectrum Disorder

This study aims to leverage handwriting analysis as a potential biomarker for Autism Spectrum Disorder (ASD) identification. With approximately 1 in 44 children worldwide diagnosed with ASD, identifying effective methods for early detection is crucial. ASD is characterized by repetitive sensory-motor behaviors, often accompanied by motor impairments that affect tasks like handwriting.

To assess the viability of handwriting as a diagnostic tool, the study compiled a dataset consisting of handwritten texts from children aged 7 to 10. Three pre-trained Transfer Learning frameworks InceptionV3, VGG19, and Xception—were employed for analysis. After evaluating these models using various quantitative performance metrics, Xception emerged as the most accurate, achieving a remarkable 98\% accuracy rate. This research suggests that handwriting analysis, combined with advanced machine learning techniques, holds promise for improving ASD detection and early intervention strategies. [17]

II.2.13. Computerized Assessment of Motor Imitation as a Scalable Method for Distinguishing Children With Autism

In this study, we used Kinect Xbox technology to track the movements of 48 children (27 with ASCs and 21 typically developing) as they imitated a model's dance. We developed an algorithm to analyze and score the key joints based on spatial and timing differences between the child and the model. To validate and ensure reliability, we compared the imitation performance of children with ASCs to that of typically developing children using CAMI and HOC methods. The results showed that children with ASCs had poorer imitation skills (ps <0.005), indicating a significant association between poorer imitation and increased core autism symptoms. (69–87) CAMI's construct validity was confirmed. CAMI scores more accurately classified children (accuracy CAMI = 87.2\%) compared to HOC scores (accuracy HOC = 74.4\%). Moreover, comparing repeated movement trials shows the strong test-retest reliability of CAMI (rs = 73–86). [18]

II.2.14. Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques

Beginning in childhood and persisting through adolescence and adulthood, autism spectrum disorder (ASD) is a condition of ongoing concern. This article delves into the potential of machine learning methodologies, such as Naïve Bayes, Support Vector Machines, Logistic Regression, KNN, Neural Networks, and Convolutional Neural Networks (CNN), in predicting and analyzing ASD across various age groups.

Three distinct non-clinical ASD datasets were utilized for evaluation purposes. The first dataset focused on ASD screening in children, comprising 292 cases and 21 attributes. The second dataset targeted ASD screening in adults, encompassing 704 cases and 21 attributes. The third dataset addressed ASD screening in adolescents, consisting of 104 cases and 21 attributes.

After employing diverse machine learning techniques and addressing missing data, the findings indicate that CNN-based prediction models outperform others across all datasets, achieving higher accuracy rates. Specifically, the CNN-based models achieved accuracies of 99.53\%, 98.30\%, and 96.88\% for screening ASD in adults, children, and adolescents, respectively. [19]

II.2.15. Diagnostic procedures in autism spectrum disorders: a systematic literature review

This article fundamentally analyzes this advance, especially centered on rebellious individuals with vigorous inquiries about their legitimacy, and hence talks about challenges related to their usage in clinical settings.

Investigate has broadly surveyed the viability of screening instruments in recognizing ASD cases over population-based and clinically alluded tests, as well as the exactness of symptomatic disobedience in adjusting with clinical best appraise analysis, considered the gold standard.

Be that as it may, generalizing these discoveries to clinical settings requires caution, recognizing that instrument execution can shift depending on the test characteristics. [20]

II.2.16. Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms

This study proposes a novel approach to identify ASD utilizing social media data and biomedical images, focusing on facial recognition. Deep learning techniques are employed to extract and analyze facial landmarks, aiding in the detection of ASD based on facial features.

The study introduces a system built upon a convolutional neural network with transfer learning and the capsule network, aimed at assisting communities and psychiatrists in identifying ASD through a user-friendly web application. Pretrained models including Xception, Visual Geometry Group Network (VGG19), and NASNetMobile are utilized for classification tasks. The dataset comprises 2,940 facial images collected from the Kaggle platform.

Evaluation metrics such as accuracy, specificity, and sensitivity are employed to assess the performance of the three deep learning models. The Xception model achieves the highest accuracy of 91\%, followed by VGG19 (80\%) and NASNetMobile (78\%). [21]

II.2.17. Identifying differences in brain activities and an accurate detection of autism spectrum disorder using resting-state functional magnetic resonance imaging: A spatial filtering approach

This paper presents a novel technique for observing critical varieties in brain movement between people with extreme introvertedness range clutter (ASD) and neurotypical subjects utilizing resting-state utilitarian attractive reverberation imaging (fMRI).

The proposed strategy involves deciding on a spatial channel that orthogonalizes the covariance lattices of blood oxygen level subordinate (strong) time-series signals from ASD patients and neurotypical subjects, improving their peculiarities.

The reverse of this channel creates a spatial design outline highlighting brain locales capable of perceivable movement contrasts between the two bunches.

Besides, profoundly discriminative log-variance highlights are extricated from the anticipated Striking time-series information to move forward with classification exactness.

In addition, the classification execution utilizing log-variance highlights outperforms that of past considers, illustrating progressed demonstrative capability. [22]

II.2.18. A Review of Machine Learning Methods of Feature Selection and Classification for Autism Spectrum Disorder

According to the DSM-5 by the American Psychiatric Association, extreme introvertedness range clutter (ASD) is characterized by shortages in social communication and interaction and nearby limited and dreary behaviors.

Children with ASD frequently battle with joint consideration, social correspondence, and communication utilizing both verbal and non-verbal signals, leading to social segregation.

To address these challenges, effective approaches for early distinguishing proof and mediation through fast symptomatic methods for ASD are basic.

This survey centers on examining and analyzing later thinks about machine learning strategies to include choice and classification of ASD.

This consider points to altogether advantage future inquiries about extreme introvertedness by utilizing a machine learning approach to include determination, classification, and taking care of imbalanced information. [23]

II.2.19. Facial Features Detection System To Identify Children With Autism Spectrum Disorder: Deep Learning Models

Extreme introvertedness range clutter (ASD) could be a neurodevelopmental clutter related to brain improvement that hence influences the physical appearance of the confront.

Extremely introverted children have diverse designs of facial highlights, which set them particularly separated from ordinarily created (TD) children.

This ponder is pointed at helping families and therapists analyze extreme introvertedness utilizing a simple strategy, viz., a profound learning-based web application for recognizing extreme introvertedness based on tentatively tried facial highlights employing a convolutional neural organize with exchange learning and a carafe system.

MobileNet, Xception, and InceptionV3 were the pre-trained models utilized for classification. The facial pictures were taken from a freely accessible dataset on Kaggle, which comprises 3,014 facial pictures of a heterogeneous bunch of children, i.e., 1,507 extremely introverted children and 1,507 nonautistic children. Given the exactness of the classification comes about for the approval information, MobileNet came to 95curacy, Xception accomplished 94\%, and InceptionV3 achieved 0.89\%. [24]

II.2.20. A Machine Learning Approach to Predict Autism Spectrum Disorder

Within the show day, extreme introvertedness range clutter (ASD) is picking up force faster than ever. Identifying extreme introverted characteristics through screening tests is exceptionally costly and time-consuming.

With the progression of manufactured insights and machine learning (ML), extreme introversion can be anticipated at an early age. In spite of the fact that a number of studies have been carried out utilizing diverse procedures, these studies didn't give any conclusive conclusions, almost foreseeing extreme introvertedness characteristics in terms of diverse age groups.

Subsequently, this paper proposes a successful forecast show based on the ML strategy and creates a versatile application for anticipating ASD for individuals of any age. As a result of this inquiry, an extreme introvertedness expectation show was created by combining Arbitrary Forest-CART (Classification and Relapse Trees) and Irregular Forest-Id3 (Iterative Dichotomiser 3), and a portable application was also created based on the proposed expectation demonstration. The proposed demonstration was assessed with the AQ-10 dataset and 250 genuine datasets collected from individuals with and without extremely introverted characteristics.

The assessment revealed that the proposed expectation demonstrated way better results in terms of precision, specificity, affectability, accuracy, and wrong positive rate (FPR) for both sorts of datasets. [25]

II.2.21. EEG Analytics for Early Detection of Autism Spectrum Disorder: A data-driven approach

In this work, analysts explored the potential of EEG estimations as adaptable biomarkers for the early discovery of autism. ASD could be a complex condition analyzed essentially based on behavioral side effects observed after the first year of life. However, the variability in the introduction and the need for simple, routine detection methods amid the earliest stages pose noteworthy challenges.

To address this, EEG, a cost-effective and user-friendly brain estimation apparatus, was utilized. EEG information was collected from 99 newborn children with a kin analyzed for ASD and 89 low-risk controls, beginning at 3 months of age and proceeding until 36 months. Nonlinear highlights extracted from EEG signals were utilized as inputs for factual learning strategies.

The comedies were promising. Expectations of ASD determination based on EEG estimations as early as 3 months of age show tall exactness, with specificity, sensitivity, and positive prescient esteem (PPV) surpassing 95\% at certain ages. Moreover, the prediction of the Autism Diagnostic Observation Schedule (ADOS)-calibrated severity scores using only EEG data from 3 months of age appeared to have a strong correlation with the actual scores.

This demonstrates the potential for extricating important computerized biomarkers from EEG estimations for early ASD location. [26]

II.3. State of the art Summary

Study	Dataset used	accuracy
Autism Spectrum Disorder Detection by Hybrid Convolutional Recurrent Neural	MRI	**96%**

Networks from Structural and Resting State Functional MRI Images	Images	
Diagnostic of autism spectrum disorder based on structural brain MRI images using, grid search optimization, and convolutional neural networks	MRI Images	**100%**
Improving the detection of autism spectrum disorder by combining structural and functional MRI information	MRI Images	**85.06%**
Implementation of Machine Learning and Deep Learning Models Based on Structural MRI for Identification of Autism Spectrum Disorder	MRI Images	**100%**
Identification of autism spectrum disorder using deep learning and the ABIDE dataset	ABIDE dataset	**70%**
Diagnosis of Autism Spectrum Disorder Based on Functional Brain Networks with Deep Learning	ABIDE dataset	82.4 **%**
Handwriting-Based ADHD Detection for Children Having ASD Using Machine Learning Approaches	Handwriting dataset	**93.10 %**
CNN-Based Handwriting Analysis for the Prediction of Autism Spectrum Disorder	Handwriting dataset	**98 %**
Computerized Assessment of Motor Imitation as a Scalable Method for Distinguishing Children With Autism	Handwriting dataset	**87.2 % (CAMI)** **74.4 % (HOC)**
Analysis and Detection of Autism Spectrum Disorder Using Machine Learning	Face image dataset	**99.53% (adults)** **99.53% (children)** **96.88% (adolusent)**

Techniques		
Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms	Face image dataset	**91%** **80% (VGG19)** **78%(NASNetMobile)**
Facial Features Detection System To Identify Children With Autism Spectrum Disorder: Deep Learning Models	Face image dataset	**95% (MobileNet)** **94% (Xception)** **0.89% (InceptionV3)**
Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms	Face image dataset	**91%** **80% (VGG19)** **78% (NASNetMobile)**
Facial Features Detection System To Identify Children With Autism Spectrum Disorder: Deep Learning Models	Face image dataset	**95% (MobileNet)** **94% (Xception)** **0.89% (InceptionV3)**

Table 1. Summary of State of the art

II.4. Conclusion

In this chapter, we examined many cutting-edge research, assessing the datasets they utilized, the methodologies they applied, and the findings they obtained for the automated identification of autism spectrum disorder (ASD).. We finished by combining all of the papers mentioned in this chapter into a single summary table for display. In the next chapter, we will describe our approach to ASD detection, including the training procedure, datasets used, data preprocessing and augmentation, and models applied.

Chapter 03: Proposed Approach

III.1. Introduction

III.2. Method of Model Training and Evaluation

III.3. Data sets used

III.4. Data preprocessing

III.5. Our Aut-net Architecture

III.6. VGG 16

III.7. Confusion matrix

III.8. Conclusion

III.1. Introduction

In our work, we will adopt two primary approaches for picture classification: Developing a conventional convolutional neural network architecture, designated as Aut-Net, and incorporating the pre-trained VGG16 model .Three distinctive datasets will be used for preparation and testing. At that point assess the execution of the proposed models utilizing confusion matrices, which are important explanatory devices for understanding blunders and misclassifications in depth.

III.2. Model Of Training and Evaluation

Each dataset was divided into two sets: 80% training and 20% testing, which could be a common practice to evaluate models and dodge overfitting, all models were prepared for up to 30 preparing cycles, where a cycle represents one passes through the information to upgrade the model weights. A fixed batch size of 64 samples was moreover utilized per iteration, to guarantee computational productivity and the capacity to viably distinguish factual designs. This precise approach guarantees a organized, reliable with best hones in machine learning.

III.3. Data sets

In this work, we used three widely available datasets: the handwriting dataset [36], the color dataset [36], and the drawing dataset below; we combine the three datasets together to obtain better performance and improved results.

III.3.1. Coloring Dataset

The coloring dataset consists of a set of colored drawings of people with ASD and healthy people. These shapes consist of a circle, a triangle at the top, and a rectangle at the bottom, all drawn on a white sheet of paper.

The required task was for infected and healthy people to color geometric shapes. Then the samples were collected and stored in the form of JPG images.

Three groups of individuals were approved according to the age group from 3 to 6 years, from 6 to 9 years, and from 9 to 12 years.

- Healthy group: 189 people (males and females) aged between 3 and 12 years (average age 7.5 years).

- Patient group: 189 people (males and females) aged between 3 and 12 years (average age 7.5 years).

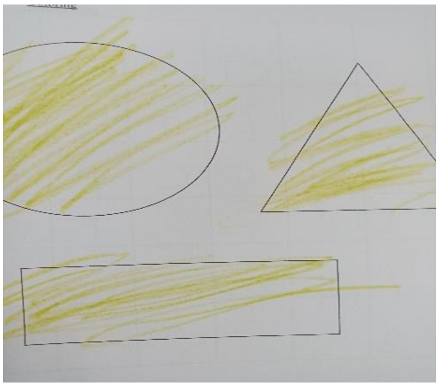

Figure III. 1. Images from the coloring data set of individuals with ASD

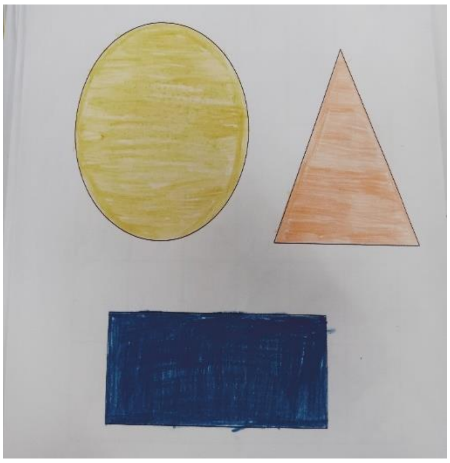

Figure III. 2. Images from the coloring data set of healthy individuals

As shown in Figure III.1 which shows the coloring process done before individuals were diagnosed with ASD, Figure III.2 shows images colored by healthy individuals.

Along with variances in age, living situation, educational attainment, and other social and environmental variables, there could be minor variations in each group member's health or the existence of certain recognized diseases.

III.3.2. The drawings dataset

Drawings of both healthy individuals and those with autism spectrum disorder are included in the drawing dataset. These drawings, which depict a variety of subjects, like flowers and trees, were all done on white paper.

Drawing was a necessary job for both healthy individuals and those with an ASD diagnosis. The samples were then gathered and saved as JPG files.

Age-wise, three groups of people were approved: those between the ages of three and six, six and nine, and nine and twelve.

Figure III. 3 Image from the drawing data set of individuals with ASD

- Healthy group: 189 people (males and females) aged between 3 and 12 years (average age 7.5 years).
- Patient group: 189 people (males and females) aged between 3 and 12 years (average age 7.5 years).

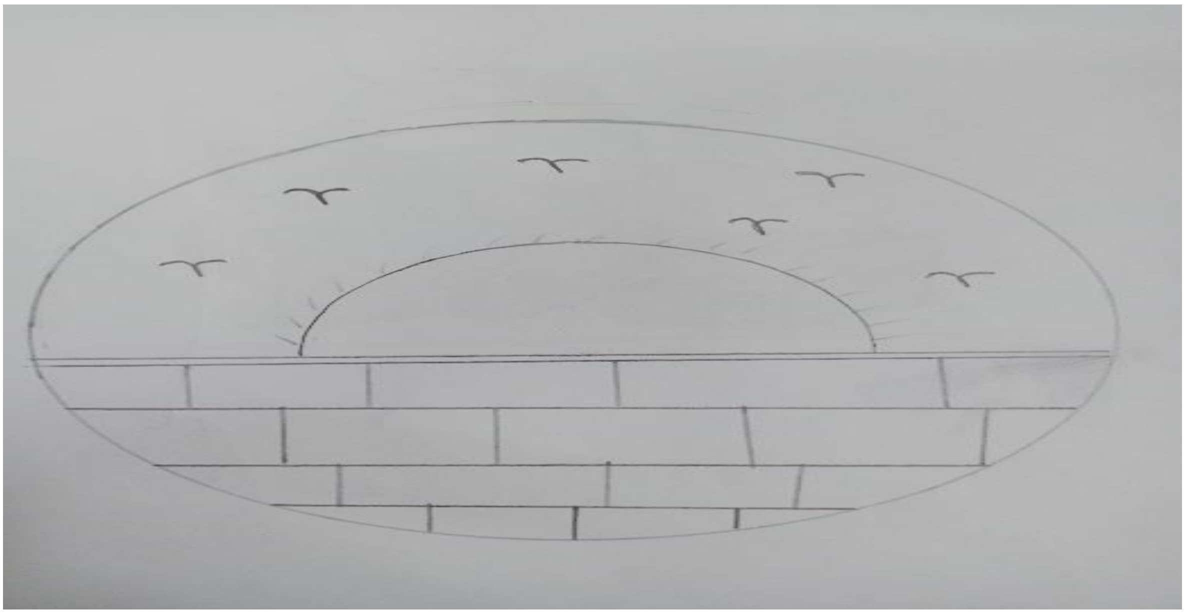

Figure III. 4 Image from the drawing data set of healthy individuals

Drawings by people with autism spectrum disorder are depicted in Figure III.3, whereas drawings by healthy people are shown in Figure III.4.

There may be minor variations in each group member's health or the existence of certain recognized diseases, in addition to variations in age, living arrangement, educational achievement, and other social and environmental factors.

III.3.3. The handwriting dataset

The handwriting dataset contains the handwriting of people with autism spectrum disorder as well as those who are healthy. These compositions were all done on white paper using a pen and pencil, and they show a range of things, including numbers, letters, and words.

For individuals without an ASD diagnosis as well as those in good health, handwriting was an essential task. After that, the samples were collected and stored as JPG files.

Three age groups were accepted: those between three and six, six and nine, and nine and twelve years old.

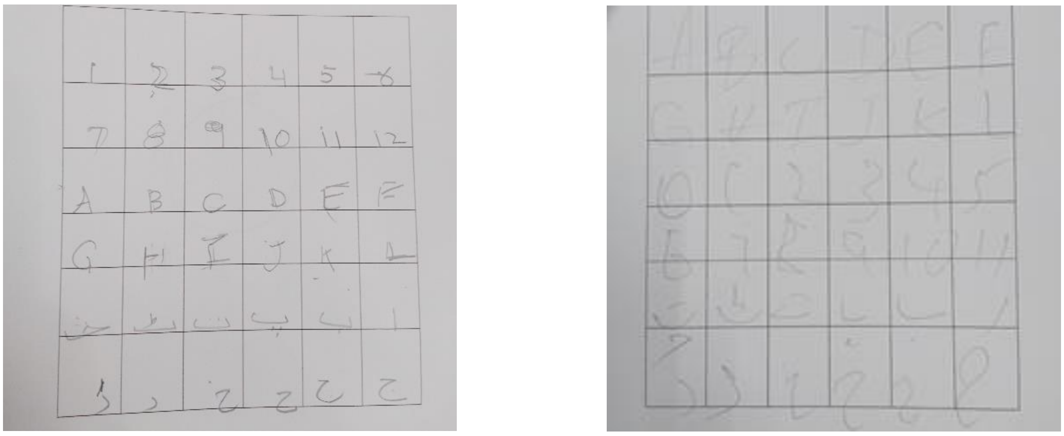

Figure III. 5 Images from the handwriting data set of individuals with ASD

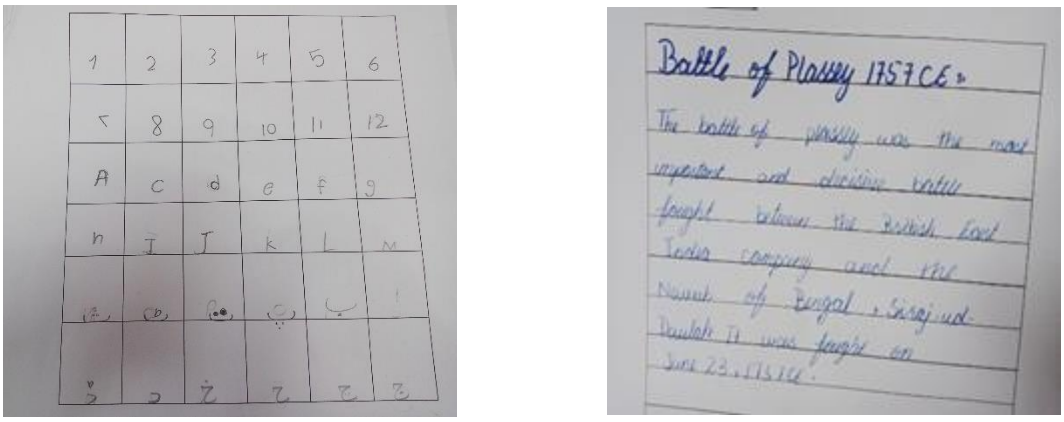

Figure III. 6 Images from the handwriting data set of healthy individuals

- Healthy group: 189 people (males and females) aged between 3 and 12 years (average age 7.5 years).

- Patient group: 189 people (males and females) aged between 3 and 12 years (average age 5- 7 years).

Figure III.5 shows writings by individuals with autism spectrum disorder, whereas Figure III.6 shows writings by healthy individuals.

Individual group members may differ somewhat in their level of health or in the presence of certain recognized diseases, in addition to differences in age, place of residence, level of education, and other social and environmental variables.

Then we used other type of dataset face recognition based on autistic and non-autistic children faces, it's contain three types:

III.3.4. Train dataset:

This dataset has different faces of children from both sex male and female with different ages it's contain: 1270 autistic and the same for non-autistic

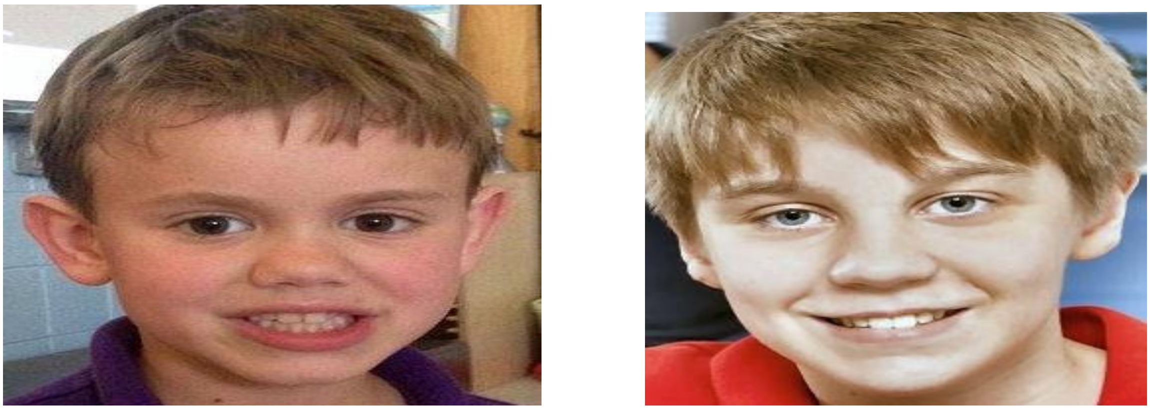

Figure III. 7 Images from the test data set of autistic children

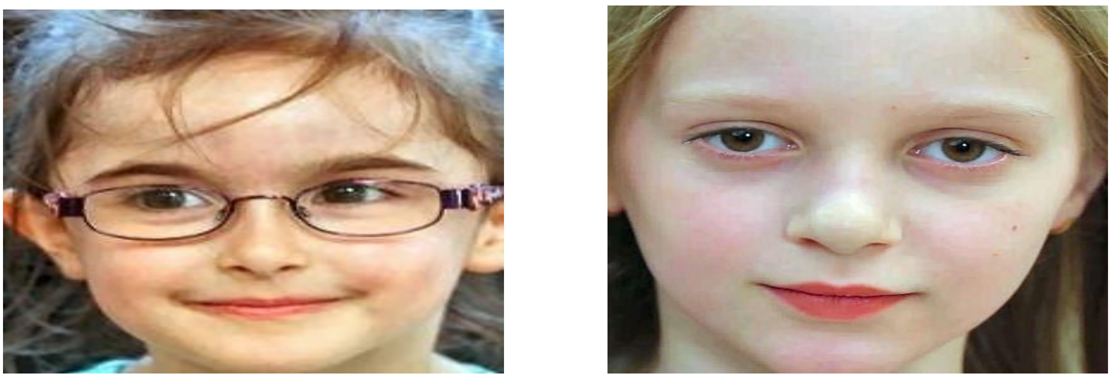

Figure III. 8 Images from the test data set of non -autistic children

III.3.5. Test dataset:

In This dataset we can find another different faces and different ages of children from both sex male and female it's contain:

150 autistic and the same for non-autistic

III.3.5. Valid dataset:

In This dataset we can find another different faces from the two dataset before of children from both sex male and female it's contain:

50 autistic and the same for non-autistic

III.4 Convolutional neural networks

III.4.1 Basic Concepts Neurons

Neurons are the fundamental building blocks of artificial neural networks, and they are a mathematical representation of real neurons in the human brain. An artificial neuron accepts inputs from other neurons or external data and generates an output by applying an activation function to the weighted sum of these inputs. [27]

Convolution:

Convolution is a mathematical procedure used in deep convolutional neural networks to extract characteristics from input like pictures and signals. To create a feature map, the convolution procedure moves a narrow window (filter) over the data and computes it at each place. This method enables the network to identify local patterns in pictures, such as edges and corners. [27]

III.4.2 Architecture Layers

Layers are the essential building elements of deep learning networks, with each network consisting of a series of interconnected layers. Each layer processes the previous layer's inputs using mathematical operations like convolution or full connection before passing the outputs to the next layer. Layers change in function and design depending on the kind of network and job. [27]

Pooling

Pooling is the technique of lowering the size of feature maps in deep learning networks by extracting the maximum or average value from specified parts of the map. This procedure reduces computational load while increasing the network's tolerance to tiny input changes. Max pooling and average pooling are two often used pooling algorithms. [27]

Activation Functions

Activation functions are mathematical functions used to neuron outputs to create non-linearity within the network. These functions enable the network to learn and articulate complicated connections in the data. The Rectified Linear Unit (ReLU), sigmoid function, and hyperbolic tangent function are some of the most prevalent activation functions. [27]

III.4.3 Training Loss Functions

Throughout the training process, loss functions are utilized to quantify the discrepancy between a neural network's actual and expected outputs. The network is being trained with the aim of minimizing the loss function's value as much as possible. For regression problems, the mean squared error is a typical loss function; for binary classification problems, the binary cross-entropy loss; and for multi-class classification problems, the categorical cross-entropy loss. [27]

Optimization Algorithms

Optimization algorithms are techniques for updating a neural network's weights during training with the purpose of reducing the loss function value. These methods compute the loss function's partial derivatives with respect to the weights, and then alter the weights in the opposite direction of these derivatives. Stochastic Gradient Descent (SGD), Adam, and Momentum are three common optimization techniques. [27]

III.4.4 Regularization Dropout

Dropout is a regularization approach that prevents overfitting in deep learning networks. This method works by randomly deleting and discarding neural units from the network throughout each training cycle. As a result, the network does not rely too much on any single brain unit, allowing it to function more broadly. Dropout is only used during training; all units stay active during testing. [28]

Batch Normalization

Batch normalization is another way for regularizing deep learning networks. This approach works by normalizing the inputs to each network layer so that they have a mean of zero and a variance of one. This improves the network's learning rate and stabilizes the input distribution, making training more consistent. Batch normalization is also beneficial for preventing gradient bursting and disappearing activations. [29]

III.4. 5 Applications Image Classification

CNNs may be used to assign a class label or category to an entire input picture, such as determining if the image comprises a dog, cat, automobile, and so on. They automatically learn key visual elements from picture data during training. [30]

Object Detection

In addition to classification, CNNs may be taught to detect and create bounding boxes around several items of interest in a single picture. [31]

Image Segmentation

CNNs can segment images pixel by pixel, splitting them into several segments or regions and categorizing each pixel as belonging to a certain item or location of interest. This creates a more exact mask for each item than simply bounding boxes. [32]

III.4.6 Challenges Overfitting

Overfitting is a significant difficulty in training deep learning networks. It happens when the network learns the training data too well and cannot generalize to new input. The problem might be a too complicated network design, inadequate training data, or a lack of appropriate regularization techniques. Overfitting may be reduced using strategies like dropout, batch normalization, early halting, and correct data partitioning. [33]

Vanishing/Exploding Gradients

Vanishing and ballooning gradients are a typical problem while training deep neural networks. This issue arises when the gradient values become too little or too big during the learning process, resulting in delayed or unstable learning. This issue might develop as a

result of inappropriate activation functions, network depth, or input variance. It may be avoided by employing proper activation functions and techniques like batch normalization, layer-wise training, and network reconfiguration. [34]

Computational Cost

Training deep learning networks necessitates a substantial amount of processing power, particularly when working with deep networks and huge datasets. This might result in significant expenses for purchasing strong computing gear, such as Graphics Processing Units (GPUs) or specialized chips designed to expedite deep learning tasks. Furthermore, training can be time-consuming, resulting in higher energy and operating expenses. This difficulty is addressed using strategies such as distributed training, layer-wise training, and network efficiency enhancements. [35]

III.5. Data preprocessing

Preprocessing is an essential stage in computer vision jobs because it gets the input data ready for the deep learning model to handle it efficiently. A variety of preprocessing techniques are used to improve the input data's quality and uniformity. Resizing is the process of uniformly adjusting an image's dimensions to a set size. Normalization is the process of scaling pixel values to a range, such as [0, 1] or [-1, 1], so that the dataset is scaled consistently. [36]

Preprocessing procedures are essential to ensure that the input data in CNN is consistent with the architecture of the model and to improve its performance. [37]

One well-known CNN model, the VGG16 architecture, was first presented by the University of Oxford's Visual Geometry Group. [38] Its first layers contain preprocessing processes. Usually, these procedures entail:

Color Space Conversion: assuming RGB color space for input pictures.

The preprocessing methods built into the model's architecture are utilized when preprocessing with VGG16; however, the preprocessing settings may vary depending on the particular implementation or pre-trained weights

Conv2D (2D Convolution) and MaxPooling2D (2D Max Pooling) are two crucial operations that are usually implemented in alternating layers across the network design. The Conv2D operation takes the input picture or feature maps from the previous layer and adds a collection of learnable filters (kernels) to it. By swiping these filters over the input data, the dot product between the input values at each spatial place and the filter is calculated. A feature map that highlights particular patterns or characteristics in the input data is the outcome of this procedure.

The network can recognize the same pattern at several spatial places since the filters are usually shared throughout the whole input and have tiny sizes (e.g., 3x3 or 5x5). [39]

The down sampling process MaxPooling2D lowers the feature maps' spatial dimensionality. The way it operates is by taking the maximum value in each of the non-overlapping rectangular sections that make up the input.

By lowering the number of parameters, this procedure helps to introduce translation invariance and lowers the network's computational cost. Pooling windows often come in two or three sizes, with a stride of the same number (e.g., a two-by-two window with a stride of 2) [40]. In CNN designs like VGG16, the Conv2D and MaxPooling2D layers are often arranged in an alternating manner. [38]

From the input data, the Conv2D layers extract progressively more complex features, while the MaxPooling2D layers down sample the feature maps and add spatial invariance. CNNs are useful for applications like object identification, semantic segmentation, and picture classification because of this mix of activities that enable them to efficiently learn hierarchical representations of the input data. [38]

III.6 Our Aut-net Architecture

Given the scarcity of relevant data on this topic, the identification of ASD through the examination of coloring, drawing, and handwriting. We present a simple neural network (CNN) model that uses Python's Keras package for deep learning. The model is intended for image classification problems, especially image categorization into two classes (binary classification). Here is a breakdown of the model architecture:

Convolutional Layers are constructed of three layers. The first layer comprises 32 3x3 filters with a ReLU activation function. It accepts input pictures of 224x224 pixels with three color channels (RGB).

The second convolutional layer has 64 3x3 filters with a ReLU activation function.

The third convolutional layer has 128 3x3 filters that use a ReLU activation algorithm.
Every convolutional layer is followed by a max-pooling layer with a window size of 2x2. Max-pooling layers are used to minimize the spatial dimensions of feature maps, thereby lowering computational complexity and introducing translation invariance.

The convolutional layers' multi-dimensional feature maps are transformed into a single flat vector by the flatten layer so that it may be sent to the fully connected layers.
The first completely linked (dense) layer contains 128 units with a ReLU activation function.
The last fully linked layer consists of two units, each with a SoftMax activation function, representing the two output classes.

The model is built using the Adam optimizer, the categorical cross-entropy loss function, and the accuracy metric.

Layer name	*Layer type*	*Size*	*Kernel size*	*Parameters*
Input	Input layer	224x224x3		
Conv1	Convolution 2D	244x244x32	3x3	896
Pool1	Max pooling 2D	112x112x32	2x2	
Conv2	Convolution 2D	112x112x64	3x3	18496
Pool2	Max pooling 2D	56x56x64	2x2	
Conv3	Convolution 2D	56x56x128	3x3	73856
Pool3	Max pooling 2D	28x28x128	2x2	
Flatten	Flatten layer	100352		
Dense1	Dense layer	128		12845184
Dense2	Dense layer	2		258

Table 2.Our Aut-net architecture in this work

III.7 ResNet

This architecture comprises convolutional layers followed by batch normalization and ReLU activation functions. Residual blocks, the key component of ResNet, consist of two convolutional layers with batch normalization and ReLU activation, along with skip connections to preserve input information.

The `build_resnet` function defines the ResNet model architecture, starting with an input layer for 220x220-pixel RGB images. It includes convolutional layers with batch normalization and ReLU activation, followed by max-pooling layers for down-sampling. Residual blocks, containing convolutional layers and skip connections, are then applied. The model ends with a global average pooling layer to aggregate spatial information and a dense layer with softmax activation for classification output. The use of batch normalization, ReLU activation, and skip connections helps in effective training of deep networks and preserving valuable input information.

Layer Name	**Layer Type**	**Size**	**Kernel Size**	**Parameters**
Input	**Input layer**	**220x220x3**	**-**	**-**
Conv1	**Convolution 2D**	**220x220x64**	**3x3**	**-**
BN1	**Batch Normalization**	**220x220x64**	**-**	**-**
ReLU1	**ReLU Activation**	**220x220x64**	**-**	**-**
Pool1	**Max Pooling 2D**	**110x110x64**	**2x2**	**-**
ResBlock1	**Residual Block**	**110x110x64**	**-**	**-**
Conv2	**Convolution 2D**	**110x110x64**	**3x3**	**-**
BN2	**Batch Normalization**	**110x110x64**	**-**	**-**
ReLU2	**ReLU Activation**	**110x110x64**	**-**	**-**
Conv3	**Convolution 2D**	**110x110x64**	**3x3**	**-**
BN3	**Batch Normalization**	**110x110x64**	**-**	**-**
SkipConn1	**Skip Connection**	**110x110x64**	**-**	**-**
ReLU3	**ReLU Activation**	**110x110x64**	**-**	**-**
ResBlock2	**Residual Block**	**110x110x128**	**-**	**-**
Conv4	**Convolution 2D**	**110x110x128**	**3x3**	**-**
BN4	**Batch Normalization**	**110x110x128**	**-**	**-**
ReLU4	**ReLU Activation**	**110x110x128**	**-**	**-**
Conv5	**Convolution 2D**	**110x110x128**	**3x3**	**-**

BN5	**Batch Normalization**	**110x110x128**	**-**	**-**
SkipConn2	**Skip Connection**	**110x110x128**	**-**	**-**
ReLU5	**ReLU Activation**	**110x110x128**	**-**	**-**
GAP	**Global Avg Pooling**	**1x1x128**	**-**	**-**
Dense	**Dense Layer**	**2**	**-**	**-**
SoftMax	**SoftMax Activation**	**2**	**-**	**-**

Table 3. ResNet Architecture Used in Our Work

III.8 VGG 16

We've opted to utilize the VGG16 convolutional neural network architecture for our picture categorization challenge. Simonyan and Zisserman introduced the VGG16 model\cite{simonyan2014very}, which has proved influential and effective in computer vision applications. It is well-known for its simplicity and efficacy, comprising a deep stack of convolutional layers, compact 3x3 filters, and maximum-pooling layers.

The model accepts input photos of size 224x224 pixels with three color channels (RGB). Despite its computational complexity, the model's depth enables it to extract increasingly abstract and discriminatory traits, adding to its outstanding performance. Using the strong and well-researched VGG16 architecture with the stated input size, we want to exploit its proven capabilities and build on a solid basis, perhaps leading to better ASD detection findings.

Layer name	*Layer type*	*Size*	*Kernel size*	*Parameters*
Input_1	Input layer	244x244x3	-	-
Block1_conv1	Convolution 2D	244x244x64	3x3	1792

Block1_conv2	Convolution 2D	112x112x 64	3x3	36928
Block1_pool	Max pooling 2D	112x112x 64	2x2	-
Block2_conv1	Convolution 2D	112x112x 128	3x3	73856
Block2_conv2	Convolution 2D	112x112x 128	3x3	147584
Block2_pool	Max pooling 2D	56x56x12 8	2x2	-
Block3_conv1	Convolution 2D	56x56x25 6	3x3	295168
Block3_conv2	Convolution 2D	56x56x25 6	3x3	590080
Block3_conv2	Convolution 2D	56x56x25 6	3x3	590080
Block3_pool	Max pooling 2D	28x28x25 6	2x2	-
Block4_conv1	Convolution 2D	28x28x51 2	3x3	1180160
Block4_conv2	Convolution 2D	28x28x51 2	3x3	2359808
Block4_conv3	Convolution 2D	28x28x51 2	3x3	2359808
Block4_pool	Max pooling 2D	14x14x51 2	2x2	-
Block5_conv1	Convolution 2D	14x14x51 2	3x3	2359808
Block5_conv2	Convolution 2D	14x14x51 2	3x3	2359808
Block5_conv3	Convolution 2D	14x14x51 2	3x3	2359808
Block5_pool	Max pooling 2D	7x7x512	2x2	-
flatten	Flatten layer	25088	-	-
Dense1	Dense layer	4096	-	102764544

Dense2	Dense layer	4096	-	16781312
Prediction	Output layer	1x1	-	4097

Table 4.VGG16 architecture used in our work

III.9 Confusion matrix

The confusion matrix, also known as the error matrix, is a table layout that allows for a convenient visualization of a model's performance, particularly in the context of supervised learning. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class, or vice versa.

Key terms related to the confusion matrix include:

- **Positives (P)**: the total number of Positives, which in the context of this work refers to autistic individuals. Alternatively: P=TP+FN
- **Negatives (N)**: the total number of Negatives, which in the context of this work refers to healthy individuals. Alternatively: N=TN+FP.
- **True Positives (TP)**: the number of positive examples that the model correctly classified as positive
- **True Negatives (TN)**: the number of negative examples that the model correctly classified as negative
- **False Positives (FP)**: the number of negative examples that the model incorrectly classified as positive
- **False Negatives (FN):** the number of positive examples that the model incorrectly classified as negative

While there are multiple data points that can be extracted from a confusion matrix, this work focuses on the following five:

➢ Sensitivity

Also known as Recall or TPR (short for True Positive Rate), it denotes all Real Positive cases. The best TPR is 1.0, while the worst is 0.0. It is defined as:

TPR=TP/P

- **Specificity**

Also known as Selectivity or TNR (short for True Negative Rate), its aim is to identify the proportion of Predicted Positive cases that are correctly Real Positives. Again, the best-case scenario is TNR = 1.0. It is defined as:

$TNR=TN/N$

- **Balanced Accuracy (ACCbal)**

Often abbreviated as ACCbal, it aims to identify the performance of a model regardless of data imbalance between the number of negatives and positives. It is defined as:

ACC"bal"=(TNR+TPR)/2

III.10 Conclusion

In this chapter, we have delved into various data preprocessing and training methods utilized in our work. Additionally, we have provided crucial insights into the datasets employed during the training process and the augmentations applied. Within the context of this thesis, we have discussed the concept of a ResNet model for image classification tasks, highlighting its architectural components such as residual blocks and skip connections.

Furthermore, we have explored the concept of fine-tuning a pre-existing and pre-trained VGG16 model, leveraging its deep architecture and proven capabilities for feature extraction.

Lastly, we have elucidated the significance of a confusion matrix and its role in our results acquisition, particularly in evaluating the performance of our trained models, including the ResNet and VGG16 architectures. All of this groundwork sets the stage for the upcoming chapter, which will showcase the experimental results obtained through our training methods and provide details on the execution environment where the model trainings took place.

Chapter 04: Experimental Results

IV.1. Introduction

In this chapter, we will delve into the execution environment utilized for our study, detailing both the hardware and software components. Additionally, we'll outline the specifics of our data splits, including sample numbers. Moving forward, we'll present the outcomes of our training phase, evaluating performance across four key metrics: Accuracy, Sensitivity, Specificity, and Balanced Accuracy. Subsequently, we will juxtapose our results with previous studies, providing a comprehensive state-of-the-art comparison.

This involves thorough analysis of the obtained results, followed by a meticulous comparison with findings from related works.

IV.2. Work Environment and tools

In this section, we'll explore the software and tools employed to construct our model.

IV.2.1. Hardware

Trainings were conducted on Google Colab's execution environment, which includes a Tesla T4 GPU, 16GB RAM, two threads on an Intel Xeon CPU, and 41GB cloud disk storage. GPU availability is limited.

IV.2.2. Software

The IDE we usually utilized was Google Colab's Notebook Manager. Tensorflow and Keras libraries version 2.8.0 are used in conjunction with Python 3.7.13. However, in the few occasions when we needed to employ a local execution environment, we used Anaconda Navigator (anaconda3) version 3.9.7 with Jupiter notebook version 6.4.8. In this situation, Tensorflow and Keras were both at version 2.6.0.

IV.3. Dataset split

In this study, we employed three datasets: coloring, drawing, and handwriting. In addition to the group formed by merging the three. As previously stated in Section, all experiments were conducted with an 80\% to 20\% dataset split for the training and validation sets, respectively. The table below displays the actual sample counts for each data set:

Datasets	*Training set*	*Validation set*	*Content*
Coloring	302	76	378
Drawings	302	76	378
Handwriting	302	76	378

Table 5.Sata Split

IV.4. Experimental results

When we worked on the Coloring dataset, the Aut-Net model displayed excellent learning skills. The Coloring dataset contains colored photos of children with autism spectrum disorder and other youngsters. After only 15 training cycles with a batch size of 32, the model achieved an astounding 98\% training and testing accuracy, as shown in the graph (Figure IV.1).

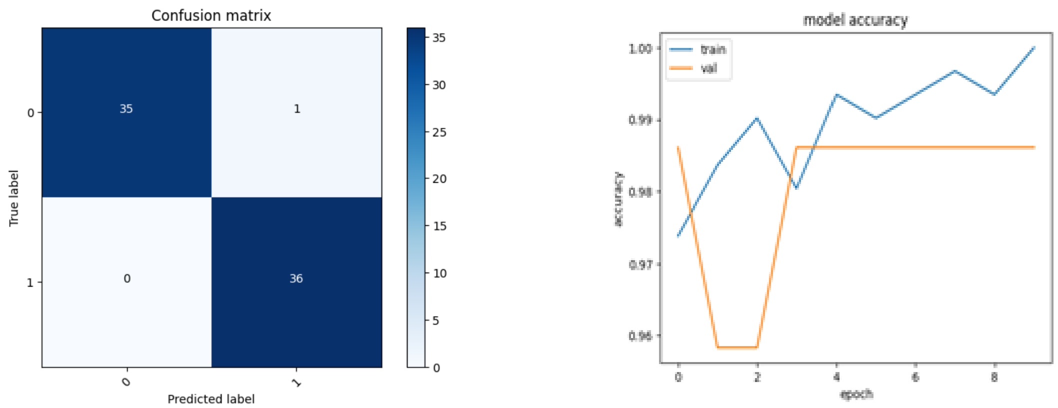

Figure IV. 1.Confusion matrix and accuracy graph of Aut-Net model with coloring dataset

This exceptional result indicates the model's superior ability to extract separate characteristics from color photos and reliably distinguish between the two groups.
Despite its strong performance, the Aut-Net model encountered new obstacles when trained on the Drawing dataset. According to the graph (Figure IV.2), we achieved a maximum training accuracy of 83\% and a maximum test accuracy of 82\% after 15 runs with a batch size of 64.

Although these findings are good, they are much lower than the spectacular results obtained with the Coloring data.

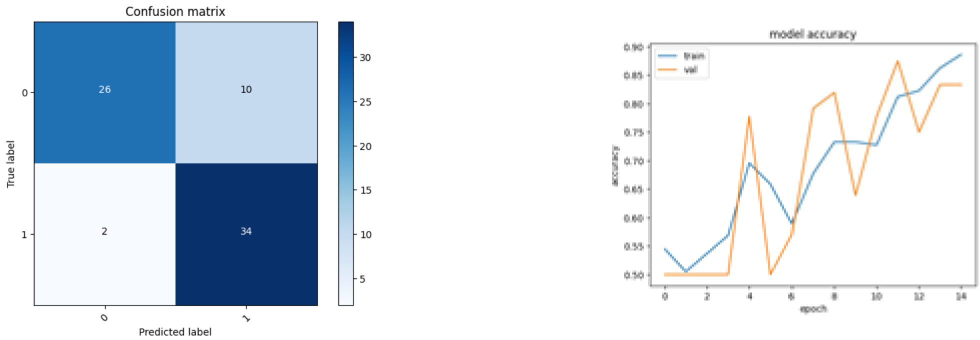

Figure IV. 2 Confusion matrix and accuracy graph of Aut-Net model with drawing dataset

This might be due to the images' simplicity and lack of diversity, which makes it difficult for the model to extract enough distinguishing characteristics to properly discriminate between the two classes, despite the model's high score.

In the CNN experiment on the handwritten dataset, the model exhibited its capacity to learn successfully from handwritten data. After 15 training cycles with a batch size of 32, the model had a training accuracy of 93\%, as indicated in (Figure IV.3).

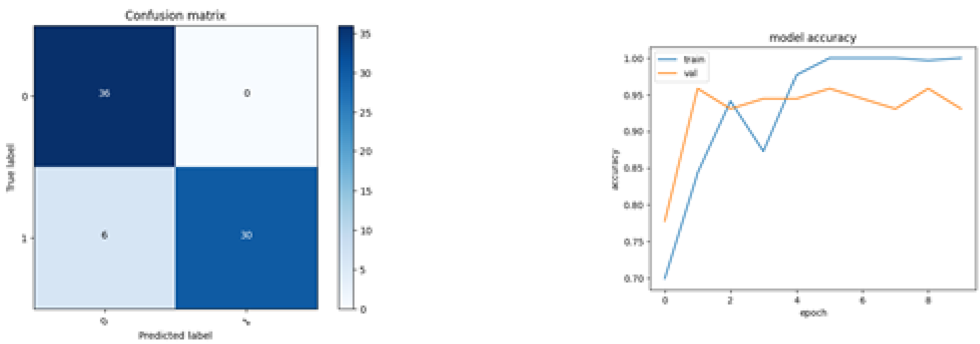

Figure IV.3 Confusion matrix and accuracy graph of Aut-Net model with handwriting dataset

Although this result falls short of the Coloring dataset's excellent results, it is still very accurate and demonstrates the model's ability to extract discrete characteristics from handwriting samples and efficiently distinguish between the two groups.

This amazing achievement demonstrates the Aut-Net model's ability to extract discrete characteristics from multiple datasets and use them to accurately diagnose autism spectrum disorder.

Comparing the model's performance across multiple datasets reveals that color photos are a rich source of distinguishing characteristics, with the model performing best on this collection. However, the model demonstrated a strong capacity to learn from basic drawings and handwriting, making it a useful option for a variety of diagnostic tasks.

In the VGG16 experiment on the Coloring dataset, the pre-trained VGG16 model was rotated over color pictures. As demonstrated in the graph (Figure IV.4), the model obtained a high training accuracy of 97\% after just 10 training cycles with a batch size of 64. This outstanding performance illustrates the VGG16 model's great capacity to learn from color images and successfully extract different characteristics in order to discriminate between the two categories with high accuracy.

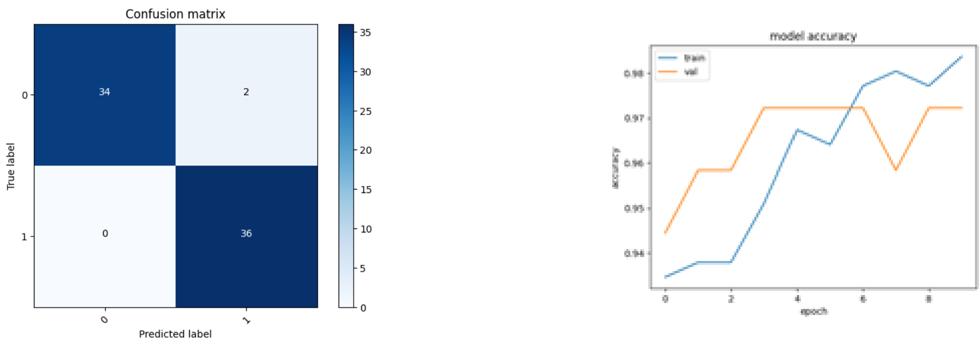

Figure IV. 4 Confusion matrix and accuracy graph of VGg16 model with coloring dataset

A comparable experiment on the Drawing dataset revealed that the VGG16 model performed exceptionally well. Following 10 training cycles with a batch size of 64, the model obtained an amazing training accuracy of 98\%, as seen in (Figure IV.5). This excellent result even exceeds the model's performance on the Coloring dataset, demonstrating the VGG16 model's extraordinary ability to learn from basic drawings and extract their distinguishing characteristics with high accuracy.

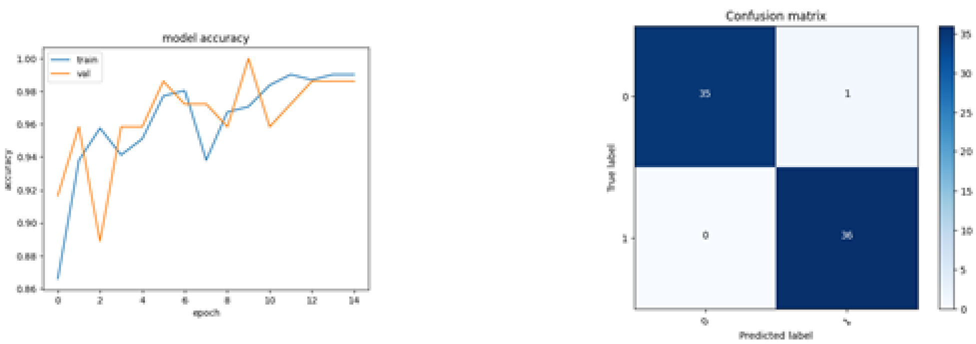

Figure IV.5 Confusion matrix and accuracy graph of VGg16 model with drawings dataset

When trained on the HandWriting dataset, the VGG16 model encountered several difficulties even though it had demonstrated exceptional performance on earlier sets.
(Figure IV.6) illustrates that the model reached a training accuracy of 93\% after 15 training cycles with a batch size of 64. While this accuracy is still rather high, it is not as high as it has been on earlier sets, and the loss value has increased to 40\%, suggesting that learning from handwriting examples is now more challenging.

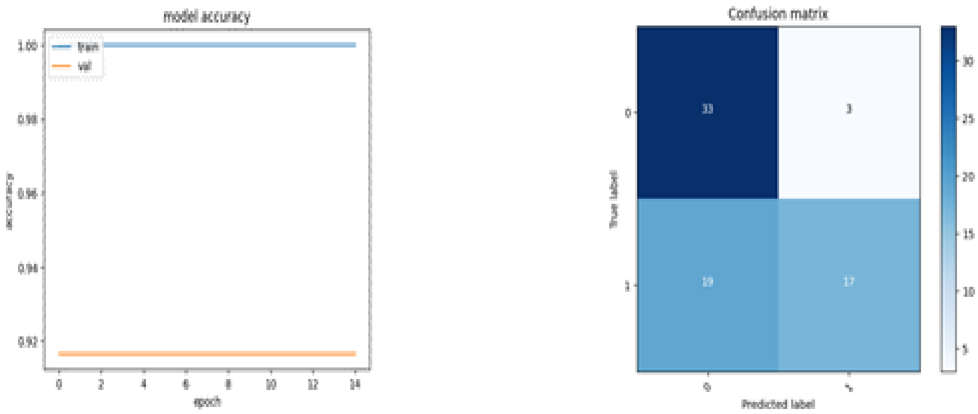

Figure IV.6 Confusion matrix and accuracy graph of VGgg16 model with handwritings dataset

The VGG16 model performed best on basic graphics and color picture sets, where it was able to extract discrete features with very high accuracy, when the model's performance was compared across different datasets. Nevertheless, the handwriting dataset presented several difficulties, maybe as a result of its complexity and great variation.

Aut-Net	Epoch	Batch size	Acc(%)	Loss(%)
Coloring	5	32	87	10
	5	64	88	12
	10	32	91	11
	10	64	96	9
	15	32	98	7
	15	64	94	6
	20	32	89	11
	20	64	87	10
Drawing	5	32	75	14
	5	64	77	16
	10	32	79	15
	10	64	80	13
	15	32	82	16
	15	64	83	14
	20	32	81	17
	20	64	78	18

HandWriting	5	32	87	15
	5	64	87	13
	10	32	86	11
	10	64	90	12
	15	32	93	12
	15	64	92	14
	20	32	89	11
	20	64	88	13

Table 6. Aut-Net accuracy and loss result (hand-writing dataset)

VGG 16	Epoch	Batch size	Acc(%)	Loss(%)
Coloring	5	32	89	10
	5	64	93	12
	10	32	95	11
	10	64	97	8
	15	32	97	10
	15	64	95	9
	20	32	93	11
	20	64	87	9
Drawing	5	32	75	12
	5	64	77	16
	10	32	79	15
	10	64	98	10
	15	32	82	10
	15	64	83	13
	20	32	81	11
	20	64	78	14
HandWriting	5	32	87	38
	5	64	86	40
	10	32	91	37
	10	64	93	40
	15	32	91	41
	15	64	92	37
	20	32	89	35
	20	64	90	44

Table 7. VGG16 accuracy and loss result (hand-writing dataset)

Res-net		
Epoch	Batch size	Acc(%)
10	**32**	**72**
10	**64**	**63**
10	**128**	**73**
20	**32**	**76**
20	**64**	**77**
20	**128**	**68**
30	**32**	**75**
30	**64**	**77**
30	**128**	**73**

Table 8. Res-Net accuracy result (Face- reconnisation dataset)

IV.5. Comparison of Aut-Net, VGG16, and Res-Net:

In the **handwriting, coloring, and drawing datasets**, both Aut-Net and VGG16 exhibited strong performance, with notable distinctions in their capabilities:

- **Color Dataset**:
  - Aut-Net achieved a remarkable 98% training accuracy, slightly surpassing VGG16's 97%.
- **Drawing Dataset**:
  - VGG16 demonstrated a substantial lead, boasting a 98% accuracy compared to Aut-Net's 83%.
- **Handwriting Dataset**:
  - Aut-Net maintained a marginal lead with 94% accuracy, while VGG16 struggled with a high loss of 40%.

These results underscore Aut-Net's efficiency in handling complex data patterns and VGG16's prowess in capturing fine details from simplistic images.

For the **face-recognition dataset**, Res-Net demonstrated varied performance across different batch sizes so we Achieved up to 77% accuracy, with variability depending on batch size.

Overall, Aut-Net excels in handling complex patterns, particularly in handwriting and coloring tasks, while VGG16 is particularly strong in capturing fine details from simplistic images such as drawings.

IV.6. Comparison with the stat of art results:

If we compare our results with those in the state of art, we find that the results obtained are similar to the studies, especially for handwriting datasets. We found that when studying some works within this field, different results were recorded, some of which were acceptable (76.2%) and (79.7%), and some of them were very high, such as obtaining (93.10%) or 98%, and sometimes even 100% in one of the studies. Our study is done by using various artificial intelligence methods. We conclude that the study achieved acceptable and different results, and this difference is due to two basic factors: the type and quality of the dataset adopted in the study, in addition to the differences in the approved learning models and even their application methods during study and experimentation.

Study of State of Art	Simular Dataset Used	Our Study	State of Art Accuracy (%)	Our Accuracy (%)
Handwriting-Based ADHD Detection for Children Having ASD Using Machine Learning Approaches	Handwriting	VGG16 (Transfer learning)	93.10	93.00
CNN-Based	Handwritten	VGG16	98.00	93.00

Handwriting Analysis for the Prediction of Autism Spectrum Disorder		**(Transfer learning)**		

Table 9. Comparison between Accuracy Results on simular used Dataset in our workand results from stat of art

Result:

Based on the results shown in ***table 7***, we can summarize our work's performance in comparison to other studies in the domain of handwriting analysis for autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) detection as follows:

For the task of handwriting-based ADHD detection in children with ASD, our work achieved comparable accuracy to the state-of-the-art results.

However, for the task of ASD prediction using handwritten data, our work fell short of the state-of-the-art accuracy of those studies .

In essence, our work demonstrates competitive performance while highlighting the need for further improvement to reach state-of-the-art levels in the other task within this domain.

IV.7. Conclusion

In this study, we compared the performance of Aut-Net, VGG16 and Res-Net across various datasets for autism spectrum disorder (ASD) identification and face recognition. For ASD identification, Aut-Net achieved 98% training accuracy on the Handwriting dataset, while VGG16 outperformed with 98% accuracy on the Drawing dataset, and up to 77% accuracy achieved by Res-Net in facial recognition .All models showed efficiency on the Coloring dataset, with Aut-Net slightly surpassing VGG16 with 98% accuracy compared to 97%.In face recognition dataset, outperforming Res-Net achieved up to 77% accuracy, with variability depending on batch size. Overall, Aut-Net shows promise in exploiting picture characteristics for ASD detection, while VGG16 excels in capturing fine details from drawings compared to Res-Net . These findings provide valuable insights for the application of these models in ASD identification and face recognition tasks.

IV.8. Future trends:

Emerging AI techniques offer promising directions for advancing ASD research:

. **Generative AI models** for data augmentation and synthetic data generation to address data scarcity and improve model generalization.

. **Self-supervised learning** to learn meaningful representations from unlabeled data, capturing subtle ASD-relevant patterns.

. **Transformer-based models and attention mechanisms** for effective multimodal ASD analysis by fusing information from different data sources.

. **Federated learning and privacy-preserving AI** to facilitate collaborative research while ensuring data privacy and security.

. **Explainable AI techniques (XAI)** to provide insights into model decision-making, enabling better interpretability and trust in ASD predictions.

. **Ethical AI practices** prioritizing fairness, accountability, and transparency in the development and deployment of AI models for ASD.

By leveraging these cutting-edge AI approaches, future studies can push boundaries, developing more accurate, interpretable, and ethical solutions for early ASD detection, diagnosis, and support.

General Conclusion

General Conclusion

This thesis introduces an innovative AI-driven solution that utilizes advanced machine learning techniques to analyse handwriting, coloring, drawing, and face recognition dataset, aiming for precise diagnosis and treatment of autism spectrum disorders (ASD). The primary contributions include developing a tailored convolutional neural network (Aut-Net) for processing ASD data like handwriting, coloring, and drawings, proposing novel feature extraction and pattern recognition techniques from these data sources. It explores transfer learning by fine-tuning VGG16 on ASD datasets, as well as integrating Aut-Net. For face recognition, ResNet's performance is evaluated on face recognition datasets, while Aut-Net and VGG16 are applied to drawing, handwriting, and coloring datasets.

The thesis covers theoretical concepts of ASD, machine/deep learning, and computer vision techniques, discussing the neurological basis of ASD, cognitive/behavioral manifestations, and current diagnostic criteria to highlight the need for more objective assessment methods. It conducts a comprehensive review of AI-based methods for ASD diagnosis and treatment, analyzing algorithms, techniques, and data modalities used in previous studies.

Experimental results show Aut-Net achieved 94% accuracy on handwriting, VGG16 98% on drawing, with both models showing efficiency on coloring, while ResNet achieved up to 77% accuracy on face recognition.

The research explored future directions that include explainable AI (XAI) methodologies and other innovative techniques for analyzing ASD, which provide a deeper understanding by clarifying how AI models make decisions. These technologies accelerate discovering new solutions by revealing specific features and patterns associated with an ASD diagnosis. Providing insights like these allows XAI and others to achieve superior precision in ASD research more quickly and efficiently. Integrating cutting-edge technologies shows promise for advancing accurate ASD detection and diagnosis.

The thesis emphasizes developing AI solutions to impact understanding and approaches to ASD, enabling early and accurate diagnosis for timely, tailored interventions to improve outcomes and quality of life. While significant progress is made, further research is needed, with promising directions outlined like multimodal data fusion, longitudinal data incorporation, and personalized treatment recommendation systems. Interdisciplinary collaboration involving neuroscience, psychology, and education experts is stressed for a comprehensive, holistic approach to ASD research and treatment.

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