Cloud-Powered Advanced Autism Detection and Curriculum

A major project report submitted in partial fulfillment of the requirement for the award of degree of

Bachelor of Technology

in

Computer Science & Engineering / Information Technology

Submitted by

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CERTIFICATION

This is to certify that the work which is being presented in the project report titled "**Cloud-Powered Advanced Autism Detection and Curriculum**" in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering and submitted to the Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat, is an authentic record of work carried out by "Angel Singh 201317" and "Anshaj Dharmani 201424" during the period from August 2023 to May 2024 under the supervision of Dr. Hari Singh Rawat, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

Angel Singh	Anshaj Dharmani
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The above statement is correct to the best of my knowledge.

Dr. Hari Singh Rawat

Assistant Professor (SG)

Department of Computer Science & Engineering/ Information Technology

Jaypee University of Information Technology

15th, May, 2024

CANDIDATE'S DECLARATION

We hereby declare that the work presented in this report entitled **'Cloud-Powered Advanced Autism Detection and Curriculum'** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering/Information Technology** submitted in the Department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from August 2023 to May 2024 under the supervision of **Dr. Hari Singh Rawat** (Assistant Professor (SG), Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

(Student Signature with Date)	(Student Signature with Date)
Student Name: Angel Singh	Student Name: Anshaj Dharmani
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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

(Supervisor Signature with Date)

Supervisor Name: Dr. Hari Singh Rawat

Designation: Assistant Professor (SG)

Department: CSE/IT

Dated: 15^{th}, May, 2024.

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Angel Singh (201317) & Anshaj Dharmani(201424)

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ABSTRACT

Autism spectrum disorder (ASD) is a neurodevelopment phenomenon having multiple symptoms with the challenge of socialization as one of them including thinking, movement, and social condition. Different from most of the medical conditions which may be accompanied by standard diagnostic criteria set, ASD is outstanding in this respect. Medication solution is not an answer instead brain rehabilitation skills will aid in brain performance development and any other development needed.

The diagnosis Autism Spectrum Disorder (ASD) seems to be multifaceted as a consequence of the lack of a particular medical test and the process of observation through external indicators fluid and critical behavioral pattern and developmental path of the child. Rather than just perceive humans, we take into account other features like age, gender, and ethnicity. The non-invasive biomarker will help in early ASD diagnosis as a novel and hopeful field. Faces reflect the brain through their own processes; thus, their emergence made them perfect tools for diagnoses in clinical health. Integrating cutting-edge neural networks used as a tool in this process of diagnosis is also as important.

Unlike coefficients, neural networks whose functionality is to handle, are less appreciated, however, it requires that they are trained via deep learning on image datasets, and they use extensive mathematical operations like derivatives, convolutions, matrix manipulations during training and so on. We used facial images that underline neural network structure including VGG19, ResNet50V2, ResNet-200, InceptionV3, MobileNetV2 and CNN. The purpose of our study is to classify the ASD as well as to use the facial images, and therefore it is necessary to employ a high-standard classification procedure, testing has been done using different key indicators, such as accuracy, precision, recall, execution time and wall time. However, the strategies we proposed constantly beat ordinary methods showing that they are good alternatives and improve efficacy of our approach.

The implications are substantial; our refined model promises to support healthcare professionals in streamlining ASD screenings, aiding in accurate and timely diagnoses for improved patient outcomes.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Autism Spectrum Disorder (ASD) is a complication that disrupts individual's daily communication [1]. Autistic person often only experience minor impairments, however, sometimes they may need special care. Individuals with ASD usually have problems in communicating; therefore, they will have trouble expressing themselves through words, gestures, or facial expressions and as a result, they will have limited interaction with others. [2] The medical experts could diagnose the ASD patients from the abnormal neurological changes produced by ASD. In the absence of prescribed therapies, early diagnosis may bring forth some degree of change into the individual’s lifestyle. Such flexibility of the brain during the development, early diagnosis of ASD symptoms can be a reason of improvement in social life of children with this disorder. Variations in ASD arise from polygenic nature, which means the interaction of human genes is the genetic cause of such kind of disorder [3]. There is no special medicine for autism spectrum disorder. Nevertheless, the aim of these methods is to minimize difficulties, improve cognitive capability, everyday living abilities as well as ASD patients’ condition in order to increase their functionality. The experts usually carry out the first and basic method, which is interview based, where the patients are checked with the help of different questionnaire protocols, such as:

ADOS-2, ADI-R, CARS, Q-CHAT, or AQ-10 [4]. These techniques are simple, truthful, and thus contribute to an accurate diagnosis. This type of methods primarily suffers from biasness like a physician’s competency, skills, and timeliness. On top of that, the participants’ parents or the attendant might never give accurate information or fill out the forms correctly. Both of these factors can affect the accuracy of diagnosis ASD interviews.

Although there are enough tools for the diagnosis of ASD patients, below are a few primary reasons for late detection. Although there are enough tools for the diagnosis of ASD patients, below are a few primary reasons for late detection:

• ASD diagnosis is mostly applied via interactive sessions with an aged of toddlers around two years old. It thereby requires a diagnosed to be performed by clinical experts.

• It's not easy for a parent to get involved with specialists; so the number of doctors accessible in areas like rural or developing countries is a lot less.

• Parents who do not have any knowledge of and are uninformed of ASD diseases would not typically think about the growth concerns of their kids by considering it a disease.

• Furthermore, students from racial or ethnic minority heritage that are given an initial examination are also less likely to have a secondary, extensive medical examination because of the high cost of the machine and personnel that are required for these tests, that will recognize the condition to be true or not. [5].

For this reason, a low cost tool that can be used by non experts is required for quick primary screening which does not heavily depend on experts or formal pathological tests. The method must be low in cost, reliable, efficient, and saving time and resources as well. In this context, actively detecting ASD among the children using facial images won't require a user interaction—maybe via an website or phone application—thus, very convenient. Therefore, the point of this work is to demonstrate the power and accuracy of the method due to the right data selection and performance scores. The face is a precious human biomarker because the nervous system that extends to the brain collects and processes information from the different elements of the face directly. The capability of distinguishing emotions that occur with different facial expressions is a major feature that can disclose brain asymmetry or neurodevelopment abnormalities [6].

Detecting ASD by facial expressions is still at its infancy stage and researchers are striving to develop feasibility studies and produce suitable algorithms. As patients are different, facial recognition remains as the most accurate way to diagnose a condition. A group of scientists from the University of Missouri found that children with the diagnosis of autism have specific facial features, such as the wide upper face, for instance with wide-set eyes. This is the way that usually they have a shorter middle region like the cheeks and the nose that differs from the children who do not have this syndrome.[7]

Fig 1: A child suffering with Autism spectrum disorder (ASD) [45]

The use of facial characteristics in diagnosing ASD is a fast-developing field of research that is valued so much in developing countries due to the social impact on them. In the early detection of ASD the method can play an important role in the primary screening that determines the ASD and normal child. New studies prove that a convolutional neural network could be used for various disease detection [8,9,10,11]. One of the most impressive characteristic of CNN is its automatic feature extraction capability through the large amount of image data. This attribute is the main reason that CNNs are known as the feature extractor, which is frequently used in object detection or image classification tasks. Even though CNNs are incredibly fast, accurate training is quite time-consuming and resource-intensive. As opposed to starting from scratch, it is even more convenient to utilize pre-trained models which have already been developed using supercomputers and huge datasets. Transfer learning is a concept where the existing pre-trained models serve as the foundation to modify the final output based on the target set of tasks, which in turn leads to better classification or prediction accuracy [12].

On the other hand a majority of the suggested CNN models use higher number of hyper parameters, hence the overall computational time gets higher and such models are not practical for the datasets of different size. A further issue was that the models were being questioned on accuracy, as the models were not always working well on noisy datasets where the results are usually offered without statistical measurements. Hence, a CNN architecture should be established that can diagnose ASD with minimum hyper parameters, thus, this can accelerate the development of the efficient CNN-based ASD diagnostic model. Reviewing this solution, 2D facial images and ready-to-use deep learning models will be used to diagnose early ASDs. The transfer learning method involves extracting features from our images and we use the publicly available Kaggle dataset.

1.2 PROBLEM STATEMENT

This project addresses the pressing need for early detection and tailored interventions for individuals with autism, a complex neurological condition which if not diagnosed on time will cause lifelong impacts on the lives of an entire family. The existing diagnostic methods, often relying on subjective evaluations, result in delays in diagnosis and subsequent interventions.

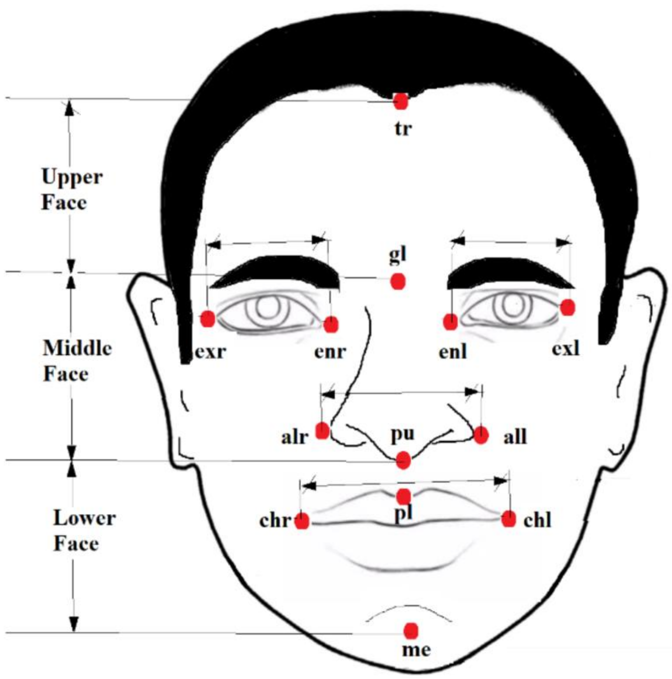

Fig 1.2 The identification features of an individual suffering with Autism.[46]

Autism detection via image categorization using convolutional neural networks (CNNs) is a difficult and essential subject that has received a lot of attention in recent years. One of the most significant barriers to developing an accurate CNN model for autism detection is a lack of access to high-quality data. A significant amount of different data must be collected in order to train a CNN model for autism identification. But getting large and varied datasets for autism detection is challenging because it necessitates getting permission from people and their families and making sure the data is properly labeled. Being a complex disorder with a wide range of symptoms, autism is challenging to accurately diagnose. The CNN model must be able to recognize tiny visual variations in images suggestive of autism and separate them from other disorders with a similar presentation. Despite numerous research efforts, the exact cause of autism remains poorly understood.

Collaborative research efforts are necessary to better understand the cause of this condition, develop effective treatments, and improve patient outcomes.

Furthermore, the educational landscape for individuals with autism lacks personalized solutions that accommodate their unique learning patterns. To overcome these challenges, this initiative proposes a comprehensive approach integrating advanced technology and cloud computing. The multi-phased strategy involves the collection and annotation of a diverse dataset encompassing visual and behavioral markers associated with autism. Expert annotations ensure the accuracy of the dataset, which serves as the foundation for the development of a state-of-the-art. This model aims to accurately identify autism-related visual patterns in images, facilitating early detection. Leveraging AWS's cloud infrastructure, the project also introduces a cloud-powered curriculum dynamically adapting educational content to align with individual learning styles and developmental stages. The potential impact is vast, with early detection enabling timely interventions and support.

The cloud-powered curriculum promises to cater to the unique cognitive profiles and learning needs of individuals with autism, significantly enhancing their educational experiences. Moreover, the fusion of CNN technology and cloud computing contributes to scientific progress in artificial intelligence and neuroscience. The "Cloud-Powered Advanced Autism Detection and Curriculum" project, driven by a commitment to technological innovation and societal responsibility, seeks to bridge the gap between autism detection and education. Through the deployment of advanced technology, the initiative aspires to usher in early interventions and enriched learning experiences, embodying values of inclusivity, innovation, and transformative change to foster a more empathetic and technologically advanced society.

1.3 OBJECTIVES

The major objective of this Project is to help detect and cure autism through whatever is possible via technology. The primary objective is improving strategies for early screening and diagnosis, identifying and characterizing autism susceptibility genes, understanding the neuropathology of autism and autism-related behaviors.

1) Develop a Precise Autism Detection Model using Convolutional Neural Networks (CNN) and use pre-trained models to compare and contrast the proposed model's performance:

The first objective of the project is to collect and preprocess a dataset of images of various individuals to classify them into "Autistic" and "Non-Autistic". For the CNN model to be accurate the data collection is a very necessary step.

This objective includes the steps below:

Data Collection and Preprocessing< Data Annotation< Model Architecture Selection< Model Training< Performance Evaluation < OUTCOME: A well-trained CNN model

● Gather the dataset of various individuals to classify them into "Autistic" and "Non-Autistic"

● Ensuring the dataset is appropriately labeled for the CNN model training process, then using these pre- grained models: VGG19, ResNet50V2, ResNet-200, InceptionV3, MobileNetV2 and CNN, to check the performance of our model.

2) Design and Implement a Cloud-Powered Personalized Curriculum on AWS: This curriculum will leverage Amazon Web Services (AWS) to dynamically adapt content based on learners' progress and cognitive profiles. In order to accomplish this, the CNN model will include numerous convolution, pooling, and fully connected layers that examine the images for distinctive features and patterns connected with the study. We will be using ResNet50 along with transfer learning for the same and then getting the desired results. The following steps are part of this objective:

Curriculum Content Development < Curriculum Digitization < AWS Infrastructure Setup < User Profiling < Adaptive Content Delivery < Real-time Feedback< OUTCOME: an adaptive and cloud-powered curriculum accessible via AWS

3) Conduct Comprehensive Validation and Impact Assessment: Comprehensive validation will involve evaluating the accuracy of the detection model and assessing the curriculum's impact on the learning outcomes and well-being of individuals with autism.

Model Validation< Curriculum Impact Assessment< Long-term Monitoring< Feedback Integration< OUTCOME: a comprehensive validation report that demonstrates the accuracy of the detection model and the positive impact of the cloud-powered curriculum on individuals with autism

4) Performance evaluation:

To evaluate the performance of the CNN model we use various metrices.

In this work, we observed and justified corresponding results considering some evaluation metrics such as accuracy, area under the curve (AUC), f-measure, g-mean, sensitivity, specificity, fall-out and miss rate. These metrics are calculated using true positive (*TP*), true negative (*TN*), false positive (*FP*) and false negative (*FN*), which are defined as follows:

- **Accuracy Accuracy:** Accuracy is a metric used to evaluate the overall correctness of a model's predictions. It measures the proportion of correct predictions made by the model among all predictions made. The formula for accuracy is

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)}$$

- **Precision:** Precision is a metric that focuses on the model's ability to avoid false positives. It measures the proportion of true positive predictions among all positive predictions made by the model. The formula for precision is

$$Precision = \frac{TP}{(TP + FP)}$$

- **Recall (Sensitivity or True Positive Rate):** Recall is a metric that focuses on the model's ability to capture all positive instances and minimize false negatives. It measures the proportion of true positive predictions among all actual positive instances in the dataset. The formula for recall is

$$Recall = \frac{TP}{(TP + FN)}$$

Where the meaning of the symbols are given below along with how we have mapped them with the same:

• True Positive (TP) = Children who are autistic and are predicted to be autistic;

• True Negative (TN) = Children who are Non-autistic and are predicted to be Non-autistic;

• False Positive (FP) = Children who are Non-autistic and are predicted to be autistic;

• False Negative (FN) = Children who are autistic and are predicted to be non-autistic;

1.4 SIGNIFICANCE/MOTIVATION OF PROJECT WORK

The detection and classification of individuals suffering from Autism Spectrum Disorder through mere judgment basis like most people is a wrong way of diagnosis, this heavily relies on human judgment and alters various results mostly by denial. It is very obvious that a parent will not have the correct judgment to whether the child is suffering with this condition or not since it is very hard to detect this condition at early stages but if we do the proper diagnosis they can be treated and they can also lead a healthy life.

With the help of powerful deep learning algorithms and advanced technology, automated systems can help to identify and classify such individuals at an early stage and make their life easier, the detection process is done quickly and accurately, potentially improving patient outcomes and saving valuable time and resources.

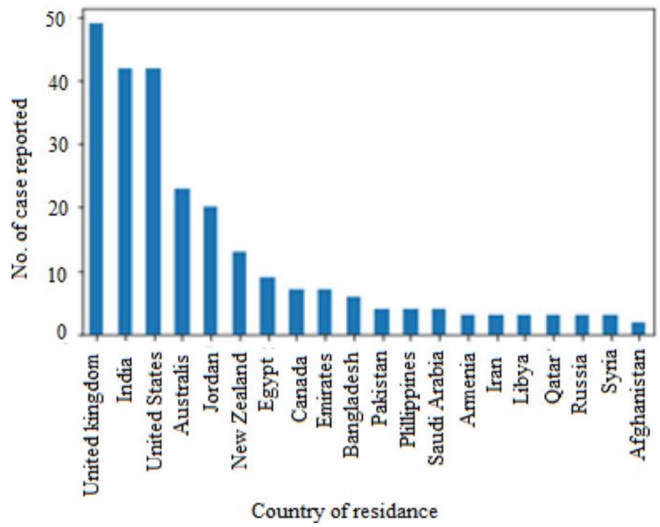

Fig 1.4.1 Showing the number of cases reported across various locations [46]

Moreover, CNNs can help identify potential biomarkers for ASD. These biomarkers could be used to improve our understanding of the underlying mechanisms of ASD, leading to the development of more effective treatments and interventions. Thanks to advances in technology and the availability of powerful deep learning algorithms, medical image analysis can now be automated for various applications, including Autism Detection.

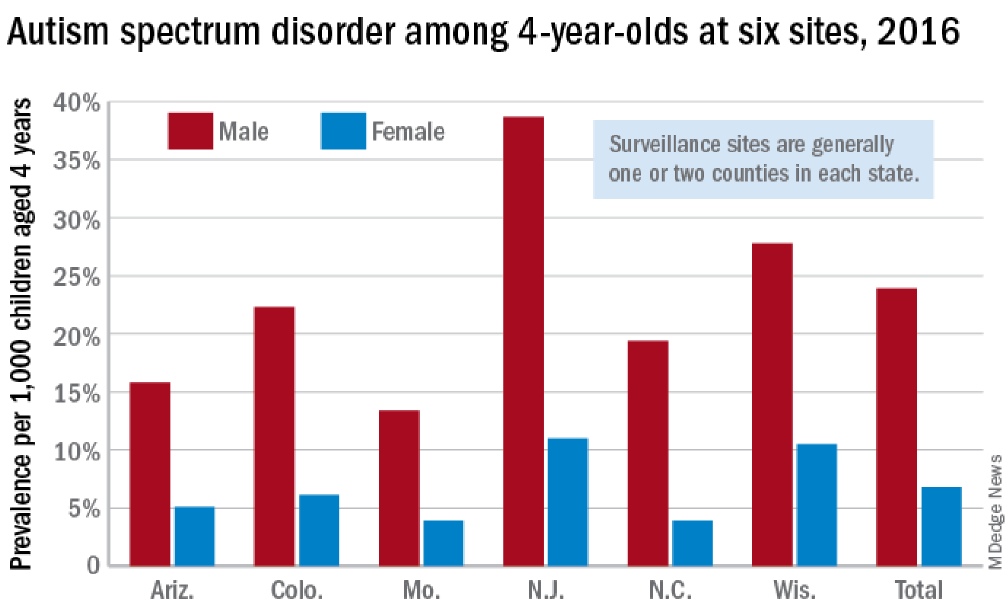

Fig 1.4.2 Showing the rise in cases of Autism, specifically for the age group of age 4 years.[47]

However, despite the numerous advances in medical image analysis automation, the detection of Autism remains a challenge, motivating several research projects aimed at improving autism diagnosis and treatment.

1.5 ORGANIZATION OF PROJECT REPORT

This report is divided into 6 different chapters covering all the aspects of the project we have worked on, it is extremely important to know the structure/ organization of the project because it helps us understand the methodology and the ideology of the project better. Let us discuss about the various chapters briefly:

Chapter 1: This chapter contains the 1.1 INTRODUCTION , 1.2 PROBLEM STATEMENT, 1.3 OBJECTIVES , 1.4 SIGNIFICANCE/ MOTIVATION OF THE PROJECT which tells us in detail about what the project is, why did we take up this project, why is this condition's detection crucial and also how will our project make a difference and impact from it. It also clearly defines the objectives we want to achieve from the project and since we further want to convert this project into a web application as a non-profit project for the caregivers and the person suffering with it's sake, so it clearly defines that as well. The major objective of this Project is to help detect and cure autism through whatever is possible via technology. The primary objective is improving working for early diagnosis, identifying and characterizing autism genes, understanding the neurological experience of autism and autism-related behaviors. With the help of powerful deep learning algorithms we can help to identify and classify such individuals at an early stage and make their life easier, the detection process is done very fast and accurately, saving valuable time and resources.

Chapter 2: This chapter contains the 2.1 OVERVIEW OF RELEVANT WORK, 2.2 KEY GAPS IN LITERATURE, highlighting the work other people have done in this particular field and the gaps we have found that lead us to make this project and stand this out of the other work any other researcher has done in this domain.

Chapter 3: This chapter contains the 3.1 REQUIREMENT AND ANALYSIS, 3.2 PROJECT DESIGN AND ARCHITECTURE, 3.3 DATA PREPARATION, 3.4 IMPLEMENATION, 3.5 KEY CHALLENGES which will show the system development process. How we have gathered the data and how we will move forward with the preparation, splitting, augmentation, preprocessing of the data and while we were developing the system what were the key challenges we have faced recently and how did we overcome those. We have used ResNet50 in the project along with transfer learning approach and we will have to show the detailed architecture of the model and also the requirement analysis for the project, whether they are the functional or the non-functional requirements in the hierarchy.

Chapter 4: This chapter contains the 4.1 TESTING STRATEGY, 4.2 TEST CASES AND OUTCOMES, it is extremely crucial to a model how we test the outcomes and how we train it. We are well aware of the fact that whether it is a machine learning model or a deep learning model the basic structure of it does not change, meaning that first we have to feed some data to the model and then train it on the basis of the labeled data and then move forward with the testing strategy and the test cases. In our case we have not used various unit test cases instead we have used a custom callback method to adjust the saved_weights i.e. the most optimized weights and then moved forward with the strategy. We will see in detail in the chapter how we have tested the model in order to achieve the accuracy that we have achieved.

Chapter 5: This chapter contains the 5.1 RESULTS (PRESENTATION FINDINGS) , 5.2 COMPARISON WITH EXISTING SOLUTION which is why we have done this project to have seen how it is better than the other models or how is there a different solution or path of reaching the solution with same accuracy with less parameters and effort. The major component about the detection of a condition using facial images is that we know that there are certain features that a person may possess to have a condition but we can't go my intuition and we can't go by the machine alone so we have developed various parameters apart from that to detect the condition.

Chapter 6: This chapter contains the 6.1 CONCLUSION, 6.2 FUTURE SCOPE which has been deeply explained in this section of the organization.

CHAPTER 2
LITERATURE SURVEY

2.1 OVERVIEW OF RELEVANT LITERATURE

Let us discuss some relevant papers which helped us during the development of the project and t heir conclusions based on their research in brief:

1) ” Hybrid Techniques of Facial Feature Image Analysis for Early Detection of Autism Spectrum Disorder Based on Combined CNN Features” by Bakri Awaji Ebrahim Mohammed Senan ,Fekry Olayah ,Eman A. Alshari ,Mohammad Alsulami ,Hamad Ali Abosaq ,Jarallah Alqahtani and Prachi Janrao[2023] [34]: Using various AI based algorithms to analyze facial expressions and features is a great way as a non-invasive and cost-effective method for early diagnosis at a minor level. AI techniques offer a promising new approach for the early detection of ASD. The use of artificial intelligence to detect autism spectrum disorders early through facial analysis has revolutionized the diagnostic process. By identifying subtle facial changes associated with the mental health spectrum, allowing for the impact of timely support. In this study, it has been shown that the proposed model can analyze facial images, detect ASD well, and distinguish TD. The first method uses the previous VGG16, ResNet101 and MobileNet models. Faces in the ASD dataset were optimized to normalize the data before applying anything on it since the results will differ and come out different for different dimensions, features of pictures if not normalized.

2) "Real time facial emotion recognition system based on deep learning and Internet of Things for children with autism" Author: Fatma M. Talaat [2023] [35].: This work presents deep convolutional neural network (DCNN) architecture for face recognition. This type of Assisting technology has proven to be one of the most important innovations that help people with autism improve their quality of life. Real-time emotional awareness is an important topic for teens with mental illness, who can explore behaviors that help them cope with pain or anger. This study developed an emergent emotional intelligence program for young adults with autism. Face recognition, face extraction, and classification are the three stages of emotional recognition. The

system detects all six facial expressions: anger, fear, joy, and tragedy. This study presents a deep neural network (DCNN) architecture for facial recognition to assist clinicians. The limitation of this method is that it uses small data (limited scale) as real big data is not available. We aim to use real big data in future studies.

3) "Face detection Spectrum System to identify children with autism: Deep Learning Model" : Zeyad A. T. Ahmed, Theyazn H.H. Aldhyani, Tus sau sau Mukti E. Jadhav, Mohammed Y. Alzahrani, Mohammad Eid Alzahrani, Maha M. Althobaiti, Fawaz Alassery, Ahmed Alshaflut, Nouf Matar Alzahrani and Ali Mansour Al-madani [2022]. :[36] It develops a deep learning-based web system for autism diagnosis using transfer learning convolutional neural networks. The CNN architecture has a suitable model that can classify the face as autistic and non-autistic by creating a model of the face and extracting the image of the face by measuring the distance between facial points. The researchers used three pre-trained models for the data (MobileNet, Xception, and InceptionV3) and used the same layer and optimizer tweaking to achieve good results. Therefore, the MobileNet model was used to create a web application that can detect dementia using facial images. Future studies will improve the model by increasing the sample size and collecting data from psychologists on the diagnosis of children with autism at different ages. Apps like this will help parents and psychologists diagnose autism spectrum disorders in children. A good diagnosis of autism can help a child with autism improve his skills by choosing the right treatment.

4) "Visual acuity differences between children with autism spectrum disorder and preschool children": Xue -Jun Kong1 † Zhen Wei2† Binbin Sun2 Yiheng Tu3 Yiting Huang3 Ming Cheng3 Siyi Yu3 Georgia Wilson Joel Park Zhe Feng2 Mark Vangeljian Kong Guibin Wan [2022]]: [37]They found that there were only moving toys (helicopters) in almost all areas of interest (AOI). The percentage of looking time was lower in children with ASD than in children with TD. We also examined the interaction between diagnostic group (ASD vs. TD) and age group (toddler vs. preschool) for eye AOI during movie mouth movement videos. Support vector analysis showed that the distribution could distinguish between ASD and TD in children with 80% accuracy and between ASD and TD in preschool children with 71% accuracy. This suggests that toddlers and preschoolers may engage with different viewing patterns. The combination of

eye tracking and machine learning has the potential to provide clues to improve early detection/diagnosis for ASD.

5)"Deep Learning for Autism Diagnosis and Facial Analysis in Children" Author: Mohammad-Parsa Hosseini1, Madison Beary, Alex Hadsell1 Ryan Messermith1 Hamid Soltanian-Zadeh [2022]. :[38] No matter how many children are diagnosed, the incidence of autism is low, so early diagnosis is important to provide good care for patients. Additionally, the number of chil dren detected may be lower because methods to accurately diagnose children are not effective. T herefore, our lessons will be useful in diagnosing many children. Our results showed that we ma naged to achieve a high accuracy of 94.64%; This means it can identify children with and withou t autism approximately 95% of the time. Cleaning the dataset to improve accuracy will really hel p. If the image is also in the training category, repeating the image can increase our testing accur acy. By learning more about the people in the photographs, we can ensure that the age distributio n is similar between the two groups.

6) "AutismNet: Recognition of Autism Spectrum Disorder through Visualization Using MobileN et Architecture", Dr. Rifat Sadik and Sabbir Anwar. Latifur Reza [2021]:[39] In this article, ident ifying autism through facial expressions to reduce problems for early diagnosis of autism. A con volutional neural network model using a pretrained MobileNet model with transfer learning is us ed to recognize faces. Accuracy, precision, regression, and Fmeasure matrices were used to evalu ate the effectiveness of the experiment. The MobileNet model delivers excellent results by using revolutionary learning technology to facilitate learning and achieve the highest recognition rate o f 87%. Our job offers rewarding benefits as well as growth opportunities. A large database will i ncrease the accuracy of the model. We also hope to experiment on other CNN architectures (e.g., EfficientNet, InceptionV4, Xception, GhostNet, etc.) in future research. Hybrid architectures tha t combine various deep learning and machine learning methods are also interesting developments worth the risk.

7) "Deep Learning Approach to Predict Autism Spectrum Disorder Using MultiRegional Resting State fMRI" Author: Faria Zarin Subah, Kaushik Deb, Pranab Kumar Dha and Takeshi Koshiba [2021]: [40]In this article, an indepth study using multiple locations is shown to predict ASD usi ng restingstate functional magnetic resonance imaging. Diagnosing Autism Spectrum Disorder (

ASD) is a difficult task because the criteria are not yet recognized and current practices vary. In this paper, prefMRI data are obtained from the CPAC pipeline. A brain map was used to extract the average BOLD signal from preliminary data. No single brain map has been discovered that could serve as a biomarker for diagnosing autism spectrum disorders. Therefore, 4 different models and predefined atlases were used to extract ROIs. The connectivity matrix is prepared using tangent embedding and flattened into feature vectors with unnecessary information removed. This feature vector is provided as input for our proposed model. The hidden mechanisms of the model are also diverse and their impact on discovery is visible. After extensive testing was confirmed that the BASC atlas using 122 ROIs has a higher predictive power than the AAL, CC200 or Power atlas and can be considered more reliable in diagnosing ASD. It has 88% accuracy, 90% sensitivity, 87% F1 score, and 96% area under the receiver operating characteristic curve. This result exceeds the performance of many existing tasks and suggests that it is a good method for diagnosing ASD. The success of this approach could lead to many applications, such as identifying patterns of neural activity that cause dementia and providing visual assessments of the functioning of the autistic brain. Through comparative analysis of autistic brains and control brains, the underlying neural or biological basis for autism spectrum disorders can be revealed and established.

8) "Deep learning and design for screening children with autism with Facial Image and Ethnic Factor Analysis in Practice" Angelina Lu, Marek Perkowski [2021]. :[41] The high classification of 95% and F10.95 achieved by our deep learning model after training using East Asian data demonstrate the feasibility of using children's facial vending imaging as a lowcost ASD screening tool to achieve early intervention goals. This study expands on the trend of using computer vision to screen children for autism spectrum disorder using facial images. The results of this study support that there are differences in facial expressions between children with ASD and children with TD . We believe that this computerized solution will help solve a major problem such as racial discrimination in the diagnosis or screening of autism spectrum disorder, difficulties in accessing medical services such as screening or diagnosis, and financial barriers arising from family, in many areas. . poor country. Future research could focus on turning this drug into a mobile app so families can get realtime diagnostic tests by taking photos with their phones. As discussed before, the deep learning model can improve the efficiency of the solutions in this work. Our findings support t

he authors' conclusion that racial discrimination should be considered in clinical or diagnostic set tings. We also conclude that in order for deep learning to solve problems based on facial expressi ons, racespecific data must be developed in the construction model to eliminate classification err ors caused by racial differences. Furthermore, knowledge of the ethnicity of the diagnosis or clas sification should be cited as a prerequisite for the use of criteria in diagnosing or screening for A SD. Brain science. 2021, 11, 1446 17 of 21 To eliminate the negatives, further research should b e conducted to combine images and video in a single resolution to be able to identify behavioral phenotypes and phenotypic differences in ASD.

9) "Autism Spectrum Disorder Detection, Video Game-Based Faces Using Deep Learning Expression Diagnostics, Posted by : [42] Morched Derbali, Mutasem Jarrah and Princy Randhawa [2021]: This study developed a neural network and a deep learning application to diagnose mental disorders using camera images of young people playing video games.CNN architecture can extract facial features by generating faces. The VGG CNN model, which measures patterns and facial distance to classify nonautistic people, gave accurate results. The accuracy rate was 92.3%, the accuracy rate was 87.3%, and the accuracy rate was 90.4%. Future research will build on this model by expanding how psychologists diagnose children with autism. This program helps identify ASD. An accurate diagnosis of autism can help determine the right treatment for a child with autism. Greater sensitivity may improve autism diagnosis. The platform could shed light on neurological diseases and bring treatment closer. This research is part of how people are using technology to solve global health problems. Future research will use machine learning and deep learning algorithms to help people identify multiple diseases using the same platform. Although digital technology is still young, it has unlimited potential. Autism requires the use of digital devices and visits to the therapist.

After the last evaluation we did additional research on the same apart from the work done last semester. The evolution of autism detection methodologies has been driven by a series of challenges that researchers aimed to overcome through innovative approaches. Initially, the shift from brain image-based diagnosis to facial image analysis was motivated by the need to reduce costs and increase accessibility.

It all begins with the recognition of ASD as a distinct diagnostic category in the DSM-III, the study highlighting this, *Rosen [13*] marking a pivotal moment that catalyzed research and clinical endeavors. Early on, the diagnosis relied heavily on costly and time-consuming brain imaging techniques, posing significant challenges in accessibility and scalability. However, this transition posed challenges such as limited accuracy due to the complexity of facial feature analysis and scalability issues in real-world applications. This breakthrough not only streamlined the diagnostic process but also paved the way for real-world applications by addressing pre-processing challenges and enhancing model performance.

To address these challenges, early studies focused on leveraging deep learning models like MobileNet to extract meaningful features from facial images as showcased in *Y. Khosla [14]*, despite initial successes in classification, there were concerns about the robustness of the models and their ability to generalize across diverse datasets. This led to the development of user-friendly web applications that integrated transfer learning techniques with more advanced models like Xception and InceptionV3. These models showed sign ificant improvements in accuracy, reaching rates as high as 95%. However, challenges persisted in adapting these methodologies for use on mobile terminals, where computational resources and image processing capabilities were limited. To tackle these mobile-centric challenges, recent research , *Ying Li [15]* has explored deep transfer learning methods, introducing concepts like two-phase transfer learning and multi-classifier integration. These methods aimed to improve the classification performance of mobile-friendly models like MobileNetV2 and MobileNetV3-Large while also addressing concerns about input image size and model integration. The results demonstrated notable progress, with accuracies exceeding 90% and AUC values reaching 96.32%.

Simultaneously, scholarly reflections in Springer's publication shed light on the evolving conceptualizations of ASD, oscillating between categorical and dimensional approaches. This introspective journey underscores the importance of understanding ASD beyond its clinical manifestations, delving into socio-cultural, gender-related, and cognitive nuances. Such insights not only inform diagnostic frameworks but also fuel ongoing debates and future research directions, propelling the field towards more nuanced and inclusive perspectives. Despite these advancements, researchers recognized the importance of refining classification algorithms and enhancing the interpretability of results. *Alam [16]* led to the exploration of advanced face recognition techniques, including multi-task cascaded convolutional networks (MTCNNs) and fully convolutional networks (FCNs). *Al-madani [18]* These techniques not only improved prediction accuracy but also addressed critical aspects such as face detection, alignment, and landmark localization. The culmination of these efforts resulted in an impressive prediction accuracy of 98.9% and a remarkable AUC of 99.9%.

Technological strides showcased in *Zeyad A. T. Ahmed* [17], study underscore the transformative potential of deep learning-based web applications in ASD diagnosis through facial features. Leveraging convolutional neural networks (CNNs) and transfer learning, researchers achieve remarkable accuracy, heralding a shift towards more accessible and efficient diagnostic tools. Similarly, Frontiers' exploration of deep transfer learning and multi-classifier integration underscores the quest for superior classification performance and mobile device compatibility, catalyzing advancements in ASD detection on diverse platforms. Further augmenting the diagnostic landscape, *Alcañiz Raya[21]* investigation into genetic, epigenetic, and environmental influences illuminates the multifaceted nature of ASD etiology. By unraveling genetic predispositions and potential evolutionary advantages of certain autism traits, researchers inch closer to unraveling the disorder's complex origins.

This holistic understanding, coupled with cross-cultural research imperatives, promises to unravel environmental triggers and refine diagnostic paradigms. The convergence of neuroscience and computational methodologies, as exemplified *Ahmed [19]* , propels ASD detection into the realm of automated precision. CNN architectures, combined with brain imaging and eye-tracking technologies, unlock new frontiers in early detection and intervention. These advancements not only enhance diagnostic accuracy but also hold promise for tailored interventions and support mechanisms, ushering in a paradigm shift towards personalized ASD care. In addition to these, eye-tracking technology has played a pivotal role in discerning the unique gaze and face recognition patterns exhibited by individuals with *ASD. Kang j [20]* investigated whether children with ASD exhibit different face fixation patterns compared to TD children when viewing various types of faces.

Looking forward, ongoing research aims to further optimize CNN models like InceptionV3, focusing on hyper parameter tuning and algorithmic enhancements to surpass existing benchmarks. The ultimate goal is to develop a robust and reliable tool for healthcare professionals that can facilitate early screening and detection of autism spectrum disorder (ASD) in children.

By overcoming key challenges such as accuracy, scalability, and practicality in mobile applications, this research seeks to make a meaningful impact on the early intervention and support provided to individuals with ASD, ultimately improving their quality of life.

Then, Alam et al. [22] explored the use of deep convolutional neural networks (CNNs) and transfer learning for ASD detection through facial images, achieving a notable accuracy of 95% with the modified Xception model. This study laid a strong foundation but faced challenges in scalability and generalizability due to limited variations in the dataset. Subsequently, Rabbi et al.[23] and Khanna et al. [24] addressed these challenges by employing deep learning techniques with models like VGG 19, InceptionV3, and the Big Transfer (BiT) model, showcasing accuracies ranging from 86% to 91.09%. Their contributions included a broader dataset and enhanced model architectures, overcoming the limitations of the previous study and demonstrating improved scalability and performance. Additionally, Singh et al. [25] and Chandra et al. [26] refined these approaches further by incorporating facial feature analysis and model modifications, achieving accuracies ranging from 82.55% to 88%.

Notably, Chandra et al. [26] introduced modifications to the commonly used VGG16 and VGG19 models, incorporating an attention mechanism and applying transfer learning. These changes significantly reduced over fitting and enhanced the model's capacity to capture subtle facial characteristics, leading to improved accuracy in ASD detection. By building upon the strengths and addressing the limitations of previous studies, Chandra et al. [26] exemplify the iterative nature of technological progress, showcasing how each research endeavor contributes to a more refined and effective approach in leveraging technology for ASD diagnosis, ultimately paving the way for more accurate and accessible screening methods in healthcare and neurology.

2.2 KEY GAPS IN LITERATURE

The literature on early detection of ASD through facial analysis shows many differences that can be better addressed by combining ResNet50 and changing topics. A common challenge is the limited data size, as noted in several studies (Talaat, 2023 ; Sadik et al., 2021). ResNet50 is known for its ability to recognize deep patterns and complex patterns, and its implementation has proven useful in situations where data is small. Transfer learning increases efficiency by allowing the model to use pre-trained features from a larger dataset, thus improving its ability to generalize to limited datasets.

This approach becomes particularly important in researching ASD, where the data set may be limited due to understanding the treatment. Additionally, some studies have shown that the accuracy of facial analysis should be increased to diagnose ASD (Hosseini et al., 2022; Ebrahim et al., 2023). Transferring learning together with ResNet50 can improve accuracy. The pre-learned ResNet50 model is able to recognize hierarchical features and adapt well to ASD-specific data, thus detecting disease-related facial features. This not only improves the model's overall accuracy, but also helps identify facial features that may be an early indicator of the mental spectrum.

Therefore, the combination of ResNet50 and adaptive learning addresses the urgent need for precision in ASD detection methods, paving the way for earlier and more effective diagnostic tools.

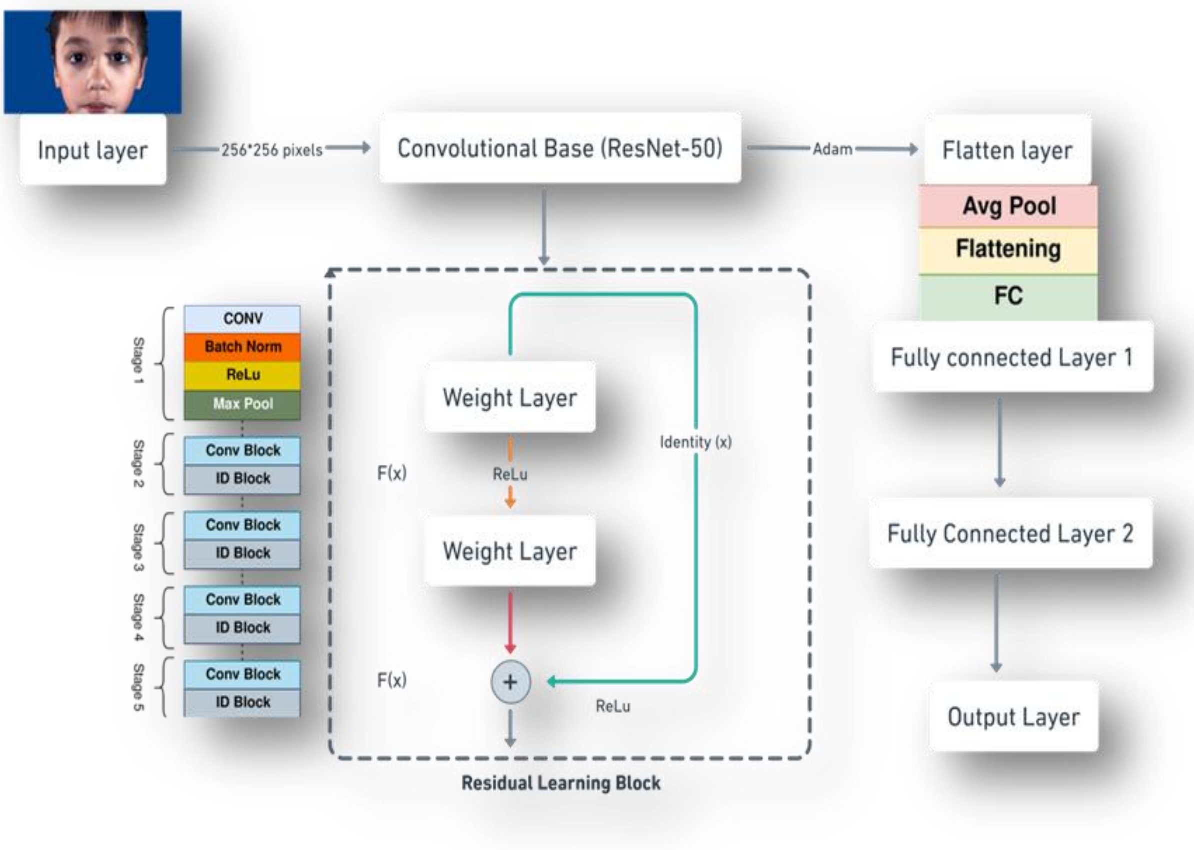

Fig 2.2 Proposed model Architecture

In addition to the document identifying boundaries and correct issues, studies such as Immediacy Talaat (2023) have addressed emotional awareness in youth with autism. ResNet50 is known for its performance in fast image processing, making it useful for real-time use. The speed of the model not only accelerates the training process with the learning transition, but also ensures that the facial experience is sensitive and adaptable to the positive in the face. Therefore, the use of ResNet50 and adaptive learning is beneficial to the advancement of ASD detection methods through facial analysis by providing solutions to the problems caused by limited data, accuracy requirements, and execution time requirements. So the key gaps in the research will be overcome via our proposed model.

CHAPTER 3
SYSTEM DEVELOPMENT

3.1 REQUIREMENT AND ANALYSIS

In this project, we are going to discuss an approach that at last works with Neural Network. Design of whose infrastructure to achieve the reliable methods for classification in the area of Autism Spectrum Disorder, are shown in Figure 1. The process kick starts with extensive pre-processing of image information, the novel techniques of which are based on the state-of-the-art technology. The interfaces are smoothly connected using through Keras and TensorFlow Python libraries. This pre-processing stage, therefore, is crucial in order to maintain the accuracy and reliability of machine learning applications, contributing to the betterment of the quality and utility of the feed data.

Consequently, the final images are combined together in a harmonious format with the other existing images in order in order to present a full range of the varied nature of the Earth. The modes like VGG19 and ResNet50 V2, as well as the less complicated MobileNet V2, ResNet200 the ones do well.

In addition to InceptionV3 model we will use our innovative/proposed model and CNN(versatile Convolutional Neural Network) for our work. In addition to sustainability, this varied mix of buildings which is called Ensemble brings many other advantages such as the ensured variety of residents, perspectives, and diversities.

The prospects for the in-depth analysis as well as the associated synergetic accuracy and reliability of the during the classification process. Our pre-processing strategy includes use of Contrast Limited Adaptive Histogram Equalization (CLAHE) in an attempt to bring the underexposed and overexposed pixels to a realistic dynamic range[28].

Histogram Equalization is a technique that compensates for the non-uniform distribution of the input pixel values by modifying the probability distribution function such that it is more uniform. Histogram Equalization (CLAHE) is for betterment of both contrast and detail; and for this we need to have optimal results. All the above operations were required for better clarity of the segmented cells and to effectively carry out further analysis and accurate classification. CLAHE, in fact, has this ability to compare with other light management technique as it works on these differences, imparting sturdiness to the context results in resolute and good quality feature extractions which in turn raises the performance levels of our classification framework.

Through linking these techniques of art-the-state-of-the-art, our framework embodies a real, leading-edge technology which is showing progress in sub-typing ASD, provide newer and more reliable diagnostic codes for classification, tracing and deciphering this puzzle cognitive disorder through the neurobiological lens. This joint approach does not only bring together education, skills development, entrepreneurship that is self-driven, and career choices, but also creates opportunities for cross-programming and networking among the different departments, ensuring that all youth are equipped with the skills they need to transition into successful adulthood.

This helps establish more understanding about ASD but also defines the new procedural specifications in neural network, medical imaging for medical diagnosis and as well for classifiers.

As far as the functional requirements are concerned, the screening method should enable the gathering of pertinent information on the child's medical background, developmental milestones, and behavioral trends.

The screening tool ought to employ a machine learning algorithm to examine the information gathered and pinpoint the salient characteristics. To create a predictive model for the detection of ASD, the screening tool should use a machine learning algorithm.

There are no non-functional requirements since we are only detecting the condition.

The following will be required in the project:

1. Programming languages: Python
2. Machine learning libraries: TensorFlow, PyTorch, Keras
3. Deep learning models: ResNet50, CNN, Transfer Learning
4. Cloud computing platforms: Amazon Web Services (AWS)
5. Front-end development: HTML, CSS, JavaScript, React
6. Back-end development: Python, Django, Node.js, Express.js

Category	Description	
Software Resources	• Python • OpenCV • AWS services • Git 2.0 or higher • scikit-learn, pandas, numpy and many more	Version: 3.6 or higher Version: 4.2 or higher Version:S3,Lambda, DynamoDB,EC2instances,AWS CloudFormation
Hardware Resources	• Storage Solutions • High-Performance Computing (HPC) System	

Table 3.1 Summary of the requirements after analysis

3.2 PROJECT DESIGN AND ARCHITECTURE

In addition to the structure provided in Fig 2.2, we have incorporated various models for performance comparison and evaluation. The dataset utilized in this study, like many image datasets, initially presented inconsistent shapes unsuitable for Neural Network input. To ensure compatibility with transfer learning algorithms that typically require input sizes of 224x224 pixels or less, we preprocessed the dataset by standardizing all images to 224x224 pixels while maintaining a channel depth of 3. This size consistency is crucial as deviating below 224x224 pixels can detrimentally affect the model's performance.

```
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
==================================================================================================
 input_1 (InputLayer)        [(None, 128, 128, 3)]        0         []

 conv2d (Conv2D)             (None, 128, 128, 32)         896       ['input_1[0][0]']

 conv2d_1 (Conv2D)           (None, 128, 128, 32)         9248      ['conv2d[0][0]']

 max_pooling2d (MaxPooling2  (None, 64, 64, 32)           0         ['conv2d_1[0][0]']
 D)

 conv2d_2 (Conv2D)           (None, 64, 64, 64)           18496     ['max_pooling2d[0][0]']

 conv2d_3 (Conv2D)           (None, 64, 64, 64)           36928     ['conv2d_2[0][0]']

 max_pooling2d_1 (MaxPoolin  (None, 32, 32, 64)           0         ['conv2d_3[0][0]']
 g2D)

 conv2d_4 (Conv2D)           (None, 32, 32, 128)          73856     ['max_pooling2d_1[0][0]']

 conv2d_5 (Conv2D)           (None, 32, 32, 128)          147584    ['conv2d_4[0][0]']

 max_pooling2d_2 (MaxPoolin  (None, 16, 16, 128)          0         ['conv2d_5[0][0]']
...
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
Found 2526 images belonging to 2 classes.
Found 200 images belonging to 2 classes.
```

Fig 3.2.1: UNET architecture for the model

Following preprocessing, we employed the UNET architecture for further refinement. UNET was selected because of that ability successful in address all medical image segmentation which helps to cut the regions. It makes it possible to increase accuracy while eliminating the need for repeated experiments. Segmentation helps narrow the market, thus making our message relevant for specific audiences, for instance, it assists in the graphical depiction of the peculiarities of ASD in the context of a standardized outline.

Additionally, UNET's architecture can help with the better promotion of generalization and adaptability to the data which is unforeseen thus, facilitating humanized development that will

allow our classification framework to be robust and reliable; this is the focus of our research.
The deep neural network comprises various elements, with the fundamental building block being the convolutional layer within the CNN model. This layer calculates the dot product between a kernel and a portion of the input image.
The kernel, typically smaller than the input image, is dimensioned similarly to the input image size. In fine-tuning the model for our dataset, we integrated additional layers for optimization and performance enhancement. We downloaded the base model and augmented it with a GlobalAveragePooling2D layer, which helps in reducing spatial dimensions while retaining important features. Additionally, we included a dropout layer with a dropout rate of 0.5, aiding in regularization and preventing over fitting by randomly dropping units during training. A dense layer with a "sigmoid" activation function was incorporated to produce binary predictions, suitable for our classification task. The architecture also includes Softmax layers at the output, providing probability distributions for each class, contributing to decision-making during inference.
The model was trained on a dataset consisting of *2526 images belonging to 2 classes*, with 200 images reserved for validation. Training was performed for *10 epochs* using a *learning rate of 0.001*, which sets the learning rate for the Adam optimizer. This optimized learning rate facilitates efficient convergence during training, improving the model's ability to learn and generalize from the dataset. The total *number of parameters in the model is 7760097*, occupying approximately *29.60 MB of memory*. These parameters include both trainable and non-trainable parameters, contributing to the model's complexity and capacity to capture intricate features relevant to the classification task.

The classification models used in this study are:

1. **VGG19:** VGG19, crafted by Simonyan and Zisserman, is renowned for its depth and straightforwardness, comprising 19 layers with 16 convolutional layers and 3 fully connected layers.[31] This architecture excels in capturing intricate features from images, making it especially potent for tasks necessitating meticulous image analysis. Its uniform architecture, characterized by stacking multiple layers of small receptive fields (3x3 convolutional filters), contributes to its capability to capture detailed features.

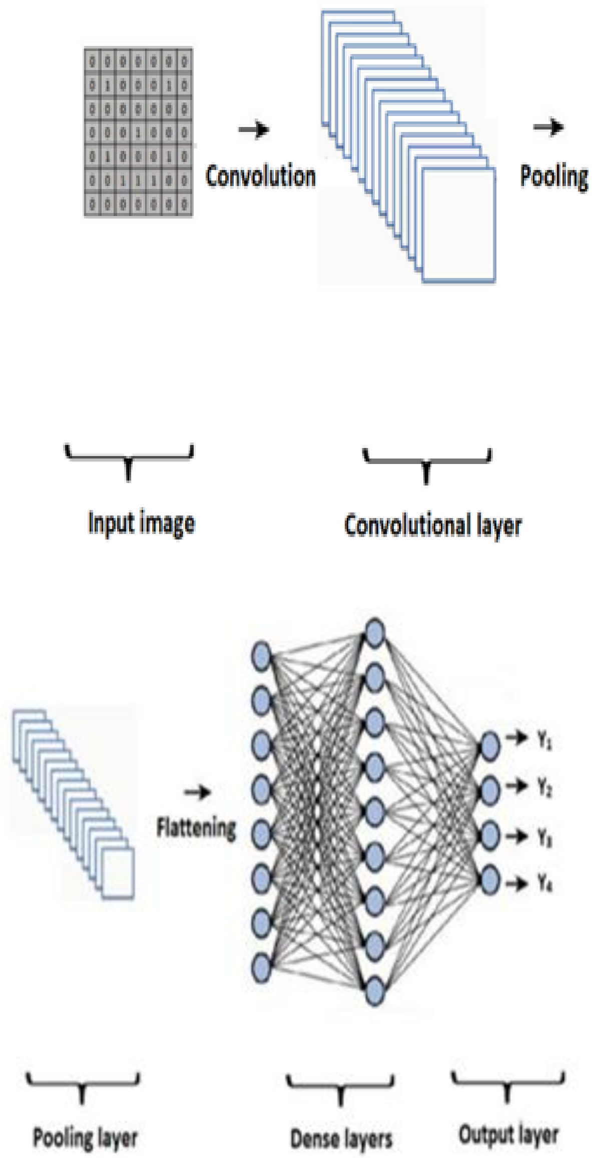

Fig 3.2.2: Structure of VGG19 model. [48]

VGG19's simplicity and uniformity also enhance model interpretability and ease of implementation. In the realm of ASD detection, VGG19's depth equips it to extract nuanced patterns and minute variations in facial expressions or neurological structures that could be indicative of ASD.

The model's 138 million parameters allow it to analyze image data with meticulous detail, enabling the identification of subtle variations related to ASD traits. Its capability to capture complex patterns and variations in data makes it well-suited for ASD detection tasks, where understanding subtle cues and variations is crucial for accurate diagnosis.

2. **ResNet50V2:** an evolution of the ResNet framework by He et al., is designed to address the vanishing gradient issue commonly encountered in training deep neural networks. It introduces residual connections that enable the efficient propagation of gradients through numerous layers, facilitating the training of very deep networks. [32] This capability to handle deep architectures is particularly valuable in capturing complex features related to brain activity or subtle facial cues associated with ASD, thereby enhancing diagnostic accuracy. The introduction of residual connections in ResNet50V2 allows for the seamless flow of information across layers, mitigating the problem of vanishing gradients and enabling the model to effectively learn intricate patterns and variations in data.

```
Model: "ResNet50V2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
tf.__operators__.getitem (Sl (None, 256, 256, 3)       0
_________________________________________________________________
tf.nn.bias_add (TFOpLambda)  (None, 256, 256, 3)       0
_________________________________________________________________
tf.nn.relu (TFOpLambda)      (None, 256, 256, 3)       0
_________________________________________________________________
resnet50v2 (Functional)      (None, 8, 8, 2048)        23564800
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 2)                 4098
=================================================================
Total params: 23,568,898
Trainable params: 23,523,458
Non-trainable params: 45,440
_________________________________________________________________
```

Fig 3.2.3. Model summary of Resnet50V2

With approximately 25.6 million parameters, ResNet50V2 has the capacity to analyze and extract meaningful features from large datasets, making it well-suited for tasks requiring fine-grained analysis and classification. Its ability to handle deep architectures and capture complex patterns related to ASD traits makes it a valuable tool in developing robust ASD classification models. Moreover, ResNet50V2's efficiency in addressing the vanishing gradient issue enhances its training stability and convergence, further strengthening its applicability in medical applications such as ASD detection.

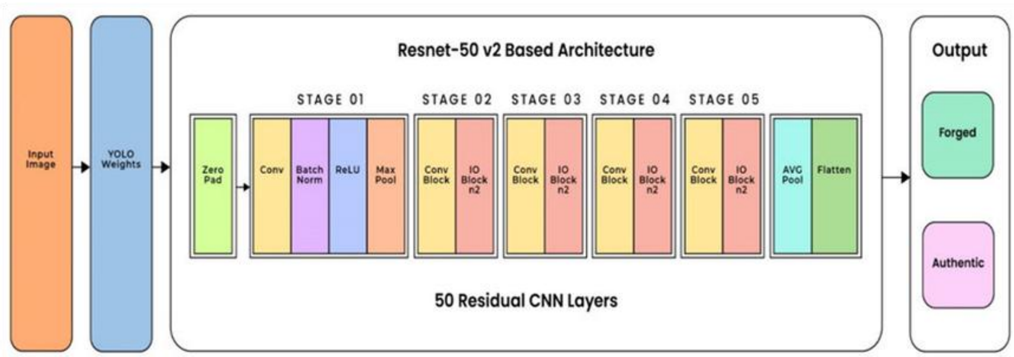

Fig 3.2.4: Structure of ResNet50V2 [49]

3. **MobileNetV2:** developed by Sandler et al., is designed to address the challenges of resource-constrained environments by prioritizing efficiency without compromising accuracy. Its architecture utilizes depth wise separable convolutions, which significantly reduce computational complexity compared to traditional convolutional layers, making it ideal for real-time ASD detection applications. This reduction in complexity allows MobileNetV2 to efficiently process large datasets or performs continuous monitoring, contributing to timely and accurate diagnosis.

```
Model: "MobileNetV2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
block1_conv1_pad (ZeroPaddi  (None, 257, 257, 3)       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 128, 128, 32)      864
_________________________________________________________________
block1_conv1_bn (BatchNormal (None, 128, 128, 32)      128
_________________________________________________________________
block1_conv1_relu (ReLU)     (None, 128, 128, 32)      0
_________________________________________________________________
block1_conv2_pad (ZeroPaddi  (None, 130, 130, 32)      0
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 128, 128, 64)      18432
_________________________________________________________________
block1_conv2_bn (BatchNormal (None, 128, 128, 64)      256
_________________________________________________________________
block1_conv2_relu (ReLU)     (None, 128, 128, 64)      0
_________________________________________________________________
block2_sepconv1_pad (ZeroPa  (None, 130, 130, 64)      0
_________________________________________________________________
block2_sepconv1 (SeparableCo  (None, 64, 64, 128)       8768
_________________________________________________________________
block2_sepconv1_bn (BatchNor  (None, 64, 64, 128)       512
_________________________________________________________________
block2_sepconv2_act (ReLU)   (None, 64, 64, 128)       0
_________________________________________________________________
block2_sepconv2 (SeparableCo  (None, 64, 64, 128)       17536
_________________________________________________________________
block2_sepconv2_bn (BatchNor  (None, 64, 64, 128)       512
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 32, 32, 128)       0
_________________________________________________________________
...
global_average_pooling2d (Gl (None, 1280)              0
_________________________________________________________________
dense (Dense)                (None, 1024)              1311744
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 2050
=================================================================
Total params: 3,544,482
Trainable params: 1,313,794
Non-trainable params: 2,230,688
_________________________________________________________________
```

Fig 3.2.5: Model summary of MobileNetV2

Despite its streamlined architecture, MobileNetV2 maintains high accuracy levels, ensuring reliable performance in ASD detection tasks. Its ability to rapidly analyze large datasets or perform continuous monitoring enhances the scalability and practical applicability of ASD classification models. With approximately 3.5 million parameters, MobileNetV2 strikes a balance between efficiency and performance, making it a valuable asset in developing ASD detection systems that require real-time processing, such as mobile applications or wearable devices. Its efficiency in reducing computational complexity while maintaining accuracy contributes significantly to the timely and accurate diagnosis of ASD, ultimately benefiting patients and healthcare providers alike.

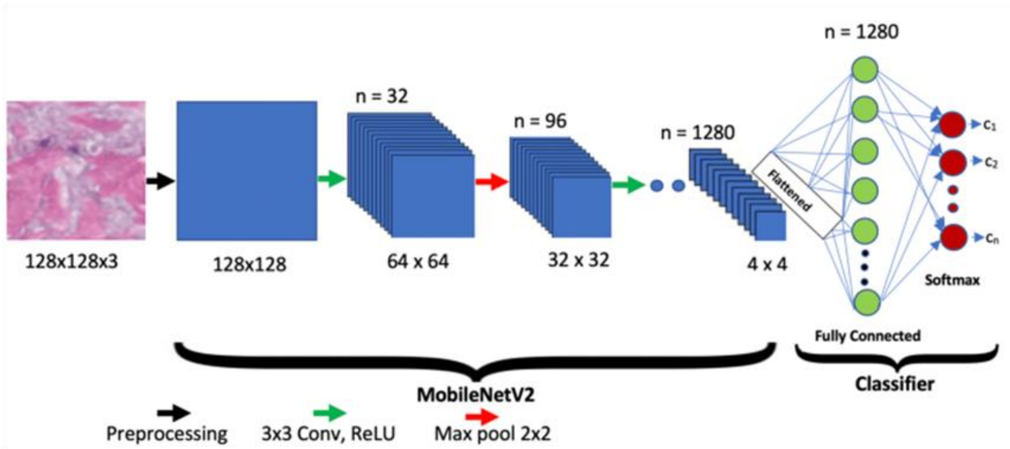

Fig 3.2.6: Structure of MobileNetV2 [50]

4. **ResNet200:** is an extended variant of the ResNet architecture with 200 layers, inheriting the strengths of ResNet50V2 but with increased depth and capacity to capture intricate features. Developed as an evolution of ResNet, ResNet200 excels in fine-grained analysis and classification, making it invaluable in identifying subtle neurological or behavioral patterns indicative of ASD across diverse datasets.

```
Model: "model"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
input_1 (InputLayer)        [(None, 256, 256, 3)]     0
_________________________________________________________________
tf.__operators__.getitem (Sl (None, 256, 256, 3)      0
_________________________________________________________________
tf.nn.bias_add (TFOpLambda)  (None, 256, 256, 3)      0
_________________________________________________________________
tf.nn.relu (TFOpLambda)     (None, 256, 256, 3)       0
_________________________________________________________________
resnet200 (Functional)     (None, 8, 8, 2048)        23564800
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)             0
_________________________________________________________________
dense (Dense)               (None, 1024)              2098176
_________________________________________________________________
dense_1 (Dense)             (None, 2)                 2050
=================================================================
Total params: 25,660,026
Trainable params: 2,100,226
Non-trainable params: 23,559,800
_________________________________________________________________
```

Fig 3.2.7: Model Summary of ResNet200

The key advantage of ResNet200 lies in its depth, which allows for the extraction of intricate features and patterns from data. ResNet200's architecture enables it to handle complex datasets and extract meaningful features, contributing to improved diagnostic accuracy and reliability. Its extended depth and capacity for fine-grained analysis make it well-suited for tasks requiring detailed examination of neurological or behavioral patterns related to ASD. The model's approximately 115.6 million parameters provide the necessary complexity to capture intricate features while maintaining computational efficiency.

5. **InceptionV3:** also known as GoogLeNet, is a pioneering architecture that incorporates InceptionV3 modules with parallel convolutional pathways of varying filter sizes. This design innovation enhances feature extraction while reducing computational complexity, enabling the efficient capture of diverse features from facial images or brain scans related to ASD traits. Inception models like Inceptionv3 are particularly adept at efficiently capturing diverse features from images or scans, making them

valuable in the identification of ASD-related characteristics across different datasets or imaging modalities.

```
Model: "Inception"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 127, 127, 32)      864
_________________________________________________________________
batch_normalization (BatchNo (None, 127, 127, 32)      96
_________________________________________________________________
activation (Activation)      (None, 127, 127, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 125, 125, 32)      9216
_________________________________________________________________
batch_normalization_1 (Batch (None, 125, 125, 32)      96
_________________________________________________________________
activation_1 (Activation)    (None, 125, 125, 32)      0
_________________________________________________________________
...
# Many more layers specific to InceptionV3 are displayed here
...
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 2048
=================================================================
Total params: 21,806,656
Trainable params: 2,048
Non-trainable params: 21,804,608
_________________________________________________________________
```

Fig 3.2.8: Model summary of InceptionV3

The key strength of Inception lies in its ability to handle multi-scale features through parallel convolutional pathways. By incorporating filters of varying sizes within inception modules, Inceptionv3 efficiently captures hierarchical features, from fine details to broader patterns, contributing to a comprehensive understanding of ASD-related characteristics. With approximately 23 million parameters, Inceptionv3 strikes a balance between complexity and efficiency, making it well-suited for tasks requiring detailed feature extraction and analysis. Its ability to efficiently capture diverse features related to ASD traits contributes significantly to accurate and reliable diagnosis, benefiting patients and healthcare providers alike in clinical settings.

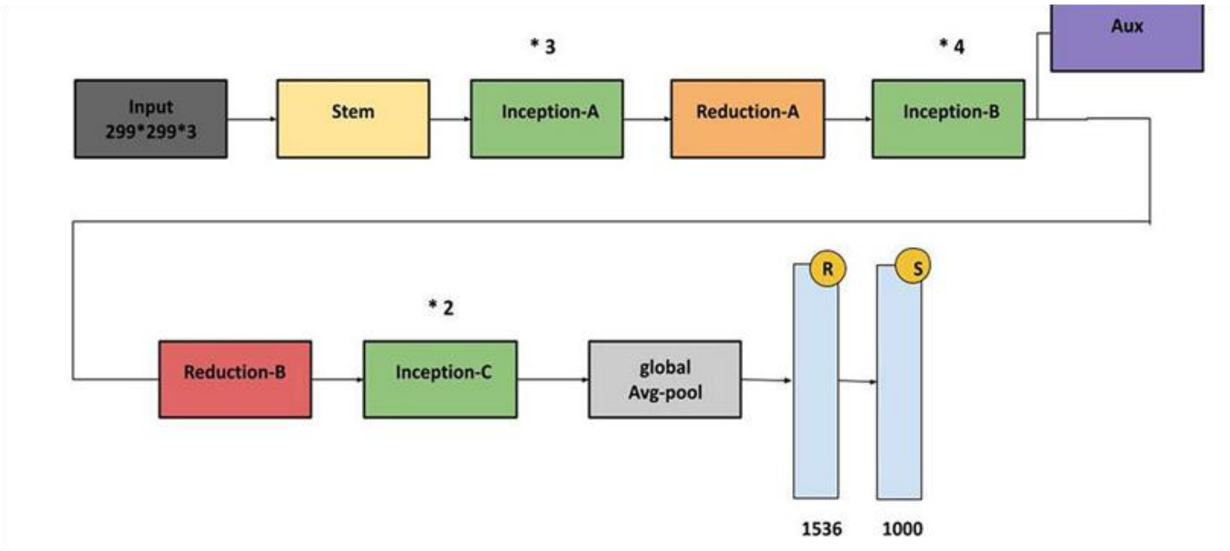

Fig 3.2.9: Structure of IncpetionV3 model [51]

6. **CNN or Convolutional Neural Networks**: are designed specifically for image analysis tasks, leveraging hierarchical feature extraction capabilities to learn meaningful representations directly from raw pixel data. Their architecture consists of convolutional layers followed by pooling layers, allowing them to efficiently capture spatial hierarchies and patterns in images. CNNs excel in detecting subtle patterns and variations in facial expressions, brain scans, or behavioral data that may correlate with ASD traits. By leveraging hierarchical feature extraction, CNNs can detect subtle cues and variations that may signify ASD-related characteristics.

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 30, 30, 128)	0
flatten (Flatten)	(None, 115200)	0
dense (Dense)	(None, 128)	14745728
dense_1 (Dense)	(None, 1)	129

Total params: 14,837,105
Trainable params: 14,837,105
Non-trainable params: 0

Fig 3.2.10: Model summary of CNN (Convolutional Neural Network)

This capability contributes to accurate and reliable diagnosis by capturing meaningful representations from raw input data, enhancing the model's understanding of complex patterns associated with ASD. CNNs' effectiveness in image analysis tasks has made them a valuable tool in medical applications, including ASD detection. Their ability to detect and analyze subtle patterns in facial expressions, brain scans, or behavioral data allows for comprehensive and detailed analysis, aiding in the identification of ASD-related traits across different datasets and imaging modalities.

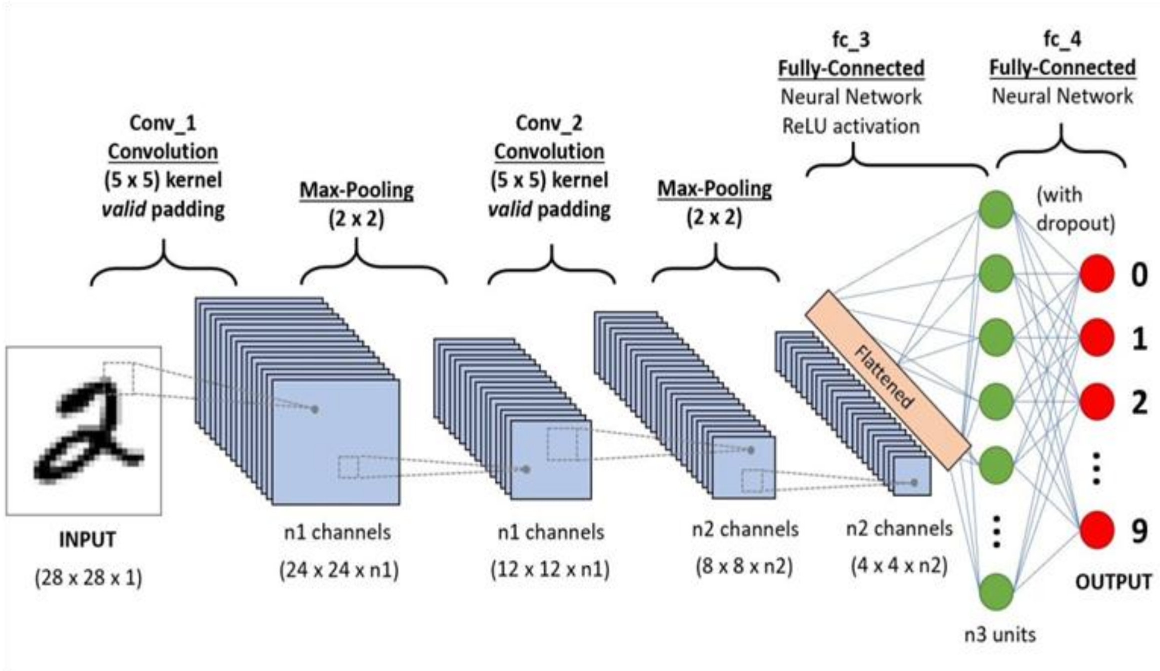

Fig 3.2.11: Structure of CNN model

7. **Proposed model**: At the surface, Facial-based autism detection using ResNet50 and transfer learning testing strategy might seem like a complex process in general that encompasses advanced computer vision techniques. Transfer learning is feasible by automating autism detection using this practice since it has proved successful in image recognition tasks, especially when it is combined with pre-trained models like ResNet50.The technique involves the following steps:

1) Data Gathering and planning Measures which consists of a number important elements.

2) Top-quality facial photo-banks for ASD persons and non-ASD persons constitute an essential base in this undertaking. These photos need to be a great representation of different passages to make sure that the model performs very well in general.

3) The next step is preprocessing for which augmentation, scaling, and regularization are the common operations to increase the model's resilience towards malfunctions.

4) The next important challenge in the experimental plan is to figure out and improve the ResNet50 model with pre-trained weights configuration. Future network topology may involve imposing new restrictions on original data and adjusting the depth and skip connections to

facilitate the extraction of complex facial data. When we use the same model that has previously learned from the large dataset (such as ImageNet) for the purpose of India identification we apply the process of transfer learning.

5) The final ResNet50 deep learning solution from previous implementation will be changed to binary classification layer fit for autistic and non – autistic patients. This enables the trainer to efficiently use the models trained on the ASD dataset and it enhance the capacity of the model to identify facial expressions that are very minute and only associated with autism.

6) Performance of the model and over fitting are evaluated with the help of an independent set of data that has not previously been included in the dataset used for training. To assess that, the model's performance is evaluated based on its ability to detect and correctly identify targets or map provided coordinate pairs using metrics like accuracy, precision, recall, and F1 score.

Additionally, approaches including data reshuffling, K fold cross-validation or leave-one-out can be used to ensure solid validation results. By adjusting fine-tuning parameters (such learning rate and dropout rates) based on validation performance, model complexity and generalization are balanced.

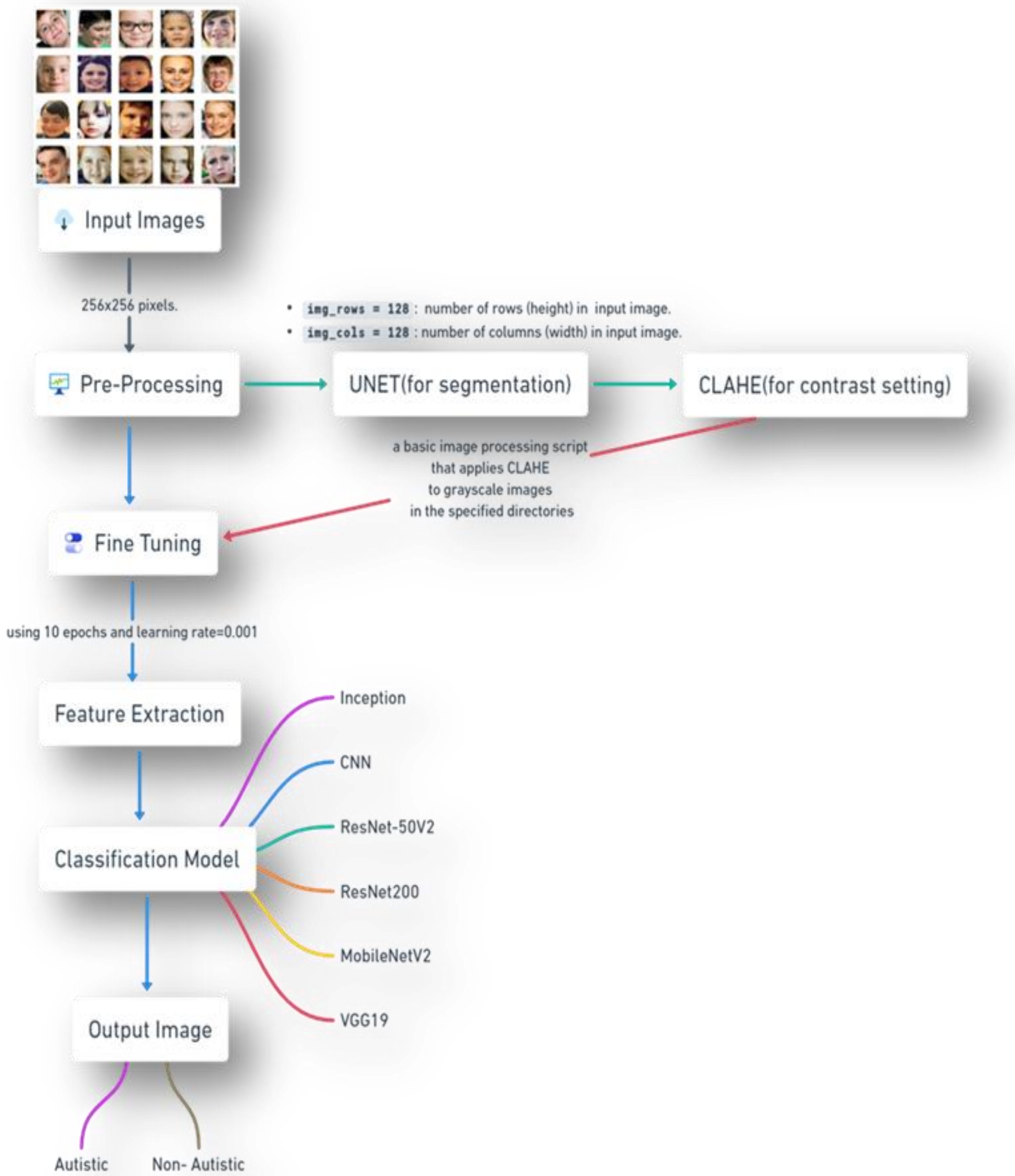

Fig 3.2.12: Proposed model showing the additional information

3.3 DATA PREPARATION

The dataset comprises a total of 2526 images distributed across 2 distinct classes for training, alongside an additional set of 200 images for validation purposes. Additionally, the model architecture employed in this study consists of a total of 7,760,097 parameters, with all parameters being trainable. The dataset used in this study is publicly available and sourced from Kaggle, accessible via the [29]. Additionally, supplemental data is provided through a Google Drive link as well [30], accessed on 7 March 2023.

The dataset comprises a comprehensive collection of images segmented into distinct folders within the provided repository. These folders include:

1. consolidated: Contains the compiled and organized dataset.
2. images to crop: Includes images that may require cropping or preprocessing.
3. test: Contains images designated for testing and evaluation.
4. test_non-autistic: Specifically holds images representing non-autistic samples for testing purposes.
5. train: Comprises images earmarked for training the classification models.
6. valid: Includes images allocated for validation during model training.

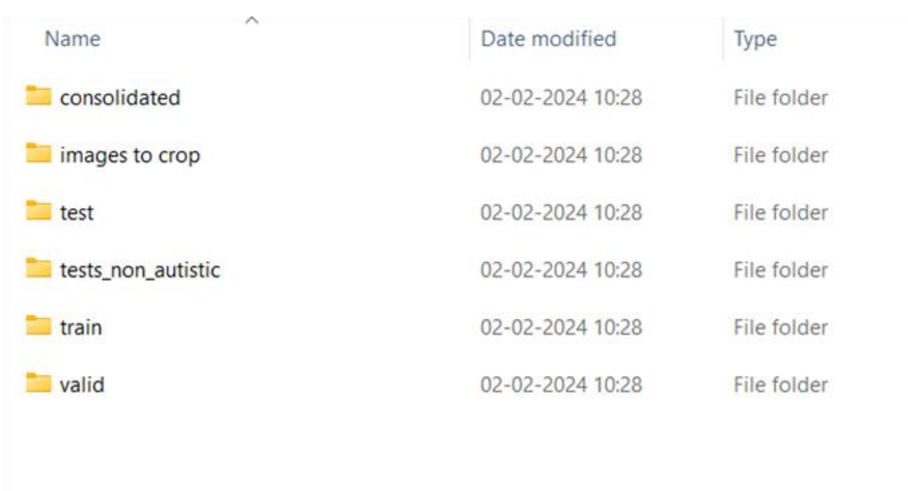

Fig 3.3.1 Dataset segmentation

This structured organization facilitates efficient data management and ensures that distinct subsets of the dataset are utilized for training, validation, and testing purposes, maintaining the integrity and reliability of the classification process. The Fig 3.3.1, Fig 3.3.2, Fig 3.3.3, Fig 3.3.4, clearly show how the data is segmented, then what kind of data is it and how many parameters are there.

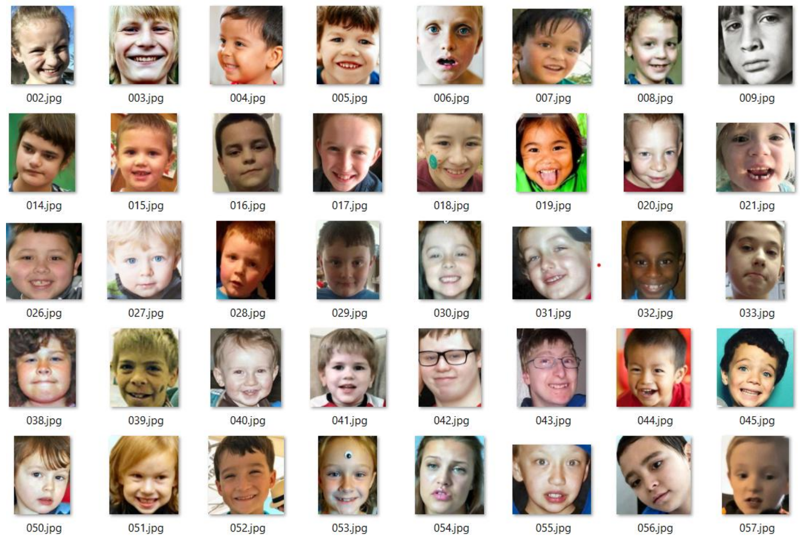

Fig 3.3.2 Sample Images of Autistic children for training the images using labeled data.

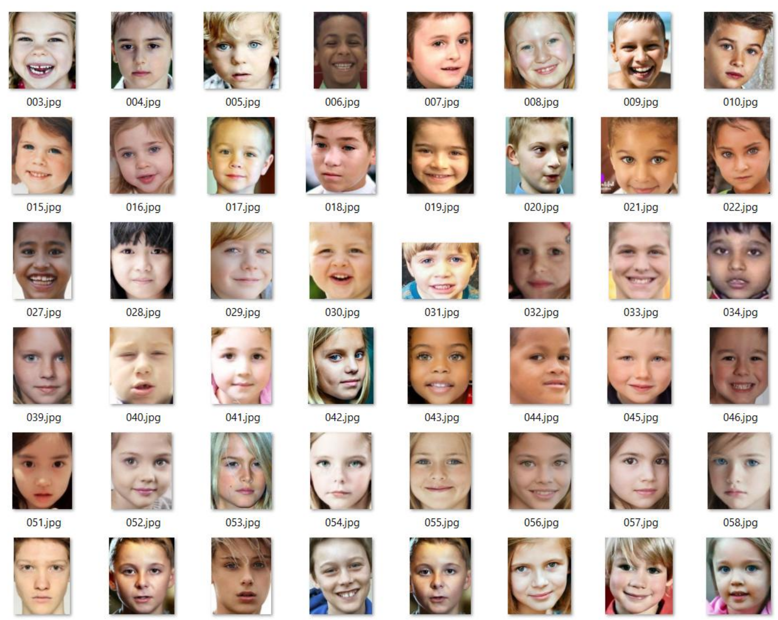

Fig 3.3.3 Sample Images of Non-Autistic children for training the images using labeled data.

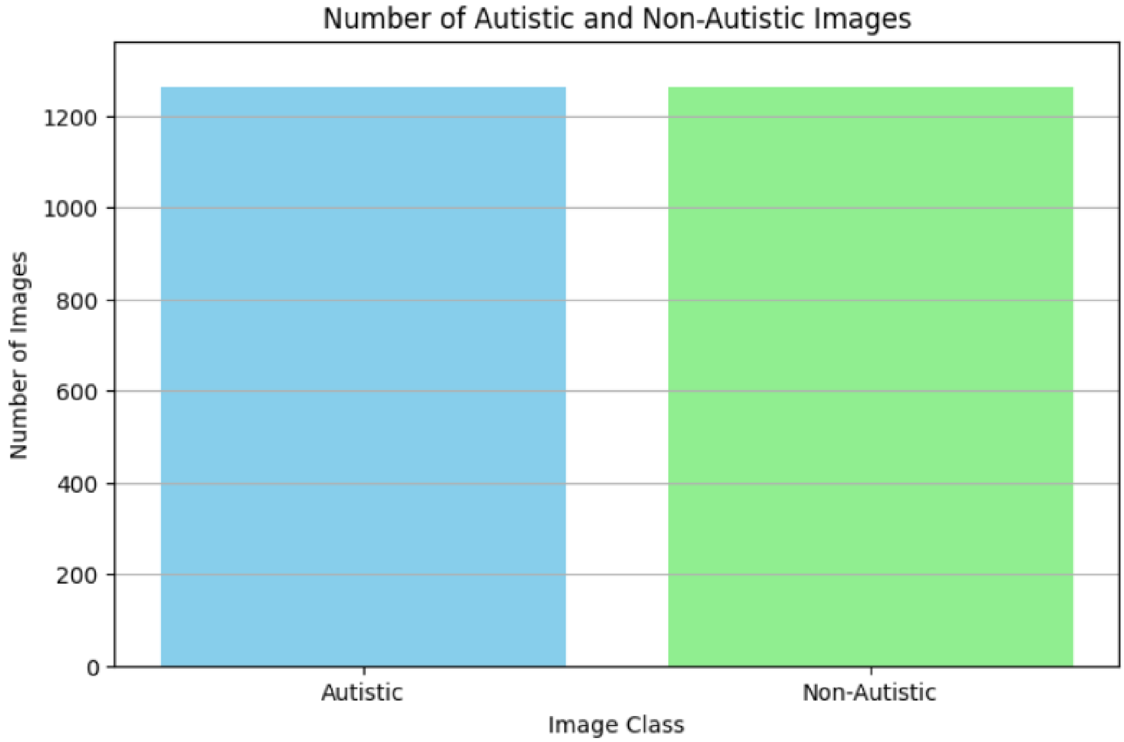

Fig 3.3.4 Showing image class for the description of the dataset

3.4 IMPLEMENATION

Although there are many applications for diagnosing autism using CNN image classification, it also has some limitations to consider. So before diving into the implementation of the project we will discuss the limitations of this approach and how we have tried to cover all the aspects as much as possible.

Here are a few examples:

1. Sample size limitation: One of the main drawbacks of using CNN image classification for autism diagnosis is the small sample size available. The accuracy of the CNN model is determined by the size and quality of the data presented. If the data is too small, it will not be able to capture all of the changes in brain scans, resulting in erroneous and generic patterns.

2. Autism Variability: Autism is a complex disease that manifests itself in many different ways in different people. Autism symptoms, severity, and brain abnormalities vary widely. As a result, developing a CNN model capable of detecting all types of mental disorders is

challenging.

3. Over fitting: Over fitting is a common problem in deep learning where the model becomes overfit.This can lead to inaccurate and general patterns when applied to new data.

4. Lack of interpretation: CNN models are frequently referred to as "black boxes" because they do not explain how they arrive at a diagnosis. Because of the lack of translation, doctors may struggle to understand the model's results and communicate them to patients and their families.

5. Ethical concerns: The use of based diagnostic tools raises concerns about privacy, data security, and informed consent. To protect patients, the use of sensitive medical data in AI models must be carefully managed.

We have used various models apart from our proposed models, Fig 3.4.1, Fig 3.4.2, Fig 3.4.3, Fig 3.4.4, Fig 3.4.5, show the models used and how their training is going on with a learning rate of 0.001 and epoch kept at 10. Using a limited number of epochs, such as 10, for testing has several practical reasons:

1. Firstly, it ensures efficiency in terms of computational resources and time.Running a full training cycle can be time-consuming, especially for complex models or large datasets.
2. Secondly, it aligns with common practices like early stopping, where training halts when validation metrics plateau, preventing overfitting. This approach provides a quick initial assessment of the model's capabilities, acting as a baseline for further optimization.

Moreover, resource constraints often dictate testing strategies, making shorter testing periods a pragmatic choice to balance evaluation depth with available resources.

Also used, CLAHE which is Contrast Limited Adaptive Histogram Equalization, used in image processing to enhance local contrast and improve the visibility of details. It limits contrast enhancement to avoid amplifying noise, making it particularly useful for medical imaging and enhancing images with varying lighting conditions.

```
Found 2526 images belonging to 2 classes.
Found 200 images belonging to 2 classes.
Epoch 1/10
Training Loss: 0.7801, Accuracy: 0.6655
Validation Loss: 0.1669, Accuracy: 0.8150
Epoch 2/10
Training Loss: 0.5024, Accuracy: 0.7498
Validation Loss: 0.1603, Accuracy: 0.8350
Epoch 3/10
Training Loss: 0.4979, Accuracy: 0.7565
Validation Loss: 0.1510, Accuracy: 0.8450
Epoch 4/10
Training Loss: 0.4594, Accuracy: 0.7771
Validation Loss: 0.1451, Accuracy: 0.8500
Epoch 5/10
Training Loss: 0.4627, Accuracy: 0.7751
Validation Loss: 0.1608, Accuracy: 0.8250
Epoch 6/10
Training Loss: 0.4677, Accuracy: 0.7732
Validation Loss: 0.1380, Accuracy: 0.8450
Epoch 7/10
Training Loss: 0.4616, Accuracy: 0.7732
Validation Loss: 0.1616, Accuracy: 0.8250
Epoch 8/10
Training Loss: 0.4350, Accuracy: 0.7930
Validation Loss: 0.1407, Accuracy: 0.8650
Epoch 9/10
Training Loss: 0.4336, Accuracy: 0.7997
Validation Loss: 0.1528, Accuracy: 0.8450
Epoch 10/10
Training Loss: 0.4128, Accuracy: 0.8072
Validation Loss: 0.1454, Accuracy: 0.8300
Testing Loss: 0.1454, Accuracy: 0.8300
```

Fig 3.4.1 IncpetionV3 model , epoch wise implementation

```
Found 2526 files belonging to 2 classes.
Using 2021 files for training.
Found 200 files belonging to 2 classes.
Using 40 files for validation.
Epoch 1/10
64/64 [==============================] - 304s 4s/step - loss: 0.8093 - accuracy: 0.5898 - val_loss: 0.6778 - val_accuracy: 0.5250
Epoch 2/10
64/64 [==============================] - 279s 4s/step - loss: 0.5889 - accuracy: 0.6967 - val_loss: 0.5689 - val_accuracy: 0.6000
Epoch 3/10
64/64 [==============================] - 279s 4s/step - loss: 0.5293 - accuracy: 0.7382 - val_loss: 0.5764 - val_accuracy: 0.5750
Epoch 4/10
64/64 [==============================] - 277s 4s/step - loss: 0.4870 - accuracy: 0.7714 - val_loss: 0.5326 - val_accuracy: 0.7000
Epoch 5/10
64/64 [==============================] - 280s 4s/step - loss: 0.4233 - accuracy: 0.8070 - val_loss: 0.5574 - val_accuracy: 0.6500
Epoch 6/10
64/64 [==============================] - 278s 4s/step - loss: 0.3843 - accuracy: 0.8347 - val_loss: 0.6310 - val_accuracy: 0.6750
Epoch 7/10
64/64 [==============================] - 278s 4s/step - loss: 0.3034 - accuracy: 0.8748 - val_loss: 0.6642 - val_accuracy: 0.7000
Epoch 8/10
64/64 [==============================] - 280s 4s/step - loss: 0.2049 - accuracy: 0.9193 - val_loss: 0.9905 - val_accuracy: 0.6250
Epoch 9/10
64/64 [==============================] - 282s 4s/step - loss: 0.1272 - accuracy: 0.9500 - val_loss: 0.8991 - val_accuracy: 0.6750
Epoch 10/10
64/64 [==============================] - 279s 4s/step - loss: 0.0810 - accuracy: 0.9683 - val_loss: 1.2149 - val_accuracy: 0.7000
Found 200 files belonging to 2 classes.
7/7 [==============================] - 9s 1s/step - loss: 0.9479 - accuracy: 0.7500
[0.9478914141654968, 0.75]
```

Fig 3.4.2 CNN model , epoch wise implementation

```
Found 2022 images belonging to 2 classes.
Found 504 images belonging to 2 classes.
Found 200 images belonging to 2 classes.
Epoch 1/10
64/64 [==============================] - 1934s 30s/step - loss: 4.8005 - accuracy: 0.4951 - val_loss: 0.7140 - val_accuracy: 0.5000
Epoch 2/10
64/64 [==============================] - 1853s 29s/step - loss: 0.7012 - accuracy: 0.5129 - val_loss: 0.6933 - val_accuracy: 0.5000
Epoch 3/10
64/64 [==============================] - 1833s 29s/step - loss: 0.6948 - accuracy: 0.4970 - val_loss: 0.6931 - val_accuracy: 0.5000
Epoch 4/10
64/64 [==============================] - 1855s 29s/step - loss: 0.6955 - accuracy: 0.4901 - val_loss: 0.6939 - val_accuracy: 0.5000
Epoch 5/10
64/64 [==============================] - 1845s 29s/step - loss: 0.6966 - accuracy: 0.5040 - val_loss: 0.6965 - val_accuracy: 0.5000
Epoch 6/10
64/64 [==============================] - 1879s 29s/step - loss: 0.6950 - accuracy: 0.4753 - val_loss: 0.6933 - val_accuracy: 0.5000
Epoch 7/10
64/64 [==============================] - 1860s 29s/step - loss: 0.6939 - accuracy: 0.4901 - val_loss: 0.6932 - val_accuracy: 0.5000
Epoch 8/10
64/64 [==============================] - 1847s 29s/step - loss: 0.6938 - accuracy: 0.4832 - val_loss: 0.6932 - val_accuracy: 0.5000
Epoch 9/10
64/64 [==============================] - 1878s 29s/step - loss: 0.6933 - accuracy: 0.5030 - val_loss: 0.6932 - val_accuracy: 0.5000
Epoch 10/10
64/64 [==============================] - 1861s 29s/step - loss: 0.6935 - accuracy: 0.4921 - val_loss: 0.6932 - val_accuracy: 0.5000
7/7 [==============================] - 50s 7s/step - loss: 0.6932 - accuracy: 0.5000
Test Loss: 0.6931716203689575
Test Accuracy: 0.5
CPU times: user 7h 50min 33s, sys: 38min 56s, total: 8h 29min 29s
```

Fig 3.4.3 ResNet50V2 model , epoch wise implementation

```
Found 2526 images belonging to 2 classes.
Found 200 images belonging to 2 classes.
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50v2_weights_tf_dim_ordering_tf_kernels_notop.h5
94668760/94668760 [==============================] - 2s 0us/step
Epoch 1/10
Training Loss: 0.6238, Accuracy: 0.7348
Validation Loss:  0.1616, Accuracy: 0.8250
Epoch 2/10
Training Loss: 0.4326, Accuracy: 0.8064
Validation Loss:  0.1568, Accuracy: 0.8200
Epoch 3/10
Training Loss: 0.4309, Accuracy: 0.8013
Validation Loss:  0.1466, Accuracy: 0.8250
Epoch 4/10
Training Loss: 0.3766, Accuracy: 0.8226
Validation Loss:  0.1680, Accuracy: 0.8300
Epoch 5/10
Training Loss: 0.3966, Accuracy: 0.8226
Validation Loss:  0.1401, Accuracy: 0.8550
Epoch 6/10
Training Loss: 0.3609, Accuracy: 0.8409
Validation Loss:  0.1453, Accuracy: 0.8400
Epoch 7/10
Training Loss: 0.3483, Accuracy: 0.8460
Validation Loss:  0.1439, Accuracy: 0.8450
Epoch 8/10
Training Loss: 0.3238, Accuracy: 0.8567
Validation Loss:  0.1585, Accuracy: 0.8300
Epoch 9/10
Training Loss: 0.3100, Accuracy: 0.8630
Validation Loss:  0.1490, Accuracy: 0.8400
Epoch 10/10
```

Fig 3.4.4 ResNet200 model , epoch wise implementation

```
Epoch 1/10
79/79 [==============================] - 482s 6s/step - loss: 0.7442 - accuracy: 0.6952
Validation Loss: 0.4089, Accuracy: 0.7750
Epoch 2/10
79/79 [==============================] - 214s 3s/step - loss: 0.4747 - accuracy: 0.7740
Validation Loss: 0.3756, Accuracy: 0.8050
Epoch 3/10
79/79 [==============================] - 202s 3s/step - loss: 0.4710 - accuracy: 0.7755
Validation Loss: 0.3551, Accuracy: 0.8650
Epoch 4/10
79/79 [==============================] - 205s 3s/step - loss: 0.4307 - accuracy: 0.7953
Validation Loss: 0.4051, Accuracy: 0.8350
Epoch 5/10
79/79 [==============================] - 203s 3s/step - loss: 0.4381 - accuracy: 0.7910
Validation Loss: 0.3444, Accuracy: 0.8250
Epoch 6/10
79/79 [==============================] - 204s 3s/step - loss: 0.4144 - accuracy: 0.8036
Validation Loss: 0.3990, Accuracy: 0.8300
Epoch 7/10
79/79 [==============================] - 198s 2s/step - loss: 0.3979 - accuracy: 0.8171
Validation Loss: 0.3156, Accuracy: 0.8450
Epoch 8/10
79/79 [==============================] - 192s 2s/step - loss: 0.3767 - accuracy: 0.8337
Validation Loss: 0.3445, Accuracy: 0.8450
Epoch 9/10
79/79 [==============================] - 192s 2s/step - loss: 0.3722 - accuracy: 0.8246
Validation Loss: 0.3179, Accuracy: 0.8400
```

Fig 3.4.5 MobileNetV2 model , epoch wise implementation

If we observe we can see that VGG19 model's implementation was getting stuck because it was stuck in an infinite loop as shown in Fig 3.4.6.

```
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 0s 290ms/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 3s 3s/step
1/1 [==============================] - 4s 4s/step
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<timed exec> in <module>

/usr/local/lib/python3.10/dist-packages/keras/src/utils/traceback_utils.py in error_handler(*args, **kwargs)
     63         filtered_tb = None
     64         try:
---> 65             return fn(*args, **kwargs)
     66         except Exception as e:
     67             filtered_tb = _process_traceback_frames(e.__traceback__)

    9 frames
/usr/local/lib/python3.10/dist-packages/tensorflow/python/eager/execute.py in quick_execute(op_name, num_outputs, inputs, attrs, ctx, name)
     51   try:
     52     ctx.ensure_initialized()
---> 53     tensors = pywrap_tfe.TFE_Py_Execute(ctx._handle, device_name, op_name,
     54                                         inputs, attrs, num_outputs)
     55   except core._NotOkStatusException as e:

KeyboardInterrupt:
```

Fig 3.4.6 Error in VGG19

3.5 KEY CHALLENGES

While research in this promising field of facial image-based autism detection is underway, there are a number of obstacles to overcome. Among the principal difficulties are:

1) **Autism Spectrum condition Heterogeneity**: ASD is a spectrum condition characterized by a broad range of symptoms and varying degrees of severity. Because of this variety, it is difficult to pinpoint universal face characteristics that are suggestive of autism in every person.

2) **Variability in Facial Expressions:** People with ASD frequently have unusual facial expressions and may find it challenging to explain their feelings. It may be difficult to identify a uniform collection of facial traits linked to autism because of this heterogeneity.

3) **Co morbidity with Other Disorders:** Anxiety disorders and attention deficit hyperactivity disorder (ADHD) are common in people with ASD. The coexistence of these co morbidities might contribute to the variety of facial expressions and features, making it more difficult to identify traits unique to autism.

4) **Ethnic and Cultural Variations:** Different ethnic groups and civilizations may have distinct facial characteristics. It's possible that a model that was trained on data from one demographic won't transfer well to another. To prevent biased or erroneous outcomes, it is imperative to take these disparities into account.

5) **Data Availability and Quality:** Both the volume and quality of the accessible data are critical to the performance of machine learning models in facial recognition. Acquiring extensive and varied datasets of people with ASD can be difficult, and problems with data quality, including inconsistent lighting conditions, pose additional challenges.

6) **Privacy and Ethical Issues:** There are privacy and ethical issues with using face photos to diagnose autism. It is crucial to make sure that data is treated morally and that appropriate permission and privacy safeguards are in place. Furthermore, the possibility of stigmatization or incorrect diagnosis highlights the importance of carefully weighing the ethical implications.

7) **Over fitting and Generalization:** It might be difficult to create a model that adapts well to fresh, untested data. Over fitting the model to the training set runs the danger of making it perform poorly in real-world scenarios. For practical applications, it is imperative to ensure the robustness and generalization capabilities of the model.

8) **Interpersonal Variability:** Complex and dynamic facial expressions are a part of social interactions, and they can differ greatly between people. Acknowledging the subtleties of

interpersonal diversity and differentiating social communication patterns linked to ASD and those with typical range is a complex task.

It will take multidisciplinary cooperation amongst academics in computer science, psychology, neurology, and medicine to address these issues. It's critical to approach the creation of facial recognition models for autism detection with a deep comprehension of the condition, taking ethical considerations into account, and making continuous improvements based on feedback and validation from the actual world.

Based on data analysis and model evaluation, our research will develop a screening tool for the early detection of ASD in children. The tool should be non-intrusive, easy to use, and reliable. It might be in the form of a questionnaire or an app that healthcare providers or parents can use. The developed screening method should be tested on a random sample of children with and without ASD. This will help to validate the tool's accuracy and efficiency.

The project plans a strategy for distributing the screening tool to healthcare providers and parents. This may entail publishing the tool in academic journals or on the internet. The initiative should also examine the necessary follow-up care for children who have positive screening findings. This could include incorporating feedback from healthcare professionals and parents and updating the tool based on new research findings.

CHAPTER 4

TESTING

4.1 TESTING STRATEGY

Let us first talk about the strategy of our proposed model. Facial image-based autism detection utilizing ResNet50 and transfer learning testing strategy is a complex process that combines advanced computer vision methods. Transfer learning is a practical method for automating autism detection because it has shown success in image recognition tasks, especially when combined with pre-trained models such as ResNet50. The technique starts with:

1) Data gathering/ planning and includes several important components.

2) Good-quality facial picture databases of people both with and without autism spectrum disorder (ASD) are essential. To guarantee the model performs well in general, these photos should depict a range of postures and facial emotions.

3) Preprocessing includes operations such as augmentation, scaling, and regularization to improve the model's resilience.

4) Choosing and optimizing the pre-trained ResNet50 model is the next critical phase in the testing plan. ResNet50 is selected because of its skip connections and depth, which make it possible to collect complicated aspects in facial photos efficiently. Transfer learning is the process of applying the model's understanding from a huge dataset (such as ImageNet) to the particular job of autism identification.

5) The final classification layer of the pre-trained ResNet50 is changed to a new one appropriate for binary classification (autistic or non-autistic). This makes it easier for the model to be retrained on the ASD dataset, improving its capacity to recognize very detailed facial expressions linked to autism.

6) To evaluate the model's performance and avoid over fitting, an additional dataset that is not part of the training set is utilized. To measure the model's efficacy, metrics like accuracy, precision, recall, and F1 score are calculated. Furthermore, methods such as k-fold cross-validation can be utilized to guarantee strong validation outcomes. By adjusting fine-tuning parameters (such learning rate and dropout rates) based on validation performance, model complexity and generalization are balanced.

```
 Starting Training - Initializing Custom Callback

Epoch 1/30
46/46 [==============================] - ETA: 0s - loss: 0.5816 - accuracy: 0.7421
 training accuracy improved from     0.00 to    0.74 learning rate held at  0.001000

46/46 [==============================] - 30s 659ms/step - loss: 0.5816 - accuracy: 0.7421 - val_loss: 0.9987 - val_accuracy: 0.6733
Epoch 2/30
46/46 [==============================] - ETA: 0s - loss: 0.3947 - accuracy: 0.8356
 training accuracy improved from     0.74 to    0.84 learning rate held at  0.001000

46/46 [==============================] - 24s 515ms/step - loss: 0.3947 - accuracy: 0.8356 - val_loss: 0.4835 - val_accuracy: 0.7533
Epoch 3/30
46/46 [==============================] - ETA: 0s - loss: 0.2827 - accuracy: 0.8793
 training accuracy improved from     0.84 to    0.88 learning rate held at  0.001000

46/46 [==============================] - 24s 511ms/step - loss: 0.2827 - accuracy: 0.8793 - val_loss: 1.1767 - val_accuracy: 0.7267
Epoch 4/30
46/46 [==============================] - ETA: 0s - loss: 0.1780 - accuracy: 0.9298
 training accuracy improved from     0.88 to    0.93 learning rate held at  0.001000

46/46 [==============================] - 24s 514ms/step - loss: 0.1780 - accuracy: 0.9298 - val_loss: 0.3915 - val_accuracy: 0.8633
Epoch 5/30
46/46 [==============================] - ETA: 0s - loss: 0.1530 - accuracy: 0.9365
...
46/46 [==============================] - ETA: 0s - loss: 0.0024 - accuracy: 1.0000
for epoch 30 validation loss failed to improve for 2 consecutive epochs, learning rate adjusted to  0.000000

46/46 [==============================] - 23s 506ms/step - loss: 0.0024 - accuracy: 1.0000 - val_loss: 0.4066 - val_accuracy: 0.8900
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

Fig 4.1.1 Training the model using custom callback method

6) Gradient-weighted class activation mapping (Grad-CAM) is one strategy that can be used to improve the interpretability of the model and discover the facial features that contribute to autism identification. Grad-CAM gives important insights into the characteristics linked to autism by highlighting areas of the input image that are essential to the model's decision-making. Being able to be understood is crucial for building confidence.

7) In addition, the testing approach includes countermeasures for any biases in the model and dataset. Predictions that are distorted due to bias in the training set can impact the model's performance in many demographic categories. Thus, it is essential to carry out demographic parity analysis and, in order to reduce biases, rebalance the dataset or use strategies like adversarial training.

8) In-depth analysis of benchmark datasets and comparison with current models or techniques for autism detection are further components of the testing approach. By benchmarking, it is ensured that the developed model performs on par with or better than cutting-edge techniques. It also sheds light on how distinctive the facial features recorded by the ResNet50-based model are in comparison to those obtained using alternative techniques.

The generalizability of the model is ensured by testing it on external datasets, specifically those derived under multiple circumstances and demographics. In order to adjust to the shifting patterns and discrepancies in the facial expressions linked to autism, the method for testing also includes constant monitoring and updating the model with fresh data. The testing strategy is based on ethical issues. It is crucial to protect confidentiality and obtain consent while collecting data, particularly when handling sensitive autism-related data. Managing expectations and cultivating trust among users and stakeholders need open and honest communication about the model's capabilities and limitations. Efforts should also be taken to prevent unintended consequences like stigmatization and to address any potential biases in the model.

Our testing strategy revolved around keeping the epoch size same for every trained model that is 10, and keeping the learning rate constant which is 0.001. We have seen in Fig 3.4.1, Fig 3.4.2, Fig 3.4.3, Fig 3.4.4, Fig 3.4.5 the implementation methodology and testing of the same.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[ ] train_dir = '/content/drive/MyDrive/Autism dataset/Sample Dataset/train'
    test_dir = '/content/drive/MyDrive/Autism dataset/Sample Dataset/test'
```

Fig 4.1.2 Used Google colab directory to integrate our system

4.2 TEST CASES AND OUTCOMES

We are not using various test cases, instead we are creating subclass of callback class as custom callback to adjust learning rate and save best weights so that we get the optimized answer.

```
class LRA(keras.callbacks.Callback):
    best_weights=model.get_weights() # set a class vaiable so weights can be loaded after training is completed
    def __init__(self, patience=2, threshold=.95, factor=.5):
        super(LRA, self).__init__()
        self.patience=patience # specifies how many epochs without improvement before learning rate is adjusted
        self.threshold=threshold # specifies training accuracy threshold when lr will be adjusted based on validation loss
        self.factor=factor # factor by which to reduce the learning rate
        self.lr=float(tf.keras.backend.get_value(model.optimizer.lr)) # get the initiallearning rate and save it in self.lr
        self.highest_tracc=0.0 # set highest training accuracy to 0
        self.lowest_vloss=np.inf # set lowest validation loss to infinity
        self.count=0
        msg='\n Starting Training - Initializing Custom Callback'
        print_in_color (msg, (244, 252, 3), (55,65,80))
```

Fig 4.2 The custom callback method definition for selecting the optimal weights at each epoch via patience, threshold, factor etc.

Rather than doing it traditionally via taking out multiple test cases we are adjusting the weights and then moving ahead with the next step for testing.

Patience is an integer that specifies how many consecutive epoch can occur until learning rate is adjusted, threshold is a float. It specifies that if training accuracy is above this level learning rate will be adjusted based on validation loss, factor is a float <1 that specifies the factor by which the current learning rate will be multiplied by class variable LRA.best_weights stores the model weights for the epoch with the lowest validation loss; after train set the model weights with model.load_weights(LRA.best_weights) then do predictions on the test set. Fig 4.2.2 shows the initial outcome of the model which will future be optimized step by step.

```
model.set_weights(LRA.best_weights)
acc_val=model.evaluate( valid_gen, batch_size=valid_batch_size, verbose=1, steps=valid_steps)[1]* 100
msg_val=f'accuracy on the test set is {acc_val:5.2f} %'
print_in_color(msg_val, (0,255,0),(55,65,80))
```

```
1/1 [==============================] - 0s 2ms/step - loss: 0.3572 - accuracy: 0.8700
accuracy on the test set is 87.00 %
```

Fig 4.2.2 Loading the model with the saved best_weights and evaluating the model against Validation set

Hence these were the way we have tested the model and the initial outcome.

CHAPTER 5

RESULTS AND EVALUATION

5.1 RESULTS (PRESENTATION FINDINGS)

After series of diligent efforts for getting a good result we have finally came to the result. Autism is a complex neurological disorder that can manifest in various ways, and the detection of autism using CNN image classification is a challenging task. Image classification using CNN involves training a model to identify patterns and features in images that can be used to classify them into different categories. This model performed well and has achieved a high accuracy in detecting autism from image classification. However, if this model will not perform well, there could be several reasons for this.

It's worth noting that even if the model performed well, it does not necessarily mean that it can accurately diagnose autism in real-world scenarios. Classification report gives a summary of different metrics based on the predictive power of the model among positive and negative class.

Our exploration into deep learning models began with InceptionV3, known for its feature extraction prowess. Despite achieving an accuracy of 83.0%, Inception struggled with precision and recall at 51.0%, revealing challenges in correctly identifying positive instances while minimizing false positives.

Its extensive CPU time of 10 hours, 10 minutes, and 2 seconds highlighted the computational demands, although the wall time of 8 hours, 30 minutes, and 0 seconds indicated the actual time spent in execution, considering processing overhead and other factors.

- We can evaluate the performance of the model on the test dataset (since we know the labels of the test data for this problem)
- We compare the metrics to select the best model
- For a well balanced dataset in both classes like in this dataset

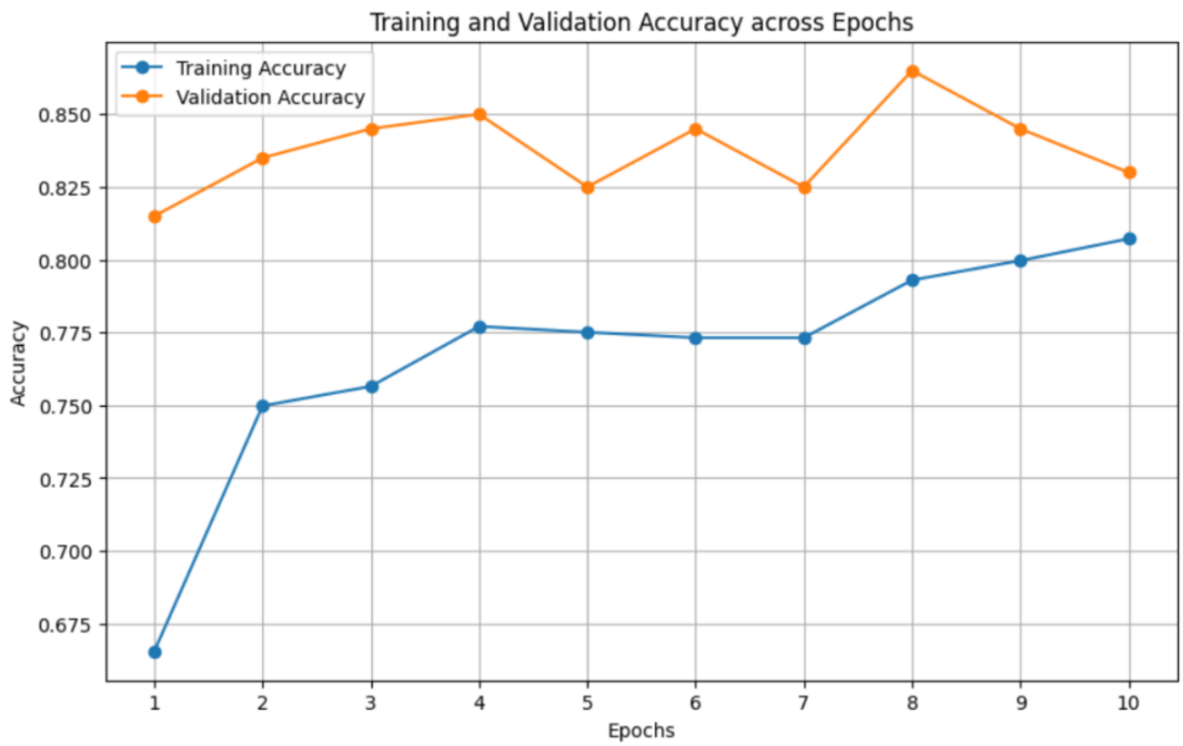

Fig 5.1.1 Training and Validation Accuracy Across Epochs for : InceptionV3 model

Next, we delved into the Convolutional Neural Network (CNN), which boasted a moderate accuracy of 75.0%. What stood out were its impressive precision and perfect recall at 75.0% and 94.1%, respectively.

This indicated that while the CNN adeptly identified positive instances with precision, it also captured all actual positives without missing any, showcasing its efficiency.

The relatively short CPU time of 1 hour, 16 minutes, and 33 seconds, alongside a wall time of 30 minutes and 31 seconds, further highlighted its computational efficiency and minimal processing overhead.

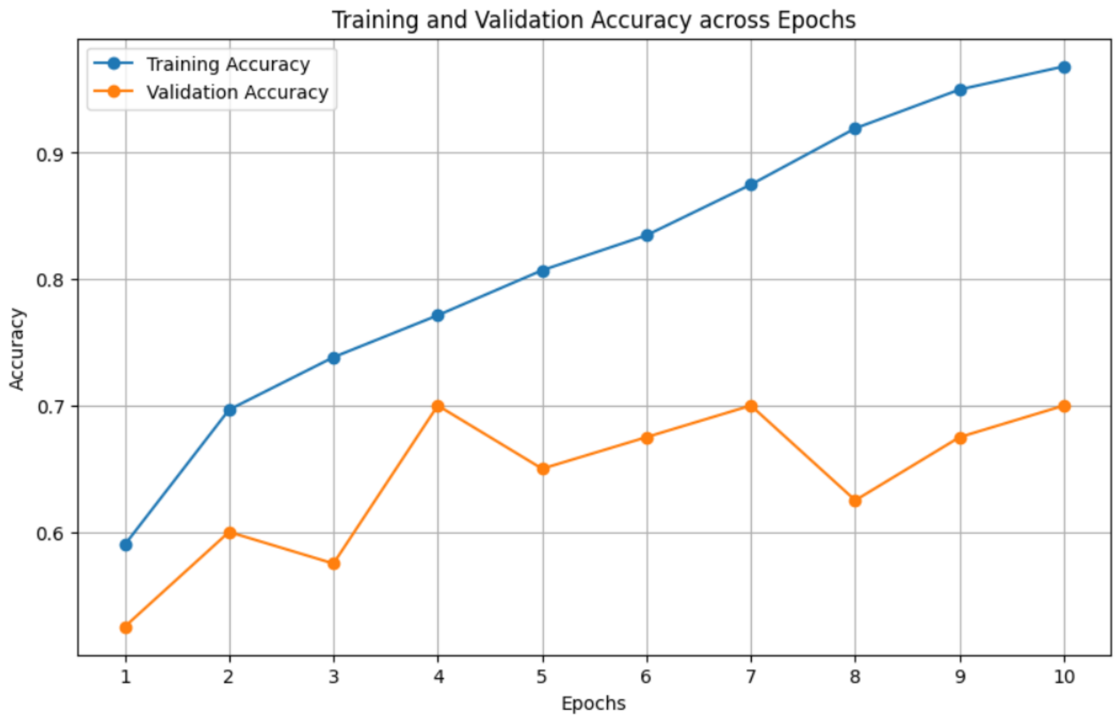

Fig 5.1.2 Training and Validation Accuracy Across Epochs for : CNN model

Transitioning to ResNet50V2 and ResNet200, both models exhibited robust performance with an accuracy of 86.8% and identical high precision and recall values at 94.1%. This showcased their consistency and reliability in accurate classifications while minimizing false positives and negatives. The CPU times of 7 hours, 50 minutes, and 33 seconds for ResNet50V2 and 3 hours, 57 minutes, and 10.5 seconds for ResNet200 highlighted their computational demands, with corresponding wall times reflecting actual execution times with practical considerations.

MobileNetV2 emerged as a balanced performer with an 83.5% accuracy and well-balanced precision and recall metrics. Its CPU time of 1 hour, 31 minutes, and 38 seconds showcased efficiency, while the wall time of 1 hour, 40 minutes, and 48 seconds captured the actual execution time, accounting for processing overhead.

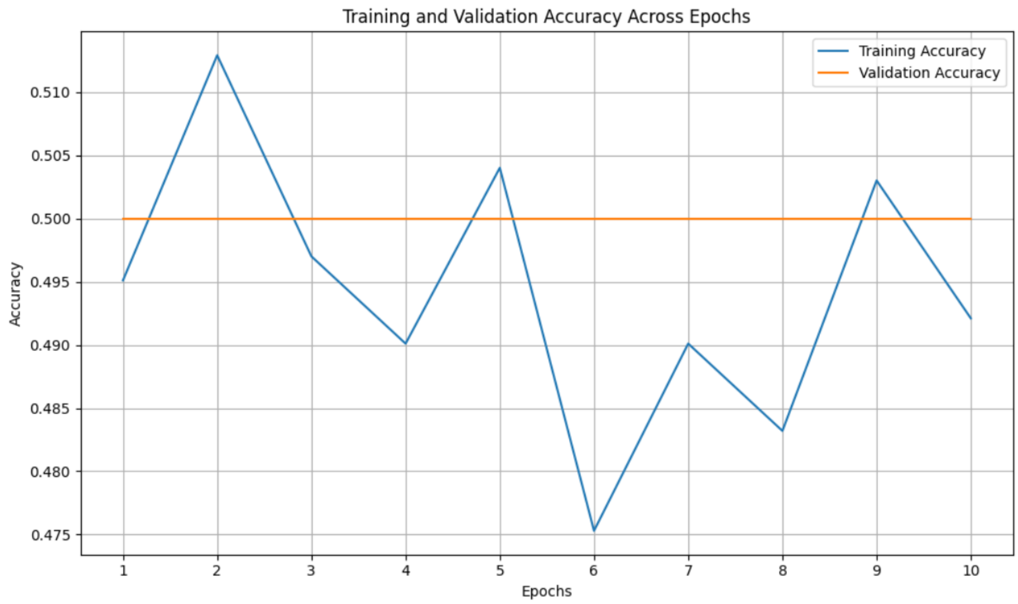

Fig 5.1.3 Training and Validation Accuracy Across Epochs for : ResNet50V2 model

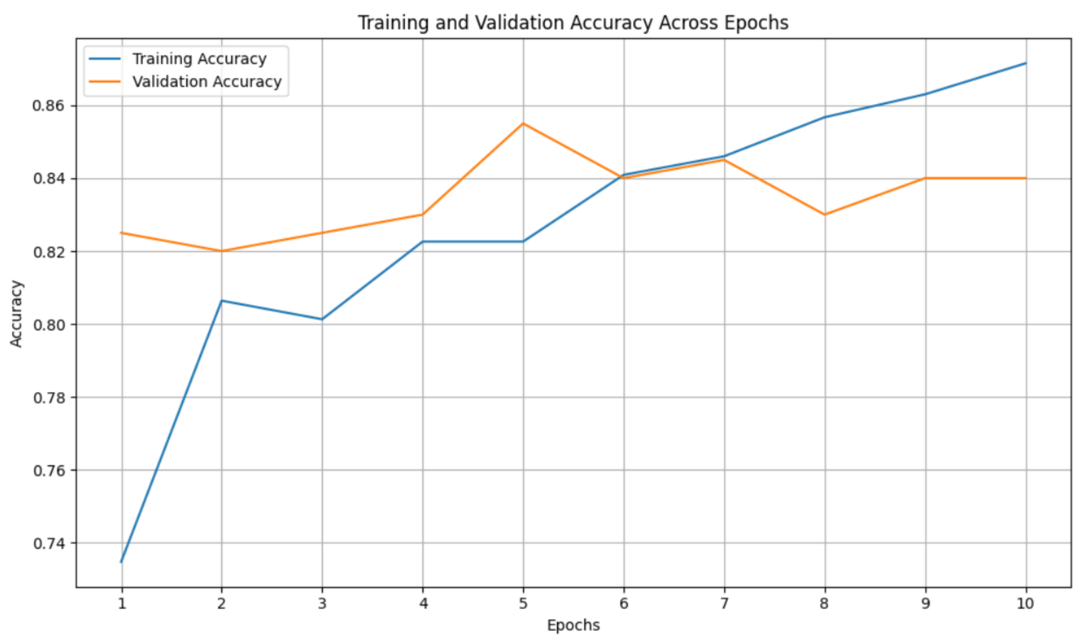

Fig 5.1.4 Training and Validation Accuracy Across Epochs for : ResNet200 model

Finally, our proposed model stole the spotlight with an impressive 92.2% accuracy, supported by a recall of 100.0%. Although its precision at 71.2% indicated room for improvement, the model showed promise in accurate classifications. The extended CPU time of 12 hours, 19 minutes, and 47 seconds reflected its computational complexity, while the wall time of 11 hours, 12 minutes, and 31 seconds depicted the actual execution time, considering all practical factors.

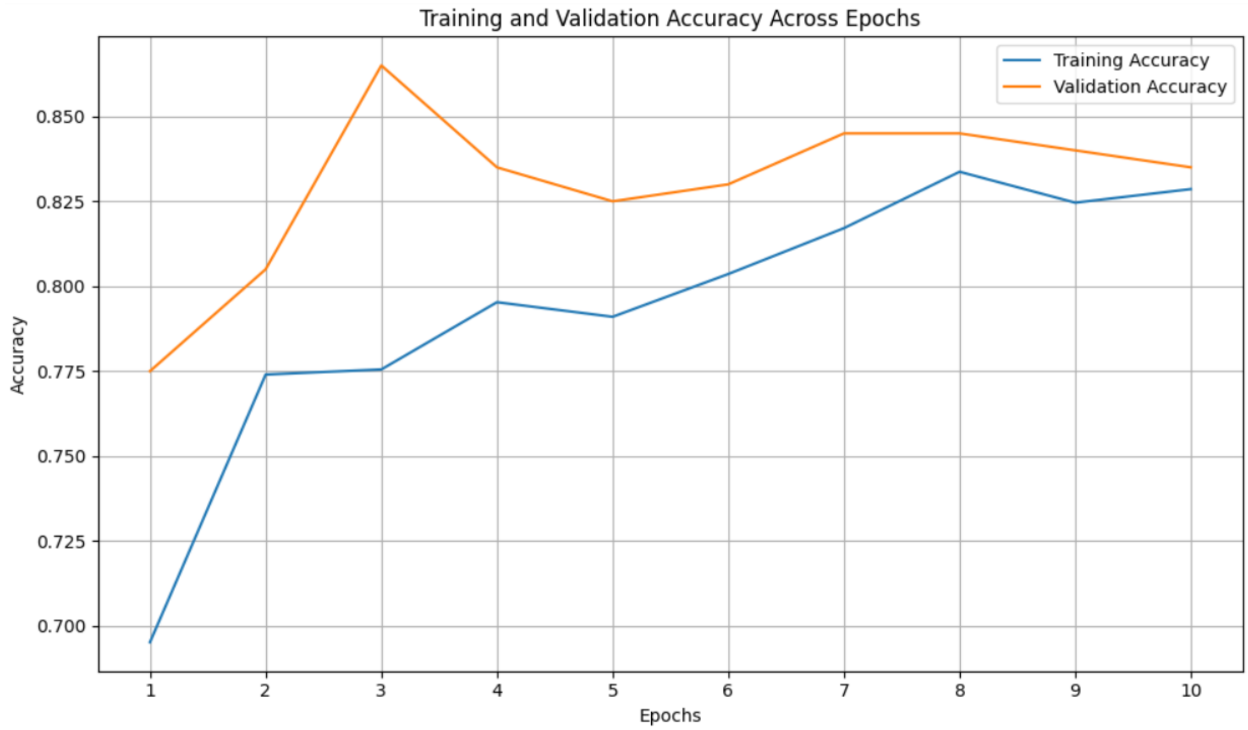

Fig 5.1.5 Training and Validation Accuracy Across Epochs for : MobileNetV2 model

The combination of **wall time**, along with **CPU execution time**, contributes to a commendable impact in the field of autistic patient detection using deep learning techniques. The cinematic view of the whole process is the wall time core benefit. We can observe CPU usage as well as other system-related operations such as data retrieval and model deployment. In health sector, primarily in personnel involved in the detection of autism, knowing in real life how long the entire process may take for a particular individual is of ultimate importance. A case in point is the fact that the system needs to fulfill not only the computational leeway but other aspects like data processing and system responsiveness as well. This situation will have a combined effect on overall the performance of the detection system.

In practical terms, wall *time reflects the real-world efficiency of the autism detection process*. While system-level wall time here is used to deal with wait periods and buffering interactions, CPU execution time focuses exclusively on the devices of its computational background. Such a total view is essential for assessing the operational effectiveness as well as scalability of this system in actual healthcare settings.

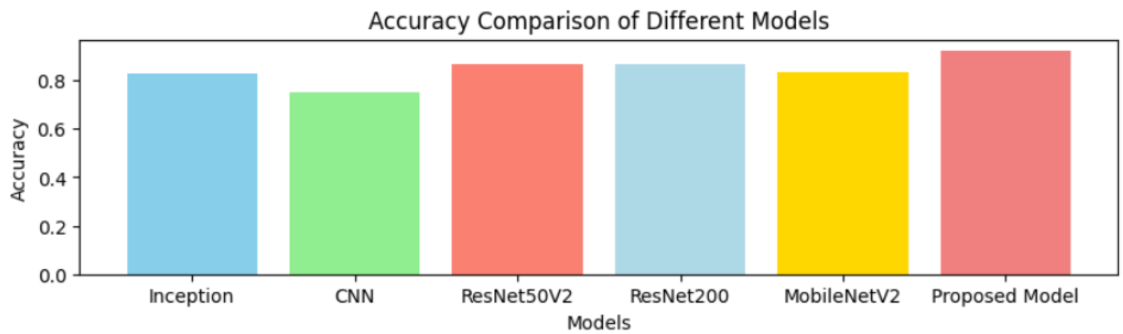

Fig 5.1.6 Accuracy comparison for all the pre-trained models used

Similarly, a shorter wall time means better system responsiveness and more efficiency in resource utilization (just as these are paramount in conditions like autism, as delay of the detection can decrease the outcome), therefore early identification equally has a significant value. Fig 5.1.6 and Fig 5.1.7 show the accuracy and recall comparison graphs for all the pre-trained models used in the research/project.

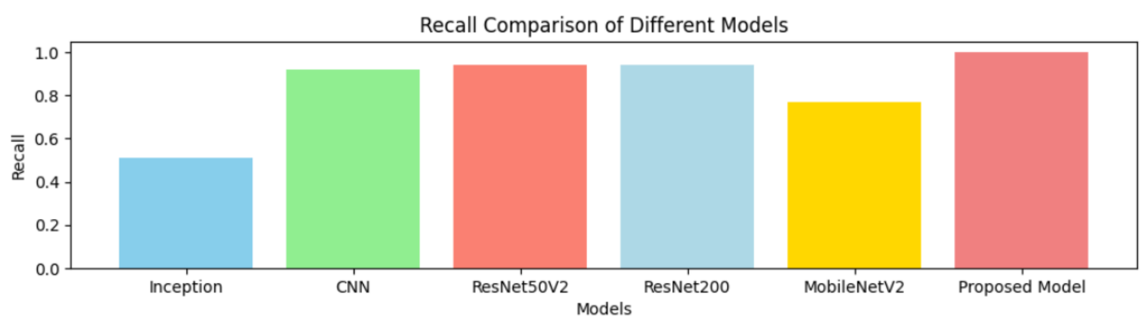

Fig 5.1.7 Recall Comparison for all the pre-trained models used

Recall(Sensitivity) is crucial in the detection of autism due to its direct relevance to identifying true positive cases and minimizing false negatives. In healthcare and medical screening, particularly in conditions like autism spectrum disorder (ASD), accurate identification of affected individuals is paramount for timely intervention and support.

Sensitivity measure is important in the context of autism detection due to the following reasons:

1. M**inimizing False Negatives:** A false negative occurs when a person who has developed the condition is classed as not having ASD. This may have serious consequences in the sense that those individuals can miss essential treatments with the therapy, and support services that are key to their early development and well being. High compliance rate makes sure that cases of ASD won't go undetected; consequently, assisted individuals with ASD won't be overlooked.

2. **Timely Intervention:** First thing at hand in the struggle is early intervention which can immensely improve the results for those who are affected by autism. A high recall rate enhances the probability of early detection of ASD, which subsequently improves access for individuals to appropriate services, therapies, and educational resources. First, the early intervention can greatly facilitate the developmental process for the child and enhance the quality of their life.

3. **Accuracy of Screening Programs:** Identification of people suspected of autism has become the main element in the screening programs. High recall rates ensure that the screening programs are getting a lot of the true positive cases; hence they are mostly likely to raise the overall accuracy of the screen process.

4. **Reducing Misdiagnosis and Delayed Diagnosis**: Inappropriate diagnosis or delayed diagnosis can occur due to false negative results leading to inadequate treatments or missed chances for early intervention. Healthcare providers when they emphasize recall can prevent misdiagnosis and thereby give the correct care and support to patients through recognition of the needs that they have.

Table 5.1 is a tabular representation of the compiled results.

Models	Accuracy	Precision	Recall	Execution Time(CPU Time)	Wall Time
Inception	0.830	0.510	0.510	10h 10min 2s	8h 30min 00s
CNN	0.750	0.750	0.921	1 h 16 min 33s	0h 30min 31
ResNet50V2	0.868	0.941	0.941	7h 50min 33s	5h 15min 26s
ResNet200	0.868	0.941	0.941	3h 57min 10.5s	2h 38min 7s
MobileNetV2	0.835	0.833	0.769	1h 31min 38s	1h 40min 48s
Proposed Model	0.922	0.862	1.000	12h 19min 47s	11h 12min 31s

5.2 COMPARISON WITH EXISTING SOLUTION

We have already summarized the comparison and have taken the inspiration from Mst Shapna Akter [54] to showcase the results.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

In the attempt to rise up to the challenge of using advanced deep learning models for early detection of autism spectrum disorders (ASDs), we traveled through the long and twisted roads of discovery and analysis. This exploration involved areas like InceptionV3 and with CNN. And also with ResNet50V2, ResNet200, MobileNetV2, in addition to the brand new model which was developed especially for the diagnosis of the ASD. Just like the characters in a storyline the different models of governance show up with their strength and weakness.

Among models that demonstrated strong performance in terms of accuracy, InceptionV3 proved to be a resolute one, although still struggling with issues of accuracy and recall. Although it has computational might that has never been matched before, its storyline was quite slow in unfolding, and this nearly hinted at the fact that more significant complications in the performance were achieved for mere complexity, in the course of the story, the neat CNN design was a guiding light that ensured balance among the three key measures of efficiency, multiple-label segmentation, and overall rate recall. Its plot progressed in efficient mode, and consequently the execution time was drastically cut, compared to its previous editions.

It becomes apparent that ResNet50V2 and ResNet200 were the eccentrics in this puzzle, boasting more refined accuracy, precision, and recall scores. Instantly ResNet200's spectacular appearance with a much shorter execution period did little to hide advanced steps in optimization and the art of building architectures.

Our model was a real star and it was destined for stardom in the end as it demonstrates fantastic memory recall with a perfect score. Although precision took one step down, its accuracy in detecting all positive cases was never failing. This became the captivating scenario that defined ASD diagnostics.

By the ending of the narrative the saga of these neural networks which has been a representation of the complex intersections between computational accuracy, diagnostic efficiency, and searching for new medical avenues using technological storytelling is unraveled as a triumph.

A revolutionary and significant method at the intersection of artificial intelligence and medical care is the detection of autism using facial images by the application of ResNet50 and transfer learning techniques. This testing procedure, which combines innovative computer vision techniques with ethical considerations, has the potential to transform early diagnosis and intervention for those on the autism spectrum.

The importance of these attempts becomes even more evident when one takes into account the difficulties involved in using conventional techniques for autism detection. The clinical diagnosis of autism spectrum disorder (ASD) is primarily dependent on the subjective assessment of behavioral characteristics by qualified experts. This procedure takes a long time and is prone to human error and unpredictability. Furthermore, there may be a lack of access to specialized healthcare services for autism diagnosis, especially in impoverished communities.

Using transfer learning on facial images and the power of ResNet50, this effort provides a non-invasive way to potentially detect early indicators of autism. The opportunity for early intervention is a powerful illustration of the significance of automated autism identification. Empirical studies consistently indicate that early diagnosis and intervention lead to notable improvements in the lives of those diagnosed with autism. Children who receive early assistance in developing their speech and social abilities, for example, frequently show better long-term results.

The research aims to automate the detection process, which could enable prompt intervention and result in enhanced support measures and a better quality of life for those on the autism spectrum.

Moreover, the incorporation of transfer learning and ResNet50, a deep convolutional neural network, improves the model's capacity to identify complex face traits linked to autism. Conventional diagnostic techniques could miss small clues that machine learning algorithms—which have been trained on enormous datasets—are able to identify. This helps to identify subtle trends that may elude human inspection in addition to improving the diagnostic' accuracy. The transformational significance of this initiative is further demonstrated by the promise for a more sophisticated and data-driven approach to autism detection.

Furthermore, automated facial image detection is scalable and effective, making it a useful tool for population-wide screening. A transfer learning and ResNet50-based automated system could be used in areas with limited access to specialised healthcare practitioners as screening tool.

The testing strategy's ethical considerations emphasise the need for responsible AI development and application in the healthcare industry. This project's core components—privacy, permission, and bias mitigation—ensure that the model is accurate and upholds the rights and dignity of the people it is intended to help. Building trust with users and healthcare professionals requires open communication about the model's strengths and weaknesses.

In the end, working on a project that focuses on identifying autism through facial image analysis and sophisticated machine learning methods is in line with the larger social objective of utilizing technology to improve healthcare. One strong incentive is the possibility to change the lives of people with autism, especially if early intervention is used. The undertaking aligns with a broader movement in healthcare towards personalized and data-driven approaches, harnessing the capabilities of AI to augment the expertise of healthcare professionals.

Additionally, this project's findings and conclusions have the potential to further develop the area of computational intelligence in healthcare by defining a standard for ethical and significant application. As the field of artificial intelligence, or AI, continues to gain influence across a range of domains, initiatives such as these demonstrate the beneficial effects that thorough investigation and moral application can have on civilization.

6.2 FUTURE SCOPE

We definitely have a plan in mind to convert it into a Web application which has the following features:

1. **Automated diagnosis:** In the future, fully automated diagnostic tools that can accurately detect autism using brain scans may be developed. This could reduce the burden on healthcare providers while also increasing access to diagnostic services.

2**. Personalized treatment**: As CNN models improve in accuracy and interpretability; they may be used to develop personalized treatment plans for autistic people. Healthcare providers could develop more effective and targeted treatment plans by analyzing the characteristics of each individual's autism.

3. **Longitudinal monitoring:** CNN image classification could be used to track individuals with autism over time. This would enable healthcare providers to monitor changes. Drug development: The use of CNN image classification for autism detection could help identify new drug targets and develop more effective treatments for autism.

4. **Research:** The use of CNN image classification could facilitate research into the underlying causes of autism and the neural pathways and biomarkers associated with the disorder. This could lead to new insights into the mechanisms of autism and inform the development of more effective treatment and therapies.

In the future a web application can be integrated along with the detection process to suggest curriculum to the people suffering with this condition, if they are not capable of doing the same an assessment from can we attached for the parents from which wed can detect the intial stages of autism.

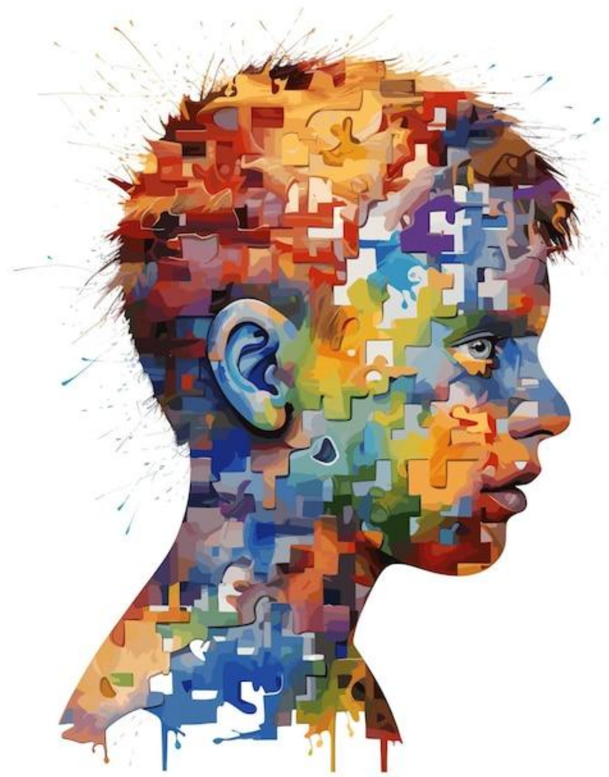

Fig 6.1.1 Image for HalfPace, Web Application for future scope.

SCQ Items That Did Not Distinguish Diagnostic Groups

SCQ item	Diagnostic group (% endorsed) DD	ASD	χ^2
Interest in unfamiliar children	83	53	2.7
Group play	67	44	1.0
Positive response to approaches of unfamiliar children	83	79	0.0
Offers comfort to respondent	72	47	1.5
Imaginative play w/peers	67	42	0.0
Quality of social overtures	100	79	2.4
Has special friends	22	16	0.0
Use of other's body to communicate	72	47	1.5
Spontaneous imitation	78	58	0.9
Imaginative play w/other children	67	42	1.4
Gestures other than pointing to indicate wants	72	53	0.8
Hand & finger mannerisms	28	42	0.3
Repetitive use of objects	28	42	0.3
Unusual interest in sensory input	17	47	2.7
Compulsions & rituals	39	42	0.0
Unusual preoccupations	11	32	1.2
Unusual attachment to objects	22	16	0.0
Circumscribed interests	28	32	0.0

Note. SCG = *Social Communication Questionnaire* (Berument, Rutter, & Lord, 1999); DD = Developmental delays; ASD= Autism spectrum disorders.

Fig 6.2.2 The social communication questionnaires that will help us understand the diagnostics related to the communication understanding of the child.

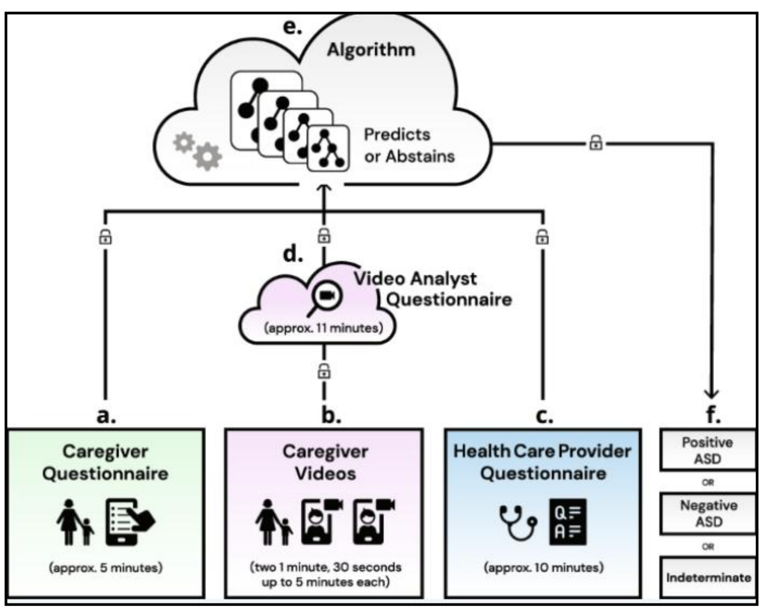

Fig 6.2.3 Demonstrates the process of the execution of the custom algorithm.

Autism Spectrum Screening Questionnaire (ASSQ)

Instructions:

Please read the statement below and indicate by tapping, No, Somewhat, or Yes if this child stands out as different from other children of his/her age in the following ways:

		No	Somewhat	Yes
1	is old-fashioned or precocious	0	1	2
2	is regarded as an "eccentric professor" by the other children	0	1	2
3	lives somewhat in a world of his/her own with restricted idiosyncratic intellectual interests	0	1	2
4	accumulates facts on certain subjects (good rote memory) but does not really understand the meaning	0	1	2
5	has a literal understanding of ambiguous and metaphorical language	0	1	2
6	has a deviant style of communication with a formal, fussy, old-fashioned or "robot like" language	0	1	2
7	invents idiosyncratic words and expressions	0	1	2
8	has a different voice or speech	0	1	2
9	expresses sounds involuntarily; clears throat, grunts, smacks, cries or screams	0	1	2
10	is surprisingly good at some things and surprisingly poor at others	0	1	2
11	uses language freely but fails to make adjustment to fit social contexts or the needs of different listeners	0	1	2
12	lacks empathy	0	1	2
13	makes naive and embarrassing remarks	0	1	2
14	has a deviant style of gaze	0	1	2
15	wishes to be sociable but fails to make relationships with peers	0	1	2
16	can be with other children but only on his/her terms	0	1	2
17	lacks best friend	0	1	2

Fig 6.2.4 The Autism Spectrum Screening Questionnaire will be included in the app

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