CHAPTER - 1
INTRODUCTION

Autism Spectrum Disorders (ASD) comprise a complex set of neurodevelopmental disorders affecting the brain, including autism, childhood disintegrative disorders, and Asperger's syndrome. The term "spectrum" emphasizes the diverse nature of these disorders, as they present with a broad array of symptoms and varying levels of severity. They are classified as Pervasive Developmental Disorders under Mental and Behavioral Disorders in the International Statistical Classification of Diseases and Related Health Problems. Signs of ASD often emerge in the first year of life, such as lack of eye contact, unresponsiveness to name calling, and disinterest in caregivers.

Some children may exhibit typical development in the first year but then display ASD symptoms between 18 and 24 months of age, characterized by repetitive and limited patterns of behavior, a restricted range of interests and activities, and poor language skills. As these disorders also affect social interaction and communication skills, children may exhibit introverted or aggressive behavior during their first five years of life. Although ASD typically develops in childhood, it persists into adolescence and adulthood. The utilization of advanced information technology, specifically artificial intelligence (AI) models, has facilitated the early detection of autism spectrum disorder (ASD) by employing facial pattern recognition.

Autism spectrum disorders (ASD) refer to a group of complex neurodevelopmental disorders of the brain such as autism, childhood disintegrative disorders, and Asperger’s syndrome, which, as the term “spectrum” implies, have a wide range of symptoms and levels of severity. These disorders are currently included in the International Statistical Classification of Diseases and Related Health Problems under Mental and Behavioral Disorders, in the category of Pervasive Developmental Disorders. The earliest symptoms of ASD often appear within the first year of life and may include lack of eye contact, lack of response to name calling, and indifference to caregivers. A small number of children appear to develop normally in the first year, and then show signs of autism between 18 and 24 months of age, including limited and repetitive patterns of behavior, a narrow range of interests and activities, and weak language skills. As these disorders also affect how a person perceives and socializes with others, children may suddenly become introverted or aggressive in the first five years of life as they experience difficulties in interacting and communicating with society. While ASD appears in childhood, it tends to persist into adolescence and adulthood.

Advanced information technology that uses artificial intelligence (AI) models has helped to diagnose ASD early through facial pattern recognition. Yolcu et al. used the convolutional neural network (CNN) algorithm to train data for extracting components of human facial expressions and proposed the use of such algorithm to detect facial expressions in many neurological disorders. In 2018, Haque and Valles, using deep learning approaches, updated the Facial Expression Recognition 2013 dataset to recognize facial expressions of autistic children. Rudovic et al. presented the Culture Net deep learning model that was used to identify 30 videos.

CHAPTER – 2
REVIEW OF LITERATURE

Numerous studies have explored various methods for detecting autism, including feature extraction, eye tracking, facial recognition, medical image analysis, and voice recognition, and have identified critical features of autism. Among these methods, facial recognition has emerged as particularly significant in detecting autism, as it focuses on objective physical features rather than subjective emotional states. Facial recognition is a widely used approach for identifying individuals and determining whether they exhibit normal or abnormal behavior, involving the analysis of relevant information to reveal behavior patterns.

The focus of research on extracting features of autism spectrum disorder (ASD) patients has been on artificial neural networks, which are used to differentiate between individuals with and without ASD. Deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and the bidirectional long short-term memory (BLSTM) model, have been employed to detect autism in children. Recent studies have also explored machine learning approaches, such as brain imaging, analysis of physical biomarkers, assessment of autistic behavior, and evaluation of clinical data. In our study, we utilized a well-trained classification model based on transfer learning to detect autism from a child's image. This model can easily provide a diagnostic test of possible autistic traits by taking an image using high-specification mobile devices. Our research offers significant contributions in this field.

(i) It utilized three pretrained deep learning algorithms - Xception and VGG19 - for detecting ASD.

(ii) Among the three pretrained deep learning algorithms, the Xception model demonstrated the most promising results.

(iii) Our team designed a system that employs eye and face recognition to aid health officials in detecting ASD.

(iv) The developed system was rigorously validated and examined using multiple techniques.

CHAPTER -3

MATERIAL AND METHOD

In this research, we propose a transfer learning-based deep learning model - Xception and VGG19 - to identify autism by analyzing facial features of children with autism and those without. Facial features can be instrumental in determining whether a child is suffered with it or not. It extracted crucial facial features from the images, and one of the significant benefits of deep learning algorithms is their ability to detect even minute details that are not apparent to the naked eye. To illustrate the framework of our study, Figure 3.1 depicts the various stages involved, from data acquisition to preprocessing and loading, model preparation and training, and performance evaluation.

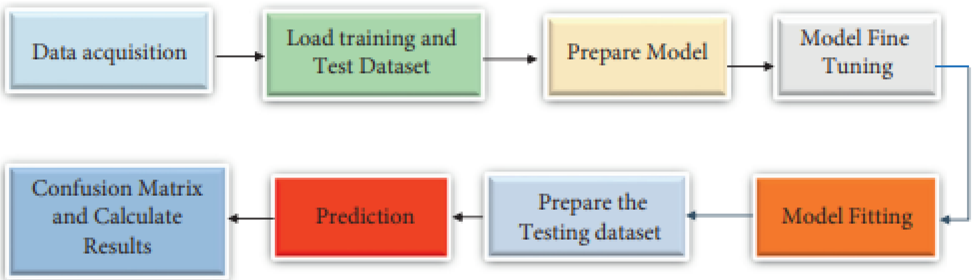


Fig: -3.1 The framework of our study

3.1 DATASET

The dataset used in this study was obtained from the publicly accessible Kaggle platform and comprised of 2,940 facial images. The dataset was split in half, with one half consisting of images of autistic children and the other half consisting of images of non-autistic children. These images were collected from various online sources, such as websites and Facebook pages dedicated to autism. Figure 3.2 illustrates the division of the input data.

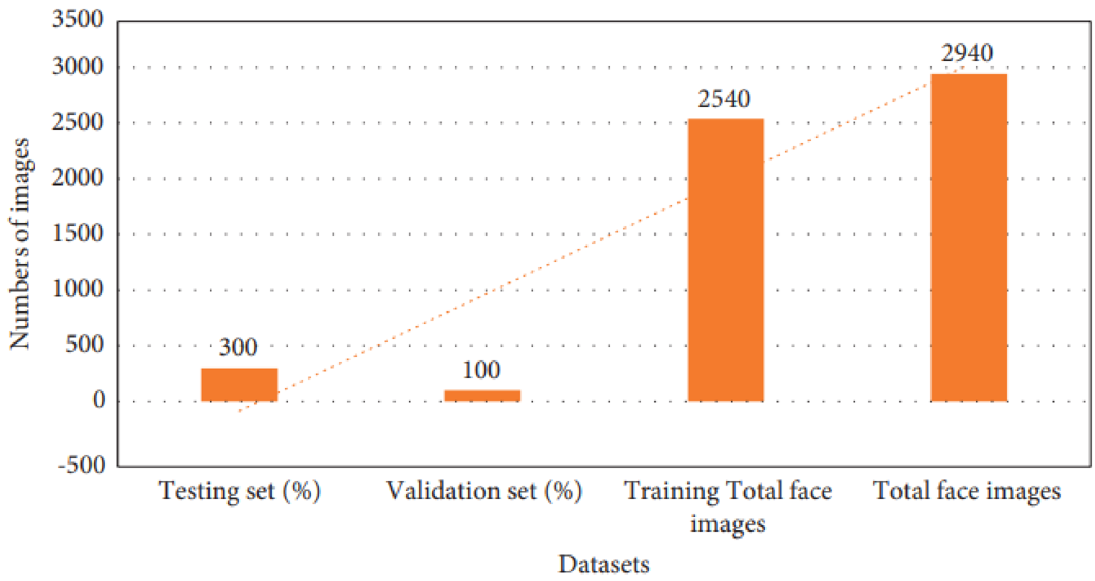


Fig: - 3.2 Splitting of the dataset

3.2 PREPROCESSING

To prepare the collected images for deep learning model training, the data preprocessing step was carried out with the goal of cleaning and cropping them. As the dataset was sourced from the Internet by Piosenka, it required preprocessing before being used in the deep learning model training. The images were initially cropped by the dataset creator to focus on the facial region. Subsequently, the dataset was divided into three sets: 2,540 images for learning, 100 for validation, and 300 for Evaluation. The normalization method was used to rescale the pixel values of all images from the range of [0, 255] to [0, 1].

3.3 CONVOLUTIONAL NEURAL NETWORK

AI has made significant progress in aiding humans with various applications in their daily lives, such as medical applications, which rely on a field of AI known as "computer vision." As a result, the CNN algorithm has been instrumental in detecting diseases and analyzing behavior and psychology. The CNN model's basic components will be explained in this section, including the input layer, convolutional layer, activation function, pooling layer, fully connected layer, and output prediction.

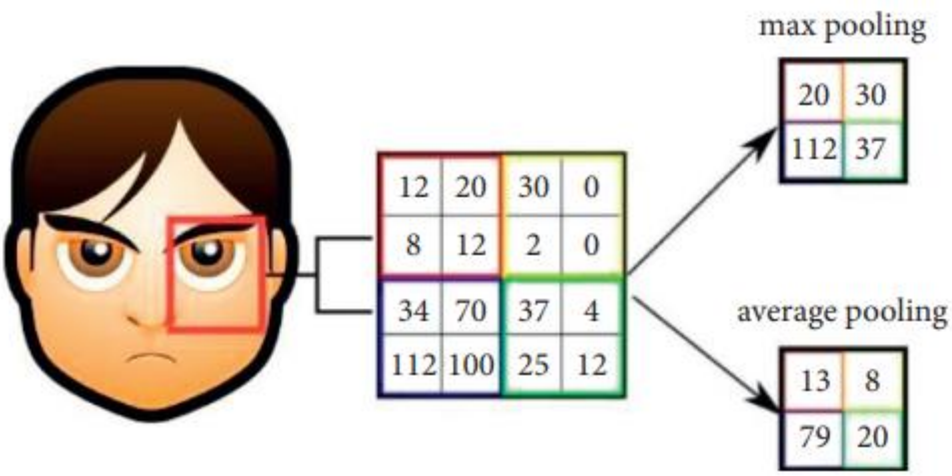


Fig: - 3.3.1 The Convolution and Pooling layer

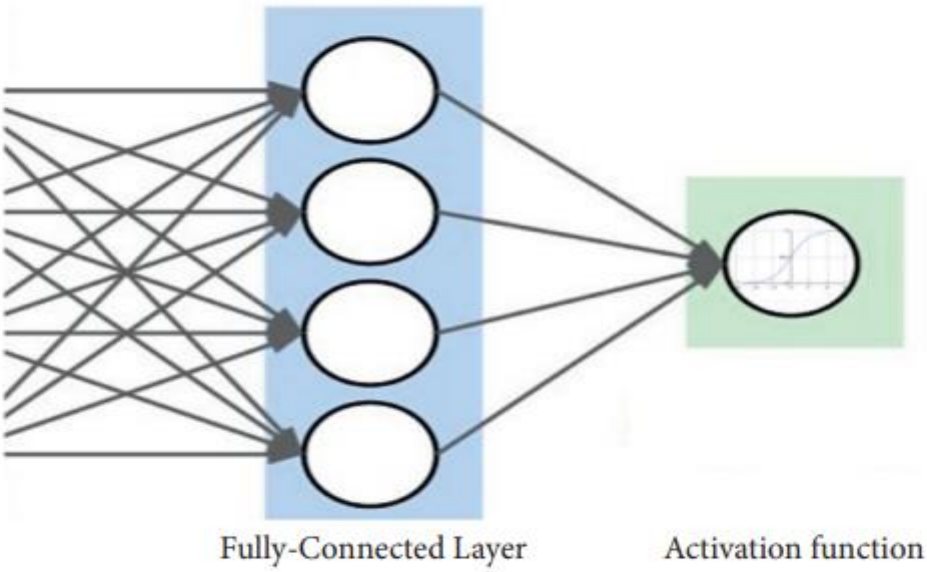


Fig: - 3.3.2 The fully connected layer and the activation function

3.4 DEEP LEARNING MODEL

This article focuses on the detection of autism using facial features images with the help of two pretrained models: VGG19, and Xception.

3.4.1 XCEPTION MODEL

The Xception architecture utilized feature maps, global max pooling layer followed by two fully connected layers with 128 and 64 units, respectively, and a ReLU activation function. The dense layer outputs were flattened to produce a vector output. Batch normalization was implemented to prevent overfitting. Early-stopping was employed using Keras to halt training when validation loss failed to improve. The RMSprop optimizer was utilized to minimize the error learning rate during CNN model parameter training. Finally, the Softmax function was used in the output layer for prediction. The architecture of Xception is illustrated in Figure 3.4.1.

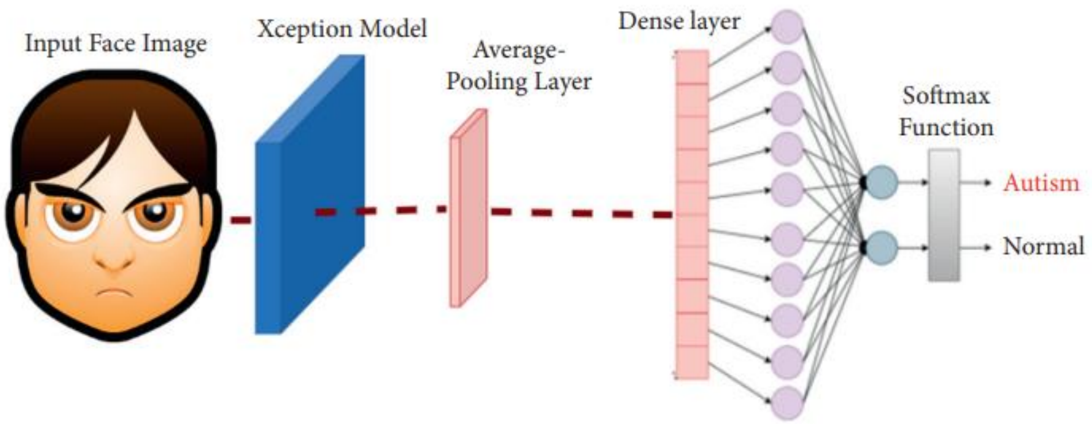


Fig: - 3.4.1 Xception model architecture in our study

3.4.2 VISUAL GEOMETRY GROUP NETWORK MODEL

The VGG19 model is a deep artificial neural network that consists of 19 layers for processing visual data. It utilizes the convolutional neural network (CNN) technique and is commonly used with the ImageNet dataset. VGG19 is known for its simplicity as it employs 3 × 3 convolutional layers to increase its depth. Max pooling layers were used to decrease the input volume size in the VGG19 structure. Two fully connected layers with 4,096 neurons each were employed to connect the layers within the model. The architecture of VGG19 is illustrated in Figure 3.4.2.

(i) The input layer performs the task of receiving and accepting image inputs with a size of 224 × 224 × 3. To ensure consistency, the creators of the model specifically selected the central 224 × 224 × 3 patch from each image for input.

(ii) The convolutional layers of VGG utilize a minimal receptive field size of 3 × 3, which is the smallest size that allows for vertical, horizontal, and diagonal movements. The convolution stride is set at 1 pixel to preserve the spatial resolution after convolution (stride refers to the number of pixel shifts over the input matrix).

(iii) ReLU is employed in all the hidden layers of the VGG network. Local Response Normalization (LRN) is not commonly utilized in VGG, as it leads to increased memory usage and longer training times. Moreover, it does not improve the overall accuracy of the model.

(iv) The fully connected layers consist of three layers. The first two layers contain 4,096 channels each, while the third layer has 1,000 channels.

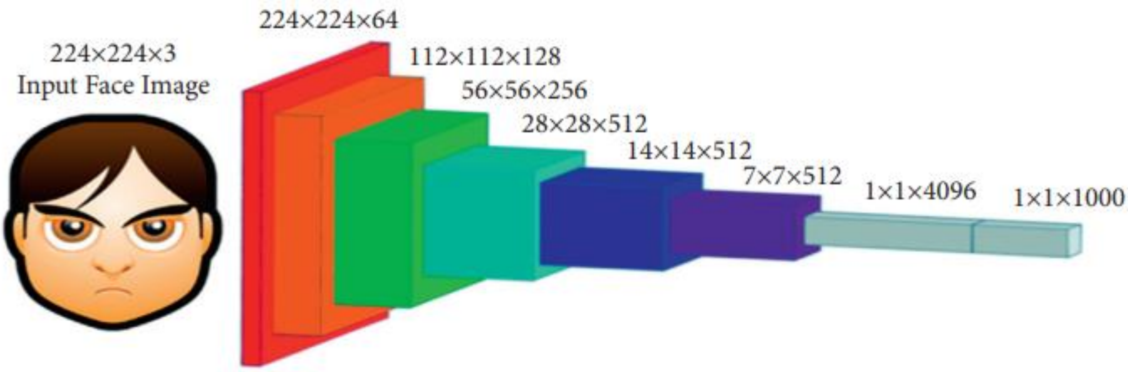
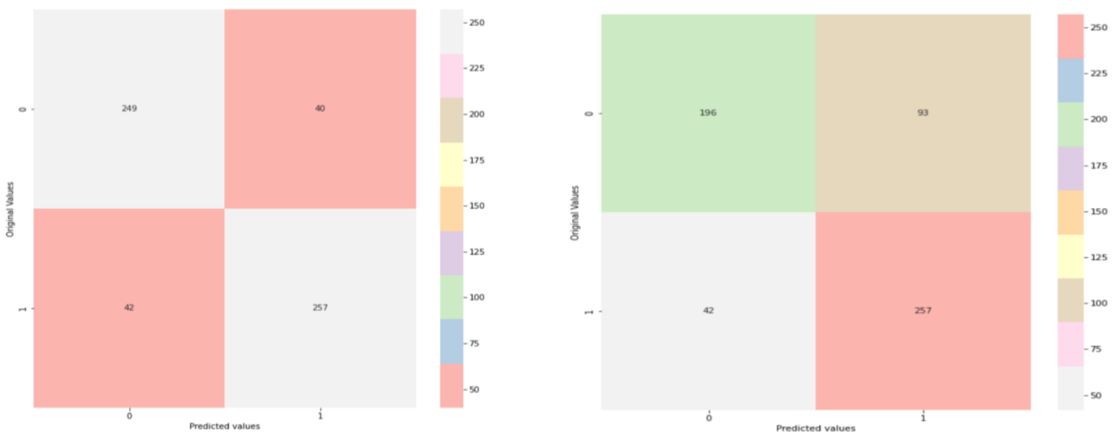


Fig: - 3.4.2 VGG19 model

CHAPTER 4

EXPERIMENTAL RESULTS

In this section, we present the results of the experiments conducted to detect ASD, summarizing the testing outcomes of the deep learning models used. The study employed three different pretrained deep learning models, namely Xception and VGG19, in order to detect autism spectrum disorder (ASD), each model underwent training and testing to identify specific facial characteristics that can classify children as either autistic or normal. Figure 4.1 showcases the confusion metrics for the three deep learning models. The outcomes reveal that the Xception model exhibited the highest testing accuracy, reaching 91%, surpassing the other models. Despite the dataset being collected from Internet sources by the data generator, which exhibited variations in age and image quality, the Xception model demonstrated the highest accuracy with a low error percentage.



(a) (b)

Fig: - 4.1 Confusion matrix for the (a) Xception model (b) VGG19 model

Figure 4.2(a) illustrates the performance of the VGG19 model in training and validating data for ASD detection. The graph illustrates the relationship between the number of epochs on the x-axis and the score percentage on the y-axis. The VGG19 model showed notable progress during the training process, with accuracy rising from 56% to 85% after 25 epochs. In the validation phase, the model achieved an accuracy of 82%. Figure 4.2(b) displays the corresponding training and validation losses, with the training loss recorded at 3.5 and the validation loss at 2.5.

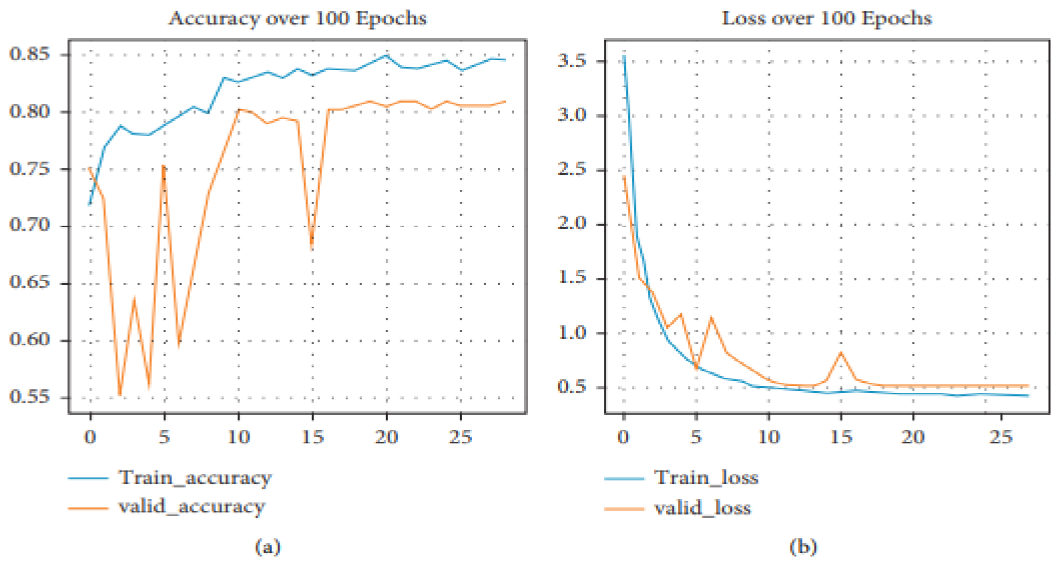


Fig: - 4.2 Overall Performance plot for the VGG19 model

The ASD detection experiments revealed that the Xception model exhibited exceptional performance with a 91% accuracy rate for the testing data and a perfect 100% accuracy for the training data. Figure 4.3(a) depicts its accuracy performance during the training process, where it steadily increased from 70% to 91% during the validation process, and maintained 100% accuracy throughout the training process. The validation loss for the Xception model was 2.0, as shown in Figure 4.3(b). The results confirmed that the Xception model was the most effective deep learning model for ASD detection.

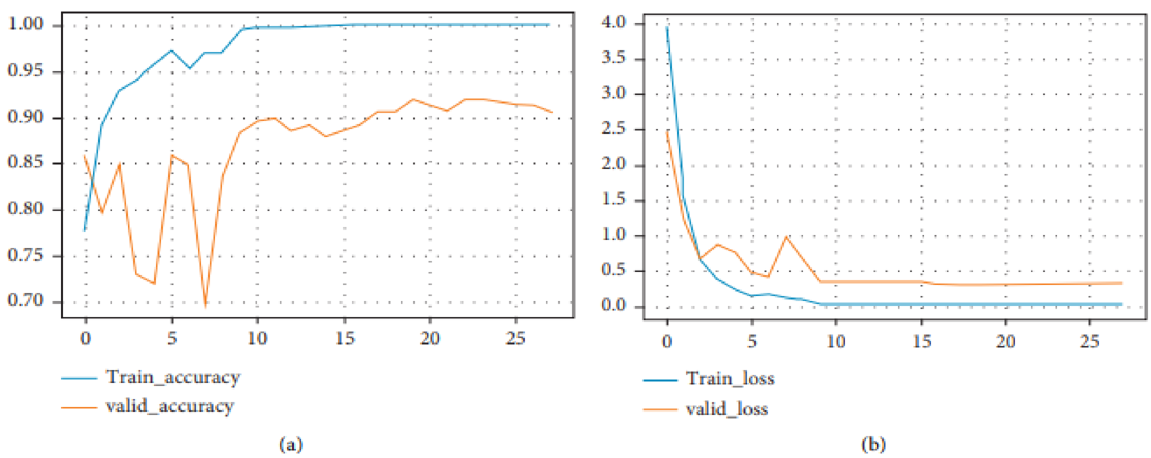


Fig: - 4.3 Overall Performance plot for the Xception model

CHAPTER 5

RESULT AND DISCUSSION

Individuals with autism struggle to comprehend the world around them, including their thoughts, feelings, and needs. The sensory experiences of a person with autism can be overwhelming and distressing, leading to intense anxiety in response to sudden changes in their environment. Early diagnosis is critical, and AI-based intelligent systems can aid in this process. Our study employed two advanced deep learning models, where Xception achieved the highest accuracy of 91%. Our system outperformed existing systems, including those utilizing ResNet50, emphasizing the potential of AI-based systems in facilitating early autism diagnosis and improving the lives of affected children.

Early diagnosis of autism plays a crucial role in safeguarding the well-being of numerous children. Leveraging the power of AI, an intelligence system has been developed to aid in the identification of autism. This study evaluated two advanced deep learning models, namely Xception, and VGG19, for their effectiveness in diagnosing autism.

By employing these three deep learning algorithms, this study not only demonstrated the significance of early autism detection but also highlighted the remarkable performance of the Xception model, surpassing the accuracy of all existing systems. The findings of this research underscore the potential of our developing system to outperform current methods and contribute to improved autism diagnosis.

CHAPTER 6
CONCLUSION

Advances in global health knowledge and capacities have led to increased interest in child autism, which has become more prevalent in recent years. Researchers and academics are working to uncover the causes of autism and develop early detection methods, as well as effective treatment programs that can help autistic individuals integrate into society.

This study utilized three deep learning models, Xception and VGG19, to detect ASD through facial features. The Xception model achieved the highest classification accuracy of 91% after being trained on a publicly available dataset. These results indicate the potential of deep learning and computer vision-based models as automatic tools for accurate and efficient autism diagnosis by specialists and families. Using computer techniques can also aid in conducting complex behavioral and psychological analyses required for autism diagnosis, which typically take longer and require significant effort.

CHAPTER 7

REFERENCES / BIBLIOGRAPHY

i. Paula, C. S., Ribeiro, S. H., Fombonne, E., & Mercadante, M. T. (2011). Brief report: prevalence of pervasive developmental disorder in Brazil: a pilot study. *Journal of autism and developmental disorders*, *41*(12), 1738-1742.

ii. Nunes, L. C., Pinheiro, P., Pinheiro, M. C. D., Pompeu, M., Comin-Nunes, R., & Pinheiro, P. G. C. D. (2019, April). A hybrid model to guide the consultation of children with autism spectrum disorder. In *The International Research & Innovation Forum* (pp. 419-431). Springer, Cham.

iii. Guha, M. (2014). Diagnostic and statistical manual of mental disorders: DSM-5. *Reference Reviews*.

iv. Carette, R., Cilia, F., Dequen, G., Bosche, J., Guerin, J. L., & Vandromme, L. (2017, October). Automatic autism spectrum disorder detection thanks to eye-tracking and neural network-based approach. In *International conference on IoT technologies for healthcare* (pp. 75-81). Springer, Cham.

v. Kanner, L. (1943). Autistic disturbances of affective contact. *Nervous child*, *2*(3), 217-250.

vi. Parikh, M. N., Li, H., & He, L. (2019). Enhancing diagnosis of autism with optimized machine learning models and personal characteristic data. *Frontiers in computational neuroscience*, *13*, 9.

vii. Thabtah, F., & Peebles, D. (2020). A new machine learning model based on induction of rules for autism detection. *Health informatics journal*, *26*(1), 264-286.

viii. Schelinski, S., Borowiak, K., & von Kriegstein, K. (2016). Temporal voice areas exist in autism spectrum disorder but are dysfunctional for voice identity recognition. *Social Cognitive and Affective Neuroscience*, *11*(11), 1812-1822.

ix. Akter, T., Satu, M. S., Barua, L., Sathi, F. F., & Ali, M. H. (2017). Statistical analysis of the activation area of fusiform gyrus of human brain to explore autism. *Int. J. Comput. Sci. Inf. Secur.(IJCSIS)*, *15*, 331-337.

x. Guillon, Q., Hadjikhani, N., Baduel, S., & Rogé, B. (2014). Visual social attention in autism spectrum disorder: Insights from eye tracking studies. *Neuroscience & Biobehavioral Reviews*, *42*, 279-297.