Autism spectrum Disorder Diagnosis Using Face Features based on Deep Learning

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Abstract

The majority of screening instruments for autism spectrum disorder (ASD) rely on subjective questions given to caregivers. Although behavioral observation is more objective, it is also more expensive, takes longer to complete, and requires a high level of competence. Therefore, there is still a dire need to create workable, scalable, and trustworthy systems that can identify ASD risk behaviors. Since there are no known causes of autism, early detection and intense therapy can significantly alter the behavior of children and people with the disorder. Artificial intelligence has made this possible, saving many lives in the process. Utilizing biological pictures, autism spectrum disorder (ASD) is a sort of mental illness that can be identified. The neurological condition known as autism spectrum disorder (ASD) is linked to brain development and affects later appearance of the flask framework, a convolutional neural network with transfer learning, and the physical impression of the face. Xception , Visual Geometry Group Network (VGG16)the classification job was carried out using the previously trained models. 2,940 face photos made up the dataset used to test these models, which was obtained via the Kaggle platform.The outputs of the three deep learning models were assessed using common assessment measures including accuracy, specificity, and sensitivity.With a 91% accuracy rate, the Xception model had the greatest results. And theVGG16 models came next with (75%) .

Keywords. autism spectrum disorders, Face Features , Deep learning ,VGG 16,Xception .
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Introduction

Autism is a type of mental condition that is particularly challenging to anticipate in its early stages in youngsters. It is a developmental illness that affects how people communicate and engage with one another. Common names for it include Autism spectral disorder (ASD). Although the exact causes of autism are unknown, those who have it exhibit behaviors that are damaging to both themselves and others. Autism varies in severity from person to person, and it can be challenging to diagnose. ASD affects over 1% of children, thus it will be advantageous to identify this condition early. According to statistics, men are more likely than women to have ASD[1] ASD affects around 5-9% of all children.[2] As the name "spectrum" suggests, these complex neurodevelopmental diseases of the brain, which include Asperger's syndrome, childhood disintegrative disorders, and autism, include a variety of symptoms and degrees of severity.[3]These illnesses are presently face recognition is more important in identifying autism. Facial recognition technology is frequently used to recognize people and establish whether they are normal or aberrant. In order to identify behavioural patterns, it includes mining relevant information.[14,15], Duda et al.[16] outlined a novel technique for creating samples of differences between attention deficit hyperactivity disorder (ADHD) and autism and using those differences to identify autism. For the datasets, 65 examples of differences in social responsiveness in facial expressions were gathered.Deshpande et al.[17] created measures to analyze brain activity and detect autism. Approaches using AI and soft computing have also been used to identify autism. Numerous research on the detection of autism have been undertaken, but few of them have emphasized brain MRI.Parikh et al.[18] developed a system for extracting the features of autism using machine learning techniques. 851 individuals that they categorized as having and not having ASD made up their dataset. Thabtah and Peebles [19] employed RBML (rule-based machine learning) to identify ASD characteristics. Al Banna et al.[20]a sophisticated system was created to keep tabs on ASD patients during the coronavirus disease 2019 (COVID-19) pandemic.AI and machine learning have been used in numerous practical applications to assist in resolving social issues. AI has been applied to every aspect of health care to assist physicians in managing conditions like autism. The extraction of ASD patient characteristics that can be utilized to distinguish between people with and without ASD has received considerable attention. Deep learning techniques, notably CNNs and recurrent neural networks, have been used or proposed to detect autism in children (RNNs) [21,22]and the BLSTM paradigm (bidirectional long short-term memory) [24]. More research has been done recently to identify ASD using machine learning techniques such [23,24] classified as Pervasive Developmental Disorders under the heading of Mental and Behavioral Disorders in the International Statistical Classification of Diseases and Related Health Problems.Early signs of ASD frequently manifest within the first year of life.[4]It might include of not making eye contact, not reacting when someone calls them names, and showing disregard for caretakers.A few kids seem to develop normally throughout the first year, but between the ages of 18 and 24 months, they start to exhibit symptoms of autism.[5]a constrained variety of interests and activities, as well as confined and recurring behavioral patterns. Children may abruptly turn introverted or violent in their first five years of life as they struggle to engage and communicate with society since these diseases also influence how a person perceives and interacts with others.Although ASD first manifests in childhood, it frequently lasts throughout adolescence and adulthood.[6] .

Through the use of face pattern recognition, cutting-edge Artificial intelligence (AI)-based information technology has aided in the early detection of ASD..[7]suggested the use of such an algorithm to identify facial expressions in numerous neurological illnesses by using the convolutional neural network (CNN) technique to train data for extracting components of human facial expressions.[8]Haque and Valles in 2018[9]upgraded the Facial Expression Recognition 2013 dataset using deep learning techniques to identify autistic children's facial expressions.[10]the 30 films that were identified using the CultureNet deep learning model were displayed. Important characteristics of autism have been identified by various research using a variety of diagnostic techniques, such as feature extraction.[11] eye movement tracking [12]medical image analysis, face recognition and voice recognition [13] But rather than a person's emotional state, people with ASD using their eyes and faces.

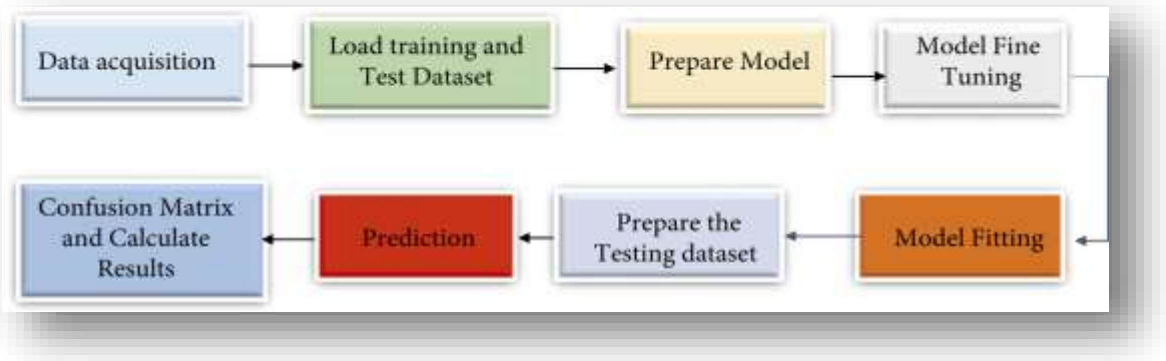
4- Several techniques have been used to validate and analyze the emerging system.

1- work methodology

This study suggests utilizing the facial characteristics of autistic and typical kids to identify autism using the deep learning models Xception and VGG16, which are based on transfer learning. It is possible to tell whether a youngster has autism or is normal based on their facial traits. Significant face traits were taken from the photographs by the models. Deep learning algorithms have the benefit of being able to extract incredibly minute features from images that a human eye cannot see. Figure 1 depicts the whole structure of our investigation, from data collection through loading and preprocessing to model development and evaluation.

brain imaging [25,26] evaluation of clinical data using a machine learning technique, evaluation of physical biomarker data, evaluation of autistic people's behavior [27,28]Our work showed how to recognize autism from a picture of a youngster using a well-trained classification model (based on transfer learning). The development of high-spec mobile devices has made it possible for this model to quickly offer a diagnostic test of alleged autistic features by shooting a picture using cameras. The following are the primary contributions of our study:

1- For the purpose of detecting ASDs, two pretrained deep learning algorithms Xception and VGG16
2- Of the two pretrained deep learning algorithms, the Xception model had the best performance.
3- A technique was created to assist health professionals in identifying



2- Dataset

This study compared the visual features of autistic and typical kids using photos from the publicly available online Kaggle platform [29]. The collection included 2,940 face photos, of which half were of children with autism and the other half were of children without autism. This data set was gathered from websites and Facebook groups with an interest in autism on the Internet. The distribution of the split dataset samples is displayed in Table 1. Figure 2 shows how the input data was divided.

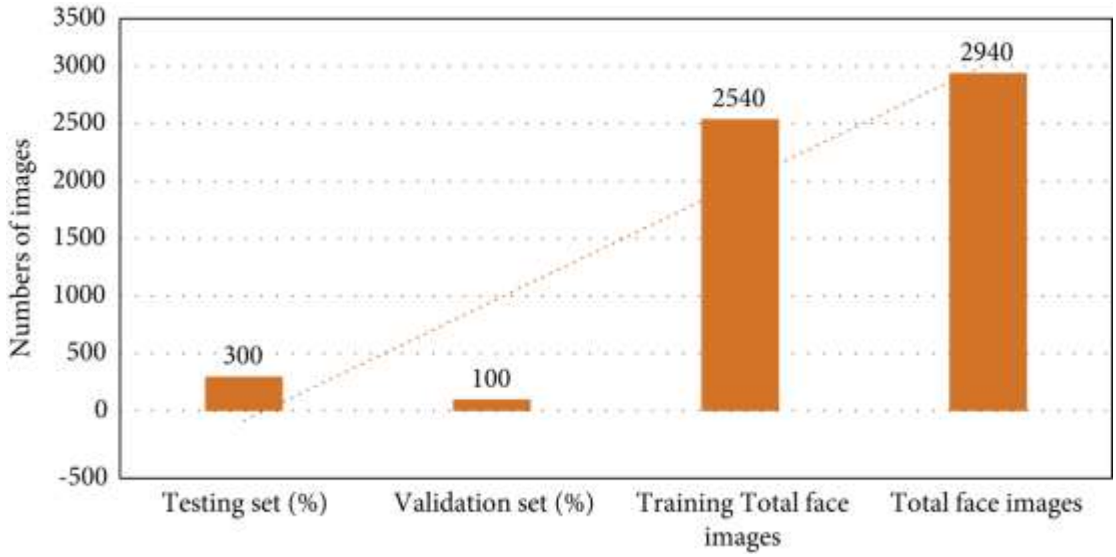


Figure 2: **dataset Details**

neuron. This section will go into great detail on the input layer, convolutional layer, activation function, pooling layer, fully connected layer, and output prediction.

B. Convolutional Layer with a Pooling Layer

A matrix of pixel values representing an image serves as the convolutional layer's input. The convolutional layer's goal is to simplify the pictures without sacrificing any of the key characteristics that will aid in the detection of autism. Low-level characteristics like edges and colour are extracted by the CNN model's first layer. The CNN model's construction allows us to add more layers to it, allowing it to extract the high-level characteristics that will aid in visual comprehension. The number of weights was decreased by utilizing either the max pooling or average pooling approaches since the convolution layer's output of a high number of parameters might greatly slow down the matrices' arithmetic operations. The maximum values in each window of the stride are the basis for max pooling, whereas the mean value of each window of the stride is the basis for average pooling. The model used in this investigation was based on maximum pooling. The convolutional layer, as well as the maximum and average pooling procedures, are displayed in Figure 3. The

3-Preprocessing

The photos were cleaned up and cropped as part of the data preparation. Piosenka's [30] collection of data from online sources need preprocessing before the deep learning model could be trained on them. The face in the original image was automatically cropped by the dataset's developer. The dataset was then divided into 300 photos for testing, 100 images for validation, and 2,540 images for training. The normalization approach was used to scale; the dataset was rescaling all of the picture parameters from [0, 255] to [0, 1].

4- Convolutional Neural Network Models

A branch of AI known as "computer vision" has been impressively developed to help humans in their daily lives, such as through medical applications. As a result, the CNN algorithm has helped with illness identification as well as behavioral and psychological analysis.

A. Basic Components of the CNN Model

The convolutional neural network (CNN) is one of the most well-known deep learning methods. It uses the input image to determine the class of the image by prioritizing learnable weights and biases. An analogy to the communication pattern of the neurons in the human brain may be made between the connection and communication between cells inside the mathematical reduction in the number of parameters through max pooling and average pooling.

kernel's sliding window turns the input picture into a matrix and extracts the features, which is followed by a

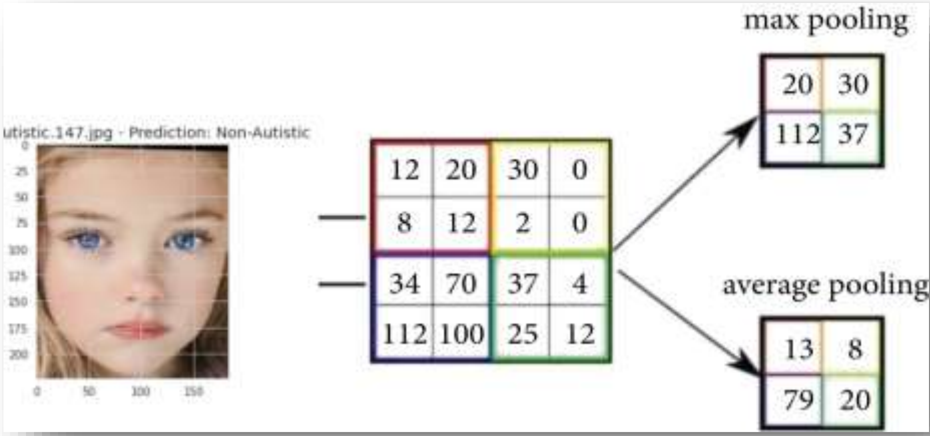


Figure 3 Max pooling, average pooling, and the convolution layer

loss mistakes in the backpropagation and learns more features. The majority of deep learning models do well as they add hidden layers and training iterations, allowing the neural network to thoroughly extract the low-level data. Figure 4 illustrates how the softmax classifier computes the attributes to predict the output after receiving the parameters from the FC layer. If a picture has a Softmax output of 0, it belongs to class 0, and if it has a Softmax output of 1, it belongs to class 1. Class 0 represents the autistic class in this study, while class 1 represents the typical class.

C. Fully Connected Layer and Activation Function

The fully connected (FC) layer is a nonlinear collection of high-level characteristics that were represented as outputs after receiving input from the hidden layers. The input picture is shown as a column vector in the FC layer. The forward neural network and backpropagation are the two paths available for the model's training. The forward neural network feeds create an output layer that is flattened. By increasing the number of training iterations, the neural network reduces

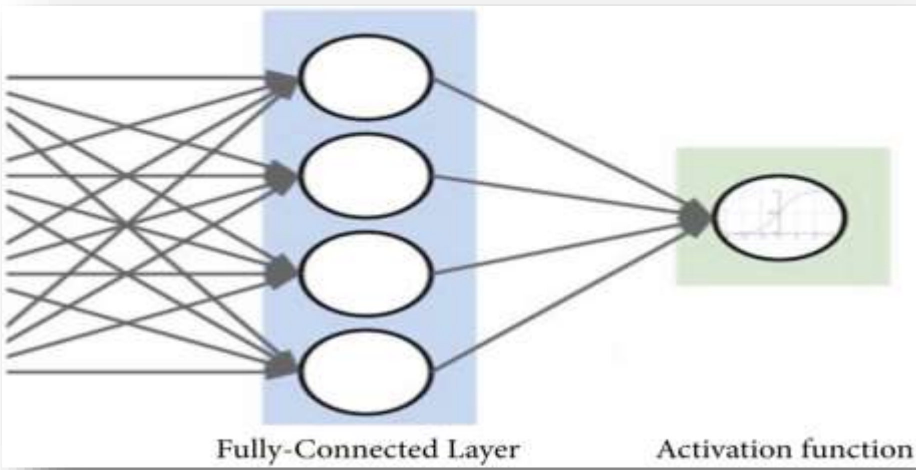


Figure 4 The activation function and The fully connected layer .

architecture to extract the picture characteristics for the dataset is seen in Figure 5. The features maps were employed in the Xception architecture, which also included two dense layers with rule activation functions that were each 128 and 64 layers thick and included a global max pooling layer. The flatten layer, which accepts a feature map as input and produces a vector as output, was then given the output of the dense layers. The output was improved by batch normalization, which prevented Overfitting.The early-stopping strategy, which halted the training when the model's validation loss did not decrease, was supported by Keras. The RMSprop optimizer was employed in this model to lower the error learning rate or loss during the training of the CNN model's parameters. The Softmax function was employed in the last layer for output prediction.

5- Deep Learning Models

The VGG16 and Xception models, two pretrained models for autism identification using facial feature photos, are the foundation of this study.

A- Xception Model

The model was trained on the dataset mentioned in section A before for the purpose of classifying and recognizing images. A deep CNN that offers new inception layers is called Xception. A point wise convolution layer comes after the depth wise convolution layers, which make up the inception layers. The ideas of feature extraction and fine-tuning are both used in transfer learning. In this work, the pretraining model, which was trained on the standard dataset, was employed in the feature extraction approach to extract the features from the new dataset and to remove the top layers of the model.features have been fine-tuned to fit a specific class. The network utilized in the Xception model

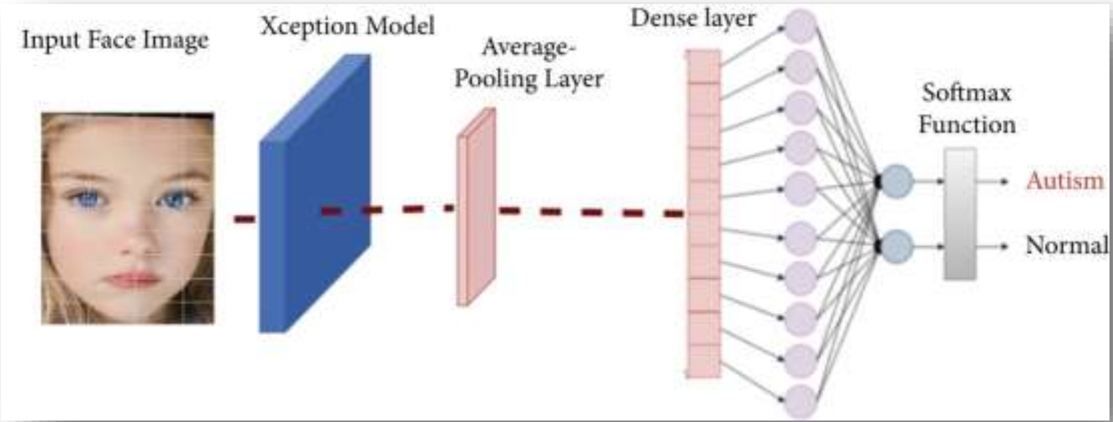


Figure 5 Max pooling, average pooling, and the convolution layer .

its picture recognition performance has been outstanding. Its effectiveness is mostly dependent on the 16 or 19 convolutional weighted layers. The deeper the network in CNN's design, the more convolutional layers there are.

B- Visual Geometry Group Network (VGG) Model

The Visual Geometry Group-16 model, often known as VGG-16, is employed in deep learning convolutional neural networks. In the case of a large dataset, appears three stacks of Convolutional layers later. The maximum pooling layer has a 22 dimension. Three thick layers came after the stack of convolutional and max pooling layers. ReLU activation functions are present in the first two dense layers, whereas Softmax activation functions are present in the last dense layer. As demonstrated in Figure (6), a dense layer is sometimes referred to as a fully connected layer.

Applying filters of (33) from left to right and from top to lower on each convolutional layer of the input data will result in a compressed picture. Additionally, it is advised to specify the RGB image's dimensions as 224 x 224. The VGG16 has level 1 set as the padding size. The max pooling layer comes after the convolutional layer, although not every convolutional layer comes after the max pooling layer. One max pooling layer

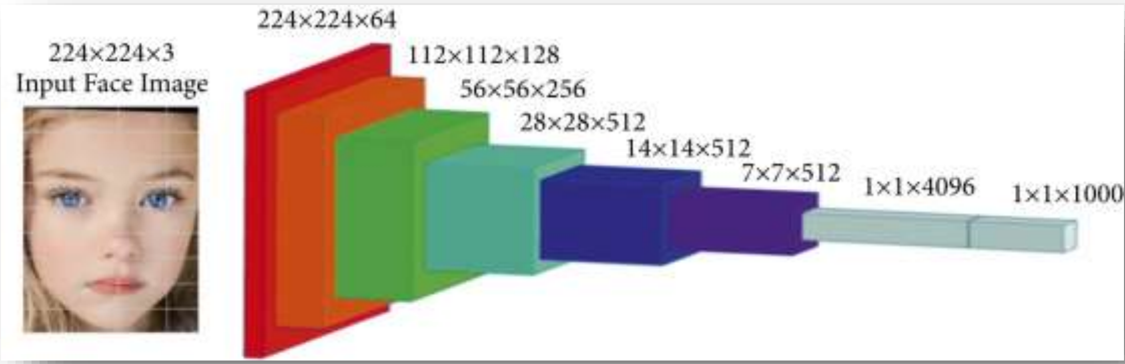


Figure 6 Visual Geometry Group Network

detecting autism using various hardware and Python modules (ADS). The primary specifications for the ADS's design are shown in Table1 and the parameters utilized in the deep learning models before training are shown in table (2)

6-Implementation and results

This part presents the deep learning model findings and declares the noteworthy system development outcomes.The experiment was conducted to create an intelligent system for

Hardware	**Software & libraries**
Processor core I5	Google drive for dataset
8 GB RAM	TensorFlow library Keras library Panda seaborn Matplotlib Numpy

Table (1) hardware and software details

Parameter name	**Value**
Global max pooling layer size	3 * 3
Dense layer	128, 64
Batch size	32
Number of epochs	100
Output classification layer	Softmax
Optimizer	ADAM
Activation function	Rule/sigmoid

Table (2) parameters

7- Metrics for evaluation

For the two pretrained models in this work, various performance assessment measures, including accuracy, sensitivity, and specificity, as well as a confusion matrix, are used. An example of a measure of classification performance is a confusion matrix, This is a table with the test findings' true and false values. True Positives represented 135 of the 150 autistic children, False Negatives represented 18, True Negatives represented 142 of the 150 typically developing children, and False Positives represented 8 of the 150 autistic children in the confusion matrix of the Xception model.The following are the formulae for these metrics:

1- $\textbf{Accurcy} = \frac{TP+TN}{FP+FN+TP+TN} * \mathbf{100\%}$

2- $\textbf{Sensitivity} = \frac{TP}{TP+FP} * \mathbf{100\%}$

3- $\textbf{Specificity} = \frac{\mathbf{TN}}{\mathbf{TN+FN}} * \mathbf{100\%}$

where TN stands for True Negative, FP for False Positive, TP for True Positive, and FP for False Positive. Specificity is the model's ability to recognize normal children, whereas sensitivity is the model's ability to recognize autistic children.

8-Results

The test results from the investigations done to look for ASD are shown in this section. The testing outcomes for the used deep learning models are presented in Table 3.

Model name	Specificity	Sensitivity	Accuracy
Xception	0.95	0.89	0.94
VGG16	0.80	0.78	0.73

Table 3 outcomes of the deep learning models' testing.

Three distinct pretrained deep learning models, including Xception and VGG16, were used in these studies to identify ASD. Each model underwent training and testing to identify the characteristics that, based on face features, classify youngsters as autism or normal. They demonstrate that the VGG16 model had the lowest performance level at 78% and the Xception model had the greatest testing accuracy, 91%. The Xception model demonstrated the best accuracy, with just a tiny proportion of mistakes, despite the dataset being compiled from Internet sources by the data generator, which clearly indicated the difference in ages and the caliber of the photos as showing in figures 7.1and 7.2 illustrate Confusion matrices for the both models Xceptionand VGG16 model

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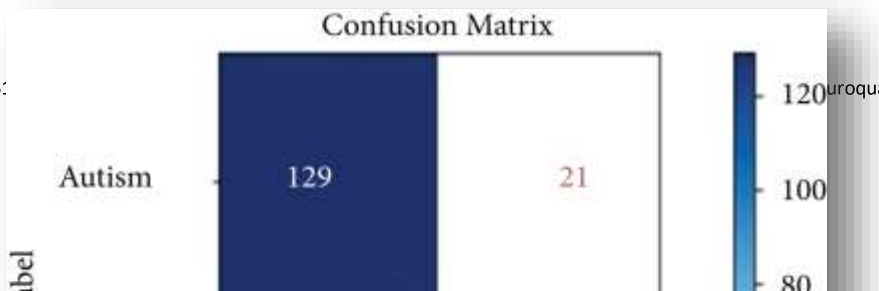

Figure 7.1 Confusion matrices for theXception model

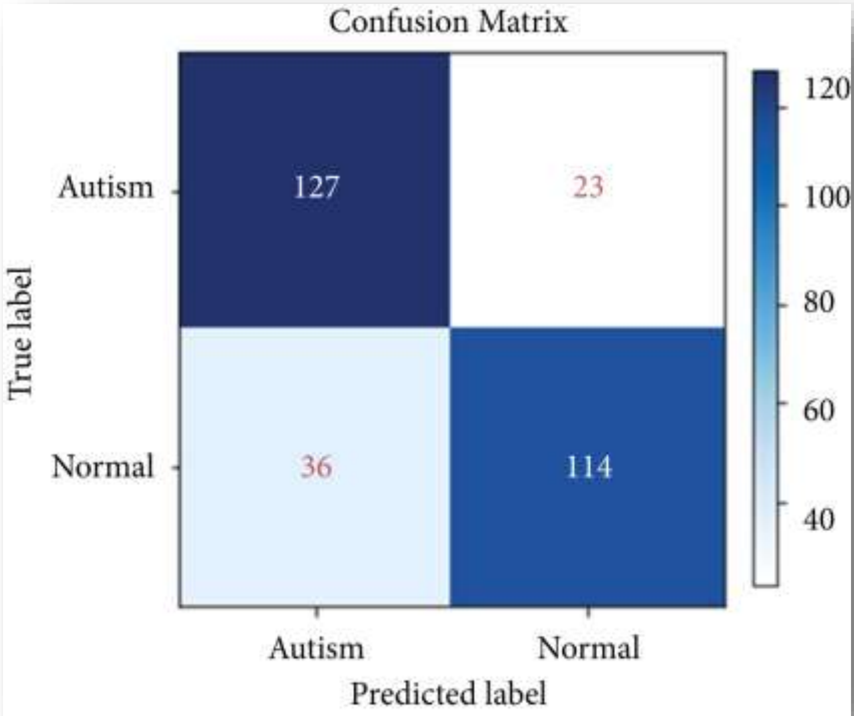

Figure 7.2 Confusion matrices for theVGG16 model

unexpected happens in their environment, they are scared that no one else will comprehend. Autism must be properly diagnosed in order to save the lives of countless youngsters. The creation of AI-based intelligence systems can aid in the early detection of autism. Three cutting-edge deep learning models, including Xception and VGG16, were taken into consideration for this study's

9-Results and Discussion

People with autism have trouble comprehending themselves, their ideas, feelings, and needs as well as the environment around them. A person with autism experiences the world around him as a horror film, and he finds particular sounds, lighting, and even food scents and tastes to be terrifying and occasionally painful. As a result, when something

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attempt to diagnose autism. When these models' empirical data were given, it was found that the Xception model had the best accuracy (91%).

10-Conclusion

The interest in pediatric autism has grown as global health knowledge and capacities have advanced. Additionally, due to the increase in the number of children with autism, researchers and academics have intensified their efforts to comprehend the causes of autism and to detect it early in order to offer behavioral development treatment programs for autistic people that should help them integrate into society and escape the isolation of the autistic world. This study evaluated the efficiency with which the VGG16 and Xception deep learning models identified ASD based on features of the face.The Xception model, which was trained using a publicly available dataset online, has the highest classification accuracy (91%). The classification results of the model showed us the possibility of using such deep learning and computer vision models as automated tools for professionals and families to more quickly and accurately diagnose autism. Computer technologies make it easier to efficiently complete time-consuming and labor-intensive behavioral and psychological studies for the diagnosis of autism.

11- Availability of Data

The study's dataset, which served as evidence for its conclusions, is accessible at https://www.kaggle.com/cihan063/autism-image-data

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