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Autism spectrum Disorder detection Using Face Features based on Deep Neural network

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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) can be defined as a mental illness type which can be identified. The neurological condition known as ASD is linked to brain development and affects later appearance of the flask framework, a convolutional neural network (CNN) with transfer learning, and 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 utilized for the testing of those models, which was obtained via Kaggle platform. Outputs of the 3 models of deep learning have been evaluated with the use of common measures of assessment, including accuracy, sensitivity and specificity. With a 91% accuracy rate, Xception model had the greatest results. And theVGG16 models came next with (75%).

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

1. 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). Even though the exact autism causes are unknown, the ones who have it show behaviors that are damaging to both themselves and others. Autism ranges in the degree of severity from one individual to another, and it may be challenging to diagnose. ASD affects over 1% of the children, which is why, it will be beneficial 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 categorized as Pervasive Developmental Disorders under the heading of Behavioral and Mental Disorders in International Statistical Classifications of the Diseases and Related Health Issues. 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 children seem to be developing normally throughout the first year, however, between ages of 18 and 24 months, they start to exhibit symptoms

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of autism. [5] a constrained variety of interests and activities, as well as confined and recurring behavioral patterns. Children may abruptly turn violent or introverted in their first 5 years of their life while 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 using such an algorithm in order to identify the face expressions in numerous neurological illnesses by using CNN technique for the training of the data for the extraction of the human facial expression components. [8] Haque & Valles in 2018 [9] have upgraded Facial Expression Recognition 2013 data-set 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, like the feature extraction. [11] eye movement tracking [12] medical image analyses, face recognition and voice recognition [13] But rather than a person's emotional state, 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 utilizing those differences in order to identify the 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 soft computing and AI have been used as well so as to identify the autism. Numerous research on the detection of autism have been undertaken, but a small number of them have emphasized brain MRI. Parikh etal. [18] developed a system for the extraction of autism features 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 ML) in order to identify ASD characteristics. Banna etal. [20] a sophisticated system was created to keep tabs on ASD patients throughout 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. DL techniques, notably CNNs and recurrent NNs, were utilized or suggested to detect autism in the children (RNNs) [21, 22] and the BLSTM paradigm (bidirectional long short-term memory) [23]. More research has been done recently to identify ASD using machine learning techniques such [23, 24] 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 model of classification (based upon the 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 DL algorithms, the Xception model had shown the best performance
3. A technique was created to assist health professionals in identifying people with ASD using their eyes and faces.
4. Several techniques have been used to validate and analyze the emerging system

2. 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.

3. 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 2940 face photos, of which half have been images of children with autism and the other half have been images of children who are without autism. This data set has been gathered from websites

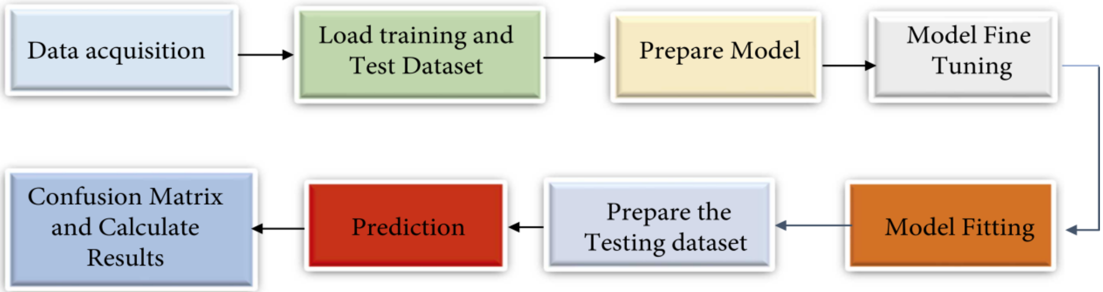

FIGURE 1. Work Architecture

and Facebook groups with an interest in autism on the Internet. Distribution of split data-set samples is displayed in Table 1. Figure 2 shows how the input data was divided.

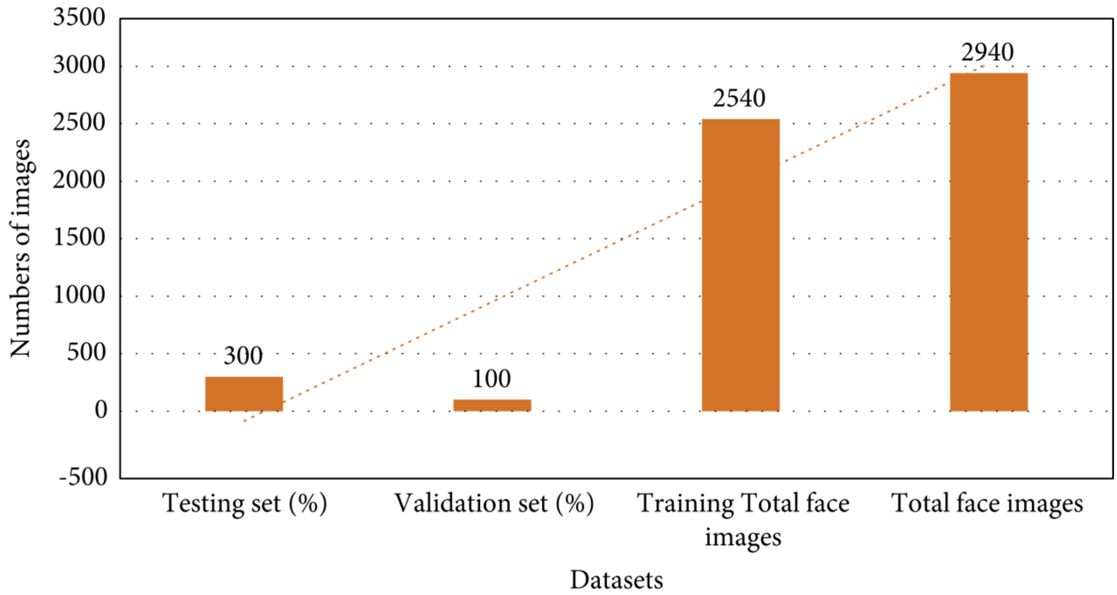

FIGURE 2. Dataset Details

4. 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 data-set has been rescaling all of the picture parameters from [0, 255] to [0, 1].

5. CNN MODELS

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

5.1 BASIC CNN MODEL COMPONENTS

CNN represents one of the most well-known methods of deep learning. It uses input image so as to determine the image class by prioritizing learnable weights and biases. An analogy to the pattern of communications of neurons in human brain may be made between the connection and communication between cells inside the neuron. This section will go into great detail on input layer, convolution layer, pooling layer, activation function, fully connected layer, and output prediction.

5.2 CONVOLUTIONAL LAYER WITH 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 the addition of more layers to it, allowing it to extract high-level characteristics which will aid in the 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. Maximal values in every window of stride are the basis for max pooling, whereas average value of every window of a stride is a 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 kernel's sliding window turns the input picture into a matrix and extracts the features, which is followed by a mathematical reduction in the number of parameters through average pooling and max pooling.

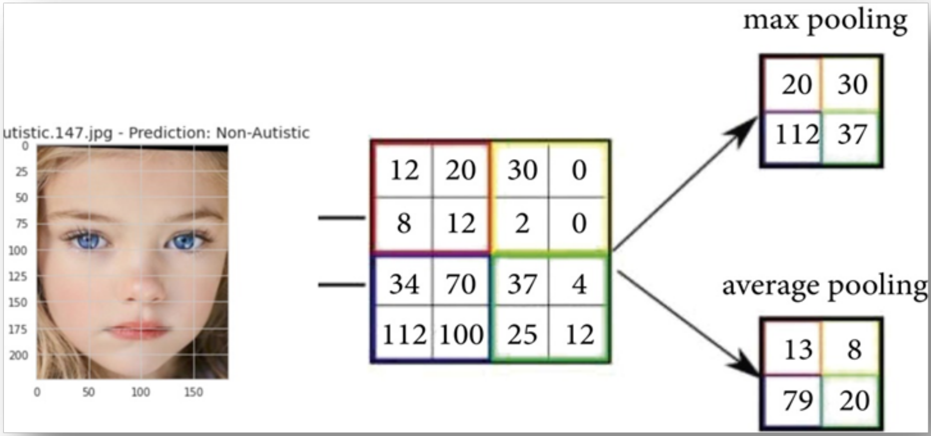

FIGURE 3. **Max pooling, average pooling, and the convolution layer**

5.3 FULLY CONNECTED (FC) LAYER AND ACTIVATION FUNCTION

FC layer represents a non-linear collection of high-level characteristics which were represented as outputs after receiving input from the hidden layers. The input picture has been shown as column vector in FC layer. The forward neural network and backpropagation are the two paths available for the model's training. The forward NN feeds create an output layer that is flattened. By increasing the number of training iterations, the neural network reduces loss mistakes in the backpropagation and learns more features. The majority of deep learning models do well as they add training iterations and hidden layers, allowing the NN to thoroughly extract low-level data. Figure 4 illustrates how the softmax classifier computes the attributes to predict the output after receiving parameters from FC layer. If a picture has 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 a typical class.

6. DEEP LEARNING MODELS

The VGG16 and Xception models, two pre-trained models for the identification of autism with the use of the facial feature photos, are the foundation of this study.

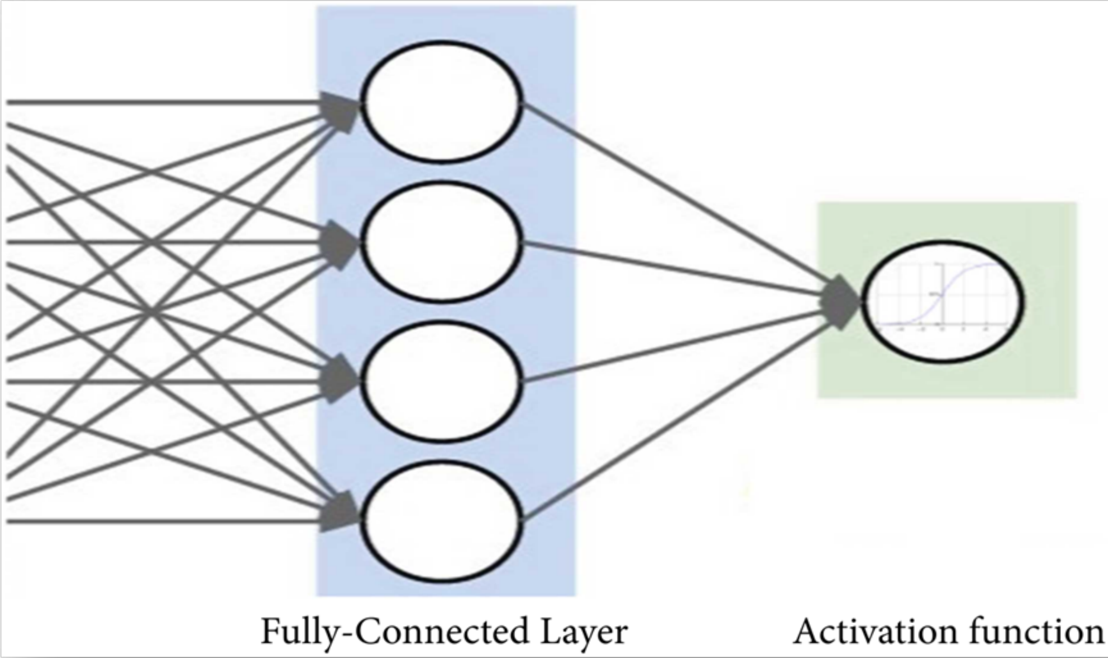

FIGURE 4. Activation function and fully connected layer.

6.1 XCEPTION MODEL

This model has been trained on data-set that has been mentioned in section A before for the purpose of classifying and recognizing images. A deep CNN which 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 fine-tuning and feature extraction are both used in the task of transfer learning. In this work, pre-training model that has been trained on standard data-set, was employed in feature extraction approach for the extraction of features from new data-set and to remove model's top layers. features have been fine-tuned to fit a specific class. The network that has been utilized in Xception model to extract the picture characteristics for data-set 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 dense layer output. The output has been improved by batch normalization, which prevented Overfitting. Early-stopping strategy that had halted training in the case where model's validation loss didn't decrease, was supported by Keras. The RMSprop optimizer was employed in this model to lower error learning rate or loss throughout training of CNN model's parameters. The Softmax function was employed in the final layer for the prediction of the output.

6.2 VGG MODEL

The VGG-16 model, which is often known as the VGG-16, is employed in the deep learning convolutional neural networks. In a case of a large dataset, 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. 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 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 2 dense layers, whereas Softmax activation

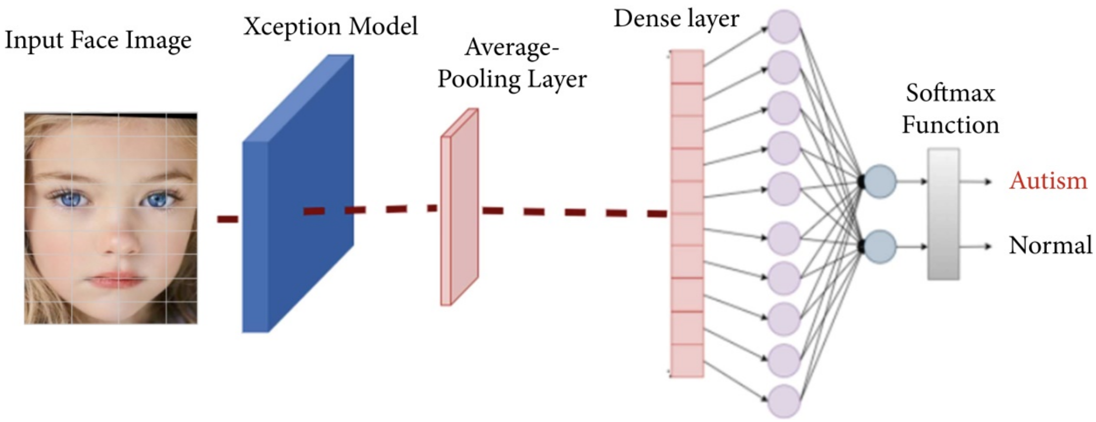

FIGURE 5. **Max pooling, average pooling, and the convolution layer.**

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.

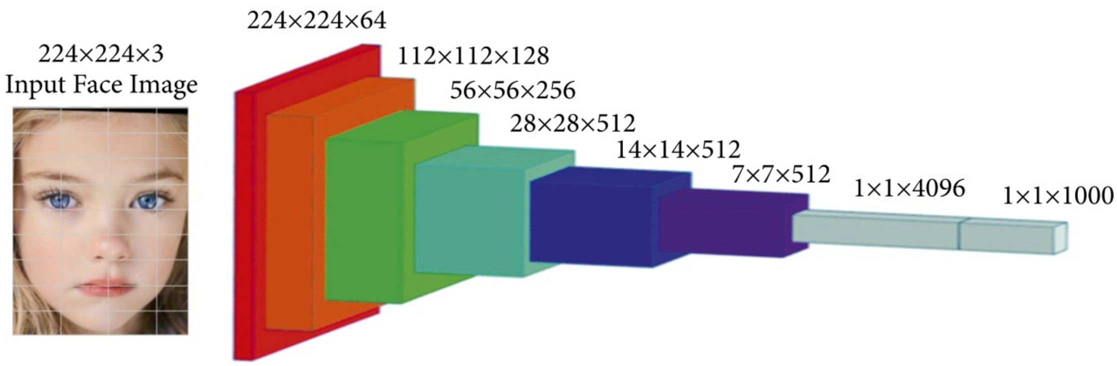

FIGURE 6. **Visual Geometry Group Network**

7. 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 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)

Table 1. **Hardware and software details**

Hardware	Software & libraries
Processor core I5	Google drive for dataset
8 GB RAM	TensorFlow libraryKeras libraryPanda seabornMatplotlibNumpy

8. 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 150 typically developing children, and False Positive cases represented 8 of the 150 autistic children in confusion matrix of Xception model. The following are the formulae for these metrics:

Table 2. **Parameters**

Parameters	Values
Global max pooling layer size	3x3
Dense layer	128, 64
No. of epochs	100
Batch size	32
Optimizer	ADAM
Output classification layer	Softmax
Activation function	Rule/ sigmoid

1. Accurcy $= \frac{TP+TN}{FP+FN+TP+TN} * 100\%$
2. Sensitivity $= \frac{TP}{TP+FP} * 100\%$
3. Specificity $= \frac{TN}{TN+FN} * 100\%$

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 for the recognition of the autistic children.

9. RESULTS

The test results from the investigations done to look for ASD are shown in this section. The testing outcomes for the utilized deep learning models have been presented in Table3.

Table 3. **Outcomes of deep learning models' testing.**

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

Three distinct pre-trained DL models, including Xception and VGG16, have been 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 Xception model had the greatest accuracy of testing, 91%. Xception model demonstrated the best accuracy, with just a tiny proportion of mistakes, despite the dataset being compiled from Internet sources by the generator of data, and that had clearly indicated a difference in the ages and caliber of photos as showing in figures 7.1and 7.2 illustrate Confusion matrices for the both models Xception and VGG16 model

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

11. CONCLUSION

The interest in the pediatric autism has grown as global health knowledge and capacities have advanced. Additionally, due to increases in the number of the children with autism, academics and researchers have intensified their attempts to comprehend autism causes and detect them early so as to offer programs of behavioral development treatment for autistic people which should help them in the integration into society and escape isolation of autistic world. The present study had evaluated the efficiency with which the VGG16 and Xception deep learning models identified ASD based on features of the face. Xception model, which has been trained using a publicly available data-set online, has the highest

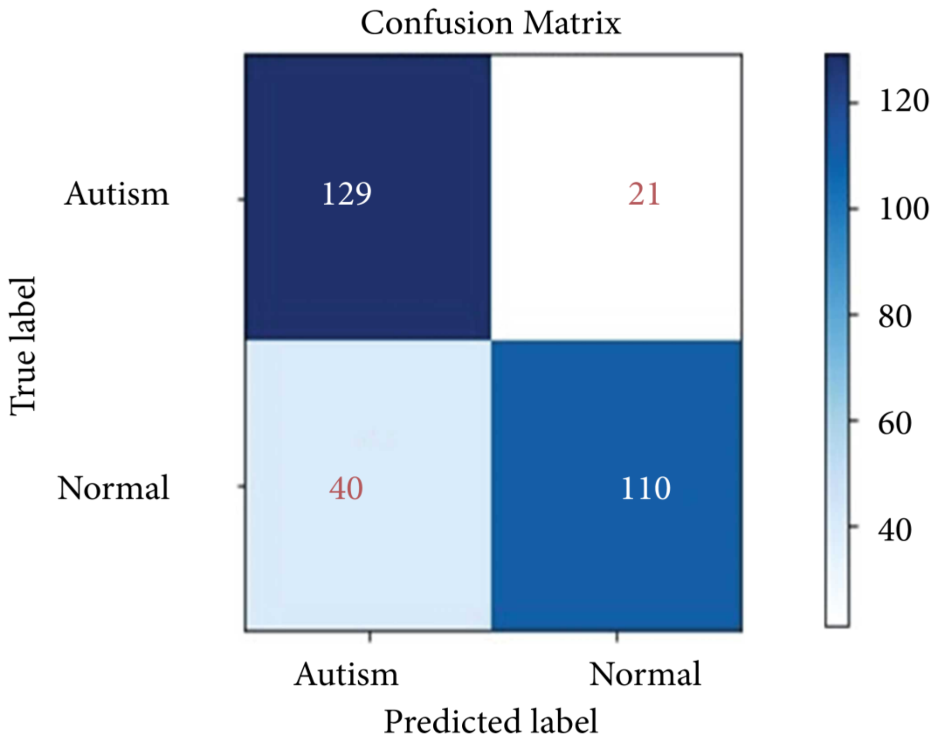

FIGURE 7. Confusion matrices for Xception model

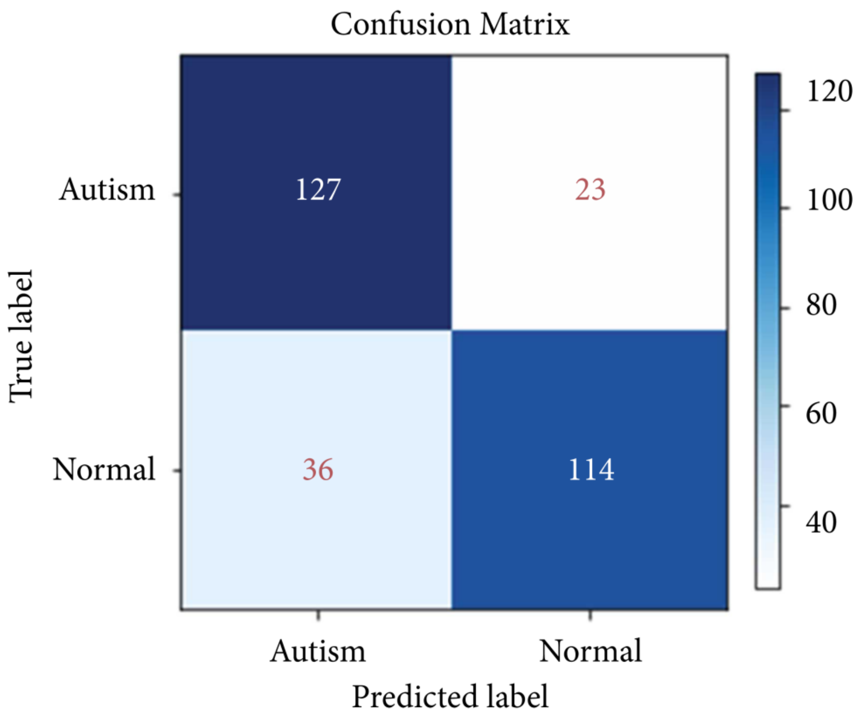

FIGURE 8. Matrices for VGG16 model

classification accuracy (91%). The model's classification results have shown the possibility of the use of such DL and computer vision models as automated tools for the 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.

12. AVAILABILITY OF DATA

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

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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