IDENTIFYING THE SEVERITY OF SYNDROME BASED ON THE ANALYSIS OF RETINAL IMAGES USING DEEP LEARNING TECHNIQUES

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Abstract

Autism Spectrum Disorder is categorized by a variety of traits, such as difficulties interacting socially, diverse learning styles, a tendency towards routines, difficulties communicating normally, and unique ways of processing sensory data. These kids' growth may be significantly aided by early intervention and the right supports. The diagnosis and screening of ASD have, however, run into significant challenges. According to the literature, specific retinal characteristics are strongly linked to ASD. In this work, we looked into applying deep learning techniques to retinal pictures in order to improve classification accuracy. For the classification job, the pretrained Convolution Neural Network (CNN) model was employed. 1,920 retinal images made up the dataset that remained utilised to test the model, which stood obtained through the Kaggle stage. Accuracy was the common evaluation metrics cast-off to assess the effectiveness of the deep learning model and achieved an accuracy result of 84.87%

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1. Introduction

The term Autism Spectrum Disorders refers to a group of severe neurodevelopmental disorders of the brain that include Asperger's syndrome, childhood disintegrative disorders, and autism. As the term "spectrum" suggests, these disorders can range widely in their severity and symptomatology [1]. The International Statistical Classification of Diseases and Related Health Problems now classifies these diseases as Pervasive Developmental Disorders under Mental and Behavioral Disorders [2]. Early indications of autism spectrum disorders typically look as if within the first year of life [3-6] and can contain avoiding eye contact, showing apathy towards carers, and not reacting when someone calls them a name. A small percentage of kids seem to develop normally in the first year before displaying autistic traits between the ages of 18 and 24 months [5], which include repetitive and constrained behaviour patterns, a limited range of hobbies and interests, and subpar language abilities. Since these illnesses also disturb how a individual observes and interacts with others, youngsters might abruptly develop quiet or violent in their first 5 years of life as they struggle to interact and communicate with society. Despite the fact that ASD first seems in childhood, it frequently persists into youth and old age [7].

Modern information expertise that makes use of artificial intelligence (AI) replicas has aided in the early identification of ASD through the use of face pattern recognition. The convolutional neural network technology and training data for removing components of human facial expressions were used to use a CNN method to detect facial expressions in a variety of neurological disorders [9]. The updated Facial Expression Recognition 2013 dataset to recognise children with autism by the use of deep learning techniques [10]. The CultureNet deep knowledge model presented, which stood used to the recognition of thirty videos [11].

In recent years, ASD has become more commonplace across the globe. A report on the prevalence of ASD amongst 8-year-old kids was published by the Centres for Disease Control and Prevention in April 2018 [39] using data from eleven sites in a one-to-one care network. ASD affected 16.8 out of every 1000 people in 2014, or around 1 in 59 people, a considerable rise from 14.7 out of every 1000 people, or roughly 1 in 68 people, in 2010. In various locations across the US, the frequency of ASD extended from 13.1 to 29.3 per 1000 8-year-old children [39].

Many studies have used a range of autism detection techniques, such as feature removal [12], eye trailing [13], facial acknowledgement [9], voice recognition [14], and medical picture analysis, to identify the main traits of autism. But when it comes to recognising autistic people, visual recognition is more reliable than emotional state. A common method for identifying people and assessing whether they are usual or irregular is face recognition. It includes searching through relevant data to find patterns in behaviour [15, 16].

[17] There has been a recent advancement in the method for generating samples of differences between ADHD and autism and using those differences to identify autism. 65 samples of varied social responsiveness in facial expressions were acquired for the datasets. The author [18] developed metrics for active brain functions to identify autism. Autism has also been identified using techniques that employ AI and soft computing. There has been a lot of study on how to recognise autism, but very little of it has focused on brain MRI. A system for extracting the traits of autism was developed using machine learning techniques[19]. They got their data from 851 people who they divided into those with and those without ASD. Rule-based machine learning (RBML) was utilised by Thabtah and Peebles [20] to identify ASD characteristics. A smart system was created [21] to keep track of 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 utilised to distinguish between people with and without ASD has received considerable attention. Children's autism has been detected using deep learning techniques, including CNNs, RNNs, and the BLSTM model. ASD has recently been the subject of additional research using machine learning methodologies, including brain imaging [24, 25], data analysis on physical biomarkers [26–28], evaluation of autistic people's behaviour [29–33], and evaluation of scientific data using the machine learning methodology [33].

The internal surface of the retina at the back of the eye seems to be a membrane physically. Glial cells, retinal ganglion cells, and axons, the latter of which generates the fibres of the optic nerve, make up this portion of the central nervous system (CNS). The retinal nerve fibre layer (RNFL) has been employed in recent studies to investigate connections with structural disorders of the brain. Retinal alterations have been linked to stroke, multiple scoliosis, Parkinson's disease, and Alzheimer's disease in prospective investigations utilising a fundus camera and optical coherence tomography [2528]. Recently, stroke and the degree of white matter hyperintensity in the brain have both been determined using algorithms for the interpretation of retinal pictures [42,43].

Retinal fluctuations are present in autism patients. The retinal nerve fibre layer stood assessed in a collection of twenty-four new individuals with ASD (of whom 11 had been identified as having "high operative autism" and 13 had "ASD") and 24 healthy controls [40, 41]. High-functioning autism patients had thinner RNFLs compared to Asperger syndrome patients or strong controls, providing evidence of retinal abnormalities in diverse ASDs. RNFL thinning could therefore be a pathophysiological sign of autism syndrome. In light of the discovery of such retinal anomalies in the autistic community, our aim was to design a screening strategy for the identification of ASD using retinal images and to ascertain whether there are features from fundus images that can differentiate persons with ASD from strong individuals.

Our research showed how to employ a trained classification model to identify autism in retinal images.

2. Materials and Methods

This study suggests combining retinal image attributes of autistic and non-autistic people to train a deep learning model based on CNN to identify autism. The presence or absence of autism can be determined by retinal image characteristics. Significant retinal features were retrieved from the photos by the models. Deep learning algorithms have the advantage of being able to extract incredibly minute features from images that a human eye cannot see. The framework of our system is depicted in Figure 1 shows the data collection process, including data loading and pre-processing, model building and training, and model performance testing.

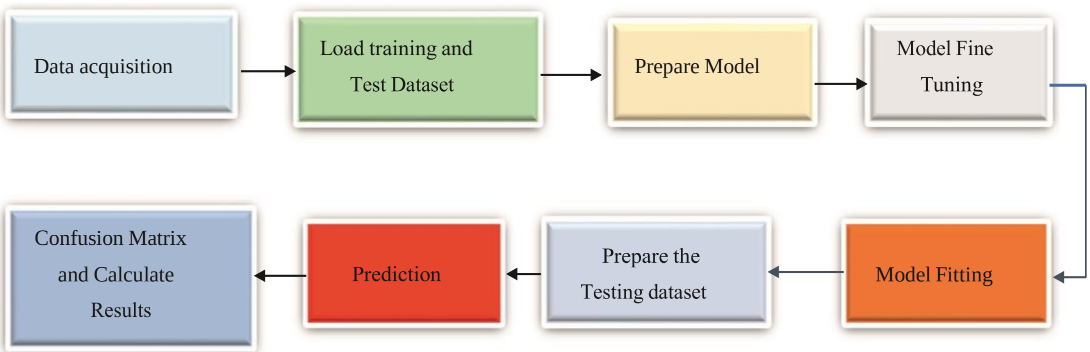

Figure 1: The background of our system.

2.1. Dataset: In this work, retinal pictures of autistic and typical individuals were evaluated. The photographs were taken from the freely available online Kaggle platform [34]. There were 1920 retinal pictures in the dataset. The dispersal of the split dataset samples is displayed in Table 1. Figure 2 shows how the input data was divided.

Table 1: Dataset split for training, testing.

Total retinal images	Training set with abnormalities (%)	Testing set (%)
1920	1519	401

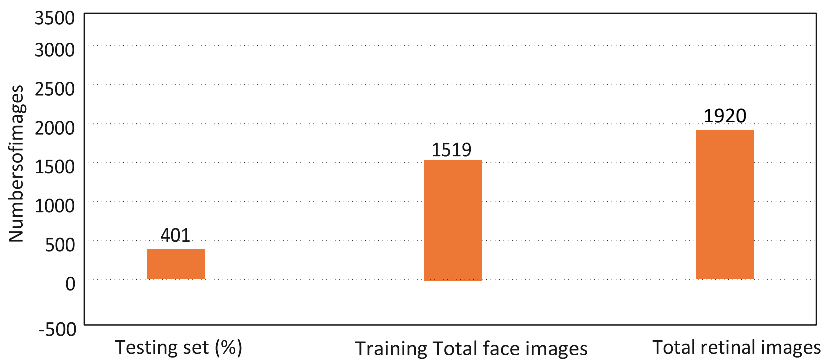

Figure 2: Split of dataset.

2.2. Pre-processing.

The images were cleaned up and cropped as part of the data preprocessing. Piosenka's [34] collection of data from online sources necessitated preprocessing before the deep learning model could be trained on them. The retinal in the original image was automatically cropped by the dataset's developer. The dataset was then divided into 401 photos for testing and 1,519 for training. The normalisation approach was used to scale; the dataset was rescaling all of the picture limits from [0, 255] to [0,1].

2.3. Convolutional Neural Network Models. A branch of AI known as "computer vision" has stood impressively established to help humans in their daily lives, such as through medicinal applications. As a result, the CNN algorithm has helped with disease identification as well as behavioural and psychological analysis. The convolutional layer model is displayed in Figure 3.

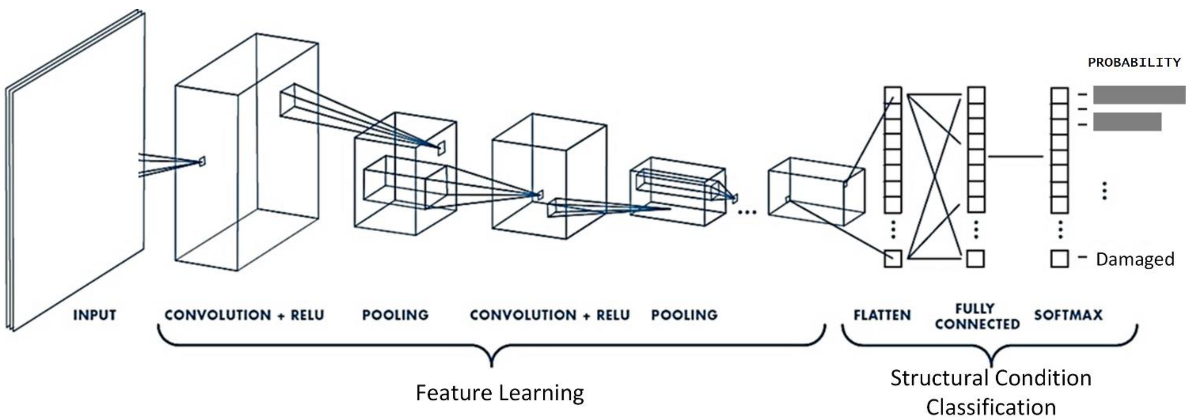

Figure 3: Convolutional Layer Model

2.3.1. The CNN Model's Fundamental Elements: One of the utmost well-known deep learning algorithms is the CNN. It uses the input image to prioritise learnable weightiness and biases in order to identify the class of the input image. The connectivity and communication between cells inside the neuron can be compared to the statement design of the neurons in the human brain. The input, convolutional, activation function, pooling, fully connected layer, and output prediction will all be covered in great detail in this section.

2.3.1.1Input Layer: The input layer of a neural network is made up of artificial input neurons, which enter data into the system for processing by artificial neurons in subsequent layers. The input layer is where an artificial neural network's process begins.

2.3.2. Convolutional Layer and Pooling Layer.

A picture is entered into the convolutional layer as a medium of pixel values. The convolutional layer's objective is to make the images more straightforward without sacrificing any of the essential traits that will help in the identification of autism. Low level features like edges and colour are extracted by the CNN model's first layer. The CNN model's construction allows us to enhance extra layers to it, allowing it to extract the elevated features that will aid in visual comprehension. The number of weights was decreased by utilising either the max pooling or average pooling approaches because the convolution layer's output of a high number of parameters could greatly slow down the matrices' arithmetic operations. Maximum pooling is built on the highest values in each space of the step, whereas average pooling is based on the mean value in each window of the stride. This learning's model was based on maximum pooling. The convolutional layer, as well as the average and maximum pooling procedures, are displayed in Figure 4. The kernel's sliding window transforms the input image into a matrix by extracting the features, and then uses max pooling and average pooling to mathematically diminish the number of constraints.

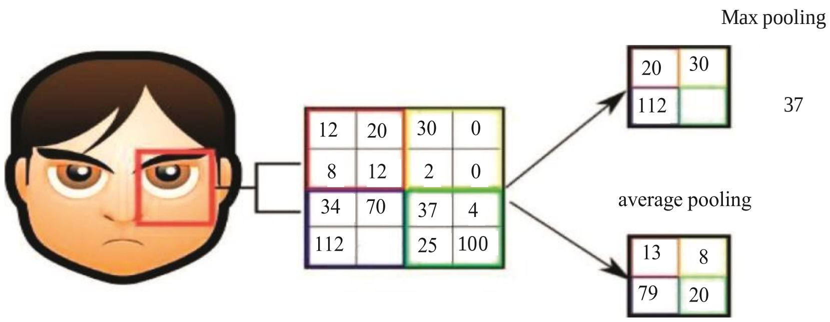

Figure 4: Convolution layer, maximum pooling layer and average pooling.

2.3.2.1ReLU Activation Function: A non-linear or piecewise linear function, the rectified linear activation function immediately outputs the input if the input is positive; else, it produces zero. It is the most often used activation function in neural networks, especially convolutional neural networks (CNNs) and multilayer perceptrons. It is more efficient than its predecessors, such as sigmoid or tanh, despite being simpler. ReLU is aesthetically depicted in figure 5 and precisely expressed as f(x)=max(0,x).

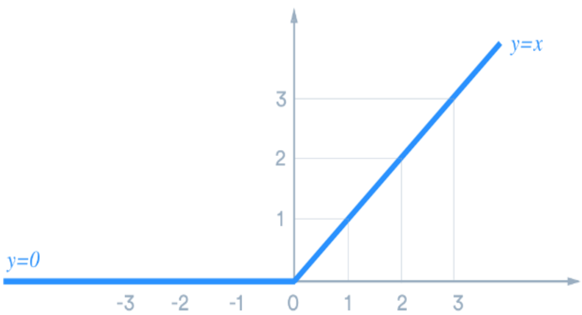

Figure 5: ReLU Activation Function

2.3.2.2 Dropout: The model will operate on a smaller neural network with each iteration, and as a result, regularisation is approaching. Dropout aids in reducing the weights' squared norm, which tends to lessen overfitting.

2.3.3. Activation Function with FC Layer

The non-linear FC layer is a mixture of highest characteristics that were represented as outputs after receiving input from the hidden layers. The participation image 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 onward neural network feeds create an output layer that is flattened. By increasing the number of training iterations, the neural network minimises loss mistakes and picks up more features during backpropagation. Most deep learning models perform well because they include unseen coats and training iterations, which enable the neuronic network to effectively extract low-level input. In order to create a probability delivery with K probabilities proportional to the exponentials of the input values, the softmax function normalises a vector z of K real numbers.t accepts this vector as an input. That is, certain vector components before applying softmax might be undesirable or greater than one, and they might not add up to 1, but after applying softmax, each component will be in the range (0,1) (0,1), and the components will add up to 1, thus they can be read as probabilities.

Mathematically, it is expressed as:

$$\sigma(z)i = \frac{e^{-i}}{\sum_{j=1}^{K} e^{zj}} \text{ for i=1,….,K and z = } (z1,…..,zK)ЄR^{K}$$

Graphically it is represented as shown in Figure 6,

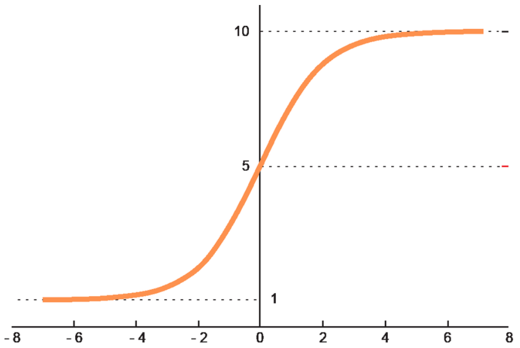

Figure 6: Softmax Function

2.4. Deep Learning Model. The proposed work is built on CNN model for ASD detection using Fundus images.

Algorithm:

Layer	**Output Shape**
Conv2D	222x222x32
batch_normalization	222x222x32
max_pooling2d	111x111x32
dropout	111x111x32
Conv2D	109x109x64
batch_normalization	109x109x64
max_pooling2d	54x54x64
dropout	54x54x64
Conv2D	52x52x64
batch_normalization	52x52x64
max_pooling2d	26x26x64
dropout	26x26x64
flatten	43264
Dense	512
batch_normalization	512
dropout	512
Dense	2

(i) Input layer: This layer's job is to receive and process an image input with dimensions of 224 x 224 x 3.

(ii) Convolutional layers: CNN's convolutional layers use the smallest possible receptive field, or 3 3, which still releases left and right and up and down. In order to uphold the spatial resolution after the convolution, the convolution stride is kept at 1 pixel (the stride is the number of pixel shifts over the input matrix).

(iii) Hidden layers: In an artificial neural network, a hidden layer is a layer that sits between the input layer and the output layer. wherein the synthetic neurons receive a number of weighted inputs and use an activation function to generate an output. Engineers can imitate the different forms of brain activity in this area of nearly and neural. ReLU is utilised by every CNN hidden layer.

3. Results and Discussion

Autism syndrome patients fail to comprehend their own needs, emotions, feelings, and perceptions of the world around them. A person with autism views the world as a horror show and discoveries certain sounds, lights, and even the flavours and smells of food to be frightening 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 many youngsters. The creation of AI-based intelligence systems can aid in the early detection of autism. In this study, the CNN deep learning model was taken into consideration for usage in autism diagnosis. This model's empirical findings were provided, and it was noticed that it had the maximum accuracy of 84.87%.

Table 5 displays the findings of the comparison estimate analysis of the CNN model and the current structure. The VGG19 model was introduced by Jahanara et al. [38] to detect autism using face pictures. In the validation accuracy process, the VGG19 model had an accuracy rate of 84%. A smaller dataset of 46 ASD Participants was used by Maria et al. to present the Automated retinal image analysis (ARIA) methodology, which resulted in Specificity = 95.7% and Sensitivity = 91.3%. In this study, CNN was employed to identify autism. Using a sizable dataset of retinal pictures, we found that the CNN model outperformed existing systems with an accuracy of 84.87%. Our method not only recognises autism but also shows the degree of the illness. The accuracy of the CNN model's training and validation plots are displayed in Figure 6 as results. Using 18 example photos, Figure 7 displays a sample of model prediction findings. Figure 8 accurately depicts the final product of the photograph and the degree to which the ASD is recognised.

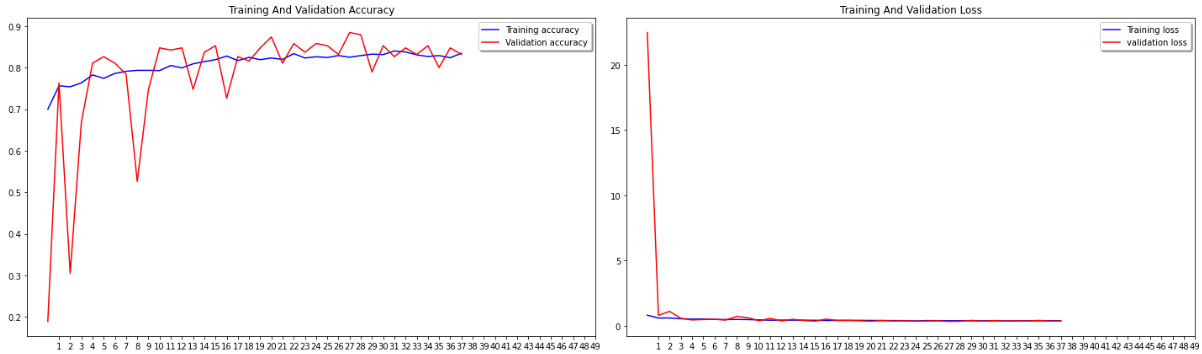

Figure 6: Plot of the training and validation accuracy of the CNN model. (a) Accuracy performance. (b) Model loss.

Table 5: Comparison of the results of our system and existing models.

Author	**Datasets**	**Model**	**Accuracy (%)**
Beary et al. [38]	Facial images	VGG19	84.0
Maria Lai [44]	46 ASD Participants (All retinal images were captured using a nonmydriatic fundus camera)	Automatic retinal image analysis (ARIA) methodology applying machine-learning technology	Specificity =95.7% and Sensitivity = 91.3%
Our Model	Our dataset with 1920 retinal images	**CNN - Deep learning**	**84.87**

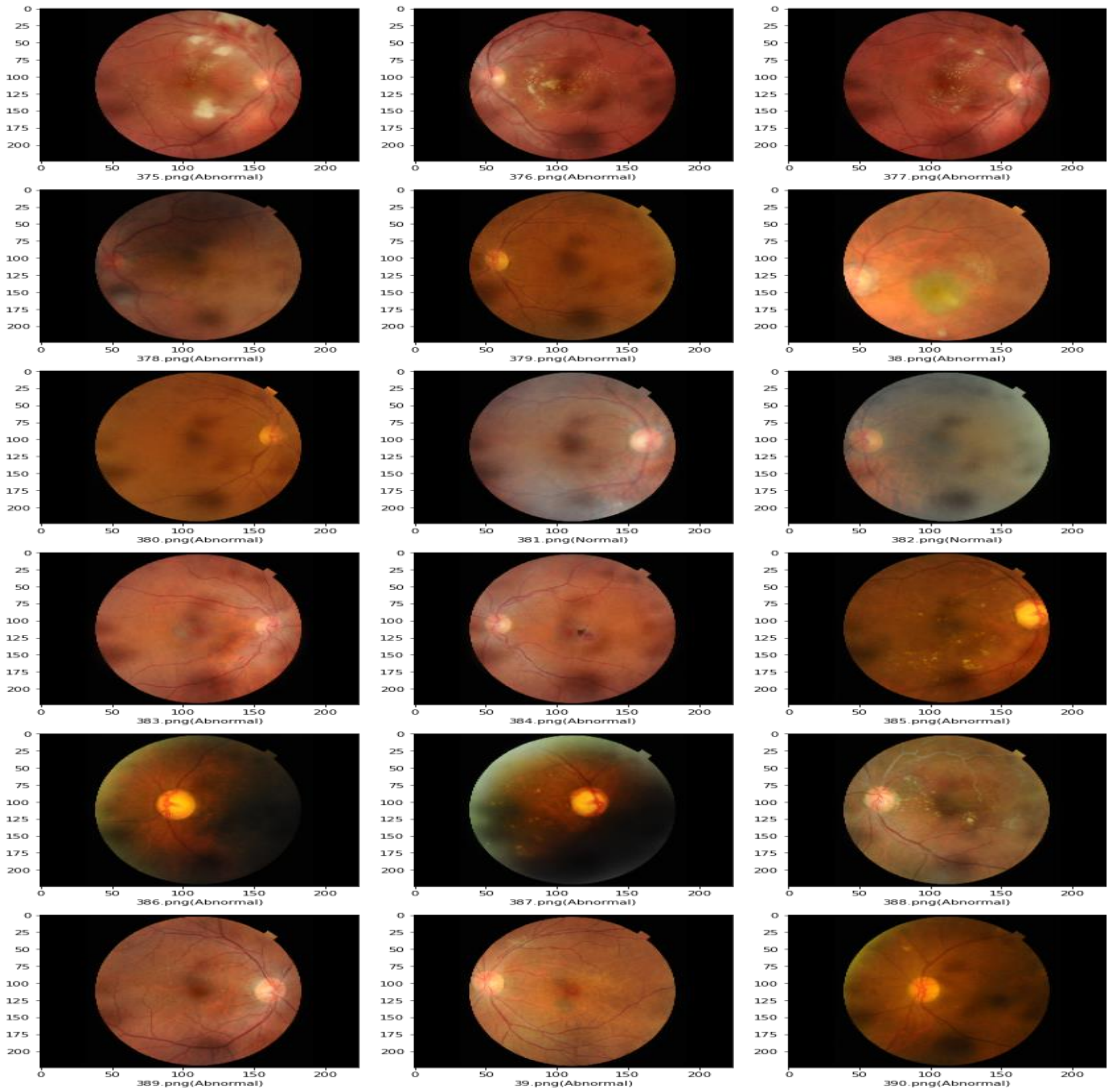

Figure 7: Model prediction results with 18 Sample images are shown below

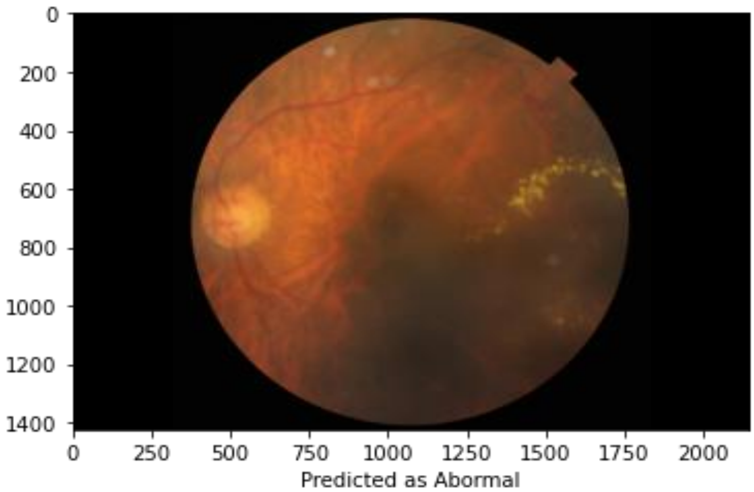

Image is abnormal, having ASD Syndrome of Level 2 : 82.48%

Figure 8: End results

4. Conclusions

The interest in autistic patients has grown as a result of developments in global health knowledge and volumes. As the number of autistic patients has enlarged recently, investigators and researchers have increased their hard work to understand the reasons of autism syndrome and to identify it early in order to provide behavioural development treatment programmes for autistic people who should help them leave the loneliness of the autistic world.

This study assessed the CNN deep learning model ability to recognise ASD based on retinal features. The CNN model was skilled using a publicly accessible online dataset, and the best organization accuracy score was 84.87%. The classification results of the model presented us the potential of employing such deep learning and computer vision models as automatic tools for professionals and relatives to more quickly and accurately identify ASD. The successful completion of complicated behavioural and psychological evaluations for the diagnosis of autism, which take a lot of time and effort, is facilitated by computer tools.

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