AUTISM SPECTRUM DISORDER DETECTION USING IMAGE PROCESSING AND CNN

P. Kalpana[1],P. Kanithkar[2],A.Manikandan[3]

[1]Assistant Professor, Department of Information Technology, M.A.M College of Engineering and Technology,Trichy.

[2]Student,Department of IT, M.A.M.College of Engineering And Technology,Trichy.

[3]Student,Department of IT, M.A.M College of Engineering And Technology,Trichy.

Abstract:

Autism is a developmental handicap of children that gets worse as they age. An autistic child has problems with interaction and communication, as well as limited behavior. If autistic children are diagnosed early, they can have a quality life by providing thorough care and therapy. However, in many developed countries, it is too late to diagnose children with autism. Besides, a trained medical expert is required to identify autism as there are no direct medical tests. Medical practitioners also take enough time to detect it because the children have to be monitored intensively. In this research, artificial intelligence algorithms have been utilized for detecting autism in children from images that are not viable for ordinary people. We have employed five different algorithms that are Multi layer Perceptron (MLP), Random Forest (RF), Gradient Boosting Machine (GBM), AdaBoost (AB) and Convolutional Neural Network (CNN) for classifying Autism Spectrum Disorder (ASD) in children. Comparing classification performances among those algorithms, we have achieved the highest accuracy of 92.31% on CNN, which outperformed the other conventional Machine Learning (ML) algorithms. Therefore, we proposed a prediction model based on CNN, which can be used for detecting ASD, especially for children.

I. INTRODUCTION

Autism is the imperfect development of children's brains that interfere with their social interaction. Many of the problems with this disease are that children do not understand, learn precisely, and have difficulties interacting and communicating [1][2]. From childhood, autism begins to persist in the age of puberty and adulthood. 1 in every 54 children has autism problems [3]. Autism tends to occur in all ethnic and racial groups, but boys are more than four times likely to be spotted with it than girls. Most children are diagnosed after the age of 4 but can be reliably diagnosed from the age of two [4]. The sooner they are identified, the faster it can be intervened. Then it can be possible to improve the behavioral and communication skill of autistic children by providing proper treatment and adequate training [5][6]. Nowadays, doctors or specialists review the behavior and growth of children to identify them as autistic or non-autistic, which is very time-consuming and requires very experienced physicians. It is a very challenging task for the doctors or physicians to identify autistic children just by seeing their behavioral activities for a certain period of time. Again, there is a shortage of experienced doctors in many rural and underdeveloped areas, and many are not financially well-off enough to consult a doctor. As a result, most family members are unaware that their child has autism and that the autistic child grows up without proper care and treatment, leading to family, domestic and social unrest. Nowadays, many researchers are trying to create computer-aided decision

support systems using machine learning methods to detect autism in children to overcome such problems. They collected data on children's behavioral activity through a variety of interviews and questionnaires, creating different prediction models based on ML methods that can be utilized to detect ASD at an early-stage. None of these researchers used children's face images to detect autism in children. Almost everyone has used text and numerical data through various interviews and questionnaires that are time consuming and prone to error. This is because children of less than eight years may be nervous during interviews and questionnaires and may give incorrect answers due to not understanding many things. Those wrong answers will later create bias in the prediction model and reduce prediction accuracy. To combat these problems, we have created a simplified prediction model using facial images of 2940 children of 2-8 years old.

In this research, we have classified ASD from children' images using five classification algorithms. The datasets we have used concludes face images of 2940 children. After completing in the pre processing step, we have compared the performances of those five classification algorithms and found that CNN in performs better in classifying ASD for children.

The remaining segment of the research article is prepared as follows: Section II concludes the literature survey done in recent times. Section III describes about the dataset and section IV presents the research methodology. Section V analyzes the experimental results. Section VI represents the proposed methodology based on experimental results.

II. LITERATURE REVIEW

The method currently used to diagnose ASD is to observe the behavioral characteristics of the person concerned. However, the most serious difficulty in diagnosing ASD utilizing this method is that it can be misleading when distinguishing it from another disease. To differentiate ASD from other neuro-developmental disorders (DDs), Bone et al. [7] developed a model using the SVM classifier for training and cross-validated the data. For this study, they collected information based on two standardized assessments, such as the social responsiveness scale and interviews for diagnosing autism. Yuan et al. [8] developed a ML model based on Natural Language Processing (NLP) for identifying autism spectrum disorder. To build this prediction model, they first converted all types of unstructured and semi-structured data to digital versions, then pre-processed them and finally completed the classification. This model simplified and condensed the ASD detection process. Omar et al. [9] developed a mobile application to diagnose ASD for the people of any stage.

They proposed a machine learning-based prediction model combining Iterative Dichotomiser3 (ID3) and Classification and Regression Trees (CART) of random forest algorithm. Öztürk et al. [10] compared the performances of RF, Radial Basis Function Network (RBFN), Naive Bayes, and K Nearest Neighbors (KNN) for classifying ASD for children. In this research, they collected Autistic Spectrum Disorder Screening Data from the UCI machine learning repository. Their results showed that RF performed better than the other classification algorithms. Dutta et al. [11] developed a prediction system that identifies all the plausible signs of ASD by utilizing the previous long-term patient records. This system can identify both the traditional and rare types of ASD. Both machine learning and colloquy theory were used to develop the system to make the matrix, facilitating all sets of associations to generate rules. It has also been mentioned that their ASD detection system utilized more limited memory to operate and was faster due to single time database access. Atlay et al. [12] employed KNN and Linear Discriminant Analysis (LDA) for classifying ASD in 4-11 years of kids. They utilized a 70:30 ratio for training and testing. Those algorithms improved the prediction accuracy and also reduced biased predictions. Thomas Martial et al. [13] introduced an innovative method to identify changes in community patterns within operational systems beneath ASD. Moreover, machine learning classifiers were applied to identify ASD affected people, and to design controls,

community pattern quality metrics were utilized as features. They achieved an accuracy of 75.01%, recall of 75.09% and precision of 75.00% for kids, and classification accuracy of 78.95%, recall of 78.75%, the precision of 78.98% for adults. Sharma et al. [14] proposed an innovative ASD detection system named "Fast and Accurate Diagnosis of Autism" based on IF-THEN rules. It was a GUI based

hierarchical fuzzy system that facilitated a speedy and
precise diagnosis of ASD. This system also emphasized the extremely damaged zone in each candidate. Heinsfeld et al. [15] employed deep learning techniques in the Autism Brain Imaging Data Exchange (ABIDE) dataset for classifying ASD. They achieved 70% of classification accuracy was better than other state art techniques.

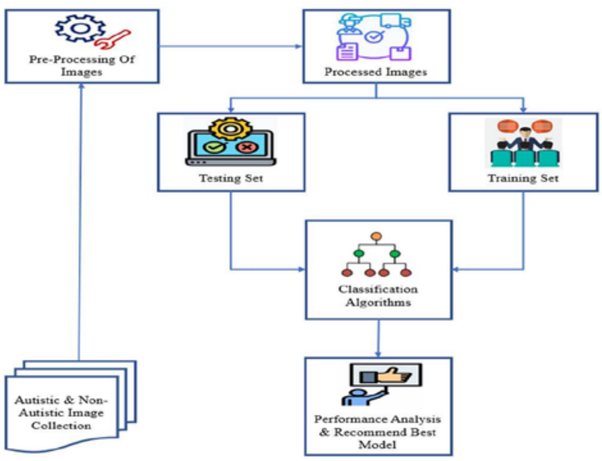
III. DATASET DESCRIPTION

In this research, we have used a publicly available dataset named Autistic children dataset collected from Kaggle repository . This dataset consists of 2940 face images of children where autistic and non-autistic classes are evenly distributed. In this dataset, the majority of the images are from 2 to 8 years children. The male and female ratio in the autistic class is 3:1, and the non-autistic class is 1:1. Some samples of face images from this dataset are shown in Fig. 1.

IV. METHODOLOGY

A. Image Preprocessing

All the images obtained from the dataset were of distinct sizes. We adopted the resize function from Python Open CV to bring all the images back to the same size. Color space conversion was performed after bringing all the images to a uniform size. All of the images were converted to the gray color space from the BGR color space. The preprocessing phase was then finished by converting all the images into arrays for further processing. The flow graph of our research work is shown in Fig.2.



.Fig. 2. Workflow of Our Research Methodology

A. Classification

1)Random Forest (RF)

Random forest, an ensemble supervised machine learning technique for solving classification and regression problems. RF follows the divide and conquers approach for creating multiple Decision Trees (DT) from the input dataset. In this study, we used the information gain as an attribute selector technique for generating each and individual decision trees. Finally, majority voting technique is used to select the final prediction result.

2) Boosting-Based Ensemble Classifier:

Boosting-based Ensemble Classifier combines multiple weak classifiers to create a robust classifier. Each iteration works by setting weights to each weak classifier to ensure correct prediction by training the sample data. The intention behind boosting is that an individual classifier can accurately predict a portion of the dataset while giving inaccurate predictions for other portions. Still, weak classifiers can accurately predict the results of incorrect portions. In this research, we have used Gradient Boosting Machine (GBM) and AdaBoost (AB) as boosting classifier. The following equation represents the combination of weak classifiers:

□.

3) Multilayer Perceptron (MLP)

A multilayer perceptron algorithm is a pathway to deep learning and consists of more than one perceptron. In a multilayer perceptron algorithm, there is one input layer for receiving the input data, one output layer for making prediction or decision against the input, and between these two layers, there are several numbers of hidden layers depends on the types of problem. These hidden layers are the main computational power of the multilayer perceptron algorithm. MLP is generally utilized for solving classification related problems. MLP trains a set of input□ output pairs and learns to find the correlations between inputs and outputs. During training, weights and biases are adjusted by adopting back propagation to lessen the errors.

4) Convolutional Neural network (CNN)

CNN, is a part of a deep neural network most commonly developed for classifying computer vision tasks. A CNN architecture is completed through the convolutional layer's connection, pooling layer, and fully connected layer. In the convolutional layer, a feature detector or kernel helps extract features from the input image and creates a convolved image. Mathematically, the following equation represents the convolutional operation:

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After completing the convolution operation, ReLU brings up non-linearity to the network.

The output of the function is outlined as follows:

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In the pooling layer, features are extracted from the convolved image to generate a pooled feature map. Then this pooled feature map is given as an input to the artificial neural network. In the fully connected layer, there is an input layer, several hidden layers, and an output layer. All nodes of the fully connected layers are fully connected, and the output layer provides the final prediction

.

B. Evaluation Measures

We employed the well-known K-fold cross-validation technique to assess the performance of the classification algorithms utilized in this research. In K-fold cross□ validation, the complete dataset is randomly divided into K number partitions of the same sizes. During model building, for the training of classification algorithms, the training is first accomplished using K-1 partitions of data. The remaining data are then utilized as testing set for final prediction results. This process is repeated for k-number of times, and the performance of the model is calculated by taking the average value of each independent test subsets. In this research, we adopted a ten-fold cross-validation technique to reduce our prediction model's biases and variance. We also used five evaluation measures, such as accuracy, ROC AUC, F-1 score, precision, recall to classification algorithms' performance. All of these evaluation measures can be calculated by using those following equations:

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The terms of those above equations represent,

TP = True Positive

TN = True Negative

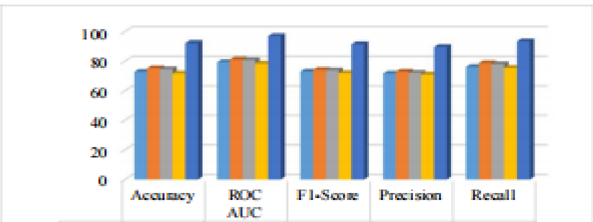
FP = False Positive

FN = False Negative

ROC AUC is a representation of a diagram that demonstrates the effectiveness of a binary classification system.

V. EXPERIMENTAL RESULTS

In this research, we have used Google's cloud-based service Google Colab [18] as an environment and Python-3 as a programming language. Google Colab's Virtual Tensor Processing Unit (TPU) has been used to increase classification algorithms' execution speed. After completing the data preprocessing step, the complete dataset is divided into an 80:20 ratio [19], where 80% of the data is utilized as a training set, and the remaining 20% is kept for testing During the training and testing of classification algorithms, a ten-fold cross-validation technique is introduced to avoid bias towards one class and avoid overfitting or underfitting [19]. In this research, we have used five classification algorithms to classify autistic and non-autistic children from autistic children dataset and compare their performance. Experimental results of the five different classification algorithms in classifying autistic children are presented and compared in Fig. 3. While reviewing the accuracy of the experimental results, we have found that RF, GBM, AB, MLP and CNN have obtained 72.78%, 75.23%, 74.56%, 71.66% and 92.31% accuracy respectively. It is clearly seen that CNN has delivered the highest accuracy of 92.31% in classifying the autistic children. Scrutinizing the ROC AUC value of different classifiers, it is found that CNN has achieved the highest ROC AUC value of 96.95%. While inspecting the F1-score and precision values, it is seen that same as before, CNN classifier has obtained the highest value of 91.54% and 89.72% for F1-score and precision respectively. In terms of recall value CNN has also attained the highest recall value of 93.45%, while the other machine learning algorithms such as RF, GBM, AB, and MLP have obtained 76.19%, 78.73%, 78.09% and 75.48% respectively. The recall value of 93.45% indicates the positive predictive rate that means 93.45% autistic positive children are classified as autistic by the CNN algorithm. From the above experimental analysis, we can say that CNN has outperformed the other machine learning algorithms in all evaluation measures in classifying autistic children using facial images.



	Accuracy	ROC AUC	F1-Score	Precision	Recall
RF	72.78	79.33	72.97	71.67	76.19
GBM	75.23	81.2	74.12	72.89	78.73
AB	74.56	80.84	73.86	72.1	78.09
MLP	71.66	78.42	71.87	71.02	75.48
CNN	92.31	96.95	91.54	89.72	93.45

Fig. 3. Performance Analysis of Classification Algorithms for ASD Detection

VI. DISCUSSION

In this segment, our proposed CNN architecture is discussed briefly. From the experimental results analysis, we have already seen that CNN algorithm has already outperformed the other conventional machine learning algorithms in terms of classification performance for predicting autism spectrum disorder of children from face images. The whole layout of our proposed CNN model is portrayed in Fig. 4. The original dataset images were of unusual shapes, so they were converted to an identical shape of 64*64. For extracting features from input images, a total of 64 filters of 3*3 sizes were applied to each of the first two convolution layers, and ReLU was preferred to be the activation function. Afterward, a Max Pooling of 2 * 2 size was added to decrease the convolved feature or feature map's dimension. Two sets of convolution and Max Pooling layers were attached where the convolution layers comprised 128 kernels of 3*3 sizes, and the Max Pooling layers were of 2*2 size. The whole thing is converted to a vector form, which is the forthcoming Artificial Neural Network input.

There were three hidden layers of 256 neurons in ANN, and again, ReLU was selected to be the activation function.

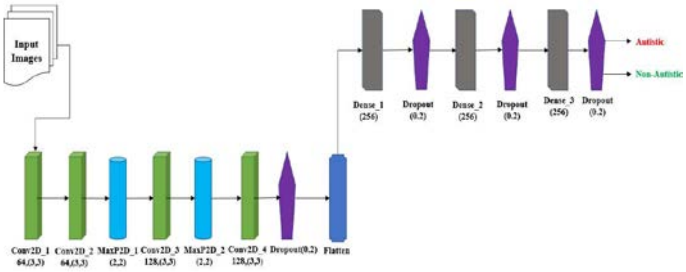


Fig. 4. Structure of Proposed CNN Model

In between those hidden layers, the dropout layers were added to prevent overfitting of the model. As screening ASD was a straightforward binary classification, hence in the final layer, Sigmoid was preferred as the activation function. We employed Adam and binary-cross entropy as optimizer and loss function, respectively. In order to make the proposed CNN model more robust and avoid overfitting□underfitting problems, the training and testing operation was performed for 60 number of epochs, and batch size (hyperparameter of gradient descent) = 16 were selected.

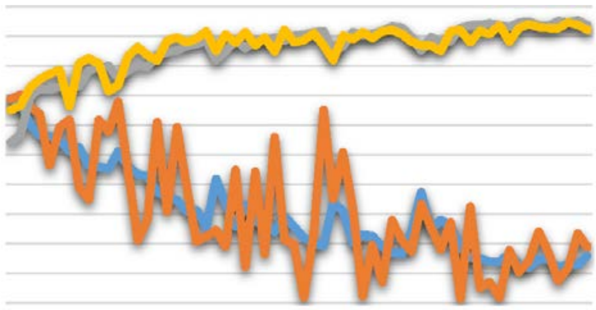


Fig. 5. Training and Testing loss, Training and Testing Accuracy Curves of Proposed CNN Model

From Fig. 5, it can be seen that at the beginning stage of the epochs, training and testing loss were relatively high, and training and testing accuracy were low. The weights were adjusted continuously according to their batch size and forwarded to the network in each step. After completion of each epoch, the loss value steadily decreased, and the accuracy improved. After completing the 60 epochs, the proposed CNN model obtained a testing accuracy of 92.31 in classifying autistic children. The overall training and testing performances of proposed CNN model for classifying autistic children from facial images is presented and compared in Fig. 6.

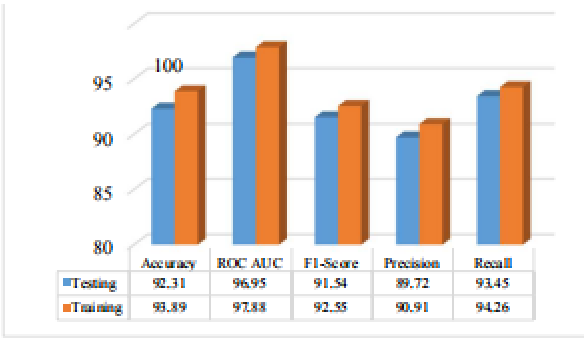


Fig. 6. Comparison of Training and Testing Performances

VII. CONCLUSION

It has already been uttered that there is no medical test to detect autism in children. Experts suggest that no one can deduce if children are autistic or not just by seeing. So, medical expertise follows a lengthy procedure to review children's behavior and activities and later conclude to a result. Artificial intelligence technologies can play a vital role in solving this problem, which can classify images of children and distinguish between autistic and non-autistic children. It may not be possible for people to detect autism by looking at the images. It can be determined by artificial intelligence because it can find and classify images with

subtle and intricate features. This research used five classification algorithms to detect autism in children and highlighted the most accurate model by comparing them. We took the help of different evaluation measures to compare and see that the CNN algorithm outperformed all other algorithms. Therefore, a doctor or expert medical practitioner can utilize this predictive model as an aiding tool along with their conventional techniques. They can also accurately diagnose autism in children as it takes little time. This experiment has been carried out with the image of 2940 children. If the number of images increases, our predictive model will be more robust and can be identified more accurately. This model can be stored in the cloud where medical practitioners can quickly diagnose a new child.

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