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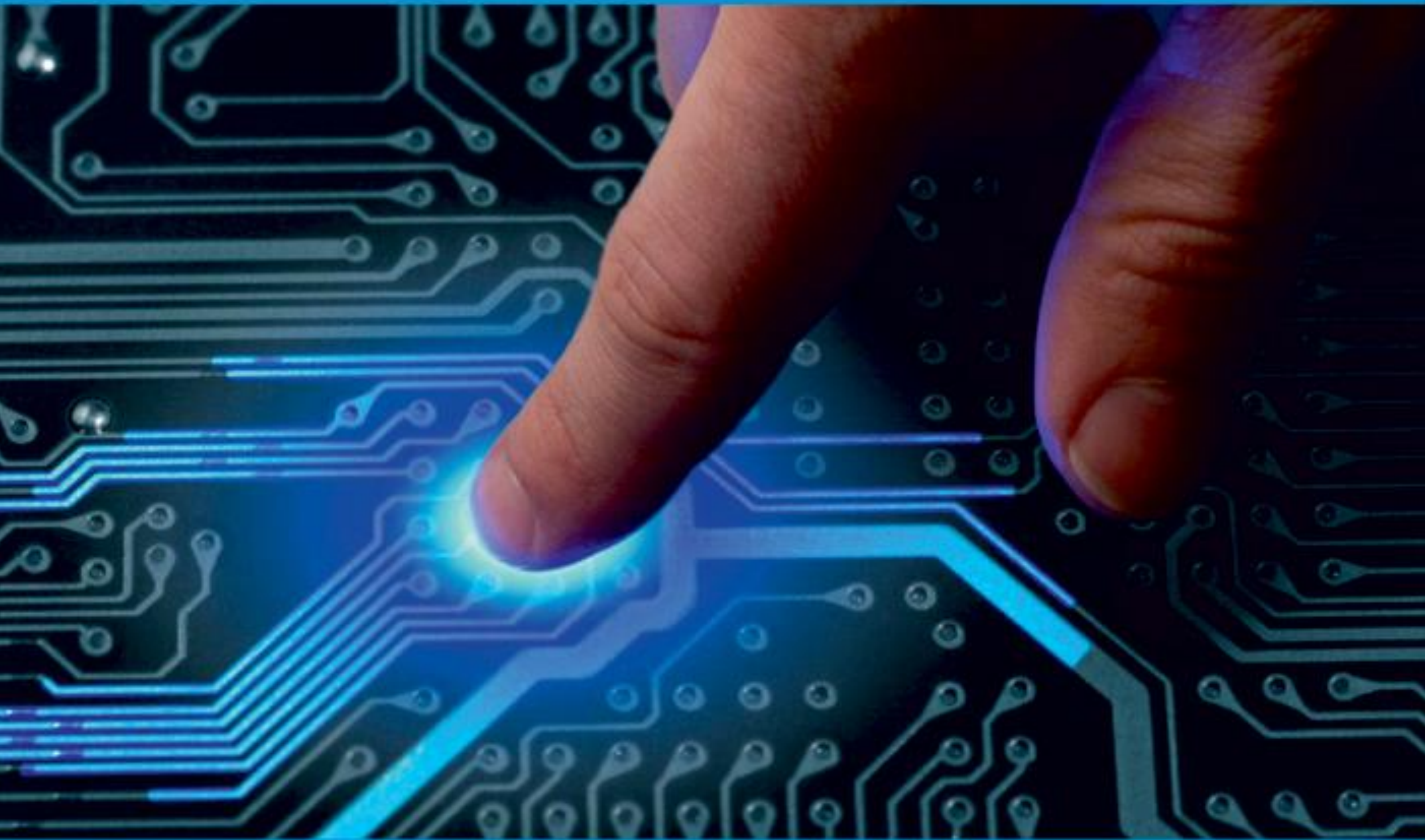

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Autism Spectrum Disorder Detection Using Deep Neural Network

Mrs D.Suguna, R.Aarthi, T.Anusha, G.Arthi

Assistant Professor, Department of Computer Science and Engineering, MRK Institute of Technology, Kattumannarkoil, Tamilnadu, India

Department of Computer Science and Engineering, MRK Institute of Technology, Kattumannarkoil, Tamilnadu, India

ABSTRACT: Autism Spectrum Disorder (ASD) is a complicated neurodevelopmental illness characterized by a variety of social, communication, and behavior difficulties. Early identification and intervention are critical for improving long-term results and maximizing the potential of people with ASD. Early intervention programmes, such as behavioral treatments and speech-language therapy, have been proven to dramatically enhance developmental outcomes for children with ASD. Initiating these treatments during the key early years can result in favorable improvements in communication skills, social interactions, and adaptive behaviors. Doctors establish a diagnosis based on the child's developmental history and behavior. Most youngsters, it appears, do not receive a genuine autism diagnosis until it is too late. In certain circumstances, parents are hesitant to accept that their child's mental development is not progressing in tandem with his or her physical development. This delay in diagnosis limits a child's capacity to receive the necessary assistance to continue developing. To address this issue, a system that can diagnose Autism and arrive to a reliable and effective conclusion without the assistance of a professional is being developed. In this approach, a deep learning model with Convolutional Neural Network is used to anticipate the Autism Spectrum Disorder using a pre-trained dataset and a deep learning model. Brain MRI has provided crucial insights into the brain functions producing ASD. Researchers have uncovered possible biomarkers that may distinguish people with ASD from people who are usually developing by looking at brain connection patterns, activation during social activities, and resting-state networks.

KEYWORDS: deep learning model; autism; facial appearance; machine learning model; recognition system

I. INTRODUCTION

Autism spectrum disorder (ASD) is a lifelong neurodevelopment condition with impairments in socio-communicative skills and the presence of repetitive behaviors and interests [1][2]. Current study indicates that autism spectrum covers nearly 1.5 percent of world's population of which many people with ASD remain undetected [3]. As per previous analysis, the early symptoms of ASD are observed during the initial 6 to 18 months in a toddler's life span. Further the symptoms are followed by developmental regression with loss in verbal, social as well as communication ability followed by abnormal motor development between 18 to 36 months of the child's life span [4]. In a child, it is easier to identify the behavioral changes easily by observation in comparison to adolescent and adult since in adolescent and adult cases; some signs of ASD may overlap with distinct mental health disorders. In order to improve the quality of life of people suffering from ASD, Early detection as well as treatment is the most crucial steps to be put forward.

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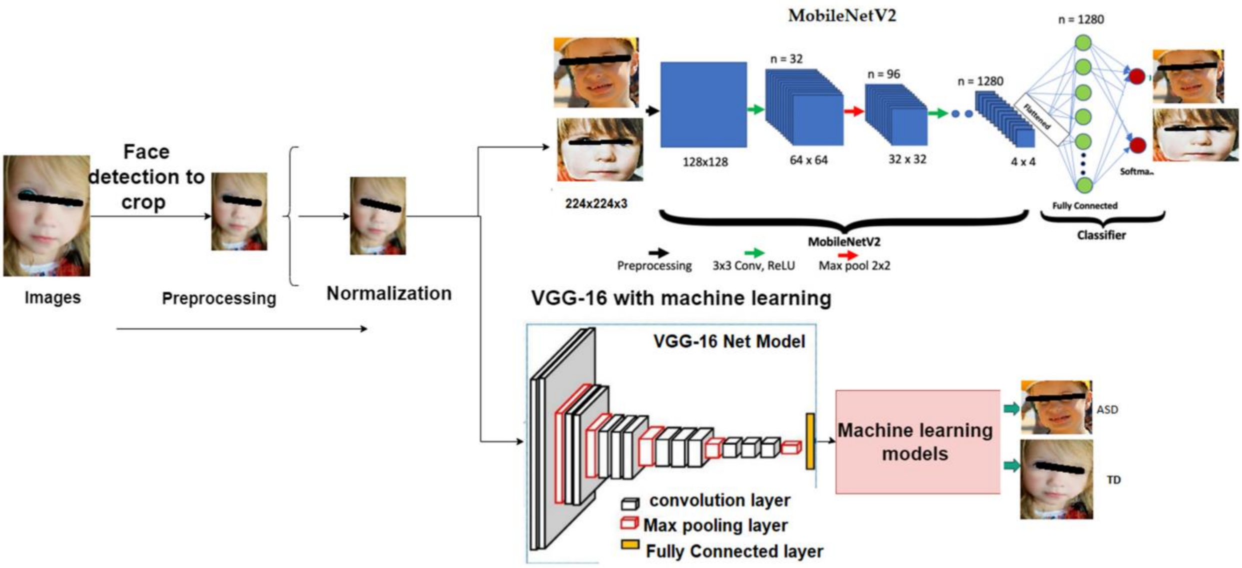

Fig 1: Autism Spectrum Disorder (ASD) is a complicated neuro developmental

This research emphasizes on classifying ASD traits from no ASD traits among toddlers (12 to 36 months), children (4 to 11 years), adolescents (12 to 16 years) and adults (17 years and above). The proposed approach uses Qualitative Checklist for Autism in Toddlers (Q-CHAT-10)[5][6]as well as Autism Spectrum Quotient (AQ-10)[7][8] based on distinct behavioral independent variables with 10 number of screening questions included in the data set. In AQ test, screening method assigns a point per question. If the individual scores more than 6, then the individual is found to be probable with ASD trait and referred for further diagnostic assessment. In adult category, for question items 1, 7, 8 and 10, if answer is either ‘slightly agree’ or ‘definitely agree’, a point is allotted and for remaining questions, a point is allotted for answer to be either ‘slightly disagree’ or ‘definitely disagree’. In adolescent category, for question items 1, 5, 8 and 10, if answer is either ‘slightly agree’ or ‘definitely agree’, a point is allotted and for standing questions, a point is allotted for the answer to be either ‘slightly disagree’ or ‘definitely disagree’. For child category, towards question items 1, 5, 7 and 10 if answer is ‘slightly agree’ or ‘definitely agree’, then a point is allotted and for rest of the questions, a point is allotted for the answer to be ‘slightly disagree’ or ‘definitely disagree’.

II. LITERATURE REVIEW

The author put forward a time efficient mobile-based ASD screening tool known as ASDTest. Followed by Q-CHAT 10 and all AQ-10 based screening, the author collected 1452 instances within a period of 4 months using the ASDTest tool enclosing all 4 categories of individuals. The toddler data set was unbalanced and hence dropped from the investigation leaving 1100 instances and 21 features corresponding to child, adolescent and adult. The adult data set comprises of 704 instances followed by adolescent one containing 104 cases and finally child data set comprising of 292 number of instances. Some missing values in two features: “ethnicity” and “who_is_taking_the_test” were found during the analysis. The wrapping filtering method extracted some of the features from the data sets. From the adult one, 12 influential features got filtered from all features: question 1 to 10 in AQ-10 Adult questionnaire, “gender” and “used app before”. In adolescent category, 8 features got selected: question 2, 5, 9 and 10 from AQ-10 Adolescent questionnaire, “gender”, “born with jaundice or not” and “used app before”. Lastly in child dataset, 4 features got selected from all features: question 1, 4, 8 and 10 in AQ-10 Child questionnaire. Two ML algorithms, Naïve Bayes (NB) and Logistic Regression (LR) were applied to classify the ASD data. The performance parameters: accuracy, sensitivity and specificity were determined for all data sets. Adult dataset achieved higher rates than adolescent as well as child datasets as it contains more number of instances in comparison to the other two datasets. From the two, LR proved to be better in comparison to NB classifier. In adult dataset, LR outperformed NB in terms of accuracy, sensitivity and specificity by 4.12, 4.2 and 3.01 percent respectively.

The researchers with an aim towards effective screening identified further fewer as well as influential features in the ASD screening process. The analysis covered the same data as used by the author in.The toddler dataset was dropped off from the entire dataset due to its unbalanced nature. In the overall dataset of 1100 instances excluding toddler one,

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there are 707 number of instances with ASD class and 393 with no ASD class present. The authors put forwarded Variable Analysis (VA) which takes into account feature to class correlation as well as decreases feature to feature correlation. VA result was compared with other filtration methods: CHI-S, Correlation Feature Set (CFS)[17] in addition with Correlation Attribute Evaluation analysis[18]. VA analysis chose 6, 8 and 8 items out of 21 from AQ-10 adult, AQ-10 adolescent as well as AQ-10 child dataset respectively. VA results got verified by two ML classifiers, Repeated Incremental Pruning to produce Error Reduction (RIPPER) as well as C4.5 (Decision Tree) in terms of specificity, sensitivity, PPV, NPV, and accuracy. To train the data set, ten-fold cross validation was used where arbitrarily the data set was split into 10 parts. In all the data sets, VA reduced the features in the most effective way as compared to other filtering methods. The authors compared the result of VA features with features of IG, CHI, correlation, CFS together with original 21 features by RIPPER and C4.5 algorithms. For adolescent data set, the accuracy rate of VA was good with IG, CHI, correlation as well as CFS with a slight fall in the rate for child and adult data set. In adolescent case, when compared with the original 21 features, the RIPPER and C4.5 classifiers derived from VA features revealed higher accuracy by 10 as well as 6 percent respectively. The specificity rate was found to be the highest in adult data set for VA features but was 2.8, 1.9, 1.4, 3.6 and 3.0 percent less than the features of no feature selection, IG, CHI, Correlation and CFS respectively. The sensitivity rate of 87.30 percent from the RIPPER classifier was the highest for VA features in adolescent case with a slight fall in adult and child cases. In adolescent case, the RIPPER algorithm derived from VA features resulted in better PPV as well as NPV than other feature sets with a slight fall but acceptable rates in adult and child cases. VA analysis selected much limited number of features from all data sets in comparison to the other filtering methods followed by classifier models processing which yielded acceptable rate of performance parameters.

III. METHODOLOGY

The proposed method is represented by Figure 1 according to which the input ASD data (Toddler, Child, Adolescent and adult), collected from Kaggle and UCI ML data repository are applied for preprocessing prior to classification of ASD class. Prior to standardization, the missing data are dropped from the data sets to be analyzed. In the first stage of pre-processing, the input samples are standardized into desired values. After standardization in second step, the inputs are encoded to binary codes for satisfying activation function boundaries. Following, the third step is continued with reduction in the dimension of dada by using Principle component analysis (PCA)[39]. In the next stage, 10-fold cross validation is used for separating the training and testing data. In further stage the training data is fed to the DNN for classification of ASD class. After training, at last stage, the predicted outputs are found from the model and are compared with the targets to calculate the performance parameters like Accuracy, Sensitivity, Specificity and f-measure.

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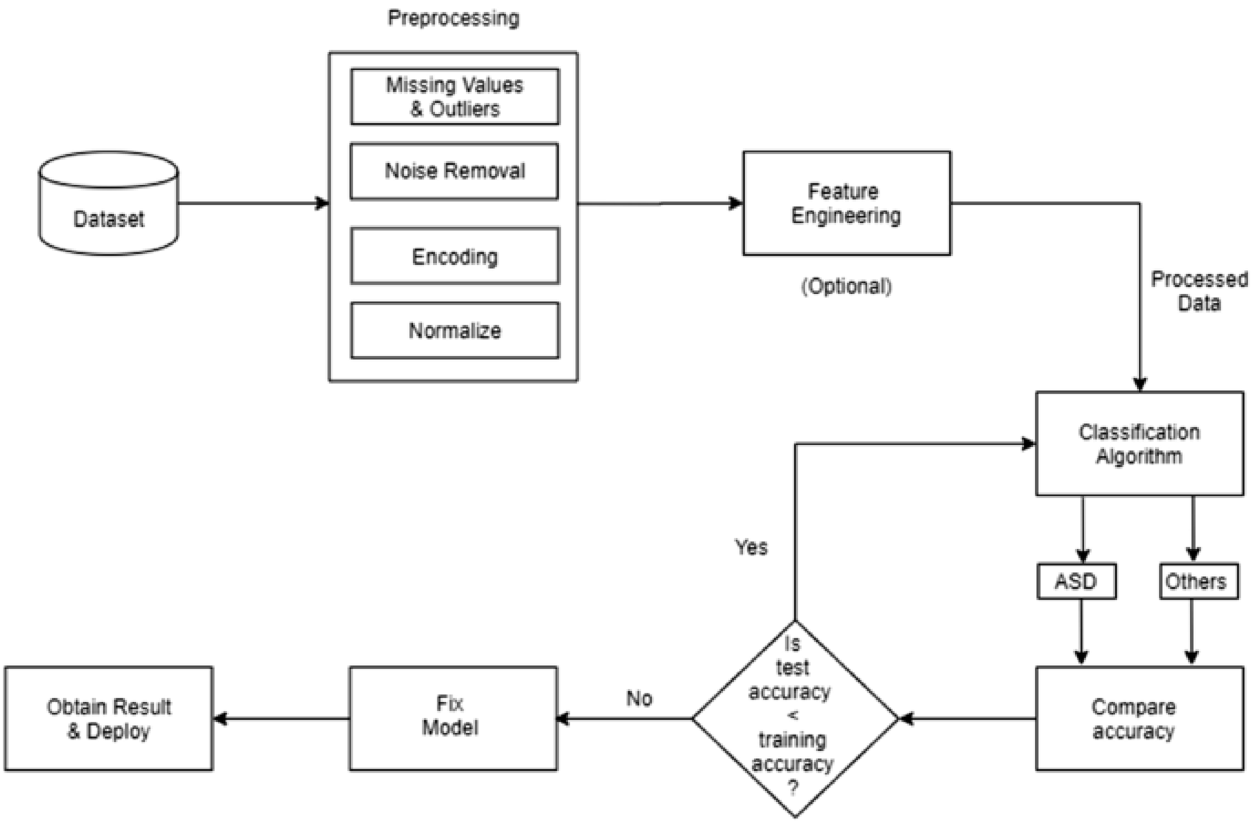

Fig 2: Work Flow

People with autistic spectrum disorders (ASDs) have difficulty recognizing and engaging with others. The symptoms of ASD may occur in a wide range of situations. There are numerous different types of functions for people with an ASD. Although it may be possible to reduce the symptoms of ASD and enhance the quality of life with appropriate treatment and support, there is no cure. Developing expert systems for identifying ASD based on the facial landmarks of children is the main contribution for improvements in the healthcare system in Saudi Arabia for detecting ASD at an early stage. However, deep learning algorithms have provided outstanding performances in a variety of pattern-recognition studies. The use of techniques based on convolutional neural networks (CNNs) has been proposed by several scholars to use in investigations of ASD. At present, there is no diagnostic test available for ASD, making this diagnosis challenging. Clinicians focus on a patient's behavior and developmental history. Therefore, using the facial landmarks of children has become very important for detecting ASDs as the face is thought to be a reflection of the brain; it has the potential to be used as a diagnostic biomarker, in addition to being an easy-to-use and practical tool for the early detection of ASDs. This study uses a variety of transfer learning approaches observed in deep CNNs to recognize autistic children based on facial landmark detection. An empirical study is conducted to discover the ideal settings for the optimizer and hyperparameters in the CNN model so that its prediction accuracy can be improved. A transfer learning approach, such as MobileNetV2 and hybrid VGG19, is used with different machine learning programs, such as logistic regression, a linear support vector machine (linear SVC), random forest, decision tree, gradient boosting, MLPClassifier, and K-nearest neighbors. The deep learning models are examined using a standard research dataset from Kaggle, which contains 2940 images of autistic and non-autistic children. The MobileNetV2 model achieved an accuracy of 92% on the test set. The results of the proposed research indicate that MobileNetV2 transfer learning strategies are better than those developed in existing systems. The updated version of our model has the potential to assist physicians in verifying the accuracy of their first screening for ASDs in child patients.

IV. RESULT ANALYSIS

Autism spectrum disorder (ASD) is a complex condition that makes it difficult to communicate on a day-to-day basis. Autism is characterized by a range of symptoms, many of which are mild but might sometimes call for specialized treatment. Patients with ASD often struggle to communicate verbally, via gestures, or through facial expressions.

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Although patients with ASD are often identified by medical professionals based on neurophysiological signals, there is neither a definitive biosignature nor a pathological method that can readily diagnose autism. An early diagnosis may offer opportunities for beneficial lifestyle changes, even though no therapy cures the condition. Children exhibiting indications of ASD may benefit from an early diagnosis due to the malleability of brain development, which might help them improve their social lives. Some research has shown that children who receive medical care before the age of two years have higher IQs than those who do not receive it until later on in life. According to the recent research, most children with ASD are not diagnosed until they are at least three years old.

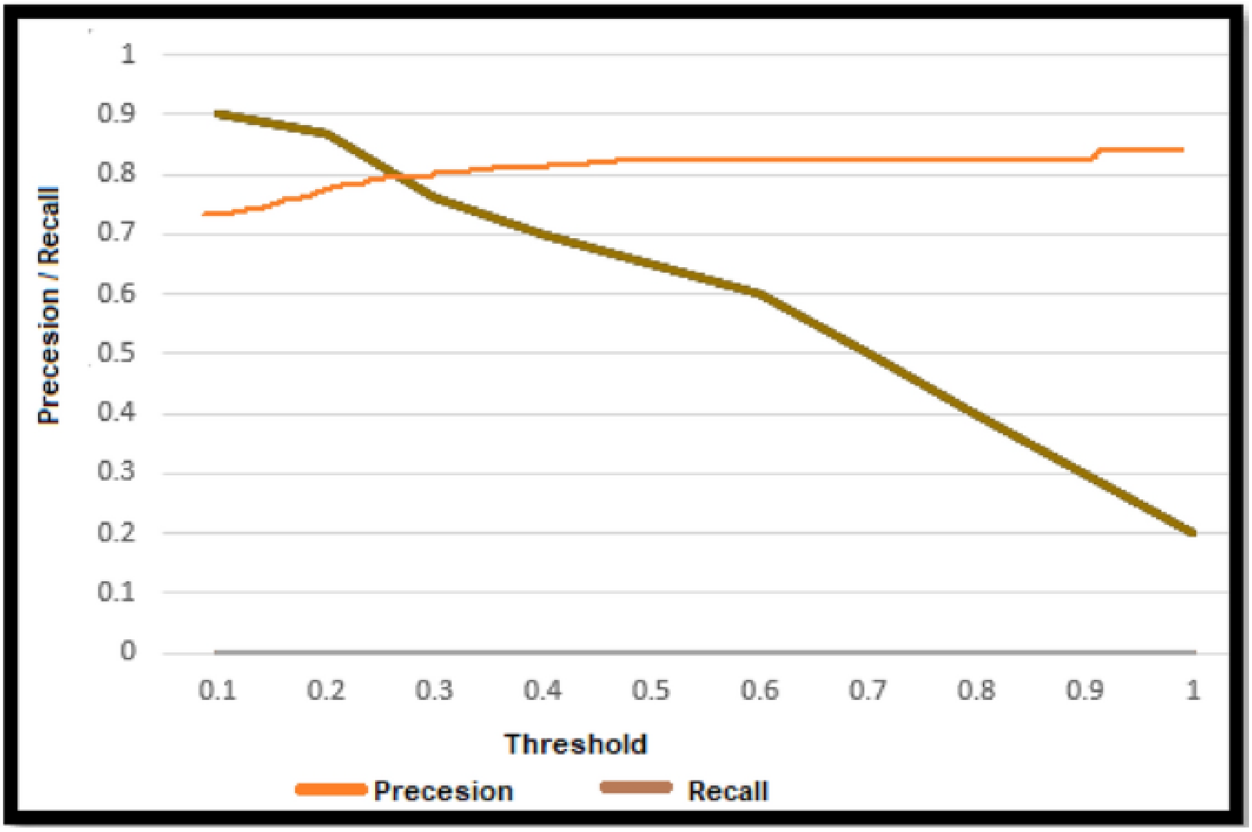

Fig 3: Detection of autism spectrum disorder

Numerous studies have investigated the important characteristics of autism through a variety of lenses, such as facial-feature extractions using eye-tracking strategies, face recognition, bio-medical image analysis, application creation, and speech recognition. Among these methods, face recognition is particularly useful for determining a person's emotional state, and it has the potential to accurately diagnose autism. It is a popular method used for analyzing human faces and extracting distinguishing characteristics between normal and abnormal faces, as well as for mining significant information to reveal behavioral patterns.

In light of the recent developments in the predictive analytics of facial-pattern recognition, several intensive initiatives are presently underway in the field of autism research to analyze the data on autistic children in an attempt to diagnose ASD at an earlier age. To automate the identification of facial expressions in diverse neurological illnesses

V. CONCLUSION

The proposed work emphasizes on early ASD detection. In this work, using PCA, there is a reduction in the number of attributes followed by use of 10-fold cross validation to train the data and finally deep learning technique to detect ASD on all categories of individuals with age group corresponding to toddler, child, adolescent and adult. Based upon contribution of minimal benefit, the attributes are reduced in the data set. The different evaluation parameters such as

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accuracy, sensitivity, specificity and F-measure yielded clinically acceptable results using DNN like other works whose results are also well acceptable. In other words, it can be assured that a deep learning model can be implemented for detecting ASD in addition with other conventional ML classifier model as earlier suggested by researchers. Generally in most of the research analysis, toddler data set is dropped because of its unbalanced nature making the detection of disorder difficult in that category. In this study, along with other categories, toddler data set is also analyzed thereby making it successful to predict ASD in toddlers.

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