Expression of Concern

DL-ASD: A Deep Learning Approach for Autism Spectrum Disorder

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Concerns were reported to IEEE regarding the use of images of minors from a non-curated dataset used in this article. The dataset is reported to contain images of children with ASD. However, the images in the dataset were reported to have been collected from the internet without any documented clinical history or confirmation of an actual ASD diagnosis. Additionally, there appeared to be no documented ethical oversight, or consent from the parents or legal guardians of the children who were included in the dataset.
In light of these ethical concerns and the reliance of the article on using potentially questionable data, IEEE is evaluating this matter and in the interim is issuing this expression of concern.

DL-ASD: A Deep Learning Approach for Autism Spectrum Disorder

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Abstract*—Identifying a person's feelings and sentiments is known as emotion recognition and analysis. The emotion analysis approach correctly recognizes normal people's facial emotions in the first attempt. Children with Autism Spectrum Disorder (ASD) who have trouble talking or expressing themselves can struggle emotionally to understand. To predict ASD and No ASD in children aged 1-10 using dynamic analysis, this work presents a robust deep learning model with multi-label categorization. We proposed a DL-ASD framework for identifying autism spectrum disorder. The proposed model has used the Kaggle dataset as an image dataset. The datasets are trained with an Improved Convolutional Neural Network (I-CNN), and the images are used to classify individuals as having autism spectrum disorder or not having ASD. Feature-based calculations of internal and exterior distances are used to identify the emotion. Optimization procedures such as dropout, batch normalization, and parameter update are used to optimize the Improved Convolutional Neural Network's (I-CNN) processing of the returning facial landmarks. The proposed method correctly predicts six emotions in addition to four general emotions. According to the experimental results, the classification accuracy of the approach proposed in this study can reach 98%.

***Keywords*—Autism Spectrum Disorder, Deep learning, DL-ASD, improved CNNKeywords— E-commerce, E-commerce products, IMEP, Social Media, IM, UCR**

I. INTRODUCTION

Characteristics of social communication in youngsters with ASD are more difficult to identify than in other conditions [1]. Because there is no accurate ASD diagnosis technique, these features are crucial in diagnosing autism spectrum disorder. Emotions, arousal, and action units on the face are also used to diagnose ASD [2].

In 2017, the face emotion image datasets EmotioNet and AffectNet were released [3][4]. CNN can learn and predict emotions using these massive datasets. ASD lacks large-scale datasets, making it difficult to train CNN specifically with ASD data [5]. As a result, the dataset used in many ASD studies comes from autistic centres and physicians and is also restricted to sponsored studies. Gerry spent a year collecting 1857 ASD and 1850 Typical Development (TD) photos from various online sources and uploading them to Kaggle.com. He is the dataset's creator [6].

Computers may use machine learning, a form of artificial intelligence, to automatically search vast databases for patterns and generate conclusions based on such searches [7]. Classification is possible in supervised machine learning by creating mathematical models that can predict the class to which that point belongs, given a data point [8]. Sparse data may be used by machine learning classifiers to properly represent complicated and high-dimensional input variables. As they are computationally efficient and work well with small sample sizes, the standard supervised machine learning methods were utilised to detect aberrant motion and postural aspects [9]. Discriminant analysis, K-nearest neighbour, naive Bayes, decision trees, support vector machines, and random forests are some examples of well-known methods. No method is ideal for all datasets because of differences in characteristics, sample sizes, and data formats [10]. Researchers typically conduct multiple experiments to determine the most efficient supervised machine-learning algorithm for classification or prediction [11].

In face detection, a rectangle is drawn around recognizable facial features [12]. This strategy employs the haar cascade classifier in conjunction with the viola jones face detection technique. One definition of face recognition is "the ability to identify an individual in a photograph [13]. The frontal face prediction method uses a face's landmarks throughout face recognition. The Dlib module of OpenCV includes 68 landmark predictors to help with face recognition, feature extraction, and emotion detection. "multi-label classification" describes assigning labels to data or objects according to multiple sets of classification results [14]. Each label represents a unique set of dependent attributes and many distinct classes. Recent studies have shown that a child's facial expressions, traits, and features can be used to predict autism spectrum disorder and gain insight into the child's behaviour. Artificial intelligence, machine learning, and deep learning assist autistic studies [15]. Examined the condition and behaviour of ASD children using facial landmarks, body position, and auditory and biosignals. The main contribution of this paper is the improved CNN algorithm for training and classification.

The rest of this paper is organized as follows. In Section 2, several writers discuss various ASD diagnostic techniques. Section 3 depicts the DL-ASD model. Section 4 deals with implementation, while Section 5 summarises the study's findings. Section 6 finishes with a discussion of the findings and future directions.

II. BACKGROUND STUDY

C. J. Brown et al. [1] for neural networks to acquire knowledge of edge-specific weighting, the author devised a unique element-wise layer that included connective and data-specific priors. Adding this layer to a deep network architecture tailored to brain network data improved the accuracy of autism spectrum disorder (ASD) prediction on 1013 functional connectives from the autistic brain imaging data exchange (ABIDE) dataset significantly.

D. Berardini et al. [3] the author shows a vast video collection of children's social interaction, painstakingly sorted into clinically significant behaviour for ASD diagnosis. A machine learning framework has been given for data collection. This research studies the use of feature selection, class rebalancing, and neural network classifiers for inferring autism spectrum illness from behavioural data. Self-supervised systems are being developed to recognise an adult's head and things of interest in image frames, boosting look-face, look-object, and behaviour detection.

M. Presecan et al. [7] In this study, the author introduces the Faster R-CNN model for object recognition. The Faster R-CNN has been widely used despite the fact that faster R-CNN models have been shown to be a high-performance, accurate, and quick solution for recognising many objects within an image.

O. Rudovic et al. [8] Children with Autism Spectrum Conditions (ASCs) who participated in a single session of robot-assisted autism therapy were photographed for this research. The author examined several deep-learning settings designed for automated engagement evaluation.

Q. Mohi-ud-Din and A. K. Jayanthy [10] this author employed a transfer learning mechanism to classify ASD patients and controls based on EEG data. The findings indicated a good degree of accuracy.

S. Sadiq et al. [12] Autism was becoming more frequent in the United States, with a corresponding rise in its prevalence among ethnic minorities and low-resource communities. It wasn't until the average child was four years old that doctors began diagnosing the condition. This study provided an independent machine learning-based approach for identifying acoustic regimes statistically predicting scores on the Autism Spectrum Disorder Social Affect Scale.

III. PROPOSED METHOD

Autism spectrum disorder has been classified with an improved CNN algorithm. The datasets are collected from the Kaggle dataset.

a) Dataset

Datasets are downloaded from https://www.kaggle.com/datasets/cihan063/autism-image-data. The dataset has a test, train, test, valid and consolidated memory size of 240MB.

b) Improved Convolution neural network (I-CNN)

Multiple varieties of deep neural networks (DNNs) are employed in image processing, and CNNs are just one of them. In terms of data processing and retrieval, it is distinct from conventional neural networks. The CNN architecture represented by Equation 1 is quite popular. The many layers that make up a CNN are as follows: Input, Convolution, Pooling, Fully Connected, and Classification Output.

A layer of Convergence CNN relies on its foundational convolution layer. When you shift these layers, tiny filters appear across the entire display. The dot product between the image and the filter is calculated to perform convolution. The filter region is modified by applying the Dot Product of each image pixel with the corresponding filter. After that, we move the filter onto the next available period. All of the pictures are hidden as you stride. Equation 2 might also help you make sense of the convolution procedure. Here is a mathematical explanation of the convolution operation between an image (x_l) and a filter vector:

$$z_j^l = \varphi\left(x_i^{l-1} * w_{ij}^{(1)l} + b_j^{(1)l}\right) \text{------ (1)}$$

It's responsible for down-sampling tasks. Some different pooling functions exist. Maximum pooling is the most popular utility. A picture is given a 2*2 filter with a stride of 2, from which the pooling procedure may be inferred. For each sub-region, the maximum pooling filter provides the greatest possible value. As a result, a feature of size (4 * 4 * 1) gets down-sampled to size (6 * 6 * 1) when the greatest pooling filter of size (6 * 6 * 1) is applied to it. The output of the pooling layer may be characterized as:

In a completely interconnected layer, all of the neurons from the previous layer are linked to those of the layer below it.

$$y_j^l = \varphi\left(z_i^{l-1} * w_{ij}^{(6)l} + b_j^{(6)l}\right) \text{------- (2)}$$

Where u represents the activation function (a sigmoid), b_{2j} is the bias, and u is the input node, we weigh the i^{th} input node and the j^{th} hidden node, denoted by w_{2ij}. For input at Layer 1, we have z_{l1j}.

Every neuron in a fully connected layer can access the data from the layer below it. As a result, several variables are related to training (weight). However, most hidden neurons are activated to a small degree. So that one hidden node, in particular, may facilitate deep learning, a low activation value of neurons is required. Activation of neurons may be regulated by adding Sparsity.

Classification Loss is calculated in this layer as part of a CNN training process. For reliable data prediction, CNN relies on the minimization of a cost function (existing), which serves as its objective function.

Eq gives the existing cost function.

$$e^{existing}(w, b) = CE + \beta \sum w^2 \text{------ (3)}$$

The cross-entropy loss is

$$CE = -\sum_{j=1}^{m} y_j^T ln y_j^p \text{------ (4)}$$

yP represents the prediction, m represents the training data, and it represents the desired outcome. The L2 regularisation parameters b are defined by the cross-entropy loss function in Eq.

Overfitting is a potential problem due to Improved CNN's many hidden parameters. As previously established, the greatest number of dormant neurons leads to the weakest possible neural activity. A concealed node's average activation value (lTJ) should be close to zero.

With the old function used to calculate the divergence of activation in Eq. the activation in the hidden layer of a convolutional neural network (CNN) may be lowered. By deactivating unused training parameters, Sparsity practice reduces the total number of them, which helps prevent over-fitting in CNN.

c) Algorithm: Improved CNN algorithm

Input: Regulation parameter: sample image x 2 RD, Learning Rate (bÞ;

Sparsity is a parameter (b1), Sparsity (l); Iteration number (N).

Output: Parameters of Weight and Bias wð1Þ ij ;wð2Þ ij ; bð1Þ j ; bð2Þ j

Step 1: The weight and bias parameters should be initialized.

For n = 1 to N, do

Step 2: Using Eq, compute the reconstruction result.

Step 3: The modified cost function equation directs you to perform the following actions.

Step 4: Weight and bias parameters are updated using a gradient method

Step 5: Steps 2 and 4 should be repeated until n = N.

End

IV. Results and Discussion

We proposed that the DL-ASD framework be implemented using python programming with 3.8 versions. The proposed framework has achieved 98% accuracy.

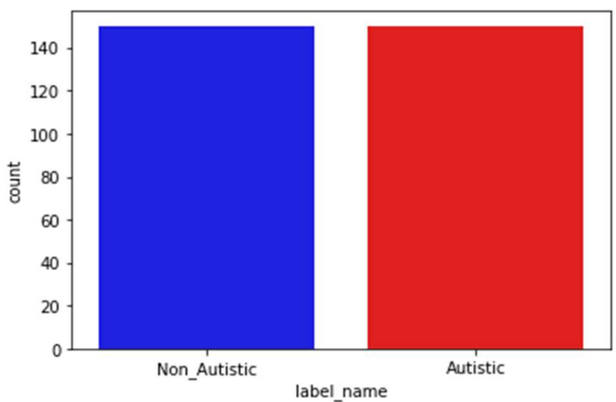

Figure 1: Classified with autistic and non-autistic

The number of images counted with non-autistic and autistic has displayed in figure 1. The label name is represented on the X-axis, and the count is represented on the Y-axis.

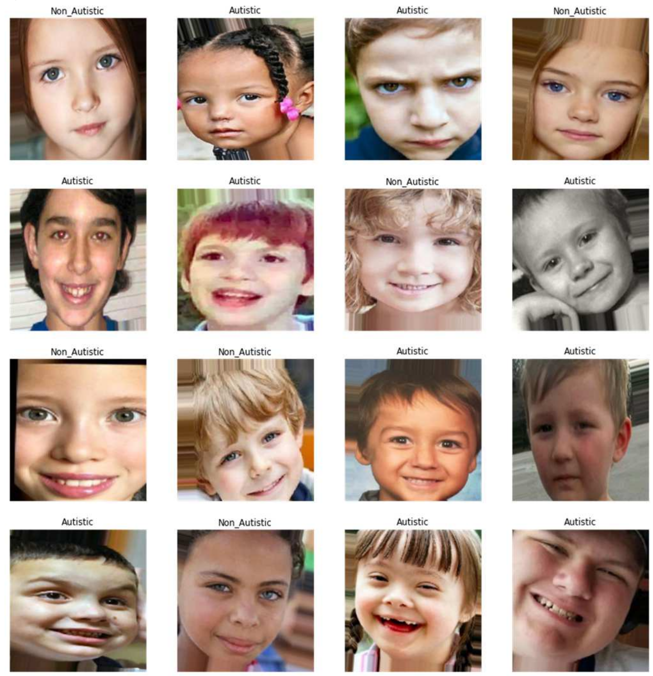

Figure 2: Classified image data

The dataset has been classified using the I-CNN algorithm with autistic and non_autistic images shown in figure 2.

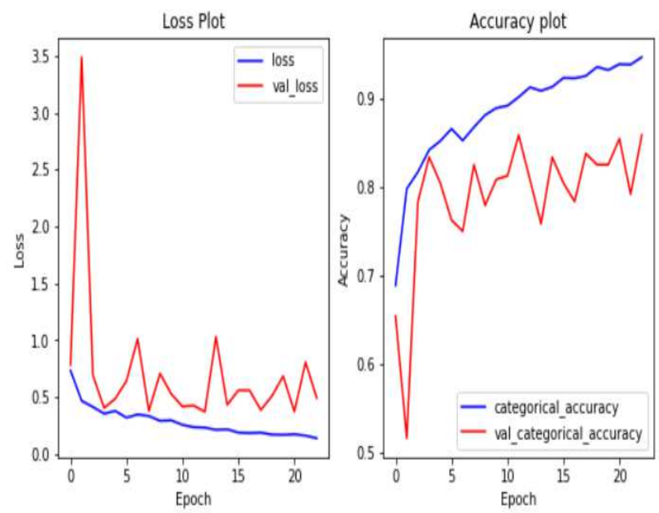

Figure 3: Training and testing values

The training and testing with 20 epochs are displayed in figure 3. The Loss Plot and Accuracy Plot are shown in figure 3.

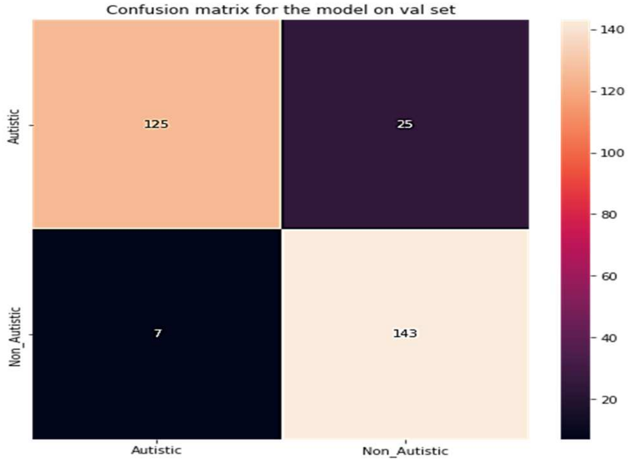

Figure 4: Confusion matrix

The confusion matrix of the proposed work has shown in figure 4. The TP is 125, FP is 143, TN is 25, and FN is 7.

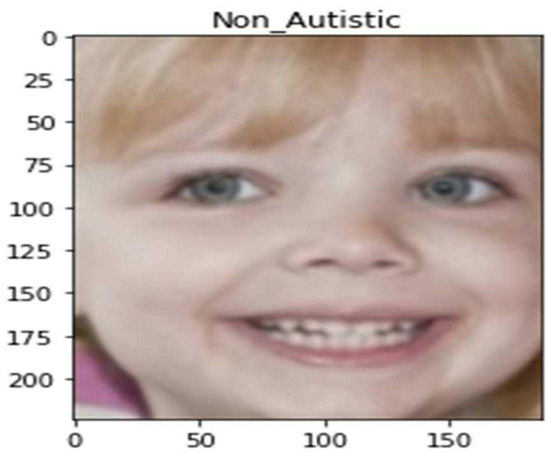

Figure 5: Predictive result

The predictive analysis has shown in figure 5. The I-CNN has predicted the exact result.

V. Conclusion

Here, we provided the DL-ASD framework for detecting ASD. The first step in this approach is to identify problematic behaviours, and the second is to use these same statistical behaviour characteristics to predict autism spectrum disorder (ASD). The deep-learning baselines were presented for behaviour recognition: two different models, one trained solely on the young subject's facial features and the other on raw video frames. Eventually, we want to develop self-supervised algorithms that recognize the faces of adults and the objects of interest in photographs, improving look-face and look-object identification. An Improved CNN model is suggested for ASD/NoASD children's ASD/NoASD and facial expression prediction. The efficiency and dependability of the suggested model are enhanced. An example application would be analyzing facial photos of autistic children to deduce their action units, arousal levels, and valence. Children's facial characteristics may be used to predict their behaviour and the likelihood that they may acquire autism spectrum disorder. To further improve the accuracy with the use of hybrid deep learning algorithms.

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