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CNN-Based Handwriting Analysis For The Prediction Of Autism Spectrum Disorder

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Abstract. Approximately 1 in 44 children worldwide has been identified as having Autism Spectrum Disorder (ASD), according to the Centers for Disease Control and Prevention (CDC). The term 'ASD' is used to characterize a collection of repetitive sensory-motor activities with strong hereditary foundations. Children with autism have a higher-than-average rate of motor impairments, which causes them to struggle with handwriting. Therefore, they generally perform worse on handwriting tasks compared to typically developing children of the same age. As a result, the purpose of this research is to identify autistic children by a comparison of their handwriting to that of typically developing children. Consequently, we investigated state-of-the-art methods for identifying ASD and evaluated whether or not handwriting might serve as bio-markers for ASD modeling. In this context, we presented a novel dataset comprised of the handwritten texts of children aged 7 to 10. Additionally, three pre-trained Transfer Learning frameworks: InceptionV3, VGG19, Xception were applied to achieve the best level of accuracy possible. We have evaluated the models on a number of quantitative performance evaluation metrics and demonstrated that Xception shows the best outcome with an accuracy of 98%.

Keywords: ASD, InceptionV3, VGG19, Xception, ROC AUC, kappa, Confusion matrix

I Introduction

Autism is a neuro-developmental condition that, in general, is identified by several characteristics: deficiencies in social interaction, stereotyped and repetitive behaviors, and difficulties in communication.In addition to these fundamental concepts, autism is linked to a high frequency of motor deficits and executive function impairments. Motor deficits hinder the development of skilled motor tasks, which are likely contributors to handwriting difficulties in children with autism. As a result, analyzing a child's handwriting can be very helpful in determining whether or not they have ASD at an early age. In fact, studies on handwriting focused on writing activities, such as loops, letters, handwritten texts, or signatures, with the purpose of diagnosing illnesses like Alzheimer's disease [1], Parkinson's disease [2], and depression. In spite of these, the study of ASD, which is the cornerstone of this research, has rarely made use of the assessment of handwriting tasks. Therefore, for the non-invasive and automated early identification of autism, we have presented a novel dataset in this study that consists of handwritings of autistic children along with the handwritings of normal children of similar age group.

Handwriting, being a psycho-mechanical activity, is a distinctive behavioral biometric trait that certifies a person's individuality. Because the handwriting of each individual is unique, it can provide insight into their backgrounds, personalities, mental health, and other aspects of their lives [3]. Hence, examining a person's handwriting has emerged as a central focus of research in a wide range of fields, including medical diagnosis, the study of psychological illnesses, forensic investigations, and a variety of other fields as well, such as e-security [4].

The act of handwriting is often narrated by specialists as a perceptual motor act. This necessitates the concurrent processing of both physical and cognitive demands. The development of a child's gross and fine motor skills, which serve as the basis for the child's ability to control precise hand-wrist movements and eye-hand coordination, plays a significant role in determining whether or not the child is ready to start writing. Studies, however, indicate that children with autism show poor outcomes in motor functions besides oral motor functions and balance coordination [5]. This results in the inability to align limbs accurately, indicating a heightened probability of handwriting difficulties among children with Autism Spectrum Disorder. As a result, the objective of this study is to develop a handwriting-based model that is capable of accurate ASD diagnosis. In this study, we look for characteristics in people's handwriting that could differentiate autistic spectrum disorder patients from healthy controls.

II Literature Review

In the following section, a synopsis of the findings of earlier research studies pertaining to the identification of autism spectrum disorder, along with the most current findings concerning handwriting analysis has been presented.

A Autism Spectrum Disorder

A study incorporated several classifiers: Random Forest, SVM, Decision Tree, KNN, Logistic Regression and Naive Bayes to detect ASD precisely at an early age [6]. In [7], authors utilized seven distinct machine learning techniques to predict autism and obtained 97% accuracy on the test cases. However, decision tree provided the maximum accuracy in another study of early ASD screening in children [8]. Again, researchers have investigated state-of-the-art classification and feature selection strategies to identify the most effective classifier along with feature set utilizing four datasets containing information on people of all ages with ASD, from toddlers to teenagers [9]. Their experiments reveal that the multilayer perceptron (MLP) classifier is superior to other benchmark classification models, accomplishing full accuracy with a small amount of characteristics across all age groups. Another research introduced a flexible and modular framework for the diagnosis of ASD and evaluated with unsupervised ML techniques [10]. A current study demonstrated that facial characteristics can be used to recognize ASD using DenseNet [11]. Furthermore, authors in [12] followed a different approach by analyzing fMRI in order to detect autism since fMRI captures better brain activities than EEG. Besides, a recent research suggested a deep learning model of assessing the resting-state functional near-infrared spectroscopy (fNIRS) signals to predict ASD [13]. To decrease the number of optical channels while obtaining high precision, the research employed the SHapley Additive exPlanations (SHAP) approach.

B Handwriting Analysis

In [3], the authors have analyzed handwriting signature to assess Neurological Disorder, i.e. Alzheimer's Disease and Parkinsonism using three classifiers: KNN, Decision Tree and SVM. They preprocessed the image dataset by filtering, smoothing and reducing noise. Another study narrates the usage of handwriting to identify personality by utilizing AlexNet architecture with 5 convolution layer and 1 fully-connected layer [14]. The authors incorporated vertical segmentation to identify the features of curves and final strokes and horizontal segmentation to identify the features of upper and middle stroke. Another paper suggested using biGRUs to detect Parkinsonism from hanwriting [15]. Authors in [16] used SVM classifier along with AutoML to analyze handwriting and detected depression with 82.5% accuracy. Additionally, researchers used BiLSTM to identify anxiety and stress states from handwriting and obtained improvement upto 8.9% compared to the baseline approaches [17]. In another research, authors have mentioned the significance of subtle changes in fine motor control to detect early dementia [18]. Their handwriting kinetics and quantitative EEG analysis based classification model achieved 96.3% accuracy using SVM with RBF kernel as the base classifier.

III Methodology

The suggested four-stage structure consists of data collection, data parsing, classification models, and accuracy testing.

A Data Acquisition

Raw handwritten samples have been captured for further analysis. 17 participants were enrolled for the experiment. In detail, the participants were composed of 11 subjects with ASD (9 males, 2 females, age: 7 to 10 years) and 6 healthy ones (2 males, 4 females, age: 7 to 10 years). Each participant was asked to complete the handwriting task on a blank piece of white A4 paper using pencil. Further, the papers have been scanned. All information obtained has been treated as strictly confidential and used exclusively for research purpose. Sample images from the dataset are depicted in Fig. 1.

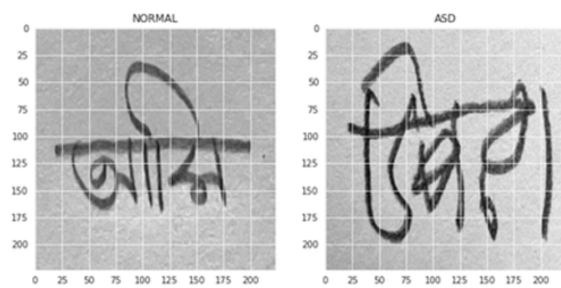

Fig. 1. Illustrations from the dataset. The image on the left represents the handwriting of a healthy child. The image on the right represent the handwriting of a child with ASD.

B Dataset Preprocessing

In a ratio of 8:2, the dataset was divided into training and testing sets. In addition, the training set was subdivided into a validation set and a training set at a 9:1 ratio. The images have been downsized to 224x224 pixels in size for a better architectural efficiency. Images were scaled down to 299x299 pixels to train InceptionV3 and Xception. Nearest-Neighbor Interpolation was utilized for uniform image resizing. Data augmentation has been employed to improve the generalizability of an over-fitted data model as well as to resolve the class imbalance issue in the dataset. The augmentation procedure was applied by randomly rotating some training images by 30 degrees, zooming by 20%, shifting horizontally 10% and shifting vertically 10% to make the model more robust to slight variations.

C Model Architecture

1) InceptionV3 A sequence of convolutional and pooling operations are performed on the input data by a succession of modules, organized into blocks, that make up the InceptionV3 model. Since our dataset only allowed for binary classification, we modified the InceptionV3 architecture by removing its top layers and adding two dense layers. There are 256 neurons present in the dense layer that comes before the output layer. To avoid overfitting, we've used the ReLu activation function 1, with a dropout of 0.5.

$$f(x) = max(0, x) \tag{1}$$

The dense layer employs the 'he_uniform' kernel initializer. The output layer classifies the images into two groups, 'ASD' and 'Normal' using Sigmoid activation function 2. The model has been trained utilizing Adam optimizer with the given specifications: learning rate = 0.001, beta_1 = 0.9, beta_2 = 0.999 and epsilon = 0.1. In addition, 'binary crossentropy' was chosen as the loss function.

$$S(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

2) VGG19 The foundation of the VGG19 model is a convolutional layer, which is followed by ReLU activation function as discussed previously in 1 and a max pooling layer.

We slightly changed the architecture by deleting the top layers and adding a dense layer followed by a flatten layer. Using Sigmoid activation function, the output layer categorizes the images into two groups: 'ASD' and 'Normal'. Adam optimizer was used to train the model with the following parameters: learning rate = 0.001, beta_1 = 0.9, beta_2 = 0.999 and epsilon = 0.1. 'Binary crossentropy' was selected as the loss function that is calculated using the equation given in 3.

$$Loss = abs(Y\_pred – Y\_actual) \tag{3}$$

3) Xception Xception has been designed to be more efficient than standard CNNs, with fewer parameters and computational resources, while still producing satisfactory results.

The input layer passes the image data through a stack of depthwise seperable convolutional blocks and skip connections. The blocks consist of a pointwise convolution and rectified linear unit (ReLU) activation function that is presented in 1. The skip connections skip additional processing and directly pass the data to the output. Following that, the output layer produces a prediction.

We fine-tuned the architecture by not including the top layers and adding one dense layer with a dropout of 0.5 followed by on flatten layer. Using the Adam optimizer, the model has been trained with the following parameters: learning rate = 0.001, beta_1 = 0.9, beta_2 = 0.999 and epsilon = 0.1. 'Binary crossentropy' was selected to be used as the loss function.

IV Experimental Results and Discussion

Precision, recall, specificity, F1-score, accuracy, cohen kappa score and roc-auc score were some of the performance metrics used to evaluate the described models. Table 1 contains a comparison of the models' performances for the mentioned parameters.

Table 1. A comparison among the models on performance evaluation metrics

InceptionV3			VGG19			Xception		
Accuracy		0.62	Accuracy		0.95	Accuracy		0.98
F1 score	ASD	0.44	F1 score	ASD	0.97	F1 score	ASD	0.98
	Normal	0.71		Normal	0.97		Normal	0.98
ROC AUC score		0.80	ROC AUC score		0.96	ROC AUC score		0.98
Cohen Kappa score		0.25	Cohen Kappa score		0.93	Cohen Kappa score		0.97

In short, table 1 illustrates that the Xception architecture outperforms other two architectures by achieving 36% and 2% higher accuracy than InceptionV3 and VGG19 respectively. The cohen's kappa value of InceptionV3 is 0.25, which interprets the test as fair. However, the model obtained an average ROC AUC score, that is 0.80. On the other hand, ROC AUC scores of both VGG19 and Xception are between 0.95 to 1.00, which suggest that both of the models are capable of identifying ASD from handwriting images perfectly. Additionally, Xception obtained the highest kappa score out of the three models that is close to 1, indicating great concordance with the assigned labels.

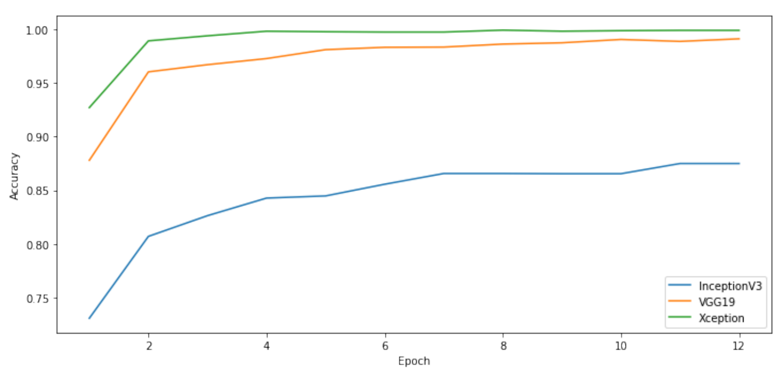

Fig. 2. Training Accuracy graph of three models.

Besides, Fig. 2 exhibits a graph comparing training accuracy of the three models. The graph demonstrates that the training accuracy of Xception is superior to that of the other two models at each epoch. Training accuracy of

InceptionV3 is comparatively lower at each epoch. On the other hand, Fig. 3 displays a graph representing the training losses of the models per epoch. The graph illustrates that the training loss of Xception becomes close to zero after four epochs. Although VGG19's training loss is initially higher than that of the other two models, it improves significantly after the first six iterations.

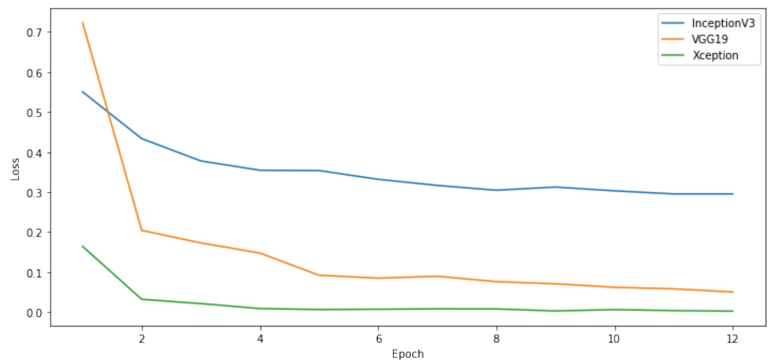

Fig. 3. Training Loss graph of three models.

Furthermore, Fig. 4 presents a diagram of validation accuracy of three models. It depicts that the accuracy of both VGG19 and Xception become 100% after four epochs. However, similar to the training accuracy, the validation accuracy of InceptionV3 is lower. Fig. 5 exhibits the validation losses of the three models per epoch. The graph signifies that validation loss of InceptionV3, in comparison to the other models, is higher at every epoch.

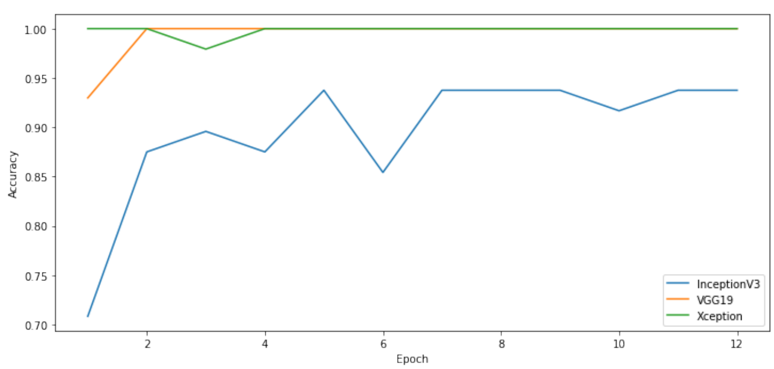

Fig. 4. Validation Accuracy graph of three models.

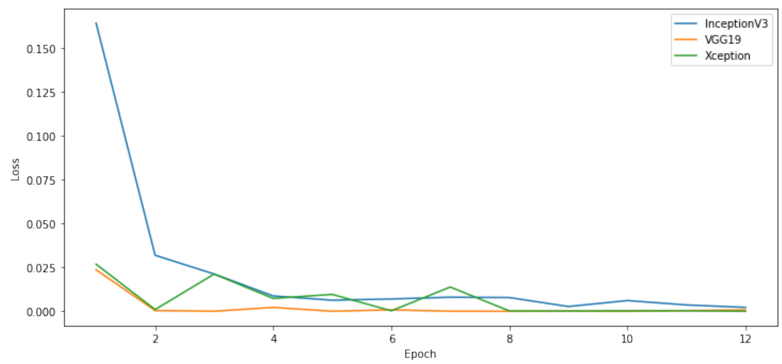

Fig. 5. Validation Loss graph of three models.

From the confusion matrices of the three models demonstrated in Fig. 6, it is visible that InceptionV3 showed overall poor outcome as evidenced by its 190 failed prediction on the test set. Conversely, Xception has accurately predicted 11 more images labeled as 'ASD' than VGG19. However, both VGG19 and Xception predicted all handwritings of normal children accurately.

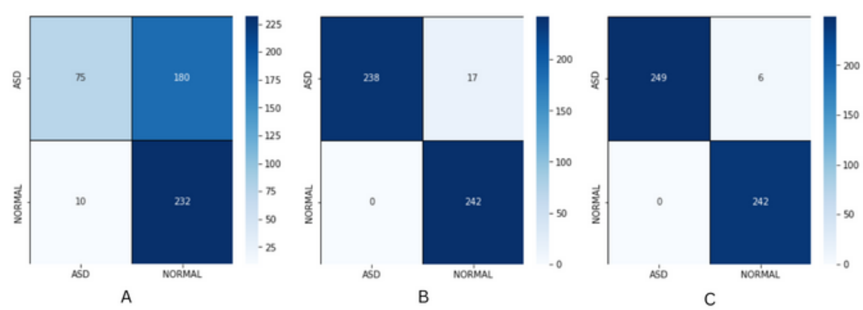

Fig. 6. Confusion matrix of the three models on test set. (A) InceptionV3 (B) VGG19 (C) Xception

One potential reason why VGG19 has outperformed InceptionV3 is because it has a deeper and more narrow architecture, with a larger number of convolutional layers and smaller filters. This allows it to capture more detailed features in the input data which makes the model more computationally expensive to train and deploy. In that case, Xception in much efficient since it utilizes depthwise separable convolutions that decompose the standard convolution operation into a depthwise convolution and a pointwise convolution, which allows the model to achieve a similar level of performance with fewer parameters and computational resources. Additionally, the architecture of Xception uses skip connections that allow it to incorporate information from multiple layers of the network and improve the flow of gradients during training.

V Conclusion

In this research, we set out to automate the difficulty of distinguishing children with autism spectrum disorder from healthy subjects by utilizing a novel approach. Studies convey that children diagnosed with ASD often struggle with both fine and gross motor skills, that include hand-wrist movements. Therefore, handwriting impairments are generally present in children diagnosed with autism. As a result, handwriting traits can be a new bio-marker for identifying ASD.

To provide evidence in support of the assertion, we gathered handwriting images of children aged between 7 to 10 years. Following that, we incorporated three architectures in order to successfully predict ASD from handwritten text images. Among the three architectures, VGG19 and Xception have shown promising outcomes for diagnosing ASD from handwriting with an accuracy rate of 95% and 98% respectively. The proposed handwriting features based automated, non-invasive, and rapid detection protocol will help screening children with autism spectrum disorder.

When doing research on forecasting ASD, we ran into certain challenges that are intended to overcome in the future. Lack of sufficiently large data with more variation to train the prediction model is the study's primary weakness. Again, the dataset only contain images of handwriting in Bangla language. Our future work will emphasize on collecting more handwriting in different languages from reliable sources so that the prediction becomes more robust.

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