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Deep Learning based Dysgraphia Symptom Prediction

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***Abstract*— People who have learning disabilities frequently struggle in the areas of reading and writing. The main effects of learning disabilities are bad grades and a lack of motivation that lasts a lifetime. Most of the time, it starts in childhood and has a big effect on academics. The early recognition by using technological prediction will assist the academicians to devise special learning strategy to accommodate such children in the teaching learning and hence perform well in academics. Specific Learning disability is a complex neurodevelopmental/neurological disorder that affects many children. Learning Disability have two major categories like Specific Learning Disability in reading (dyslexia) and Specific Learning Disability in writing (dysgraphia). Our primary focus is to predict the symptoms of dysgraphia using deep learning algorithms. Deep learning algorithms are general-purpose methods of artificial intelligence that can learn patterns from data without the need to define them apriori. Convolutional Neural Network is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. To generate automated and trained models that reduce the amount of human intervention by significant margins is the primary goal of deep learning. For experimentation purpose, we have used MNIST alphabets dataset to analyse the problem. For this research, we have reviewed several methods like handwriting analysis, eye tracking, Tests, questionnaire, games; etc but we choose handwriting modality for our research. In this paper, experimental study done on convolutional neural network and transfer learning models for predict the dysgraphia symptoms and implemented using publicly available dataset of MNIST alphabet dataset. We compared the accuracy of the VGG16, VGG19, and ResNet50 architectures. Based on the analysis, we have arrived at the conclusion that the VGG16 architecture is the most superior option in training and validation phase.**

***Index Terms*— Dysgraphia, Learning disabilities, Specific Learning disability, Convolution Neural Network**

I. Introduction

Dyslexia is a learning disorder that cannot be prevented or cured, although early discovery and intervention can help manage its symptoms. The earlier a student with a learning disability is diagnosed, the more likely teachers are to establish individualised educational programmes for them, which boosts the student's academic achievement. Dyslexic youngsters can learn to read and write provided their instruction is tailored to their requirements. Due to the fact that children don't show symptoms of learning until six years old, despite the fact that all children start learning from birth. The focus is on children between seven- and twelve-years old children (As per AIMS report).

Many deep learning techniques are useful for predicting learning impairment symptoms. The basic objective of

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deep learning is to develop automated and trained models that drastically reduce the amount of human interaction. Training, algorithm improvement, and layer organisation can all be used to increase the accuracy of deep learning systems. These models can increase their precision by using data clusters and by incorporating additional data points. Artificial neural networks have been the most popular sort of computer model for a very long time. Due to their powerful learning algorithms, they are able to quickly and easily incorporate fresh data into their systems. Importantly, this network exclusively forwards information from its neurons to its deeper layers, making it a "feed-forward" neural network. With quick serial transformations, the data can be manipulated and transmitted from one hidden layer to another with ease. Many Convolutional Neural Network (CNN) models, including VGG16, VGG19, and Resnet50, have been the subject of our research. With the existing data set, we achieved good precision.

II. RELATED WORK

Following work contains the comprehensive review on journey of technological support to predict the symptoms learning disability. Mainly it is related to dyslexia and dysgraphia symptom detection using different approaches.

TABLE I. MULTIPLE MODALITY APPROACHES WITH OUTCOME AND ACCURACY

Ref No	Method	Measures	Algorithm with accuracy	Predict Dyslexia/ Dysgraphia
[13,14, 15]	Video or image capturing	Facial expression	CNN 96%	Dyslexia
[16,17]	Eye movement tracking	Gaze position, pupil movement, Saccades (fixation intervened with rapid ballistic)	SVM 89.7%	Dyslexia
[18,19]	Gamified test	Game/test	RF 89.2%	Dyslexia
[20,21]	MRI and EEG scan	Electrical impulse	SVM 95.4%	Dyslexia
[22]	MEG scans	cortical activity	SVM 80%	Dyslexia
[23]	Handwritten Data	Handwritten alphabets	CNN 87%	Dysgraphia
[24]	MRI scans	Linear SVM, LR, RF	LR = 65, RF = 64	Dyslexia
[25]	MRI scans	Linear SVM, LR	Linear SVM = 83.6, LR = 73.8	Dyslexia
[26]	MRI scans, DTI scans	SVM	80	Dyslexia
[27]	Eye tracker	SVM	84.6	Dyslexia
[28]	Eye tracker	SVM-RFE, RF	SVM-RFE = 95.6, RF = 95.3	Dyslexia
[29]	EEG scans	SVM, KNN	SVM = 95,4, KNN =86	Dyslexia
[30]	Eye tracker	SVM	80.2	Dyslexia
[31]	Hand writing images	CNN	55.7	Dysgraphia
[32]	Hand writing images	CNN	77.6	Dysgraphia
[33]	fMRI scans	3D CNN	72.7	Dyslexia
[34]	MRI scans	Two way cascaded CNN	84.6	Dyslexia

For this research, we have reviewed several methods like handwriting analysis, eye tracking, Tests, questionnaire, games; etc. for dyslexia and dysgraphia detection. As per study, we can see the very less work done for dysgraphia or writing difficulties of child and there is scope to work on it. So, we focused the review on dysgraphia. In our review, we have referred following papers which given us insights for research.

Giovanni Dimauro et. al. in [42], this research and software have enabled the establishment of a support system for doctors who organise systematic screenings and widespread BHK tests (in 1987, the University of Leiden Department of Developmental Psychology introduced the Beknopte Beoordelingsmethode voor Kinderhandschriften (BHK) method), which can ease their laborious and boring work and conserve resources and reduce expenses, as anticipated. The primary objective is to identify early signs and screen more children in a shorter amount of time. Throughout the course of this investigation, document analysis algorithms were utilised. In order to accomplish this goal, both the algorithm for the non-aligned left margin and the mechanism for skewed writing have been modified.

Expanding on research on digitizer handwriting, Sara Rosenblum et al[43] .'s study reveals a connection between the conventional appearance of dysgraphia children's writing and quantitative digitizer measurements (In Air time and length). The combined findings of traditional methods and those based on digitizers may shed light on the flawed processing pathways utilised by these children. The findings have implications for educational and clinical professionals who identify and treat disorders related to children's handwriting. There is a need for additional research to develop strategies utilising computerised data in order to create a comprehensive and systematic

evaluation system for children of all ages who have dysgraphic handwriting. This system would be based on analysing the handwriting process in addition to the handwritten product.
Marianne Engen Matre et. al,[44] proposed idea and there is a clear need for more rigorous research on the use of STT in secondary education before a systematic review can provide more insights into its impacts on writing related abilities and performance for struggling writers, as only eight peer-reviewed articles were included in this scoping study. [Citation needed] Because each of the studies that were discovered was carried out in just one of three countries—Sweden, the United States, or Scotland—there is an urgent need for additional research to be carried out on a global scale. Accuracy can vary greatly depending on the language being used with the technology; hence, accuracy is an essential component to consider when analysing the writings produced by students and their experiences using STT in the classroom. Studies are required to identify how the use of STT affects at-risk adolescent writers while they are engaged in educational activities because the standard of educational technology is continually rising and STT is now acknowledged as another true instrument for writing.
The methodologies of visual and procedural analysis were discussed in Momina Moetesum et al.'s[45] article. At the completion of the task, offline graphomotor response samples are evaluated using visual analysis. The graphomotor reaction dynamics are the primary focus of the procedural analysis methodologies. The research also analyses handwriting representation and estimation methodologies that have been employed in the literature, along with their respective benefits and limitations. This is done because both sets of strategies attempt to properly represent domain information. It also demonstrates the limitations of the methods that are currently in use and the challenges involved in constructing such systems.
The research done by Zoltan Galaz and colleagues [46] demonstrates that sophisticated characteristics of online handwriting are able to quantify subtle and largely invisible signs of GD through coordinated movement of the fingers, wrist, elbow, and shoulder. Visuospatial cognitive skills are also taken into account in this research.

III. METHODOLOGY

For dysgraphia prediction, we have choose handwriting modality and accordingly we have applied deep learning models to find out the better model which will work on the handwriting dataset. Following steps consider for our research.

1. Data Collection
2. Pre-processing
3. CNN Model used for classification
4. Result evaluation

So, in data collection, we have used MNIST dataset which contain alphabets. We discovered the existence of 151649 images that needed to be classified into 3 different unique categories of corrected, normal and reversal. The data set was split with a ratio of 70:30 into testing and training datasets. The images that were found in the data set were clearly of greater size than the ones with which the convolution layers could be input with and hence they had to be compressed to the size of 224×224×3. The features of the images were extracted separately with the help of VGG16, VGG19, and ResNet50. The data set was run with an Epoch of 1, 2, 3, 4 and 5. The accuracies of each architecture were then observed and compared.
Following Fig 3.1, is showing the architecture of CNN which we have used for predict the symptoms of dysgraphia.

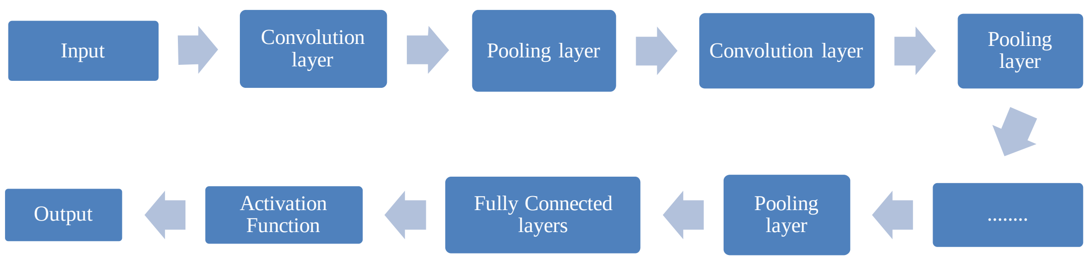

Fig 1. CNN Architecture

This type of network is created by stacking numerous hidden layers in a particular order. CNN is able to collect knowledge about hierarchical properties thanks to its sequential construction. We have tried to predict the accuracy and loss of every model and trying to compare it with each other to find out the best model will be useful for dysgraphia prediction.

IV. RESULTS

We utilise three groups to categorise people's handwriting: a "corrected" group with 65534 examples, a "regular" group with 39335 examples, and a "reversal" group with 46780 examples[23]. We've implemented models for handwriting classification with VGG16, VGG19, and ResNet. We used 151649 photos that needed to be sorted into the three distinct classes of corected, regular, and reversed. There was a 70:30 split between the test and training datasets. Evidently, the photos in the data set were larger than the ones that could be supplied to the convolution layers, therefore they were reduced to a size of 224x224x3. VGG16, VGG19, and ResNet50 were used independently to extract the images' characteristics. Epochs 1, 2, 3, 4, and 5 were used to analyse the data set. Each architecture's precision was then measured and compared to the others. The categorization process was executed on a Core i5 (CPU) running 64-bit Windows 11 OS. Keras API has been utilised to run all the picture classification and recognition models. All these architectures employ Softmax as their activation function and Categorical cross-entropy as their Loss function for tuning. In the process of fitting the model to the training data, we calculated its accuracy, and we did the same for the test data. This epoch's starting batch size is 5. The VGG19 model shows promising performance in picture classification with the training data set, with a 99.01% accuracy recorded for the training data at Epoch 5. The 98.96% accuracy reported by VGG 19 at Epoch 5 suggests that the model can correctly categorise examples from the test data set.

TABLE II. ANALYSIS OF MODELS ACCURACY

Epoch	VGG16 Training Accuracy	VGG16 Val Accuracy	VGG19 Training Accuracy	VGG19 Val Accuracy	ResNet50 Training Accuracy	ResNet50 Val Accuracy
1	0.9952	0.9948	0.7900	0.9647	0.5486	0.6362
2	0.9959	0.9943	0.9701	0.9574	0.6425	0.6893
3	0.9968	0.9862	0.9823	0.9696	0.6665	0.7124
4	0.9970	0.9938	0.9871	0.9907	0.6820	0.7264
5	0.9973	0.9950	0.9901	0.9896	0.6911	0.7268

TABLE III. ANALYSIS OF MODELS LOSS[41]

Epoch	VGG16 Training Loss	VGG16 Val Loss	VGG19 Training Loss	VGG19 Val Loss	ResNet50 Training Loss	ResNet50 Val Loss
1	0.0145	0.0166	0.4644	0.1027	0.9695	0.8430
2	0.0128	0.0188	0.0909	0.1408	0.8294	0.7677
3	0.0099	0.0711	0.0546	0.0822	0.7788	0.7218
4	0.0095	0.0202	0.0398	0.0279	0.7490	0.6909
5	0.0085	0.0165	0.0296	0.0344	0.7283	0.6701

As we can see that VGG-16 models is better than ResNet-50 and VGG19 models for Image categorization. The two losses (both loss and val_loss) are decreasing and the two acc (acc and val_acc) are increasing. So this indicates the model is trained in a good way. The val_acc is the measure of how good the predictions of your model are. So for my case, it looks like the model was trained pretty well after 5 epochs.

Both training and validation accuracy scores is in increasing manner and loss is in decrease manner. In other words, both of the losses (both loss and val loss) are going down, while both of the gains (both acc and val acc) are going up. Therefore, this provides evidence that the modelling is trained in an effective manner. The val acc is a measurement that determines how accurate the predictions of your model are. Following table will give detail of testing accuracy, precision and f1 score.

TABLE IV. TESTING WITH ACCURACY, PRECISION AND F1 SCORE WITH TIME

Sr. No.	Model	Accuracy	Precision	f1 score	Training time in minutes
1	VGG16	87.50	90.44	0.87	30
2	VGG19	78.12	82.25	0.78	32
3	ResNet50	62.50	62.95	0.59	6

Therefore, this provides evidence that the models are trained in an effective manner. The val acc is a measurement that determines how accurate the predictions of your model are.

V. CONCLUSION

VGG16, VGG19, and ResNet50 architectures were compared for accuracy in this study. The VGG16 architecture is best for training and validation, according to our findings as it is one time learning. If we wanted a lightweight model then we will have scope to improve the ResNet50 with hyper tuning. As per our experimentations, VGG16, VGG19, and ResNet50 had 99.50%, 98.96%, and 72.68% accuracy.

We reviewed numerous modalities and used CNN model to categorise images. CNN models learn high-level abstract features directly from images using VGG16, VGG19, and ResNet model and trying to find out the loss and accuracy of model and accordingly will take decision to choose the best model. We wanted to see if a convoluted neural network (CNN) model could be used to classify handwritten images in real life.

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