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Dysgraphia Detection Using Deep Learning

Devika C S[1], Roshni Nayankara[2], Teena Vinod[3], Joyna Jose[4], Athira A K[5]

[1,2,3,4]*Student, Department of Computer Science and Engineering, IES College of Engineering, Thrissur, Kerala, India*

[5] *Assistant Professor, Department of Computer Science and Engineering, IES College of Engineering, Thrissur, Kerala, India*

Email_id: devikasubij86@gmail.com, roshninayankara@gmail.com, teenavinod20@gmail.com, joynajose06@gmail.com, athiraak@iesce.info

Abstract

Dysgraphia is a neurobiological disorder that impairs an individual's ability to write, often resulting in unclear and irregular handwriting, reduced writing speed, and difficulties with pencil grip and spacing. Early detection and accurate classification of these disabilities are essential for effective intervention and support. Traditional assessment methods, including manual evaluations lack the precision needed for reliable diagnosis, leading to inconsistent identification of learning disabilities. Here, the proposed system is based on deep learning for the detection and classification of learning disabilities through handwriting analysis. Utilizing a dataset of handwritten samples from children, the model employs advanced Convolutional Neural Network (CNN) architectures and Vision Transformers, to accurately identify and classify handwriting patterns indicative of dysgraphia. By leveraging these sophisticated models, this proposed system provides timely and precise diagnoses, enabling tailored educational strategies and interventions for affected children, ultimately enhancing their learning outcomes and quality of life.

Keywords: Deep Learning, CNN, Vision Transformers, Handwriting Analysis, Learning Disabilities, Dysgraphia

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1. Introduction

Dysgraphia is a learning disability that affects a person's ability to write clearly, legibly, and efficiently due to difficulties with fine motor skills, spelling, or handwriting organization. Mostly found in children, early detection of dysgraphia is important to provide timely interventions that can improve a child's writing skills, academic performance, and overall confidence. The traditional image modality for dysgraphia detection is scanned or photographed handwriting samples, used because they visually capture the fine motor patterns and inconsistencies essential for identifying writing difficulties. However, traditional dysgraphia diagnosis typically depends on manual assessment by educators or specialists, which is time-consuming, subjective, and prone to inconsistencies, especially when detecting mild or early-stage symptoms. As a result, there is a growing need for automated and accurate diagnostic systems that can assist educators and specialists in efficiently identifying and classifying dysgraphia in students. To address these challenges, the proposed system presents an AI-powered solution utilizing deep learning for automatic dysgraphia detection and classification from handwriting samples. The system leverages the power of Convolutional Neural Networks (CNNs) and Vision Transformers (ViT), both of which are effective in extracting complex spatial and contextual features from visual data. These models are trained on diverse handwriting datasets to accurately identify subtle patterns associated with dysgraphia. To ensure high input quality and boost classification performance, the system incorporates image preprocessing techniques such as normalization and noise reduction. By using CNN and ViT, the model benefits from both local feature extraction and global context understanding, leading to improved accuracy and reliability for practical use in educational and clinical settings.

2. Literature Review

The "Dysgraphia detection through machine learning" uses machine learning, especially the AdaBoost algorithm, to detect dysgraphia but there are challenges including limited data, variation in handwriting styles[2]. "Deep-learning for dysgraphia detection in children handwritings" applies deep learning and smart pens to detect dysgraphia in children, but difficulty distinguishing dysgraphia from normal variations in handwriting, and the need for further validation with larger and more diverse samples remains as a challenge[3].

"Dysgraphia Identification from Handwriting with Support Vector Machine Method" uses Support Vector Machine (SVM) to classify dysgraphia in children into four levels normal, light, moderate, and severe with the RBF kernel yet the imbalanced data, variations in handwriting due to writing on a smartphone screen is a constraint[4]. CNN based models in"Early Detection Of Dysgraphia Using CNN" and "Method for Dysgraphia Disorder Detection using CNN"" improve classification and segmentation, but require large labeled datasets and face spatial consistency issues[5] [6].

"Rapid Diagnosis of Developmental Dysgraphia Based on Computer Vision and Deep Learning"y develops a prototype application using computer vision and DL techniques but the need for further research to improve model classification is a challenge[7].

3. Proposed System

The proposed model presents a comprehensive deep learning approach to detect learning disabilities, particularly Dysgraphia, by analyzing children's handwriting. Motor Dysgraphia is a neurological disorder that affects writing ability, often presenting as inconsistent letter shapes, slanted or mirrored characters, and irregular spacing. Early detection of such disabilities is crucial, as delayed diagnosis can impact a child's academic development and confidence.

To address these challenges, this study introduces a non-invasive, automated system leveraging deep learning technologies—Convolutional Neural Networks (CNN) and Vision Transformers (ViT)to classify handwritten alphabets as either normal or abnormal.

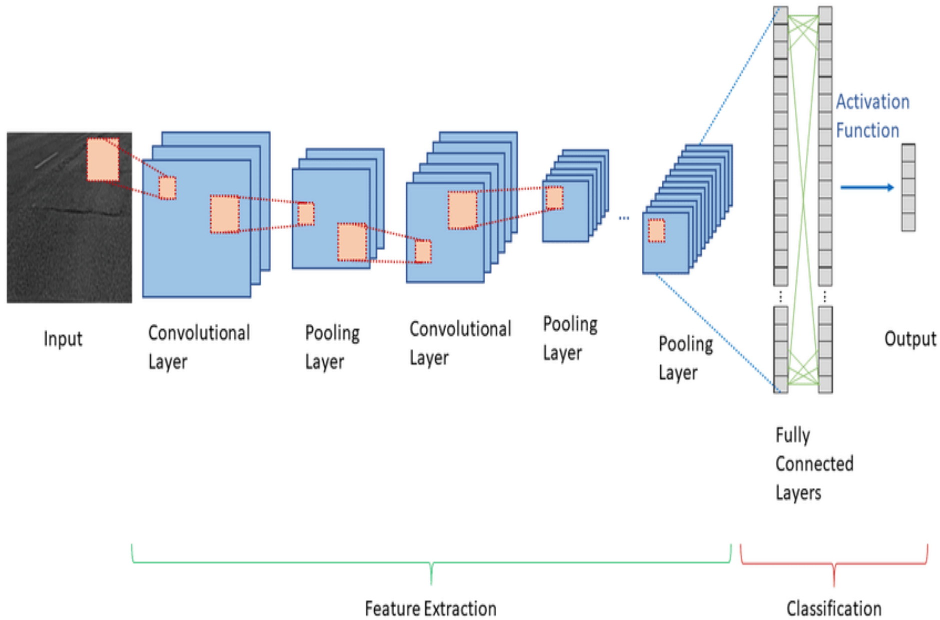

Figure 1: CNN Architecture

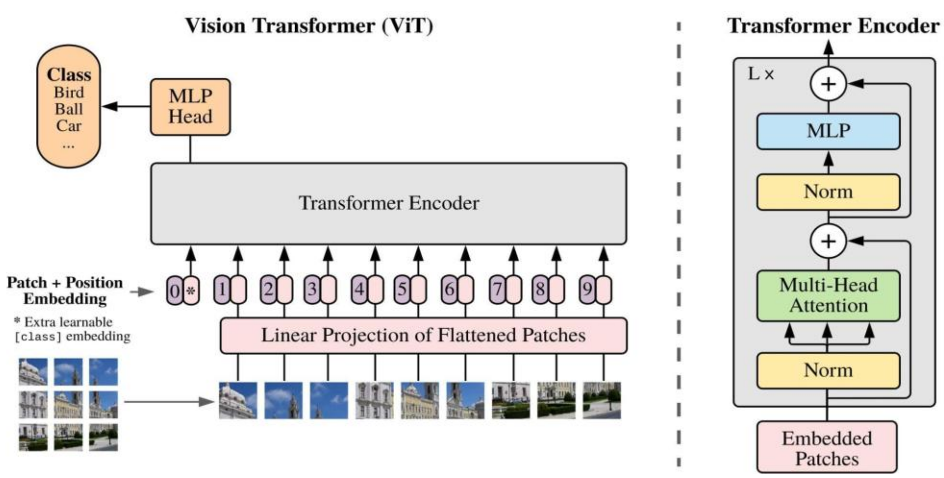

Figure 2: ViT Architecture

3.1 Level 0

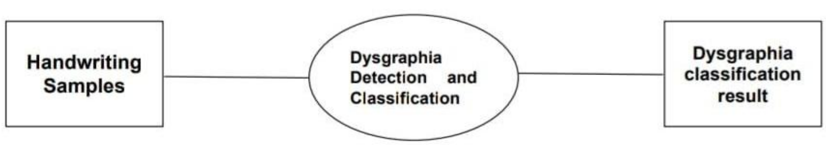

Figure 3: Level 0

At this high-level view, handwriting samples serve as the primary input to the system. These samples are processed through a classification module that leverages Convolutional Neural Networks (CNN) and Vision Transformers (ViT) to detect and classify dysgraphia. The output is a dysgraphia classification result, indicating whether or not the subject shows signs of the condition.

3.2 Level 1

Database: The storage location where data is stored. This could be a hospital's medical records, a research repository, or a publicly available dataset.

Dataset Collection: The process of gathering images from the database or further processing. This step may also involve preprocessing tasks like resizing, filtering, and augmentation to prepare the data for training cable.

Dataset Division: The collected dataset is split into different subsets to ensure effective model training and evaluation. Typically, it is divided into a training set and a testing set.

Training Set: The portion of the dataset used to train the machine learning model. The model learns patterns, features, and characteristics from these images to develop predictive capabilities.

Testing Set: The portion of the dataset used to evaluate the model's accuracy and generalization. It consists of images that the model has not seen before, helping to assess how well it performs on new data.

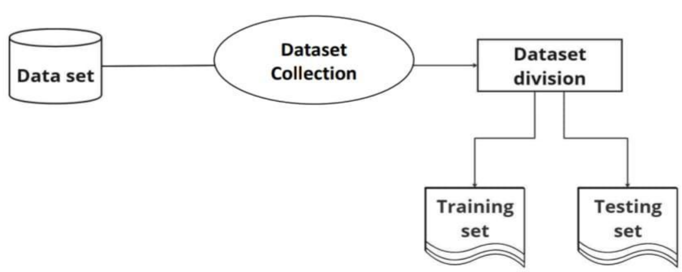

Figure 4: Level 1

3.3 Level 2

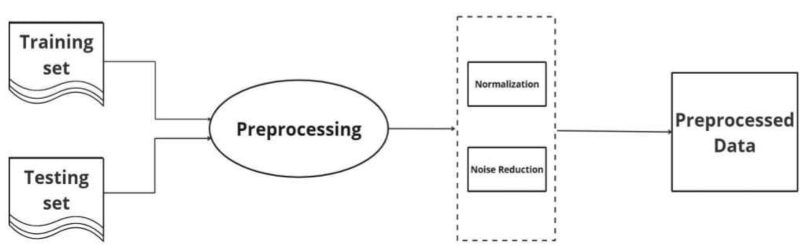

Figure 5: Level 2

Training & Testing Sets: Dataset is split into training (for model learning) and testing (for evaluation), both undergo preprocessing.

Preprocessing Stage: Enhances raw images for better model input.

Preprocessing Techniques:

Normalization: Adjusts the pixel values of an image so that they are within the same range. This helps the deep learning model process the images more easily and improves training speed and accuracy.

Noise Reduction: Removes unwanted random spots or distortions in the handwriting. This makes the image clearer by focusing on important features like edges and helps the model detect dysgraphia more accurately.

Output: Preprocessed images ready for model training and testing.

3.4 Level 3

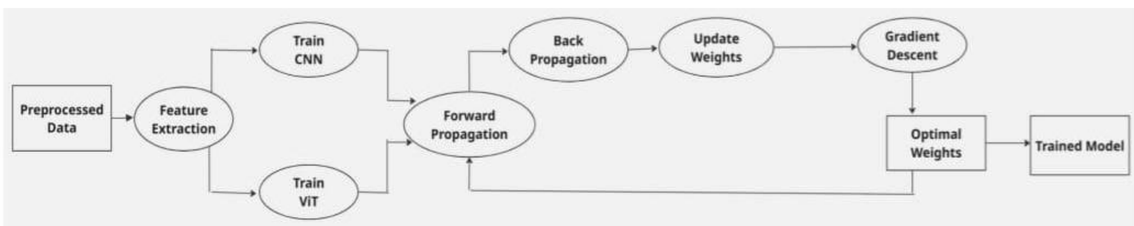

Figure 6: Level 3

Feature Extraction: Feature extraction is carried out using CNN and ViT models—CNN focuses on capturing fine-grained local details such as stroke patterns and spacing, while ViT extracts global contextual relationships across the handwriting. They enable a comprehensive understanding of handwriting features crucial for accurate dysgraphia detection.

Training Phase: In this phase, images are used to train two deep learning models: CNN, ViT. Each of these models learns to recognize patterns and features related to different dysgraphia from the training data. The more the model sees, the better it becomes at understanding what dysgraphia looks like.

Forward Propagation: Once the training begins, the images are passed through the layers of the model. This step is called forward propagation. The model analyzes the input image and makes an initial prediction.

Backpropagation: After the model makes a prediction, the system checks how far the result is from the correct answer. The error or loss is then sent backward through the model. This process is called backpropagation. It helps the model understand what went wrong.

Update Weights: Using the feedback from backpropagation, the model updates the internal values called weights. These weights are what the model uses to make decisions. Adjusting them helps the model improve its predictions in the next training cycle.

Gradient Descent: To make these weight updates, an optimization method like Stochastic Gradient Descent (SGD) or Adam is used. These methods help the model find the best values for the weights so that the prediction error becomes smaller and smaller over time.

Optimal Weights: As training continues, the model keeps adjusting its weights. Once the prediction error is as low as possible and the model is performing well, the best (or optimal) weights are saved. These weights represent the learned knowledge of the model.

Trained Model: After many rounds of training, adjusting, and improving, the final trained model is ready. It can now accurately classify handwriting into normal or abnormal based on what it has learned during training.

3.5 Level 4

Test Data: Images used to test the model's classification accuracy.

Inference with CNN: It takes in a new handwriting image, passes it through multiple convolutional layers, and produces a prediction. Feature maps are extracted through convolution and pooling. These features are passed through fully connected layers to make a final prediction.

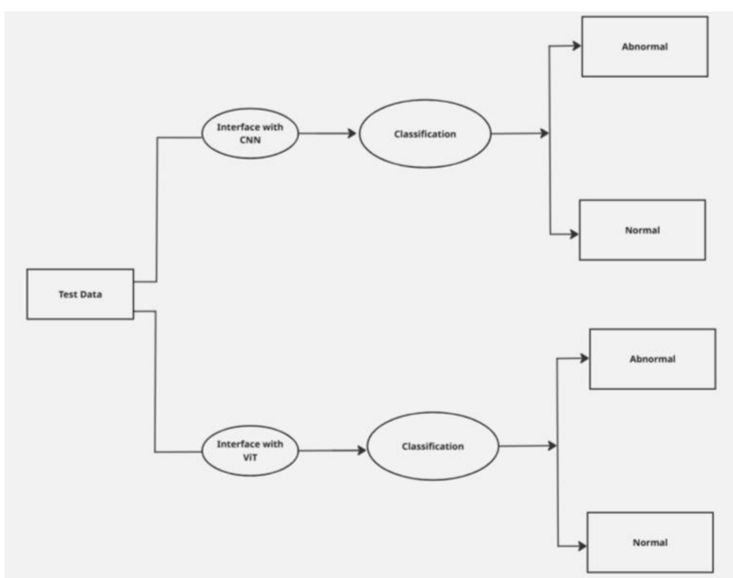

Figure 7: Level 4

Inference with ViT: It treats the image as a sequence of patches (like tokens in text) and learns relationships between them using self-attention mechanisms.The handwriting image is split into small patches.Each patch is embedded and passed through transformer layers.

Classification: The system outputs CNN and ViT to classify normal and abnormal handwriting.

3.6 Level 5

Model Predictions and Ground Truth: Compares model predictions with actual labels to assess accuracy.

Calculate Accuracy: Measures the percentage of correct predictions to evaluate overall performance.

It is the ratio of (True Positives + True Negatives) to Total Predictions:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Calculate Precision: Determines how many predicted tumors are correct, minimizing false positives.

It is the ratio of True Positives to Total Predicted Positives:

Precision = TP / (TP + FP)

Calculate Recall: Measure shows well the model identifies actual tumor cases, reducing false negatives.

It is the ratio of True Positives to Total Actual Positives:

Recall = TP / (TP + FN)

Calculate F1-Score: Balances precision and recall for a single performance metric, especially for imbalanced data.

It is the ratio of twice the product of Precision and Recall to their sum:

F1-Score = (2 * Precision * Recall) / (Precision + Recall)

Generate Confusion Matrix: Provides a detailed breakdown of correct and incorrect predictions for each category.

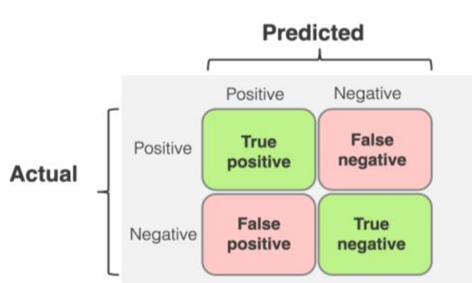

Figure 8: Confusion Matrix

Classification Report: Summarizes all metrics into a report to evaluate the model's strengths and weaknesses.

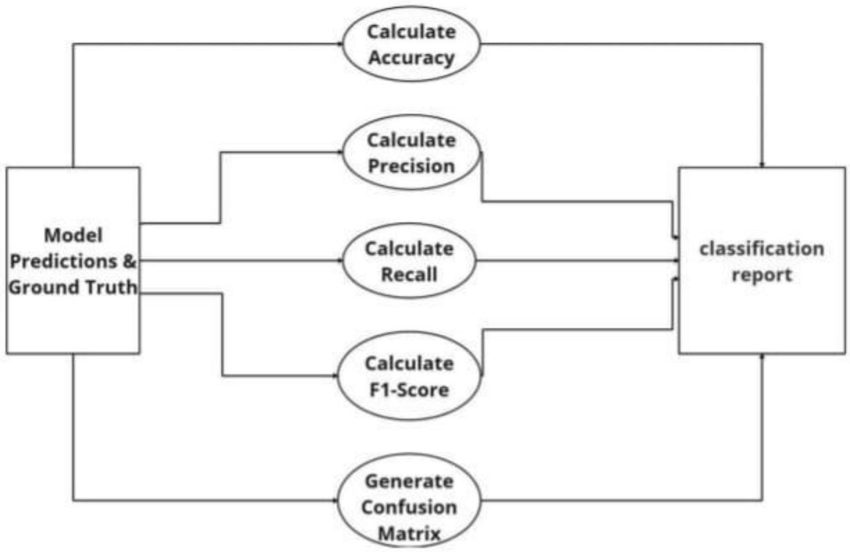

Figure 9: Model Predictions

4. Requirement Specification

The development and implementation of the proposed dysgraphia detection system using deep learning requires a clear specification of hardware, software, and functional requirements to ensure an accurate, efficient, and user-friendly system.

Hardware Requirements:

Processor: AMD Ryzen 5000 Series / Intel Core i5 or above- to provide high processing power for handling complex computations, data processing.

RAM: 16 GB or more- to ensure smooth multitasking, real-time data processing, and seamless execution.

Software Requirements:

Operating System: Windows 10 or above- to ensure compatibility with development tools, AI libraries.

Programming Language: Python-used for backend development and AI based forensic evidence processing.

Libraries: TensorFlow, OpenCV, Matplotlib, NumPy, Pandas, Scikit-learn– essential for machine learning, deep learning, numerical computing, and image processing tasks in forensic investigations.

5. Result and Discussion

The dysgraphia detection and classification system integrates two deep learning models ViT, CNN. Among them, ViT delivered the highest accuracy and overall performance. All models successfully processed handwriting images, extracted handwriting features, and classified them into categories such as normal and abnormal. Preprocessing and augmentation techniques enhanced model generalization across datasets. The classification module effectively minimized false positives and distinguished normal from abnormal handwriting. A clear visualization interface supported fast, reliable diagnosis. The system's modular design ensured smooth operation and accurate dysgraphia detection from start to finish.

	CNN		VIT	
	EXISTING SYSTEM	PROPOSED SYSTEM	EXISTING SYSTEM	PROPOSED SYSTEM
ACCURACY	79.47	92.77	79.47	94.32
PRECISION	78.12	92.77	78.12	93.85
RECALL	79.25	92.14	79.25	94.78
F1-SCORE	78.68	91.88	78.68	94.31

Table 1. Result Comparison

The table compares the performance of various models used for dysgraphia classification based on handwriting images. It evaluates four key metrics: accuracy, precision, recall, and F1-score. Among the models, ViT outperforms all others with a consistent score of around 94% across all metrics, indicating exceptional classification ability. CNN also shows strong performance with 92% in every category. These results highlight the effectiveness of advanced deep learning models over traditional methods. The improvement in precision and recall, in particular, suggests that the newer models are better at correctly identifying dysgraphia cases while minimizing false positives and negatives, making them more reliable.

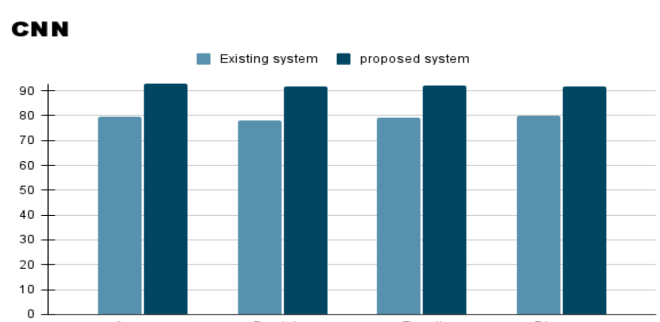

Figure 10: CNN Graph

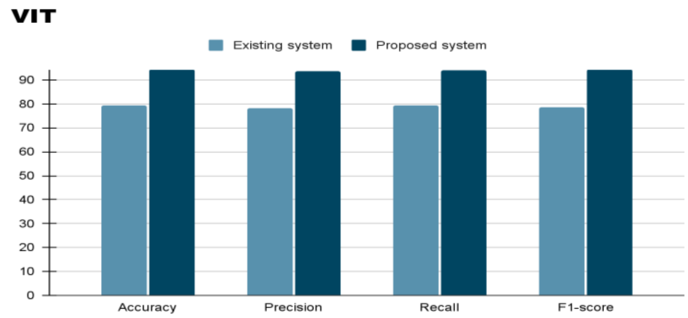

Figure 11: VIT Graph

7. Conclusion

The proposed dysgraphia detection system successfully uses deep learning models such as ViT,CNN to classify handwritings into normal and abnormal cases. With effective preprocessing steps including normalization, noise reduction, and data augmentation, the system ensures improved image clarity and better model generalization. The automated classification approach reduces the dependency on manual diagnosis, leading to quicker and more accurate results. By combining multiple CNN and ViT architectures and rigorous training, the system enhances diagnostic precision, minimizes errors, and supports early detection. This project demonstrates how AI-powered tools can play a vital role in advancing healthcare and improving outcomes.

8. Reference

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