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Design and Development of Exam Kit for Children with Dysgraphia Disorder

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Abstract- Children with Dysgraphia, a learning disorder that affects handwriting and fine motor skills, face significant barriers to academic progress and confidence building. This project introduces a novel. By integrating a Raspberry Pi with Optical Character Recognition (OCR) and advanced machine learning algorithms, the system provides precise, real-time feedback on let- ter formation, spacing, and stroke direction. The kit incorporates an intuitive interface, supported by a TFT display, QPC 1010 camera, and peripheral devices, ensuring accessibility and ease of use.To enhance engagement, gamified learning elements are in- tegrated, fostering an enjoyable and motivational environment for skill development. The system seeks to increase self-confidence, enhance motor coordination, and improve handwriting accuracy. By establishing a connection between technology and education. This project provides a portable and scalable solution for schooling that enables kids with dysgraphia to overcome obstacles and succeed academically.

Index Terms- Dysgraphia, Raspberry Pi, Optical Character Recognition (OCR), Machine Learning, Gamified Learning, Education Technology

I. INTRODUCTION

Education is a universal right and a critical enabler of social and economic development. As a basic component of literacy, writing is essential for communication, self-expression, and cognitive development. However, for children with Dysgraphia, a specific learning disability that disrupts fine motor skills and handwriting, mastering this essential skill can be an overwhelming challenge. Dysgraphia affects the ability to write legibly, align letters properly, and maintain consistency in writing speed and spacing. This disorder can lead to frustration, lowered academic performance, and diminished confidence, creating barriers to a child's overall development Dysgraphia is a multifaceted disorder influenced by neurological, motor, and cognitive factors. Traditional remediation strategies often involve repetitive handwriting exercises, which lack personalized guidance and fail to address the diverse needs of affected children. As classrooms grow more inclusive, there is an urgent demand for technological interventions that provide tailored support to children with learning disabilities like Dysgraphia.

This project introduces an advanced, technology-driven solution: an interactive writing kit tailored to assist children with Dysgraphia. The system uses a Raspberry Pi and a QPC 1010 camera to record handwritten inputs. It then uses ML methods in conjunction with optical character recognition (OCR) to evaluate the writing in real time. The analysis focuses on key aspects of handwriting such as letter formation, spacing, and stroke direction. Using a TFT display, the system provides visual feedback that enables children to correct mistakes immediately, thereby reinforcing proper writing habits.

Unlike traditional methods, the kit incorporates gamified learning elements to foster engagement and motivation. Interactive tasks and rewards incentivize sustained practice, transforming handwriting improvement into an enjoyable experience. The gamified approach ensures that children remain interested while progressively developing their handwriting skills and motor coordination.

This kit's affordability and portability make it a scalable solution that may be used in rehabilitation facilities, classrooms, and homes. By providing real-time guidance and positive reinforcement, the system aims to enhance handwriting accuracy, build self-confidence, and promote academic success. Beyond its immediate application, the project exemplifies the potential of technology to address the diverse needs of learners, contributing to the broader vision of inclusive education and equal opportunities for all.

This paper outlines the design, implementation, and potential impact of the proposed system, highlighting its capacity to empower children with Dysgraphia to overcome their challenges and thrive in educational environments. Various approaches to handwriting assistance have been proposed by different authors:

In[1] The author proposes a comprehensive review of the use of handwriting recognition, The work demonstrates how CNN-based models can analyze handwriting features with excellent accuracy in tasks like letter and digit recognition. It also highlights important drawbacks of existing methods, such as their susceptibility to noise, image quality, and variations in handwriting styles, such as uneven or slanted text lines. Despite their effectiveness, traditional dysgraphia detection techniques are labor-intensive, specialized, and sensitive to subjectivity. The paper highlights the need for improvements, including undertaking studies with bigger and more representative populations, testing proposed approaches against state-of-the-art methodologies, and increasing datasets to include more diverse handwriting samples. Researchers can enhance early identification and intervention efforts for children with dysgraphia by tackling these issues and creating more reliable and accurate handwriting recognition technologies.

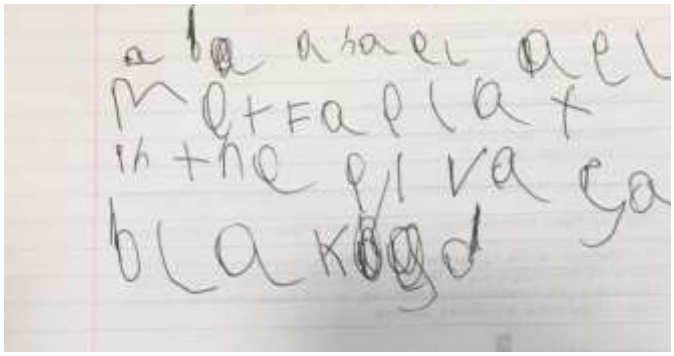

Fig. 1. Example of Dysgraphia student writing Courtesy https://bilarabiya.net/29016.html

In[2]Vojtech Zvoncak et al. prposes a novel method for identifying handwriting difficulties (HD) in children with developmental dysgraphia. The study presents new online handwriting features based on the tunable Q-factor wavelet transform (TQWT) and records handwriting on digitizing tablets. When compared to traditional parameters, these features perform better when assessed using random forest and support vector machine classifiers. With a classification accuracy of 84.6%, the study demonstrates the potential of TQWT-based characteristics to increase the precision of automated HD identification.

In[3]Peter J. Chung et al. proposes a comprehensive overview of dysgraphia, a specific learning disorder affecting writing skills. The authors discuss the various subtypes of dysgraphia, including motor, spatial, and linguistic dysgraphia, and highlight the challenges in diagnosing and managing this condition. The significance of early diagnosis and intervention is emphasized in the research, along with the part pediatricians play in helping kids who struggle with dysgraphia. The study also explores the high rate of co-morbidity with other learning and psychiatric disorders, and the need for a multidisciplinary approach to treatment. This research is valuable for understanding the complexities of dysgraphia and the strategies for effective management and support.

II. LITRETURE SURVEY

Various approaches to handwriting assistance have been proposed in the literature.

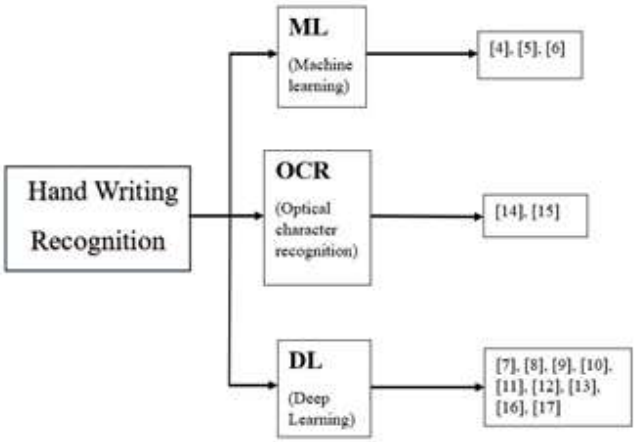

Fig. 2. Litreture Survey

In [4], Jayakanth Kunhoth proposed the use of machine learning algorithms such as K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Random Forest (RF) to diagnose dysgraphia by analyzing handwriting. It highlights the effectiveness of kinematic and dynamic handwriting features, achieving a 77% accuracy with fewer features compared to state-of-the-art methods. It emphasizes the importance of early diagnosis and the potential of automated systems to reduce the need for manual assessments by professionals. This research provides valuable insights into the application of ML for dysgraphia screening and can serve as a foundation for further advancements in this field.

In[5]Dr. G. Vijaya et al. proposed a various ML algorithms for improving the accuracy of handwritten character recognition (HCR). The study highlights the challenges faced by traditional HCR systems, such as variability in writing styles, noise, and cursive handwriting. The authors discuss the use of Convolutional Neural Networks (CNNs), Support Vector ‘Machines (SVMs), and k-Nearest Neighbours (k-NN) for HCR, emphasizing the importance of preprocessing techniques and evaluation metrics. The research demonstrates that CNNs, with their ability to learn complex features from raw pixel data, offer superior performance in recognizing handwritten characters. The paper concludes that advancements in ML algorithms can significantly enhance the accuracy and efficiency of HCR systems, making them

valuable for applications like document digitization and signature verification.

In[6]. Sudarchanan MS et al. proposes on building a system that can recognize and digitize handwritten text using advanced ML and deep learning methods. It addresses the challenge of how different handwriting styles can make it hard for machines to understand written text, something humans do naturally. By using models like CNNs, RNNs, and LSTMs, the system aims to achieve high accuracy. What makes this approach unique is the addition of a spell-checking feature, ensuring the final output is more reliable and error-free. The paper highlights the potential of this system to handle noisy data and large datasets, making it a step forward from previous research efforts.

In[7]. Vilasini V et al. proposes the use of deep learning models, specifically Convolutional Neural Networks (CNN) and Vision Transformers (ViT), to identify learning disabilities like dysgraphia by analyzing handwriting. They mainly focus on pre-school and primary school children, using a dataset of normal and abnormal handwriting samples. The CNN model achieved a testing accuracy of 79.47%, while the ViT model outperformed it with an accuracy of 86.22%. This paper highlights the potential of deep learning techniques in early detection of learning disabilities, providing a foundation for further advancements in this field.

In[8]. Sharmila C et al. proposes a novel approach to identifying Dysgraphia in children through handwriting analysis. The study employs Convolutional Neural Networks (CNNs), including Inception V3, ResNet, and VGG16, to classify handwritten images and detect abnormalities. The research highlights the use of deep learning techniques to automate the identification process, aiming to improve early detection and intervention for children with dysgraphia. The proposed system demonstrates high accuracy in distinguishing between normal and Dysgraphic handwriting, making it a valuable tool for educators and clinicians in diagnosing and managing learning disabilities, The CNN model achieved an accuracy of 93.07%, while ResNet outperformed it with an accuracy of 98.22%. The research highlights the potential of deep learning techniques in early detection of learning disabilities.

In[9] Arbaj Ansari et al. proposes the challenges of recognizing handwritten text using advanced deep learning techniques. The authors employ Convolutional Neural Networks (CNNs), Long Short-Term Memories (LSTMs) built on Recurrent Neural Network (RNN) architecture, and Connectionist Temporal Classification (CTC) to enhance the accuracy of handwriting recognition. The study utilizes the Information Acquisition MNIST dataset for training and evaluation, leveraging OpenCV for image processing and TensorFlow for word recognition and training. The proposed system aims to improve the accuracy and efficiency of handwritten text recognition, addressing issues faced by traditional Optical Character Recognition (OCR) systems. The research demonstrates that the hybrid CNN-RNN model, combined with CTC, offers superior performance in recognizing handwritten text, making it a valuable contribution to the field of computer vision and pattern recognition. In[10] Nurhani Harun et al. proposes the challenge of recognizing dysgraphia handwriting using

Convolutional Neural Networks (CNN). The study focuses on image augmentation techniques, such as rotation and brightness adjustments, to create synthetic images that enhance the training dataset. This approach aims to improve the accuracy of CNN models in classifying four types of dysgraphia handwriting: normal, low-risk, medium-risk, and high-risk. The results demonstrate a significant improvement in classification accuracy, from 73% to 77%, when using augmented data. The research highlights the importance of data augmentation in overcoming the limitations of small datasets and suggests further implementation of intelligence-based augmentation methods for more effective dysgraphia detection

In[11] Nikolay et al. proposes a comprehensive review of recent advancements in Handwritten Text Recognition (HTR) using Deep Learning techniques. It highlights the transition from traditional methods to state-of-the-art approaches like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Sequence-to-Sequence (Seq2Seq) models with attention mechanisms. The paper also focuses on techniques like Connectionist Temporal Classification (CTC) and Transformers, which have enhanced the flexibility and accuracy of HTR systems. The authors evaluate various models based on datasets like IAM and metrics such as Character Error Rate (CER). Additionally, they compare CTC-based and Seq2Seq-based methods, outlining their strengths and weaknesses. Finally, the paper discusses the limitations of current techniques and identifies challenges, such as handling diverse handwriting styles and improving recognition accuracy, as key areas for future research.

In[12] Mugdim Bublin et al. proposes the use of deep learning algorithms to detect handwriting learning disabilities, such as Dysgraphia, in children. The study employs the SensoGrip smart pen, equipped with sensors to capture handwriting dynamics, and utilizes Long Short-Term Memory (LSTM) networks for automatic feature extraction and SEMS score prediction. The research demonstrates that the proposed method achieves a root-mean-square error of less than 1, indicating high accuracy in handwriting evaluation. This approach offers significant advancements over traditional methods by providing a finer granularity in handwriting assessment and enabling more realistic writing scenarios. The findings highlight the potential of integrating smart sensors

and deep learning for early detection and targeted intervention of handwriting difficulties in children.

In[13] S. Rakesh et al. proposes a comprehensive overview of the advancements in handwritten text recognition (HTR) using deep learning. The authors discuss the integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to enhance the accuracy of HTR systems. The study highlights the importance of preprocessing techniques to improve image quality and the use of diverse training datasets for effective model training. The paper also emphasizes the role of post-processing tools, such as language models and spell checkers, in refining recognition outcomes. The research demonstrates that deep learning advancements significantly enhance the accuracy and efficiency of HTR, making it a valuable tool for digitizing historical records, automated form processing, and aiding individuals with disabilities. This survey serves as a valuable resource for understanding the current state and future directions of HTR research.

In[14] Benedict Vinusha. V et al. proposes a addresses the challenge of converting handwritten text into editable digital formats using OCR technology. The study leverages machine learning models, including Convolutional Neural Networks (CNN) and Natural Language Processing (NLP) libraries, to recognize and convert text in both native and English languages. The research highlights the significance of OCR in digitizing documents and improving document management across various industries. The proposed system demonstrates high accuracy and efficiency, particularly in recognizing regional languages, making it a valuable tool for businesses dealing with large volumes of handwritten documents. The findings suggest that OCR technology can significantly enhance the productivity and cost-effectiveness in document management processes.

In[15] Ajay Agarwal et al. proposes an extensive review of the techniques, methodologies, and recent advancements in handwritten character recognition (HCR). The authors discuss various approaches, including feature extraction, classification algorithms, deep learning techniques, and dataset creation.

They highlight the challenges and open research areas in HCR, such as variability in handwriting styles, poor quality and noise in handwritten documents, and the need for large annotated datasets. The paper also explores preprocessing and image enhancement techniques, the use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), and the integration of contextual information and language models to improve recognition accuracy. This comprehensive survey serves as a valuable resource for understanding the current state and future directions of HCR research.

In[16] Vasileios Alevizos et al. proposes a identification of handwriting anomalies indicative of dyslexia and dysgraphia using advanced geometrical patterns and recurrent neural networks (RNN).

The study focuses on feature extraction techniques, such as baseline deviations, letter connectivity, and stroke thickness, to identify irregularities in handwriting. The proposed RNN-based auto encoder model analyses these features to differentiate between normal handwriting and handwriting affected by dyslexia and dysgraphia. The research highlights the challenges associated with complex pattern adaptation and emphasizes the potential of AI in improving the accuracy of diagnosing learning disabilities.

This innovative approach offers significant advancements in the field of handwriting analysis and learning disability detection.

In[17] Neha N. Doshi et al. proposes an innovative approach to detecting dysgraphia, a learning disability that makes writing difficult for individuals. It begins by addressing the challenges with current testing methods, which are manual, intimidating, and sometimes inaccurate, especially for children. The authors propose a solution using advanced ML techniques—specifically combining CNNs and RNNs—to analyze handwriting.

The system looks for common errors made by individuals with dysgraphia, such as letter reversals, omissions, and substitutions, and calculates a ”risk factor” to identify the likelihood of the condition. What’s great is that it presents these results in a simple and engaging interface designed for children, while also providing detailed insights for parents, teachers, and counselors. The goal is to make testing less stressful, more efficient, and accessible. The paper also mentions exciting possibilities for the future, like extending the system to detect other learning disabilities and supporting multiple languages.

In[18] Richa Guptha et al. proposes an comprehensive approach to aiding individuals with dysgraphia. The proposed system integrates multiple AI algorithms to address various challenges faced by dysgraphia individuals, including poor handwriting, spelling mistakes, and grammatical errors.

The system employs a CNN-RNN-CTC model for handwritten text recognition, SymSpell and Phoneme models for spelling correction, and the GECToR model for grammar correction. Additionally, a text-to-speech functionality is included to enhance usability. The experimental results demonstrate significant improvements in handwriting quality, making this system a valuable tool for assisting people with dysgraphia in their daily activities and communication

In literature survey many methods has been used by authors below table provides the clear information about the papers:

Machine Learning

Table 1: Comparison table on the ML methods

Paper Title	Objective	Methodology	Results	Key points
Machine Learning Methods for Dysgraphia Screening	Diagnosing dysgraphia using handwriting features	KNN, SVM, ANN, RF; kinematic/dynamic handwriting features	77% of accuracy	Early diagnosis using fewer features than state-of-the-art
Machine Learning for HCR	Improving HCR through advanced machine learning	CNN, SVM, k-NN	Different styles of handwriting	Emphasizes CNN's performance in HCR
HTR Using ML and DL	Recognizing and digitizing handwritten text	CNN, RNN, LSTM with spell-check integration	High Accuracy	Steps forward in handling noisy and large datasets

Deep Learning

Table 2: Comparison table on the Deep learning methods

Paper Title	Objective	Methodology	Results	Key points
Deep Learning Techniques to Detect Learning Disabilities	Identifying learning disabilities via handwriting	CNN, Vision Transformers (ViT)	CNN:79.47%, ViT: 86.22%	Demonstrated ViT's superiority for handwriting analysis
Automated System for Dysgraphia Detection	Early dysgraphia detection in children	CNN, Inception V3, ResNet, VGG16	CNN: 93.07%, ResNet: 98.22%	Advanced deep learning models validated for handwriting analysis
HTR Using Deep Learning Algorithms	Improving handwritten text recognition	CNN, LSTM, RNN hybrid	Superior recognition	Tackles OCR challenges
Dysgraphia Handwriting Image Augmentation	Enhancing dysgraphia handwriting classification	Image augmentation (rotation, brightness)	Improved: 73% → 77%	Importance of augmentation for small datasets
Deep Learning for HTR: Existing Approaches and Challenges	Reviewing advancements in handwriting text recognition	CNNs, RNNs, Seq2Seq, Transformers, CTC	Recognizing accuracy is more	Challenges and directions in HTR research
Handwriting Evaluation Using DL with SensoGrip	Handwriting disability detection in children	SensoGrip smart pen, LSTM	RMSE < 1	Smart sensors for realistic writing scenarios
HTR Using DL Techniques: A Survey	Reviewing deep learning in handwritten text recognition	CNN, RNN; preprocessing, post-processing	Improved HTR accuracy	Valuable survey of HTR advancements
Handwriting Anomalies Through RNN	Detecting dyslexia/dysgraphia using handwriting geometry	RNN-based autoencoder, geometric patterns	NA	Innovative approach for handwriting-related learning disabilities
Convolutional RNN Model for Dysgraphia Prediction	Dysgraphia detection using CNN-RNN hybrid	CNN-RNN hybrid model	NA	Simple interface with detailed insights for educators and parents

Optical Character

Table 3: Comparison table on the Optical Character Recognition methods

Paper Title	Objective	Methodology	Results	Key points
Advancing OCR for Handwritten Text	Converting handwritten text to digital format	CNN, NLP libraries	High accuracy	Significant OCR advancements for document management
Handwritten Character Recognition: A Survey	Reviewing HCR techniques and challenges	Various approaches: feature extraction, CNNs, RNNs	NA	Explores challenges, open areas for HCR research

III. CONCLUSION

This paper presents the study of various literature which are related to handwriting recognition and detection for the dysgraphia disorder. In this paper mainly we have taken three types of methods like ML, Deep learning and Optical character. In ML methods require large, high-quality datasets to function effectively . In Optical Character Recognition methods it will not effectively work for the poor image quality, leading to inaccuracies in text recognition and also difficulty in recognizing the special characters, symbols. In Deep learning methods which amplifies their efficiency and accuracy in complex task such as image and speech recognition and also as the capability to handle large number of datasets efficiently. Compared to ML and optical character recognition methods, deep learning exceeds due to its ability to process large data sets, handle complex structures, and adapt to variations in handwriting. This makes it particularly suitable for address- ing the challenges associated with handwriting detection and correction for Dysgraphia.

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