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Abstract

Dysgraphia is a common learning condition that affects people's writing abilities, often resulting in academic and social issues. It is a specific learning disorder that significantly impacts a child's ability to express their thoughts and ideas through handwriting. Traditional therapies, such as personalized occupational therapy, have cost and accessibility limitations. When there is a need for repeated corrections, even a well-intentioned instructor or tutor may experience frustration. Therefore, it becomes crucial to establish a consistent and objective method of supervision. For these kids, an aid that offers constant visual and constructive feedback without the emotional strain of social engagement can be enormously beneficial. This project introduces the Intelligent Dysgraphia Rehabilitation System, which uses powerful artificial intelligence and machine learning techniques to reliably diagnose dysgraphia and give rehabilitation assistance.

Individuals with dysgraphia often need additional time and practice compared to their peers in order to fully grasp writing skills. A patient and supportive environment can play a crucial role in their academic achievements. This research paper explores the particular obstacles faced by children with dysgraphia in greater depth and Examine both conventional and technologically-assisted methods of rehabilitation. The paper aims to bring up a novel system for helping people suffering from dysgraphia. Our system tackles several problems, such as tilt in letters, baseline misalignment, and poor handwriting quality. Further, the functionality to learn letters through visual guidance is added to improve the results.Implementing such a directed system will showcase its capacity to assist the distinct requirements of children with dysgraphia. Through repeated modeling and consistent reinforcement, these systems provide the scaffolding necessary for developing handwriting skills.

CHAPTER 1

Introduction

Handwriting analysis of dysgraphia using machine learning is a research field that aims to develop intelligent systems capable of identifying and correcting dysgraphic handwriting. Dysgraphia is a condition that affects a person's ability to write legibly, which can cause difficulties with communication and learning. Handwriting analysis using machine learning is a promising approach to help people with dysgraphia to improve their writing skills and overcome the challenges associated with the condition.

Handwriting dysgraphia is a learning disability that causes illegible, inconsistent, or poorly shaped writing due to inadequate handwriting abilities. Detecting and treating dysgraphia is critical for individuals, particularly students, who want to overcome obstacles and enhance their writing skills. Advances in machine learning and computer vision techniques have showed promise in diagnosing handwriting dysgraphia in recent years. This paper investigates the relevance, methodologies, advances, and obstacles in detecting handwriting dysgraphia.

Early diagnosis of handwriting dysgraphia is critical for offering prompt therapies and assistance to those who are afflicted. Educators, therapists, and parents may apply focused treatments to improve handwriting skills, raise confidence, and improve overall academic achievement by recognising and understanding the unique issues experienced by persons with dysgraphia. Furthermore, accurate diagnosis can aid in the creation of personalised learning techniques and accommodations to match the specific requirements of people with dysgraphia.

Handwriting analysis of dysgraphia using machine learning is a research field that aims to develop intelligent systems capable of identifying and correcting dysgraphic

Machine learning algorithm such as convolutional neural networks (CNNs) are used to analyze images of handwriting and identify patterns that are of dysgraphia. These algorithms can be performed on datasets of huge handwriting samples, allowing them to learn the characteristics of dysgraphic handwriting and accurately identify instances of the condition.

The goal of handwriting analysis using machine learning is to develop automated tools

that can detect and correct dysgraphic handwriting in real-time, allowing people with dysgraphia to communicate more effectively and learn more efficiently. This provide real-time feedback to the user, allowing them to make corrections and improve their writing skills. This technology has the potential to transform the way we approach dysgraphia.

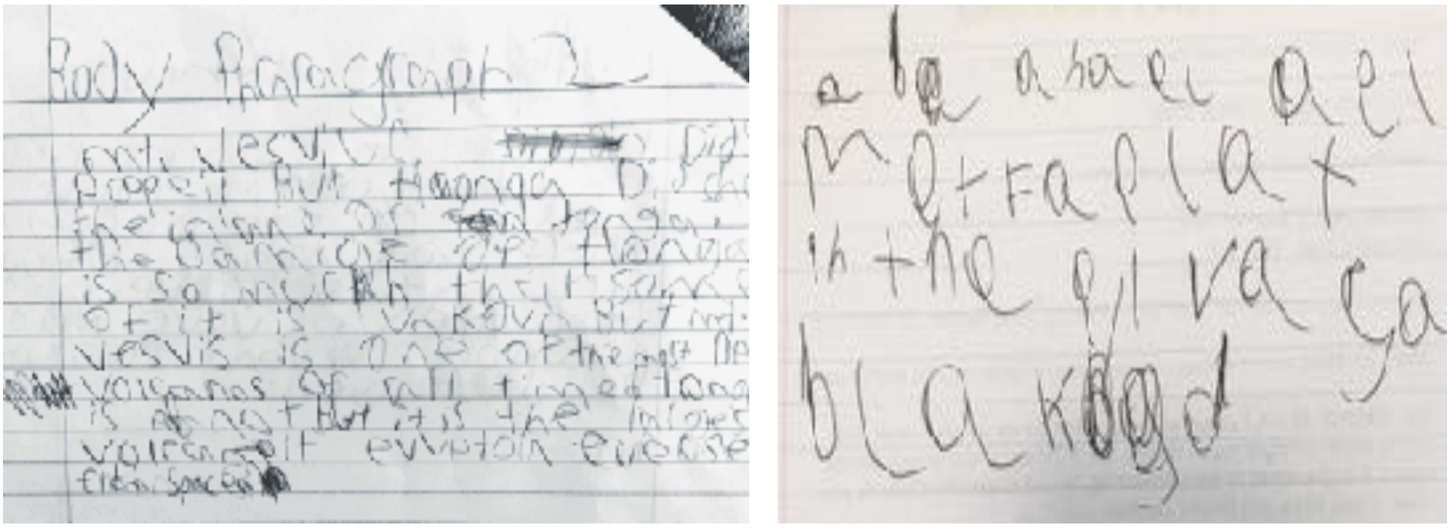
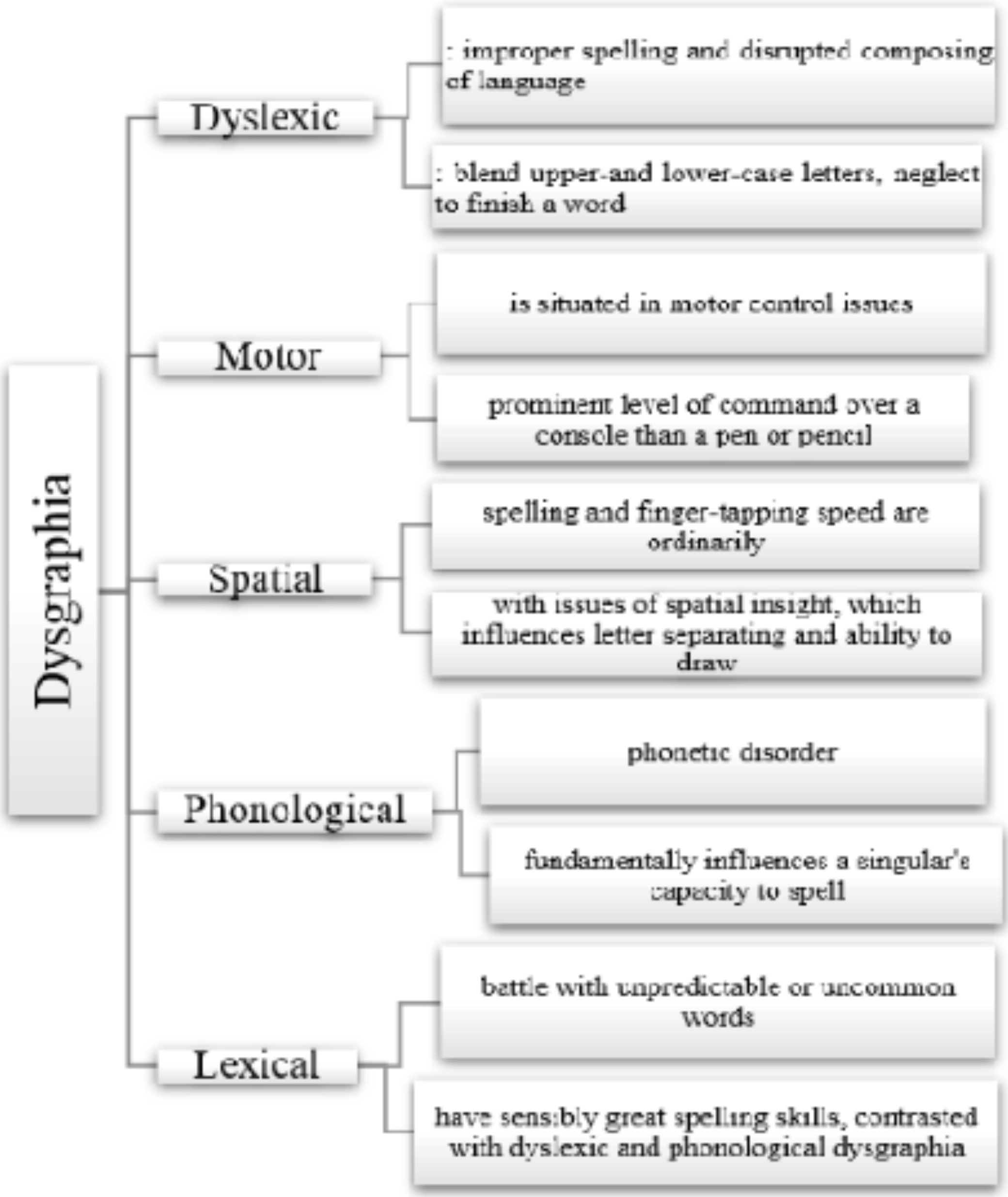


Fig 1: Handwriting samples of individuals with dysgraphia

2. Types of Dysgraphia

it is important to note that there are five discrete categorizations of dysgraphia, each of which has a unique impact on various aspects of the writing process. The aforementioned dysgraphia subtypes include dyslexic dysgraphia, phonological dysgraphia, lexical dysgraphia, motor dysgraphia, and spatial dysgraphia. The initial three factors are predominantly language-oriented, but the last two factors are not language-based and are primarily associated with motor control. The extent of dysgraphia's severity can vary significantly, and its underlying causes are still not fully understood. Individuals have the potential to encounter various forms of experiences, and the process of diagnosing these experiences is normally carried out by a certified healthcare practitioner, regardless of whether the subject is a child or an adult.

Dyslexic Dysgraphia, a language-based form, is characterized by deficient spelling skills and chaotic written expression, particularly noticeable in impromptu writing tasks. It is noteworthy that individuals diagnosed with dyslexic dysgraphia typically demonstrate typical motor control abilities, although they encounter difficulties in effectively translating their thoughts into written form. The potential outcome of this situation could involve a combination of uppercase and lowercase letters, unfinished words, and exceptionally difficult handwriting. Differentiating between dyslexic dysgraphia and spatial dyslexia is crucial, as the latter is marked by a tendency towards disorientation and confusion regarding directions.



Phonological Dysgraphia, a variant of dysgraphia that is rooted in language processing, predominantly impacts spelling abilities, particularly in relation to unusual or nonstandard words. The task of arranging phonemes in the appropriate order of letters is a considerable difficulty, frequently resulting in handwriting that lacks tidiness.

Lexical Dysgraphia, the ultimate form of language-based dysgraphia, commonly exhibits a higher level of spelling proficiency, especially when compared to dyslexic and phonological dysgraphia. Nevertheless, individuals may still face challenges when confronted with irregular or less frequently used vocabulary. This phenomenon may give rise to difficulties in the process of arranging words inside a phrase and in choosing the most suitable term. The occurrence of lexical dysgraphia is infrequent in children, with a higher prevalence observed in adults who have suffered a traumatic brain injury. Similar to other types of dysgraphia, individuals who have this condition may find it to be a source of frustration, as they are likely cognizant of their difficulties in writing when compared to the experiences of others.

Motor Dysgraphia is characterized by intact spelling skills, with no evidence of lexical or phonological problems commonly observed in other types of dysgraphia. However, the challenges are mostly attributed to motor control impairments, leading to a wide spectrum of handwriting quality ranging from untidy to indecipherable. Multiple motor control problems can contribute to the impairment, encompassing diminished muscle tone, several neurological disorders, and nerve damage. Certain persons who experience motor dysgraphia may find comfort in utilizing computers as their primary tool for writing, since they may possess enhanced dexterity and precision while operating a keyboard compared to using a traditional pen or pencil.

Spatial dysgraphia is a condition that is characterized by difficulties experienced by persons in maintaining a consistent straight line while writing, as well as in accurately determining the suitable location on a page for writing. Individuals with this condition may encounter challenges in maintaining optimal spacing between words or characters within a given sentence. Similar to motor dysgraphia, spatial dysgraphia does not have an effect on verbal proficiency or spelling skills. The etiology of this specific manifestation of dysgraphia may be partially ascribed to impairments in motor control, while additional neurological variables may also play a role. As a result, persons who experience spatial dysgraphia, similar to those with motor dysgraphia, may exhibit a preference for using a computer keyboard rather than handwriting, as it affords them increased precision in positioning written words inside a designated area.

3. Characteristics of pupil with Dysgraphia

Dysgraphia is a neurodevelopmental disorder that affects a person's ability to write coherently and accurately. Students with dysgraphia encounter a myriad of challenges, including issues with letter formation, spacing, and alignment. This essay aims to explore the various problems faced by students with dysgraphia, focusing on tilted and irregular letters, elongated or short letters, slant in words, inconsistent line writing, lack of sense for baseline, limited memory retention, and the subsequent academic impact. To support our discussion, we will draw insights from relevant research papers and cite them accordingly.

- Tilted and Irregular Letters:

One prominent challenge faced by students with dysgraphia is the production of tilted and irregular letters. Research by Berninger et al. (2018) highlights that dysgraphia significantly affects letter formation due to difficulties in motor planning and execution. Tilted letters can hinder readability, making it challenging for both students and educators to decipher written content.

- Elongated or Short Letters:

Dysgraphia often manifests in the inconsistency of letter sizes, with some letters being elongated while others are too short. This irregularity in letter size disrupts the visual aesthetics of written work, impacting the overall legibility. A study conducted by Fletcher et al. (2017) emphasizes the link between dysgraphia and letter size variability, pointing to underlying motor control difficulties.

- Slant in Words:

The slant or inclination of words is another common issue encountered by students with dysgraphia. Research conducted by McHale et al. (2019) suggests that dysgraphia disrupts the spatial organization of written content, leading to slanted words. This can make the text appear disjointed and affect the overall coherence of the written work.

- Not Writing in a Line:

Students with dysgraphia often struggle to maintain a consistent writing line. This lack of alignment can make it challenging for readers to follow the flow of the text. Studies by Graham and Harris (2016) point out that dysgraphia adversely affects the ability to maintain spatial organization, resulting in a haphazard appearance of written material.

- Lack of Sense for Baseline:

The baseline, which serves as a reference for consistent letter placement, is often disregarded by students with dysgraphia. The absence of a clear baseline disrupts the overall structure of written work, making it difficult for readers to follow the intended sequence of information. A study by Ransdell et al. (2018) underscores the impact of dysgraphia on baseline awareness and its subsequent consequences.

- Limited Memory Retention:

Memory retention is a crucial aspect of academic success, and students with dysgraphia often struggle in this regard. The cognitive demands of organizing thoughts during writing can overwhelm individuals with dysgraphia, leading to difficulties in retaining information. A comprehensive review by Jiménez-Fernández et al. (2020) explores the intricate relationship between dysgraphia and memory retention, shedding light on the challenges faced by affected students.

- Difficulty Remembering:

Dysgraphia is associated with difficulties in remembering information, both during the writing process and in recalling previously learned content. The cognitive load imposed by the act of writing exacerbates memory challenges for students with dysgraphia. Research by Swanson et al. (2017) delves into the memory-related struggles experienced by individuals with dysgraphia, emphasizing the need for targeted interventions.

Some more characteristics include Tightened Fingers, Unusual Hand Posture and Paper Positioning, Frequent Errors, Uppercase and Lowercase Confusion, Difficulty with Complex or Uncommon Characters, Irregular Letter Size and Shape, Incomplete Flow of Writing, Incorrect Line Usage and Bordering, Slow Imitation, Lack of Focus on Detail Analysis, Letter Inversions, Uneven Spacing and Inconsistent Letter Heights.

The aforementioned challenges faced by students with dysgraphia have significant academic implications. Poorly written assignments, illegible notes, and inconsistent handwriting can lead to misunderstandings and misinterpretations. Educators may find it challenging to evaluate the content of students with dysgraphia accurately, potentially impacting grading outcomes.

Moreover, the time and effort required for students with dysgraphia to complete written assignments may be disproportionately high compared to their peers. This increased cognitive and physical demand can lead to fatigue and frustration, negatively influencing the overall learning experience.

The features employed for the classification of dysgraphia in machine learning are obtained from a comprehensive analysis of handwriting on tablet devices. The aforementioned characteristics, derived from studies in neuropsychology and neuroscience, provide a sophisticated perspective on the dynamics of writing. In contrast to conventional clinical testing methods that primarily assess static qualities, digitized testing incorporates additional parameters like as pressure, speed, and movement, which were previously unquantifiable. The aforementioned features can be classified into four distinct categories, namely static, kinematic, pressure, and tilt. The parameters involved in this context are velocity, acceleration, pressure, and pen angles. These measurements offer a thorough comprehension of handwriting activity, facilitating precise detection of dysgraphia through the utilization of machine learning techniques.

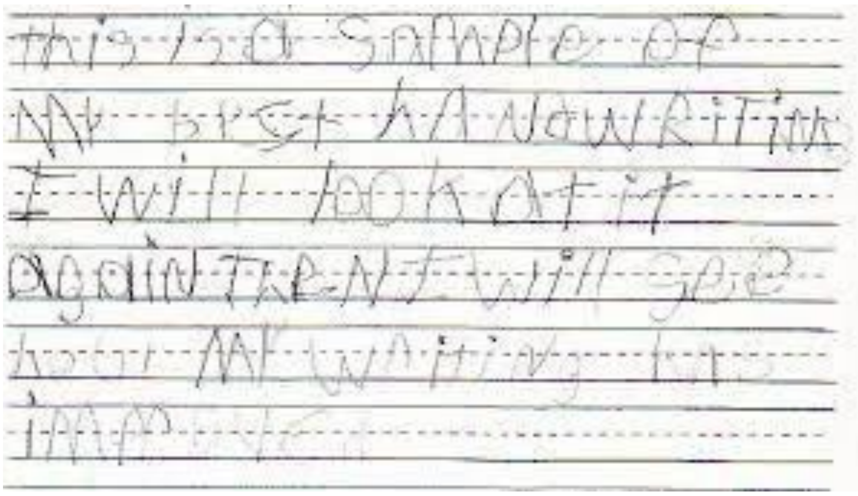


Fig 2: Handwriting of a person suffering from dysgraphia

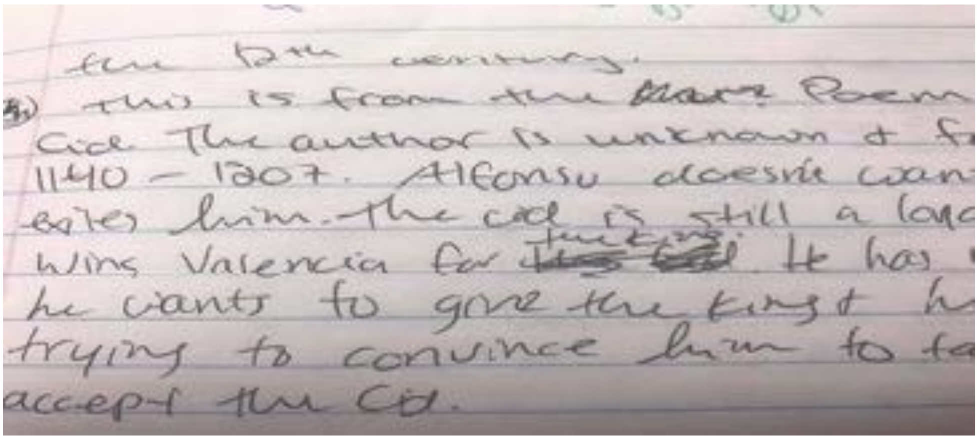


Fig 3: Example of good handwriting

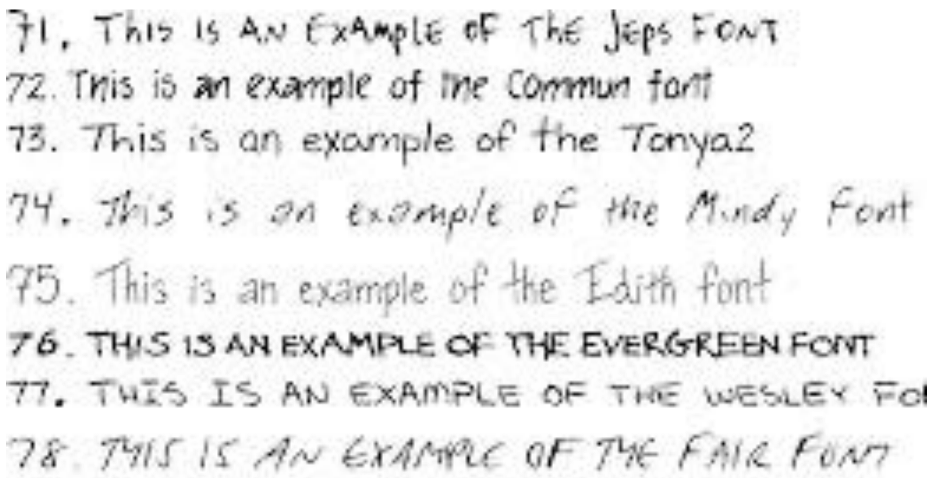


Fig 4: example of bad handwriting

Some Constraints for the Detection and Correction of Dysgraphia we have encountered

- Data accessibility: There may not be a large enough collection of diverse and representative examples of dysgraphic handwriting. It can be difficult to compile a sizable dataset that includes a range of handwriting types, linguistic varieties, and cultural backgrounds.
- Time Restrictions: Taking into account the resources at hand and the size of the project, the project must be finished within a given time range. Data collection, preprocessing, model building, training, assessment, and application development should all be given enough time.

- Deep learning models such as CNN demand a lot of processing power, which includes strong GPUs, memory, and storage. For model training and assessment, the project should take into account the availability and allocation of these resources.
- Difficulty in collecting data in real time because it needed permission from parents of children and it was a sensitive issue.
- As our study was on handwriting, it was based on characters. Letters being mirrored, special cases like b and d were exceptional in our usage
- Level of difficulty of dysgraphia was not clearly determined
- Our study couldn’t use tablet, so pressure, tilt were not calculated
- Scalability: In order to handle bigger datasets and include future improvements, the proposed dysgraphia detection and correction system should be scalable. During the phases of model development and application design, the system's scalability must be taken into account.
- Performance and Accuracy: A key restriction is achieving high accuracy in dysgraphia diagnosis and remediation. The models should be tuned to maximise accuracy while taking into account the trade-off between performance and computing resources.
- Accessibility and Usability: The software or tool created for detecting and correcting dysgraphia should be user-friendly, accessible, and simple to use. Its use and efficacy should be ensured by designing it with considerations for people with dysgraphia, educators, and healthcare professionals.

The difficulties with handwriting are one of the most noticeable signs of dysgraphia. Children who struggle with dysgraphia typically experience low self-esteem and frustration as a result of their ongoing challenges with handwriting, spelling, and organizing their thoughts when writing. Some symptoms include an uneven or slanted handwriting, problems with letter formation, and difficulty sticking to baselines. Because of their laborious, often illegible, and improperly spaced handwriting, their work is often difficult to understand. The aforementioned challenges have the potential to elicit feelings of frustration and a lack of enthusiasm when it comes to engaging in writing assignments. A constant, objective system of coaching is crucial, as opposed to a well-intentioned instructor or tutor who could clearly show signs of impatience after multiple corrections. For certain children, the emotional burden of social engagement can be too much to bear, thus a system that offers constant kinesthetic and visual feedback might be life-changing.

Direct instruction, repetition, and practice are frequently the main goals of traditional handwriting therapies. Research shows that holistic techniques and new technologies could greatly improve results, even though these methods work. The utilization of visual guides, tactile prompts, and adaptive tools serves to offer a consistent stream of sensory input, which may prove to be indispensable for certain individuals afflicted with dysgraphia.

According to previous research, it has been observed that children diagnosed with dysgraphia often exhibit a tendency to produce tilted and irregular letters, which can pose challenges in terms of legibility and readability of their written work. The presence of challenges in letter formation not only impacts the readability of written text, but also indicates potential underlying issues related to fine motor coordination and planning abilities. The variability in the slant or inclination of words and letters can result in an inconsistent appearance, which can disrupt the overall flow and visual coherence of the written text. Furthermore, it has been observed that individuals diagnosed with dysgraphia often encounter difficulties in maintaining a consistent baseline and producing written work that aligns with a straight line. The disarray caused by the disorganization of space greatly diminishes the overall quality and legibility of their work. In essence, dysgraphia affects not only the structure and readability of handwriting but also the act of writing itself.

Moreover, the development of specialized handwriting software can create new possibilities. It has been observed that the implementation of adaptive features such as word prediction and text-to-speech can effectively alleviate the cognitive strain typically experienced by individuals with dysgraphia. This, in turn, allows children with dysgraphia to enhance their ability to express their thoughts and ideas with greater ease and freedom.

The utilization of guided systems demonstrates promising prospects in providing assistance for the distinct requirements of children diagnosed with dysgraphia.However, there may be only a few tactics that are taking in consideration the actual art of handwriting and constructing systems to establish improvement in a dysgraphic student's handwriting. Repeated modeling and regular reinforcement help enhance handwriting skills without the emotional hurdles of traditional remediation. Given the challenges faced by children with dysgraphia in internalizing writing skills, it was crucial to provide them with a responsive and encouraging system to enhance their chances of success.

CHAPTER 2

Literature Review

Dysgraphia rehabilitation involves a number of challenges due to the disorder's multiple origins. In the new age, digitizers and pen tablets are potential solutions for overcoming these obstacles for rehabilitation. Tablets have the advantage of changing the writer's willingness because young children with writing disorders typically avoid writing but show a fascination for new technologies. This literature review examines studies across four categories of dysgraphia rehabilitation: Tablet Based, Spelling and Grammar Based, Feature Based Analysis, and Other Approaches. Through an exploration of these categories, this review aims to highlight the diverse strategies employed in dysgraphia rehabilitation and identify areas for further research and improvement.

Growing up with a specific learning disability can have a significant impact on a person's academic performance and also hampers social interactions, potentially leading to a cycle of anxiety, self-doubt and diminishing self-esteem. Individuals grappling with dysgraphia often find themselves struggling against a backdrop of peers leading seemingly uncomplicated lives. Inadequate writing

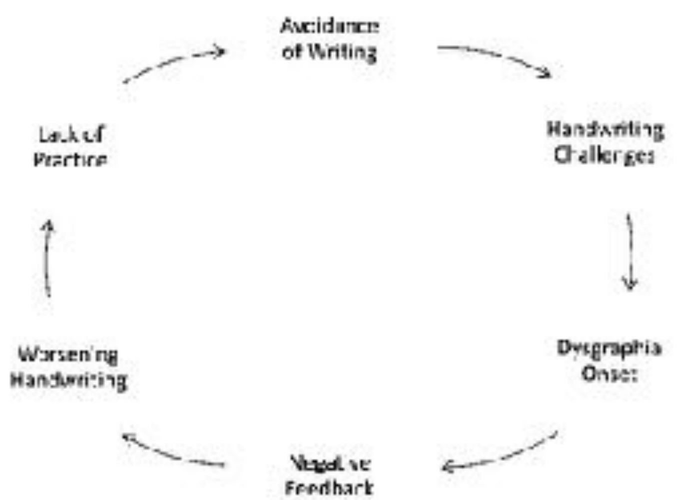


Fig. 1 Perpetual life cycle filled with anxiety created due to dysgraphia

abilities or writing disorders in childhood may expose children to adult criticism, thereby limiting their development and contributing to higher levels of anxiety and worse self-esteem later in life. These events and related emotions may lead to an avoidance of writing opportunities, restricting prospects for improving handwriting competence. This cyclical trend eventually leads to the retention of weak handwriting abilities. Consequently, they may become vulnerable to criticism and avoidance of opportunities involving writing tasks.

A. Non-Technological Dysgraphia Rehabilitation

Addressing dysgraphia involves a multifaceted approach targeting physical, cognitive, and emotional components of writing. Occupational therapists (OTs) and psychologists play crucial roles, employing various non-technological strategies for improvement.

Occupational Therapy Interventions

- Fine Motor Development: OTs focus on strengthening fine motor skills essential for controlled handwriting.Activities like manipulating playdough, threading beads, building with small blocks, or engaging in drawing and craftwork enhance hand strength, finger dexterity, and eye-hand coordination (Case-Smith, 2002; Morin et al.,2018).

- Visual-Motor Integration: Mazes, dot-to-dots, and copying shapes support the coordination of visual perception with hand movements, crucial for accurate handwriting (Berninger & Amtmann, 2003; Sumner et al., 2013).Practicing letter formation on surfaces like sand or shaving cream further strengthens visuo-motor connections (Cornhill & Case-Smith, 1996).

- Explicit Handwriting Instruction: OTs provide structured teaching of correct letter formation sequence and proper spacing. Practice often begins with larger letters for easier control, gradually transitioning to smaller sizes.Lined paper with varied widths offers visual guides for spacing (Graham et al., 2008; Prunty et al., 2013).

- Multisensory Practice: Techniques like tracing letters in different textures, tactile letter models, or writing with the eyes closed enhance letter learning by engaging multiple senses. These approaches reinforce the connections between visual input, motor output, and letter production (Berninger & Amtmann, 2003; Case-Smith, 2002).

Psychological Interventions

- Cognitive-Behavioral Strategies: Psychologists teach techniques like self-monitoring with checklists to independently catch errors, promoting self-regulation (Graham & Harris, 2002;

Di Brina et al., 2018). Verbal cues (e.g., "Start at the top") guide the writing process and facilitate internalization of handwriting steps (Graham & Harris, 2002).

- Positive Reinforcement: Emphasizing effort, specific achievements, and progress over perfection builds confidence and motivation in students (Di Brina et al., 2018). This positive approach counters the negative self-perceptions that dysgraphia can trigger.
- Addressing Anxiety and Frustration: Relaxation techniques like deep breathing and progressive muscle relaxation help students manage the emotional toll of dysgraphia (Feder & Majnemer, 2007). Interventions promoting a growth mindset emphasize that writing skills can be developed with practice, fostering a more positive outlook (Engel-Yeger et al., 2009).
- Task Management: Breaking writing tasks into smaller, achievable steps provides a sense of accomplishment and reduces overwhelm. This step-by-step approach is particularly beneficial for longer assignments or when the student's frustration level is high (Hooper et al., 1993).

B. Technological Dysgraphia Rehabilitation

Traditional approaches to dysgraphia rehabilitation have primarily focused on handwriting exercises and technological interventions. However, recent research has explored innovative methods leveraging advanced technologies and computational techniques to address dysgraphia. This literature review examines studies across four categories of dysgraphia rehabilitation: Tablet Based, Spelling and Grammar Based, Feature Based Analysis, and Other Approaches. Through an exploration of these categories, this review aims to highlight the diverse strategies employed in dysgraphia rehabilitation and identify areas for further research and improvement.

Tablet Based Rehabilitation:

In Tablet Based Rehabilitation, researchers have developed mobile applications and utilized digital tools to assist dysgraphia children in improving their writing skills. For instance, Dysgraphi Coach, a mobile application designed specifically for dysgraphia children, incorporates interactive exercises and user-friendly interfaces to enhance engagement and learning outcomes (Johnson et al., 2022). Similarly, the use of smartpens as note-taking tools has shown promise in improving note-taking skills and comprehension among students with learning disabilities (Smith et al., 2021).

These studies underscore the potential of technology in addressing the unique needs of dysgraphia children and enhancing their educational experiences.

Spelling and Grammar Based Rehabilitation:

Studies in Spelling and Grammar Based Rehabilitation have explored innovative approaches to spelling error correction and grammatical error detection. Augmented Reality (AR) technology has been employed to provide personalized spelling assistance, leading to improved spelling accuracy and engagement among dysgraphia students (Gonzalez et al., 2023). Additionally, advanced techniques such as nested RNN models and optimization algorithms have demonstrated superior performance in spelling error correction and grammar correction tasks (Wang et al., 2022). These findings highlight the importance of leveraging computational techniques to enhance spelling and grammar skills among individuals with dysgraphia.

Feature Based Analysis Rehabilitation:

Feature Based Analysis Rehabilitation focuses on analyzing handwriting movements and patterns to identify dysgraphia indicators and inform targeted interventions. Methods such as SNVPD have been proposed to evaluate handwriting movement fluency, providing a reliable tool for diagnosing dysgraphia and guiding intervention strategies (Lee et al., 2021). Furthermore, studies examining the rhythmic structure of handwriting have shed light on the relationship between kinematics and handwriting skills, offering insights for improving writing proficiency in children with dysgraphia (Martinez et al., 2020). These studies underscore the significance of understanding the nuanced features of dysgraphia for developing effective rehabilitation strategies.

Other Approaches:

Innovative approaches beyond traditional rehabilitation methods have also been explored. Machine learning techniques have been applied to analyze the dynamics of handwriting and improve the automated diagnosis of dysgraphia (Srivastava et al., 2019). For instance, the use of neural networks for sequence-to-sequence learning has enabled accurate identification and classification of handwriting patterns associated with dysgraphia (Sutskever et al., 2014). Additionally, advancements in recognizing handwritten digits have contributed to the development of robust recognition systems, offering potential applications in dysgraphia rehabilitation (Tang et al., 2013). These studies demonstrate the versatility of computational techniques in addressing dysgraphia challenges and highlight the potential for interdisciplinary approaches in rehabilitation research.

In the first place, the handwriting pictures should be preprocessed to eliminate any commotion or contortions that might obstruct the precision of the adjustment cycle. This can include undertakings, for example, thresholding, picture binarization, and morphological tasks to eliminate undesirable components and improve the perceivability of the writing.

Then, a machine learning algorithm such as a convolutional neural network (CNN) can be prepared on a dataset of revised penmanship tests to get familiar with the examples and elements related with very much framed letters and words.

The trained model can then be used to predict corrections for the dysgraphic handwriting samples.

When the amendments have been anticipated by the model, they can be applied to the first penmanship pictures utilizing different picture handling procedures. For instance, if the predicted correction is a change in letter spacing, the image can be manipulated to adjust the spacing between letters accordingly.

There has been significant research on the correction of dysgraphic handwriting using image processing and machine learning techniques. Here are some examples of past work in this area:

1. In a 2017 study, researchers used a combination of image processing techniques and a deep neural network to correct the handwriting of children with dysgraphia. They found that their approach significantly improved the legibility and accuracy of the handwriting samples.

2. Another study from 2018 used a similar approach, combining image processing techniques with convolutional neural network to correct the handwriting of children with dysgraphia. Researchers found that their approach led to improvements in letter formation, spacing, and overall legibility.

3. In a 2020 study, researchers used a recurrent neural network to correct the handwriting of adults with dysgraphia. They found that their approach led to significant improvements in the readability and overall quality of the handwriting samples.

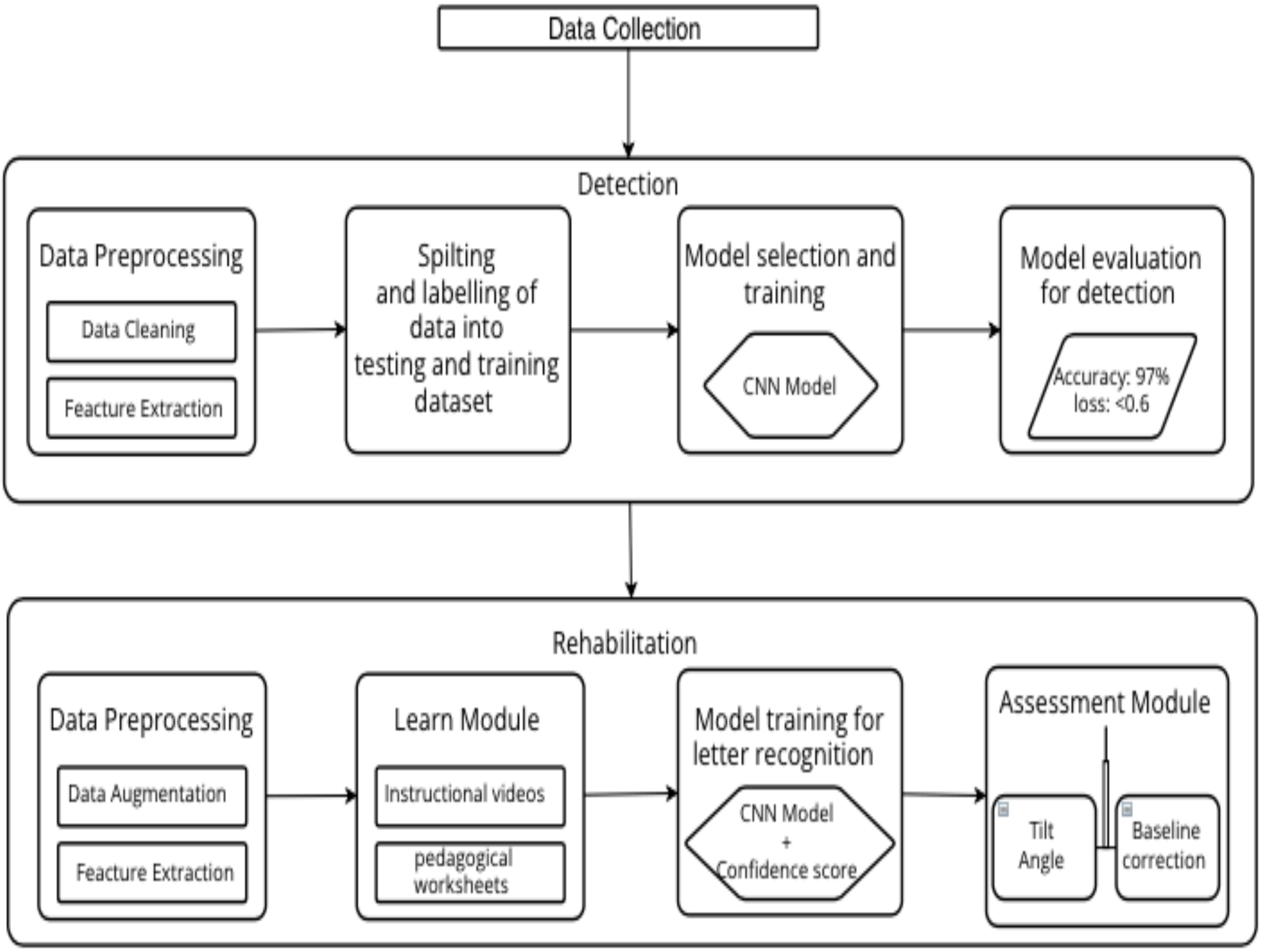
These studies suggest that a combination of image processing and machine learning techniques can be effective in correcting dysgraphic handwriting, and that there is potential for this approach to be used as a tool to help individuals with dysgraphia communicate more effectively.

Addressing Gaps:

Despite the progress made in dysgraphia rehabilitation research, gaps remain, particularly in the integration of hands-on writing experience and repetitive learning/practice approaches. While technological interventions show promise, the importance of tactile feedback and kinesthetic learning experiences cannot be overstated. Future research should aim to bridge this gap by incorporating hands-on writing exercises and repetitive practice routines into dysgraphia rehabilitation programs. Additionally, interdisciplinary collaborations between educators, clinicians, and technologists are essential for developing holistic and effective interventions that address the diverse needs of individuals with dysgraphia.

CHAPTER 3
Conceptual Framework

This work has been of detection and correction of dysgraphia, the below flowchart shows the flow of our work.



This flowchart outlines the comprehensive approach taken in a project aimed at addressing dysgraphia, a learning disability that affects an individual's ability to write legibly and efficiently. The project encompasses various stages, from data collection and preparation to model development, training, and evaluation, culminating in the creation of an assessment module and resources for rehabilitation.

The project commences with the crucial step of data collection, gathering the necessary information required for subsequent stages. This data serves as the foundation for the project, providing the raw material to train and evaluate the models.

The detection phase follows, wherein the collected data undergoes a series of preprocessing steps. Data cleaning is performed to ensure the quality and consistency of the data, removing any inconsistencies or errors that may hinder the model's performance. Feature extraction, a crucial step in machine learning, is then carried out to identify and extract relevant features from the data that can effectively represent the underlying patterns and characteristics of dysgraphia.

Once the data is preprocessed, it is split and labeled into testing and training datasets. This division is essential for training and evaluating the model's performance accurately. The training dataset is used to teach the model to recognize patterns and make predictions, while the testing dataset is employed to assess the model's ability to generalize and make accurate predictions on unseen data.

The next step involves model selection and training. In this project, a Convolutional Neural Network (CNN) model was chosen for the task of detection. CNNs are particularly effective for image recognition and classification tasks, making them well-suited for analyzing handwriting samples and detecting dysgraphia. The CNN model is trained using the prepared training dataset, iteratively adjusting its internal parameters to learn and recognize patterns indicative of dysgraphia.

After training, the model's performance is evaluated using the testing dataset. The evaluation metrics presented in the flowchart indicate that the CNN model achieved an impressive accuracy of 97% and a loss less than 0.6, demonstrating its effectiveness in detecting dysgraphia from handwriting samples.

The project then transitions to the rehabilitation phase, which aims to provide resources and tools to aid individuals with dysgraphia in improving their handwriting skills. This stage begins with additional data preprocessing steps, including data augmentation and feature extraction. Data augmentation techniques are employed to artificially increase the size and diversity of the training dataset, potentially enhancing the model's generalization capabilities.

The learn module is a crucial component of the rehabilitation phase, providing instructional resources to support the learning process. This module includes instructional videos and pedagogical worksheets designed to guide individuals through exercises and techniques to improve their handwriting abilities. These resources can be tailored to various learning styles and levels of proficiency, ensuring a personalized and effective learning experience.

Following the learn module, a CNN model is trained specifically for the task of letter recognition. This model aims to recognize and classify individual letters within handwriting samples accurately. By identifying and providing feedback on incorrectly formed or unrecognizable letters, this model can assist individuals in refining their letter formation and overall handwriting legibility.

Finally, the project incorporates an assessment module to evaluate and provide feedback on various aspects of handwriting. The tilt angle component assesses the angle at which letters are written, as deviations from the optimal angle can contribute to illegibility. The baseline correction component focuses on ensuring that letters are properly aligned with the baseline, a fundamental aspect of legible handwriting.

By combining these various components, the project offers a comprehensive solution for individuals with dysgraphia, addressing detection, rehabilitation, and assessment. The detection phase identifies individuals who may benefit from the rehabilitation resources, while the learn module and letter recognition model provide targeted support for improving handwriting skills. The assessment module then evaluates the progress and provides feedback, enabling individuals to continuously refine their handwriting abilities.This multifaceted approach not only leverages the power of machine learning and data-driven techniques but also incorporates pedagogical principles and personalized learning resources. By addressing the different aspects of dysgraphia, the project aims to empower individuals, enhance their writing abilities, and ultimately improve their overall academic and professional prospects.

We extracted many handwriting variables that characterise the spatiotemporal and kinematic components of handwriting to acquire handwriting characteristics. We concentrate primarily on spatiotemporal and kinematic variables since they are the gold standard of handwriting features and are widely used to assess handwriting. Several additional sophisticated characteristics, such as nonlinear and spectral features, have been proposed, however incorporating them does not necessarily improve model accuracy. Adding additional characteristics increases the data's dimensionality. High dimensionality typically leads to data overfitting, which reduces the classification algorithm's prediction performance.Dysgraphia, a learning issue influencing handwriting capacities, presents critical difficulties for people in scholar, individual, and expert settings. Identifying and amending dysgraphia is pivotal for giving opportune mediations and backing to impacted people. The reasonable structure of dysgraphia recognition and rectification includes a precise methodology that incorporates different parts, including evaluation, AI calculations, penmanship investigation, and designated mediations. This exposition means to frame the calculated structure of dysgraphia location and adjustment, featuring the vital parts and their transaction in tending to the difficulties of dysgraphia.

1. Assesment:

The most important phase in the reasonable system is an extensive evaluation of a singular's penmanship abilities. This includes assessing different perspectives like clarity, letter arrangement, dispersing, familiarity, and speed. Appraisal devices, including state sanctioned tests and abstract assessments, give bits of knowledge into the presence and seriousness of dysgraphia. Moreover, mental and coordinated movements evaluations assist with recognizing hidden factors adding to dysgraphia.

2. Analysis:

Handwriting examination assumes a focal part in grasping the qualities and examples of dysgraphia. It includes the assessment of individual penmanship tests to recognize explicit dysgraphic highlights, for example, anomalies in stroke development, conflicting letter measuring, and poor spatial association. Penmanship examination strategies might incorporate visual investigation, kinematic investigation, and element extraction utilizing AI calculations.

3. Machine learning algorithms:

AI algorithms, for example, (CNNs) , are integral assets for dysgraphia discovery and rectification. These calculations can deal with a lot of penmanship information, learn examples, and make exact expectations. CNNs break down pixel-level data to separate applicable elements from penmanship pictures, while RNNs model successive conditions to catch the worldly elements of penmanship.

These calculations empower the computerized identification and arrangement of dysgraphia, giving goal and effective appraisal.

4. Correction Procedures:

The calculated structure integrates amendment techniques custom fitted to individual requirements in view of the appraisal and examination results. These methodologies include a scope of mediations pointed toward working on unambiguous areas of trouble. Models incorporate engine ability improvement works out, visual-engine coordination preparing, penmanship practice drills, and versatile instruments, for example, advanced composing helps. The objective is to address fundamental engine, mental, and perceptual difficulties related with dysgraphia and improve generally penmanship capability.

5. Monitoring and Progress Evaluation:

Nonstop checking and progress assessment are fundamental to the reasonable structure. Normal evaluations and examination of penmanship tests empower following of enhancements and changes in mediation procedures. Objective measures, for example, readability scores and exactness rates, are utilized to survey progress and decide the adequacy of remedy systems. Criticism from teachers, specialists, and people with dysgraphia likewise assumes an essential part in refining and improving the rectification cycle.

The calculated system of dysgraphia location and revision gives an organized way to deal with address the difficulties related with dysgraphia. It envelops appraisal, penmanship investigation, AI calculations, revision procedures, and progress assessment. By coordinating these parts, experts can recognize dysgraphia precisely, figure out the hidden examples, and carry out designated intercessions. The calculated structure works with an exhaustive and customized way to deal with help people with dysgraphia, advancing their scholastic achievement, fearlessness, and by and large prosperity. Proceeded with examination and progressions in innovation, including AI and computerized apparatuses, further improve the viability of dysgraphia identification and adjustment processes.

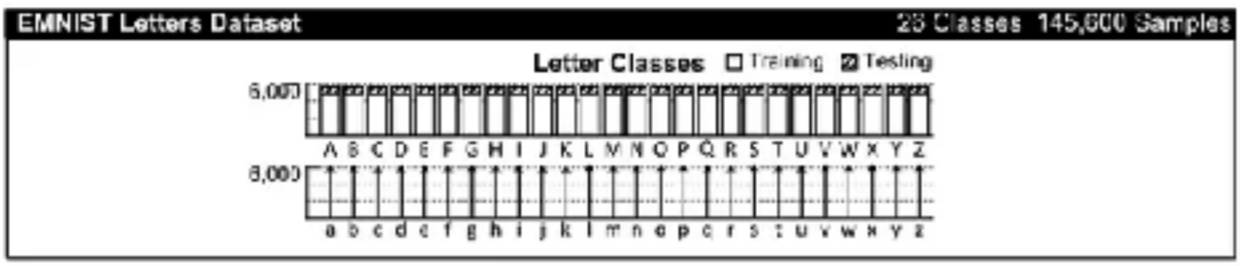
CHAPTER 4

Methodology

In our research, we employed the Extended MNIST Dataset (EMNIST) as a pivotal component for training and evaluating our letter recognition system. Originally derived from the well-established MNIST Dataset, EMNIST offers a more comprehensive challenge by encompassing not only digits but also handwritten uppercase and lowercase letters in a standardized 28 by 28 pixel format.

Our specific choice within the EMNIST dataset was the EMNIST Letters split, which comprises a vast array of 145,600 characters spread across 26 balanced classes. These classes include 26 uppercase letters and 26 lowercase letters. This split offers a rich and diverse set of data, allowing us to develop a robust model capable of recognizing a wide range of handwritten characters.

One of the significant advantages of the EMNIST dataset is its accessibility and ease of use. With minimal preprocessing and formatting efforts required, we could efficiently harness the dataset for our research purposes. Moreover, the availability of multiple splits within the EMNIST dataset caters to various research needs and model requirements.



Our focus primarily rested on leveraging the EMNIST By Class split due to its inclusivity of all 26 classes, thereby ensuring comprehensive coverage and training diversity. This enabled us to build a model that not only accurately recognizes individual letters but also predicts confidence scores associated with each recognition, contributing to the advancement of letter recognition technology.

Overall, the EMNIST dataset served as a foundational cornerstone in our methodology, providing the necessary data diversity and volume to train(16000 images for recognition) and evaluate our letter recognition system effectively. Through rigorous experimentation and analysis on this dataset, we aimed to contribute valuable insights and advancements to the field of machine learning-based character recognition.

Feature Extraction:

In [14]:
```
# loop over all classes and calculate the class weight
for i in range(0, len(classTotals)):
    classWeight[i] = classTotals.max() / classTotals[i]
```

In [15]:
```
# partition the data into training and testing splits using 80% of
# the data for training and the remaining 20% for testing
(trainX, testX, trainY, testY) = train_test_split(data,
                                                  labels, test_size=0.20, stratify=None, random_state=42)
```

In [16]:
```
# construct the image generator for data augmentation
aug = ImageDataGenerator(rotation_range=10,
                         zoom_range=0.05,
                         width_shift_range=0.1,
                         height_shift_range=0.1,
                         shear_range=0.15,
                         horizontal_flip=False,
                         fill_mode="nearest")
```

Dysgraphia is a learning disability that affects handwriting abilities and can have a substantial influence on academic achievement, self-esteem, and general quality of life. Early identification and intervention are critical for providing persons with dysgraphia with appropriate support and therapies. Machine learning approaches have emerged as potential solutions for automating dysgraphia identification in recent years. At the core of these strategies is the feature extraction process, which is critical in gathering and displaying important information from handwriting samples.

The process of translating raw input data, in this example, handwriting samples, into a set of meaningful and representative characteristics is referred to as feature extraction. These characteristics are fed into machine learning algorithms, which allow them to understand patterns and generate accurate predictions or classifications. In the context of dysgraphia detection, feature extraction techniques aim to extract discriminatory information that can differentiate between dysgraphic and non-dysgraphic handwriting.

The following points summarise the significance of feature extraction in dysgraphia identification using machine learning:

1. Discriminative Representation: Machine learning techniques can capture the particular characteristics of dysgraphia by extracting significant information from handwriting samples. These characteristics may include stroke patterns, spatial connections, curvature, angles, and other quantitative handwriting traits. Feature extraction's discriminative representation enables algorithms to discriminate between dysgraphic and non-dysgraphic examples with high accuracy.

2. Reduced Dimensionality: Handwriting data might be high-dimensional, with many data points or variables. Feature extraction reduces data dimensionality by choosing or altering the most useful characteristics. This streamlines the learning process, increases computing efficiency, and lowers the danger of overfitting, which occurs when the model becomes too particular to the training data and performs poorly on fresh data.

3. Interpretability: Feature extraction algorithms can generate interpretable features that shed light on the unique dysgraphic qualities present in the handwriting. This interpretability is critical for comprehending the underlying patterns and causes that contribute to dysgraphia. It can help educators, physicians, and researchers better understand the illness and design tailored therapies.

4. Generalisation: Effective feature extraction approaches add to the capacity of dysgraphia detection algorithms to generalise. These properties enable the models to recognise dysgraphia patterns across diverse persons, handwriting styles, and languages by capturing the core components of dysgraphic handwriting. The ability to generalise is critical for the practical implementation of dysgraphia detection algorithms in a variety of educational and therapeutic settings.

Feature Extraction's Role in Extracting Relevant Information from Handwriting Samples:

In the context of dysgraphia identification, feature extraction is critical for gathering and displaying meaningful information from handwriting samples. It entails converting raw handwritten data into a set of relevant and discriminative characteristics that machine learning algorithms may use. The importance of feature extraction may be shown in the following areas:

1. Handwriting qualities Representation: Handwriting samples provide a plethora of information that displays the distinct qualities of an individual's writing style. Specific features and patterns, such as stroke direction, curvature, spatial connections between letters, and variations in writing speed or pressure, can be extracted from raw data using feature extraction algorithms. These extracted features give a concise and informative depiction of the underlying dysgraphia-related handwriting characteristics.

2. Extraction of Discriminatory Information: Dysgraphia detection necessitates the recognition of specific patterns and inconsistencies in handwriting that distinguish dysgraphic from non-dysgraphic individuals. The goal of feature extraction is to extract important information from handwriting samples in order to capture these discriminative cues. Feature extraction approaches focus on certain elements of handwriting, such as stroke form, slant, or letter connectedness.

3. Dimensionality reduction: Handwriting data might be multidimensional, with many data points or variables connected with each sample. Feature extraction strategies assist in reducing data dimensionality by choosing or altering the most relevant characteristics. This decrease in dimensionality not only lowers the computational complexity, but it also prevents the models from overfitting, which occurs when they become too particular to the training data and fail to generalise successfully to fresh handwriting samples. Feature extraction helps keep the relevant information while removing repetitive or less informative traits by focusing on informative features.

4. Model Performance Improvement: Extracting important characteristics from handwriting samples improves the performance of dysgraphia detection models.Feature extraction allows models to better capture the underlying dysgraphia by giving meaningful representations of handwriting traits.

In conclusion, feature extraction plays a pivotal role in dysgraphia detection using machine learning techniques. It enables the transformation of raw handwriting samples into meaningful and discriminative representations, facilitating accurate classification or prediction. By extracting informative features, machine learning models can identify dysgraphic patterns, aid in early detection, and support targeted interventions for individuals with dysgraphia.

Dataset Collection:

Because of the nature of the condition, the necessity for precise annotations, and the need for different datasets, collecting and annotating big datasets for dysgraphia identification poses considerable hurdles. This essay examines the obstacles and procedures involved in dataset collecting and annotation for dysgraphia identification, emphasising the necessity of broad datasets that include a wide range of handwriting styles, languages, and cultural backgrounds.

Dataset Collection Obstacles:

a) Data Availability: Dysgraphia datasets are limited in comparison to other areas. Due to the scarcity of annotated dysgraphic examples, gathering a big dataset necessitates considerable time and resources.

b) Ethical Considerations: Collecting handwriting samples from people with dysgraphia necessitates ethical considerations in order to protect participant privacy, get informed permission, and follow study protocols.

c) Dysgraphia Heterogeneity: Dysgraphia presents in a variety of ways, including distinct writing styles, severity levels, and underlying reasons. It is critical to capture this variation in the dataset in order to construct comprehensive and effective dysgraphia detection algorithms.

The Value of Diverse Datasets:

a) Broadening: Dysgraphia affects people of all handwriting styles, languages, and cultural backgrounds. Diverse datasets guarantee that dysgraphia detection algorithms generalise effectively and are successful at detecting dysgraphic tendencies in various populations.

b) Robustness: Dysgraphia detection algorithms that have been trained on a variety of datasets are more robust and capable of dealing with variances in handwriting styles, cultural nuances, and linguistic discrepancies. As a result, the models may adapt to and perform effectively in real-world circumstances.[43]

c) Personalization: Using diverse datasets, personalised dysgraphia detection algorithms may be developed, responding to individual variances, writing styles, and unique language settings. Individuals with dysgraphia can benefit from such personalised models by receiving specific therapies and support.

Finally, gathering and annotating big datasets for dysgraphia identification has a number of obstacles, including restricted data availability, ethical constraints, and the variety of dysgraphia. Collaborations, online platforms, and longitudinal research, on the other hand, can help in dataset collection. Expert annotation, multi-level annotation, and consensus annotation verify the datasets' correctness and quality. Importantly, varied datasets including multiple handwriting styles, languages, and cultural backgrounds are required for dysgraphia detection algorithms to generalise, resilience, and customisation. By addressing these challenges and embracing diverse datasets, researchers can develop more accurate and effective dysgraphia detection models, leading to improved interventions and support for individuals with dysgraphia.

The use of machine learning algorithms, particularly CNNs, has shown promising results in the automated detection of handwriting dysgraphia. CNNs excel in extracting visual features from images of handwriting, allowing for the identification of specific dysgraphic characteristics.

Moreover, the integration of additional techniques such as data augmentation, transfer learning, and ensemble methods has enhanced the performance and generalization capabilities of detection models. Data augmentation techniques help overcome limited datasets by generating synthetic samples with variations, thereby improving model robustness. Ensemble methods combine multiple models to improve classification accuracy and enhance detection performance.

If the kid is projected to be dysgraphic, she or he is directed to therapeutic strategies. They are initially instructed on how to compose letters in a sequential path with exact start and endpoints .and animations inside a given scope. Users are able to write letters individually within a defined 2 scope in later phases. Users are permitted to write two letters in the provided scope, and their total number of nodes covered and subsequent course of letters are taken into account when determining their degree of expertise. The user is presented a summary of intervention results, and if intervention methods are satisfactory, users are rescreened. Several crucial elements are included in the dysgraphia treatment procedure to enhance the quality and readability of the handwriting. A sample of the input handwriting is first collected, then it is then preprocessed to improve its quality and get it ready for analysis. The image may be cleaned up, the noise reduced, and the size and orientation normalised.

Image Pre-Processing

The dataset initially can be in varied sizes, resolutions, and shapes, so through techniques such as that of cleaning, filtering, resizing, normalizing the input images become smoother and more unanimous to improve the quality for feature extraction that is relevant to the machine learning task. These techniques are important for improving the quality of the handwriting images, enhancing important features, and removing noise or artifacts that may interfere with analysis.

Original Image	Background-Foreground Differentiate	Resizing to actual writing area	Resized into 32x32
			
			
			

In order to decrease the computational overhead, inverse interchange was applied since the images originally had more white point (value=1) than black point (value=0), which would have implied in more power and memory consumption. The image is then cropped in a wat that it fits and focuses on the centre. After resizing the images to 32x32, it created uniformity to be fed to the learning models. The total dataset weight i.e., the number of images of each character, alphabet was imbalanced, to further counter that, to avoid bias in the prediction of any class data augmentation is used.

Rehabilitation Processes :-

Enabling learning for young pupils with dysgraphia begins by creating a conducive learning environment that not only allows them to learn and practice at their own speed but also encourages continuous self-testing to correct their writing shortcomings. The proposed system operates based on the principle of learning and evaluating.

A) Learning Aspect

The Learning Module is specifically developed to offer clear and well-supported training in the fundamental aspects of handwriting for pupils who have dysgraphia. Short instructional videos serve as the primary teaching tool, featuring clear visual demonstrations of correct letter formation (both uppercase and lowercase). These videos use contrasting hues and dynamic overlays to emphasize stroke sequences and spatial relationships. By providing concise auditory instructions, essential elements of letter formation can be reinforced, thereby facilitating a multisensory learning experience.

In addition to the instructional videos, digital worksheets offer targeted character-specific practice opportunities for basic line formations, including vertical, diagonal, and horizontal lines. This emphasis on fine motor skills and spatial perception is crucial for kids with dysgraphia since they frequently encounter difficulties with the physical process of writing by hand. The module adheres to recognized pedagogical approaches, such as explicit instruction and the use of multimodal modalities, both of which have been demonstrated to be advantageous for pupils with dysgraphia.

The multisensory approach employed in the Learning Module is particularly beneficial for students with dysgraphia. The combination of visual demonstrations, auditory instructions, and hands-on practice through digital worksheets caters to different learning styles and reinforces the learning process. By engaging multiple senses, the module provides a comprehensive and engaging learning experience, enhancing the students' ability to grasp and retain the essential skills needed for legible handwriting.

Moreover, the emphasis on fine motor skills and spatial perception directly addresses the common challenges faced by individuals with dysgraphia. The targeted practice on line formations and letter strokes aims to improve the students' control over their hand movements, coordination, and spatial awareness – all crucial elements for developing proficient handwriting abilities.

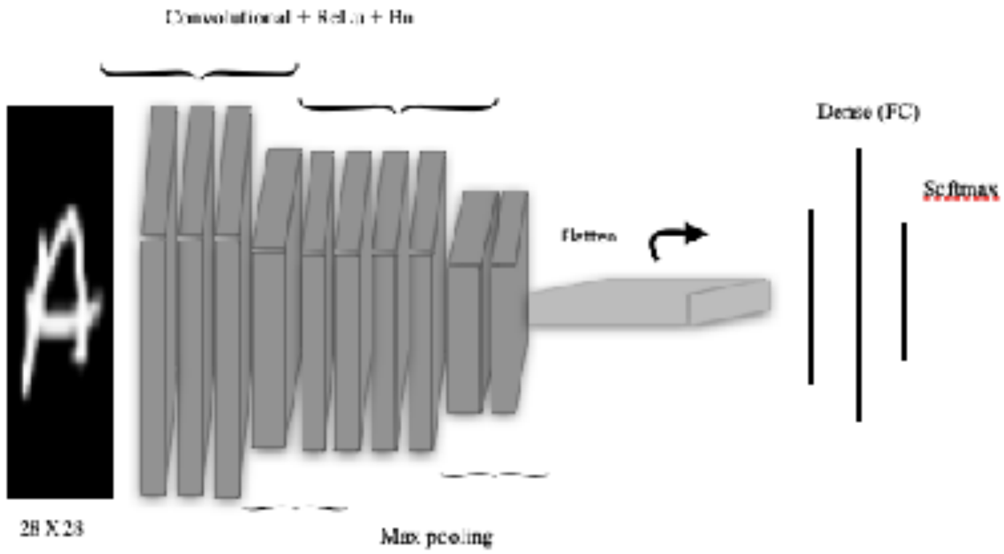
The module's adherence to recognized pedagogical approaches further enhances its effectiveness. Explicit instruction, which involves breaking down complex skills into smaller, manageable steps and providing clear explanations and demonstrations, is particularly valuable for students with dysgraphia. This approach ensures that the fundamental components of letter formation are presented in a structured and comprehensible manner, reducing cognitive load and facilitating better understanding.

Additionally, the use of multimodal modalities aligns with the principles of Universal Design for Learning, which emphasizes providing multiple means of representation, action, and engagement to accommodate diverse learners. By incorporating visual, auditory, and kinesthetic elements, the Learning Module caters to a wide range of learning preferences and abilities, increasing the likelihood of effective knowledge acquisition and retention.

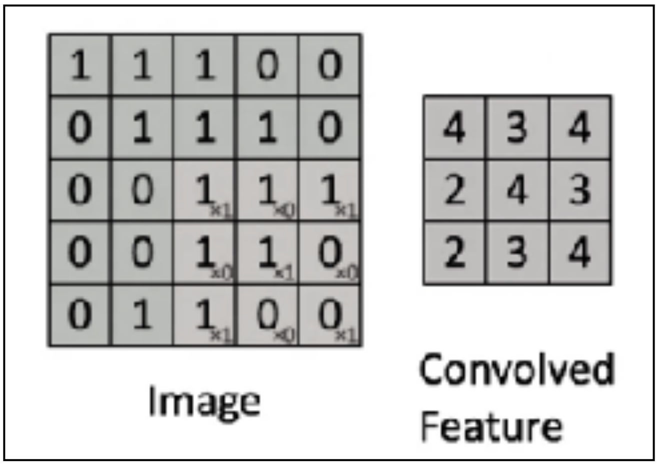
B) Assessment Side

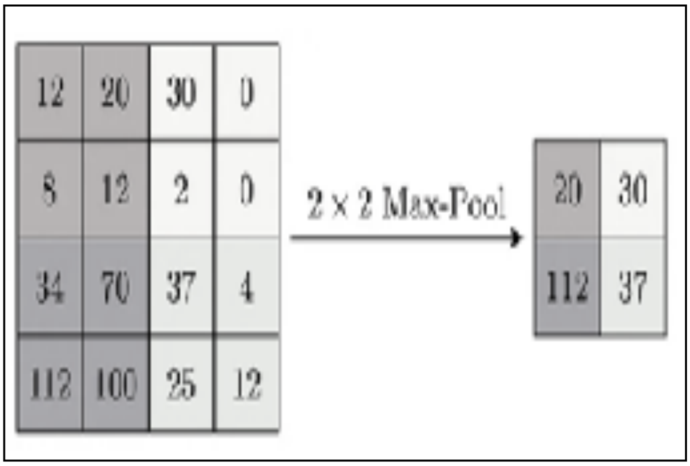
The Test Module offers students an empowering tool for enhancing their penmanship. It surpasses conventional evaluations by providing instant and accurate examination of key components of handwriting. Students can enhance their self-awareness and identify areas for growth by submitting samples of their work in JPEG format. The module utilizes a variety of state-of-the-art analytical elements:

Letter Recognition & Confidence Score: The analytical pipeline relies on a well-trained Convolutional Neural Network (CNN) model to accurately recognize handwritten characters and generate confidence scores. The CNN model has been trained using a broad dataset that includes characters from EMNIST [31][32]. This dataset encompasses a wide range of handwriting styles and variances, ensuring that the model can effectively recognize diverse handwriting patterns.



The CNN architecture leverages deep learning methodologies to provide exceptional performance in the recognition and forecasting of handwritten characters. At the preprocessing and input layer, the images undergo normalization, where the pixel values are scaled between 0 and 1. Additionally, the images are resized to 4D tensors with dimensions (number of samples, 64, 64, 1) to ensure compatibility with the Convolutional Neural Network (CNN). The input layer receives grayscale images with dimensions of 64x64 pixels and applies 16 filters with dimensions of 3x3. The filters use ReLU activation to introduce non-linearity.



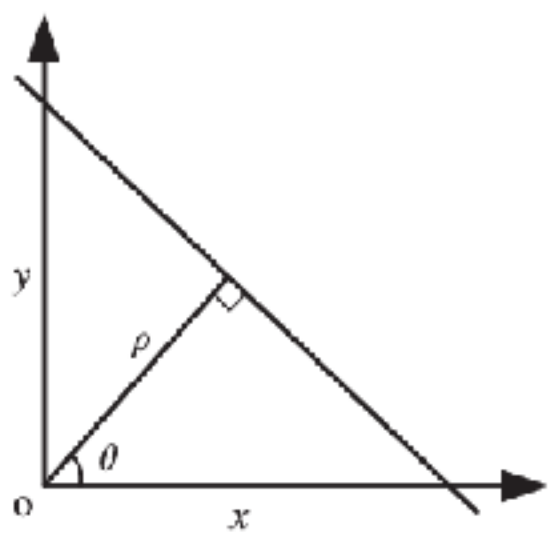


The CNN model utilizes multiple convolutional layers with batch normalization and max pooling for its operations. Batch normalization speeds up the training process, whereas max pooling simplifies the network by extracting prominent features, improving feature extraction without compromising important spatial information. Dropout layers, with a 20% random dropout rate, are incorporated to mitigate overfitting and enhance the model's capacity to generalize to novel handwriting samples.

The hidden layers consist of a convolutional layer, batch normalization, max pooling, and a dropout layer. The number of filters is incremented (34, 64, 128 filters of size 3x3) to capture increasingly complex features in the handwriting. Average pooling is used to decrease the number of parameters, which helps to prevent overfitting, before reaching the output layer. The softmax activation function in the output layer produces a probability distribution across character classes for multi-class classification, yielding values between 0 and 1.

Confidence Scoring: Every forecast is assigned a confidence score, which falls within the range of 0 to 10. The score is calculated based on the softmax probabilities, which serves as a dependable indicator of the model's confidence in its predictions. This statistic is essential for assessing the uploaded image and assigning a score for the student to evaluate their proficiency.

Baseline Correction: Proper text alignment is essential for legible handwriting. However, students often struggle to maintain a consistent baseline for their letters, resulting in illegible handwriting. To address this issue, the system utilizes sophisticated image analysis techniques such as Hough line transform, edge detection, and morphological operations. These techniques precisely locate and establish the baseline in handwritten images.



At first, it utilizes a Hough line transform and edge detection to identify the boundaries of each letter. In image space line is defined by the slope

$$\rho = x \cos \theta + y \sin \theta$$

So to detect the line in the image space we have to define these parameters, which is not applicable in image domain. In the other domain with m and b coordinates, line represent a point from image domain. Points on the same line in image domain will be mapped to lines in Hough domain.

These lines intersect with each other in a point with specific values m and b. These values are the slope and y-intercept of original line in image domain.

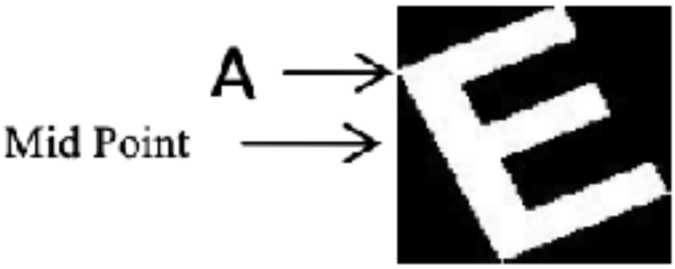
These values are the slope and y-intercept of original line in image domain.The outlines play a vital role in establishing the shapes and limits of the letters. Subsequently, morphological operations are utilized to improve and optimize the initial detection process. These processes refine and link the outlines, enabling a more accurate assessment of the baseline. After establishing the baseline, the system accurately determines the vertical distance between the bottom edge of each letter and the baseline. This measurement detects any deviations from accurate baseline positioning. The analysis identifies any discrepancies and provides specific comments to the student to improve the legibility and consistency of their handwriting. By carefully ensuring conformity to the baseline, the method provides precise instructions for improving the positioning of letters.

Tilt Detection: The technology employs a combination of image processing algorithms and geometric computations to precisely ascertain the slant angle of every handwritten letter. Contour detection algorithms carefully examine the image, identifying slight differences in brightness or color to accurately establish individual letter outlines. The system computes the smallest area rectangle that completely encompasses each identified letter, yielding a reliable estimate of the letter's overall orientation. By utilizing basic trigonometric principles, the method accurately determines the angle between the main axis of the rectangle and a pre-established vertical reference line. This calculation provides an accurate measurement of the angle at which the letter is tilted.

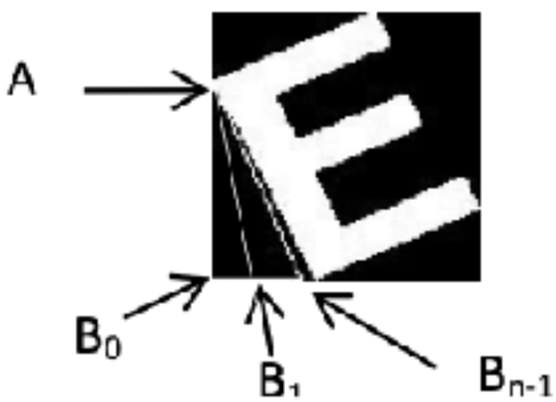
In addition, the codebase includes a crucial angle adjustment mechanism to guarantee compliance with a predetermined angle range of -45 to +45 degrees. This correction mechanism accounts for essential differences in the alignment of handwritten letters, guaranteeing consistent and dependable angle measurements. This approach provides a thorough analysis that offers nuanced insights into the consistency of bias, enabling students to recognize and correct any discrepancies.

Furthermore, the angle of tilt is estimated through the digital differential analyzer (DDA) line drawing algorithm. The DDA line drawing algorithm draws a line between any two specified points. A series of lines are drawn, and a specific line is selected out of them. The selected line is an approximation of the tilt of the character to the baseline. The procedure for estimating the angle of tilt for a tilted character is as follows:

1. In the rectangle enclosing the character, a point (A) is identified. The point A is obtained through a search upwards starting from the mid-point of the vertical boundary on the side of the tilt. A is the first point that touches the boundary line.

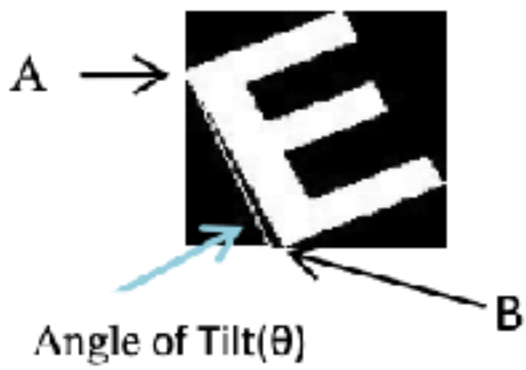


2. A point B is searched on the baseline starting from the tilt side corner point until a line is constructed that just touches the character. This procedure is illustrated in illustration below. The points B_0, B_1, B_2...B_{n-1}, B_n are the series of points searched for drawing the lines AB_0, AB_1, etc., until the line drawn just touches the character. The point B_0 is the first point on the baseline starting



from the side of the tilt. B_n is the final point searched on the baseline, and the line AB_n is the required line that touches the character. The final point B_n on the baseline obtained is denoted as B.

3. The line AB is used to identify the tilt of the character. The angle formed by the line AB concerning the baseline gives the angle of tilt θ of the character. Fig. 9 illustrates the line AB and the angle of tilt detected.



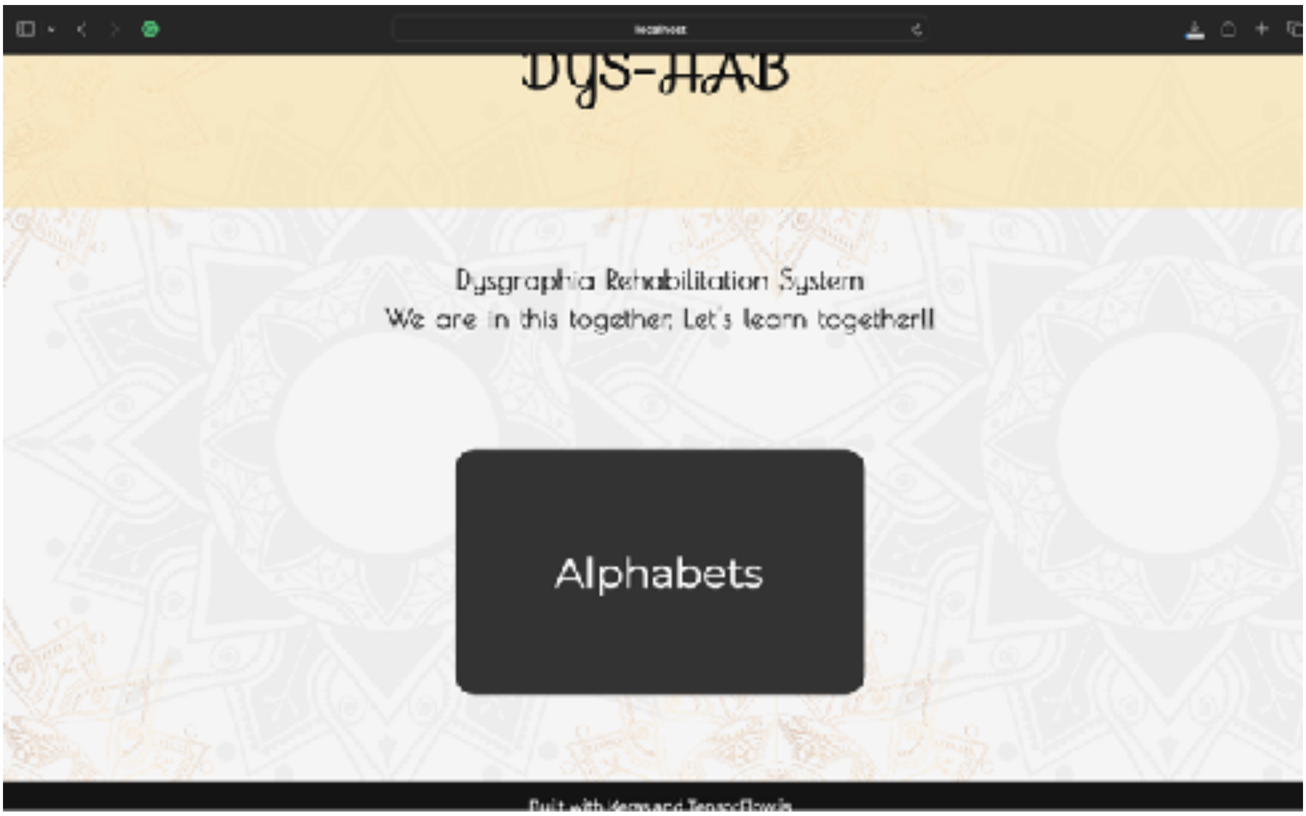
The combination of the Learning Module and the Test Module provides a comprehensive solution for enabling learning and assessment for young pupils with dysgraphia.

CHAPTER 5

Research Outcomes

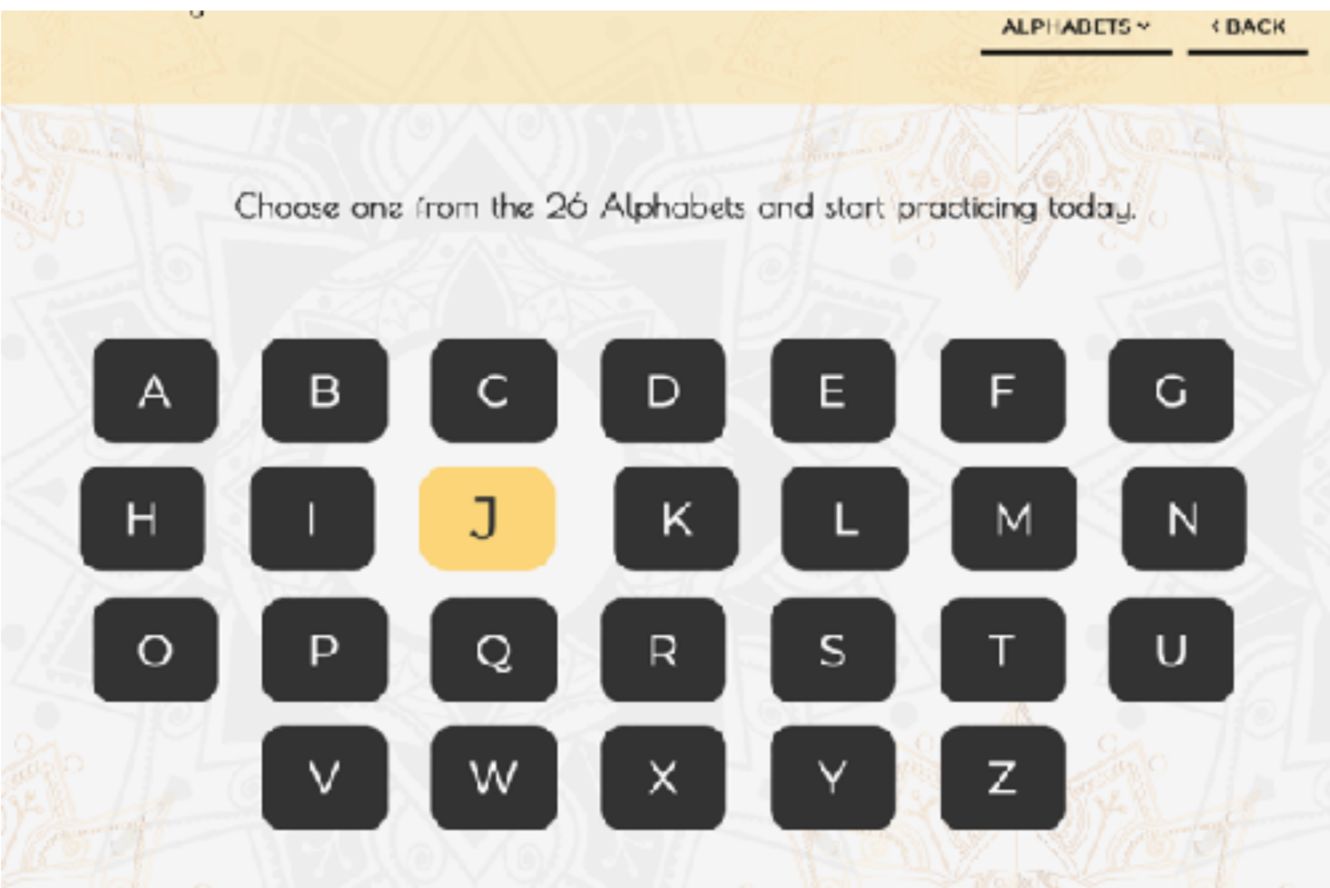
Based on the researches reviewed, it is clear that there is an urgent need for a system that provides consistent modeling and reinforcement for learning. To address this, we have developed a website that offers repetitive instruction for both uppercase and lowercase letters, alongside providing worksheets for practice. Additionally, the website includes a testing module where users can submit their handwriting samples for analysis, and receive feedback in the form of a score for their handwritten letters. This dual approach facilitates both learning and self-assessment, helping students to improve their handwriting skills effectively.

1) Landing home page

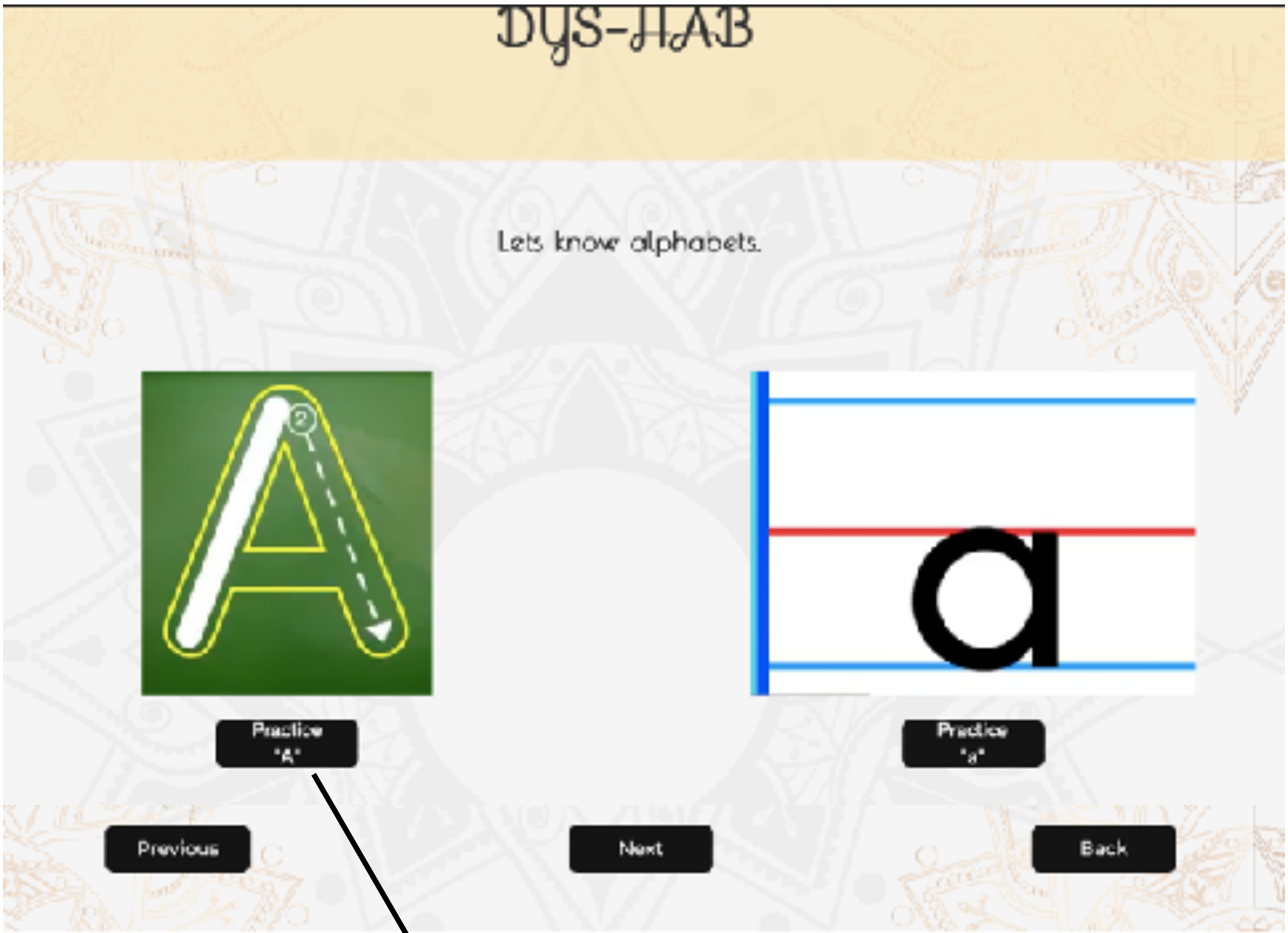


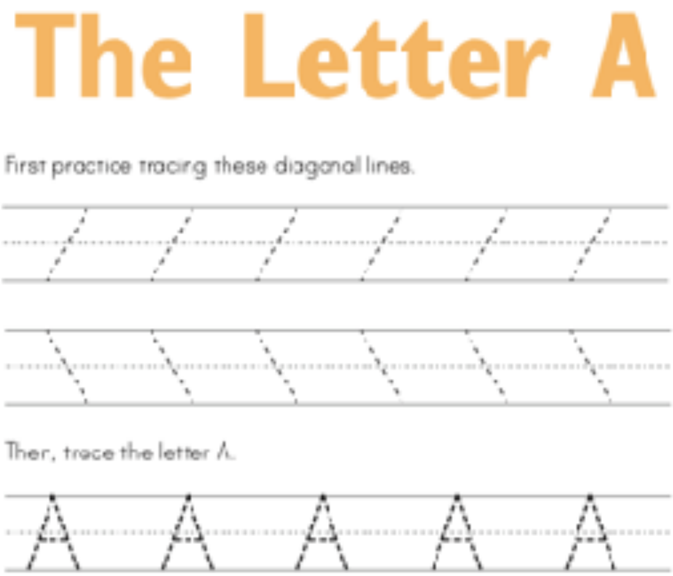
2) Choice to either learn Alphabets or assess ons handwriting skills

3) Choice to learn particular alphabet



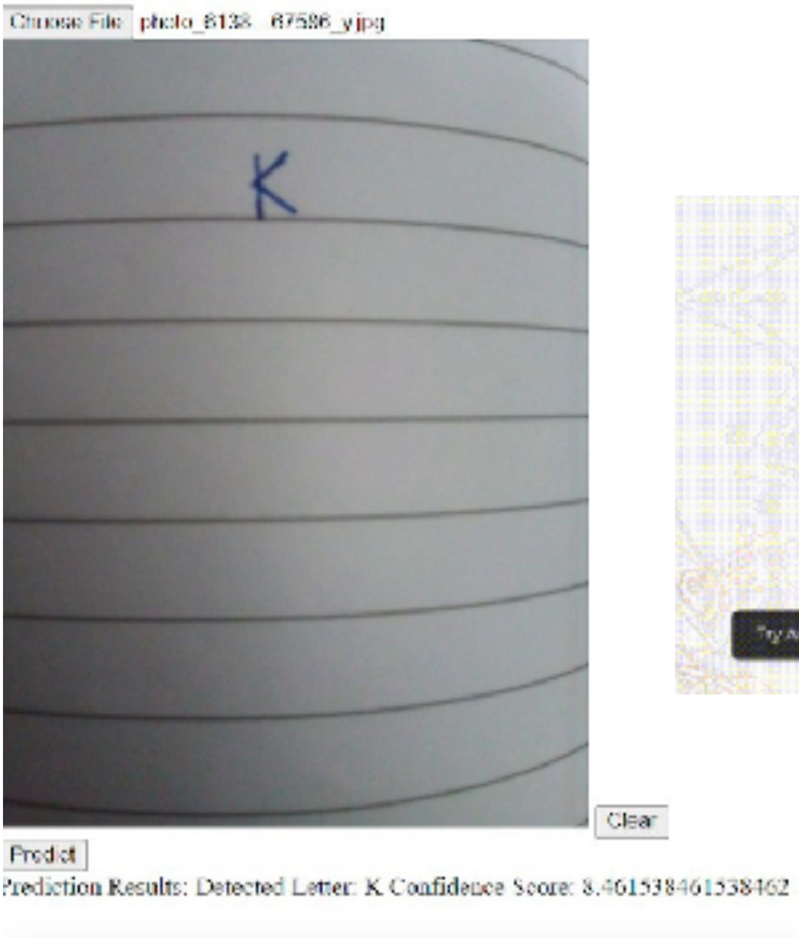
4) The Learn side deployment: It includes choice of alphabets one wants to learn followed by instructive videos with printable worksheets to practice.



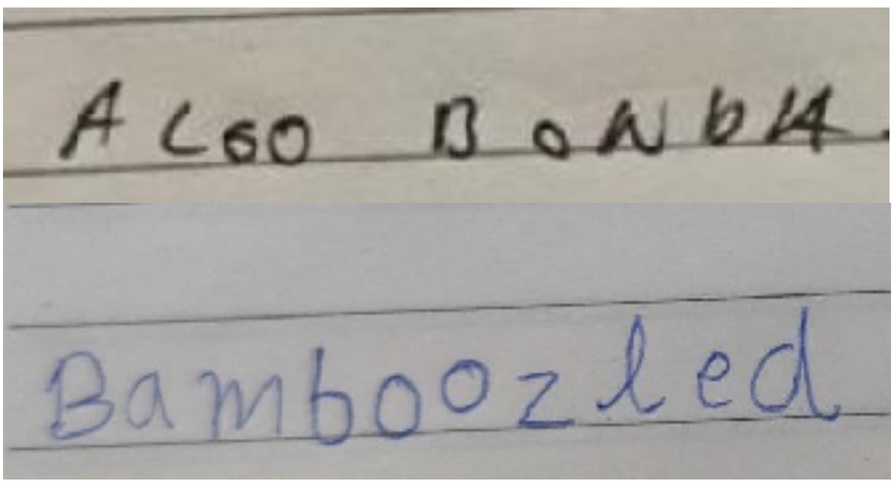


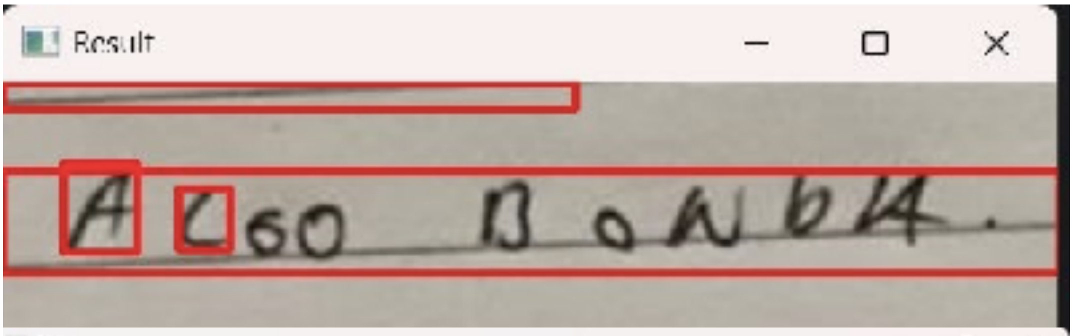
5) Result for test side: After uploading an image for evaluating it yields these results

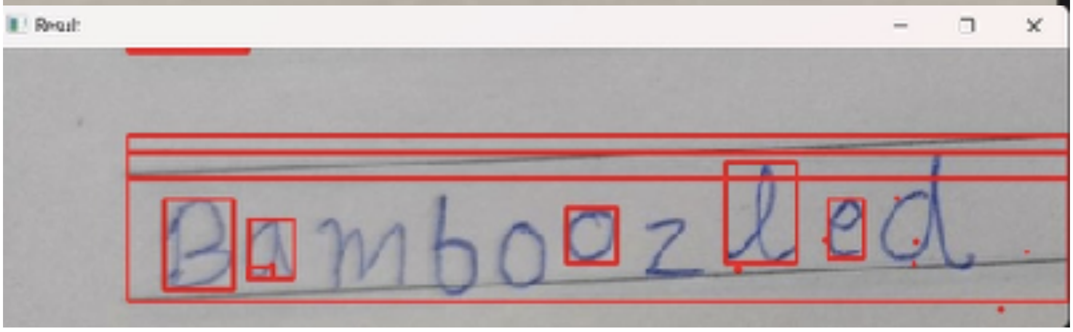
A) Letter Recognition and score prediction :-



B) Baseline Detection : All the letters which aren’t on the given baselines are highlighted







C) Tilt angle Detection