A simplified app for assessment of reading and writing difficulties in persons with Specific Learning Disabilities

SUBMITTED IN PARTIAL FULFILLMENT FOR THE REQUIREMENT OF THE AWARD OF DEGREE OF

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE

Submitted by

AAYUSH KUMAR SHRIVASTAVA (2100290120003)
ABHISHEK VERMA (2100290120009)
ARCHIT GOEL (2100290120045)
KARTIK VERMA (2100290120093)

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Supervised by

DR. RAJ KUMAR
Additional HoD
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KIET GROUP OF INSTITUTIONS, GHAZIABAD

(Affiliated to Dr. A. P. J. Abdul Kalam Technical University, Lucknow, U.P., India)

May 2025

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I/We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Signature:	Signature:
Name : Aayush Kumar Shrivastava	Name : Abhishek Verma
Roll No.: 2100290120003	Roll No.: 2100290120009
Signature:	Signature:
Name : Archit Goel	Name : Kartik Verma
Roll No.: 2100290120045	Roll No.: 2100290120093

Date:-

CERTIFICATE

This is to certify that Project Report entitled " A simplified app for assessment of reading and writing difficulties in persons with Specific Learning Disabilities " which is submitted by Aayush Kumar Shrivastava, Abhishek Verma, Archit Goel , Kartik Verma in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

.

Date: **Supervisor**

DR. RAJ KUMAR
Additional HoD

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Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

Date :

Signature:	Signature:
Name : Aayush Kumar Shrivastava	Name : Abhishek Verma
Roll No.: 2100290120003	Roll No.: 2100290120009
Signature:	Signature:
Name : Archit Goel	Name : Kartik Verma
Roll No.: 2100290120045	Roll No.: 2100290120093

ABSTRACT

Dyslexia affects how a person reads, writes, and spells, and it is often undiagnosed because traditional assessment methods have inherent flaws. This study looks into how machine learning techniques can be applied to automate the process of diagnosing dyslexia through analyzing handwriting patterns. The research employs Decision Tree and Random Forest algorithms to classify the handwriting samples based on key linguistic and phonetic characteristics such as spelling, grammar, letter spacing, stroke inconsistencies, and phonetic alignment. To enhance detection precision, the proposed model also uses phonetic OCR techniques, specifically Levenshtein Distance, Soundex, and Metaphone analysis. Experimental outcomes demonstrated that the Decision Tree model reached an accuracy level of 96% while the Random Forest model achieved 86.03%, indicating the usefulness of machine learning in the early screening of dyslexia. Moreover, a cognitive evaluation in the form of a quiz was added to improve classification accuracy. The results imply that AI-based systems for detecting dyslexia could serve as efficient, accessible solutions in comparison with conventional methods, allowing earlier educational and cognitive support. Future enhancements may involve the integration of deep learning models, real-time speech evaluation, and mobile application development to increase accessibility and usability.

TABLE OF CONTENTS

Page No.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

API	Application Program Interface
OCR	Optical Character Recognition

SDG MAPPING WITH JUSTIFICATION

SDG 3: Good Health and Well-Being

- Dyslexia is a common learning disorder affecting reading, writing, and spelling.
- The DyslexiLens project utilizes machine learning algorithms like Random Forest and Decision Trees for early detection.
- Early diagnosis improves quality of life by enabling access to appropriate support and resources.
- This project contributes to SDG 3 by:
  1. Promoting mental well-being
  2. Supporting individuals with learning disabilities
  3. Helping them lead healthier, more fulfilling lives

Fig.1 SDG 3 Good Health and Well-Being.

SDG 10: Reduced Inequality

- Individuals with learning disabilities, like dyslexia, face barriers to educational success, leading to social and economic inequalities.
- DyslexiaLens aims to reduce these inequalities by providing:

    1. An accessible and affordable tool for early diagnosis.
    2. A focus on underprivileged regions with scarce educational resources.

- By expanding dyslexia detection access, the project:

    1. Empowers individuals regardless of socio-economic status.
    2. Ensures equal educational opportunities for all.
    3. Helps reduce inequality in educational outcomes.

Fig.2 SDG 10: Reduced Inequality

CHAPTER 1
INTRODUCTION

1.1 Introduction

Dyslexia is a learning disability in which a person has difficulty reading, writing and spelling. Unlike people with developmental disabilities, people with dyslexia have normal intelligence (IQ) and level of education and experience. The global prevalence of dyslexia is estimated to be between 5 to 10% of the population, making it one of the most common learning disabilities. Early diagnosis and intervention are key in reducing dyslexia's impact on reading and writing outcomes, self-esteem, identity and developmental milestones. However, traditional route to diagnosis requires a long and costly assessment process, further done in some areas by specialists who are not easily accessible. Once delays occur, the chances of intervention lessens and the challenges of students increase.

As computer aided design systems are being utilized with regularity, possibilities for new capabilities and techniques emerged to assist researchers in automating time and labour intensive processes. Machine learning is one of the more recognized offshoots of artificial intelligence. With the ability to classify data automatically after training, machines can now be utilized to analyze writing styles and detect dyslexia at different levels.

Modern day paradigms like handwriting analysis, natural language processing and pattern recognition along with machine learning can help create systems which are capable of detecting dyslexia at an unprecedented level. Through machine learning models, distinguishing features of dyslexia like letter spacing, stroke irregularities of writing, phonetic inconsistencies along with errors which occur while spelling words can be detected. Such automated structures have the capability to dramatically lessen the focus on human help, obstacles and input in the process which makes it easier to identify an ailment in its primary stages making treatment more affordable.

There are two major methods proposed for examine the earliest signs of dyslexia by analyzing handwritten samples from different subjects. This research concentrates on constructing a machine learning system that overcomes the challenges of early and accurate detection of dyslexia drawing its foundation through advanced ai techniques and deep learning algorithms, starting with capturing optical images of handwritten notes. Feedback from sampled texts is analyzed through various metrics including the SpellChecker engine along with phonetic groupers Soundex and Metaphone. Moreover, grammar approximators help provide additional feedback on the sample text converting it into digital form using Optical Character Recognition (OCR). After this is completed, the study classifies extremly accurate multi-level Word-Spelling distinctions through Decision Tree and Random Forest methods ensuring advanced levels of reliability in performance and trustworthiness.

In this new model, not only will the preliminary conditions of dyslexia be clearly defined but also the explanation for all estimations and their justifications being based on scientifically proven objective parameters ensuring unparalleled reliability and stability in performance.

With the use of modern computer techniques, this study attempts to change the way dyslexia is assessed by incorporating AI-powered screening tools alongside traditional methods. To improve the system in the future, accessibility and ease of use may be enhanced with the addition of real-time speech evaluation, deep-learning-driven handwriting recognition, and mobile app deployment. If such a system is successfully applied, it could revolutionize the diagnosis of dyslexia and guarantee that individuals receive essential services early on, thereby enhancing their learning potential and quality of life.

1.2 Project Category

The project seeks to leverage machine learning approaches for the development of tools and models for diagnosing learning disabilities, and it is within the educational technology and health informatics domain. The project intends to use state-of-the-art machine learning algorithms to enhance recognition and understanding of different learning disabilities; the objective is to provide a data-driven method for recognizing disabilities that may hinder a person's ability to learn. The initiative seeks to engage cutting-edge methods in the educational technology field to analyze and assess learning patterns, helping teachers and medical professionals identify children who may need extra support or intervention.

1.3 Objectives

- **Early Detection:** To make sure children or adults with learning disabilities get the help they need early on this project focuses on early detection spotting conditions like dyslexia at an early stage is important because it allows timely support which can greatly improve how well these issues are managed when symptoms are identified early teachers and healthcare professionals can provide the right support before the difficulties become harder to overcome making it easier for individuals to build strong reading and writing skills.

- **Personalized Learning:** The project aims to provide personal insights for every student helping in shape learn different methods that fit their specific needs since everyone learns differently this data-based approach makes it possible to create learning plans that match each persons style by knowing what a student is good at and where they struggle teachers can change the way they teach to better support that student this could mean changing reading speeds using different types of tests or giving special practice activities personalized learning helps make sure every student can succeed in a way that works best for them.

- **Accessible Assessment:** One of the main focuses of the project is to have a simple and accessible approach to checking for learning disabilities for anybody teachers, parents or even the individuals themselves. The platform has been designed to be instinctively straight forward so that people don't need any form of additional training to identify a reading or writing difficulty, it is user friendly so they can just do it. This accessible approach allows teachers and parents to easily identify if a student is having issues without the need for intermediate testing. This means sooner help and a more successful outcome.
- **Accurate Predictions:** The foundation of the project is built upon a highly credible machine learning model, which has the potential to give highly accurate predictions. The models incorporate the different parameters like reading speed, writing ability and other mental capabilities to accurately identify learning disabilities. Getting accurate predictions is critical to ensure that people receive the correct advice and support. The machine

learning models are able to learn from massive datasets and continually improve with time; this helps to make more dependable predictions for teachers and health sector professionals to devise better and more targeted support which will ultimately improve the learning circumstances for people with difficulties.

- **Educator Support:** The other intent of the project is to support educators with useful data-based information to inform and improve teachers practice. Educators now have rich reports at their fingertips that describe a student's learning behaviours but also how they might think about adapting their practice to support children with learning differences. For example, educators can use the reports to think about using special exercises to develop reading skills and/or to adjust classroom elements to support students who experience dyslexia. This project has given educators realistic, useable information that has resulted improvement for students, while also reflecting barriers to success. The post hoc reports immediately provide educators with the opportunity to create an inclusive and supportive place for all students experiencing challenges with learning.

1.4 Structure of Report

The structure of report is as follows:-

- **Chapter 1 : Introduction** – Introduction about the project and its objectives.
- **Chapter 2: Literature Review** – Discusses existing research on dyslexia detection and the application of machine learning in educational diagnostics.
- **Chapter 3: Proposed System** – Details the design and unique features of the proposed dyslexia detection system.
- **Chapter 4: Requirement Analysis and System Specification** – Outlines the feasibility study, software requirements, and system design.
- **Chapter 5: Implementation** – Describes the tools, technologies, and datasets used in developing the system.
- **Chapter 6: Testing and Maintenance** – Presents the testing methodologies and maintenance strategies employed.
- **Chapter 7: Results and Discussions** – Provides an analysis of the system's performance and key findings.

- **Chapter 8: Conclusion and Future Scope** – the project outcomes and suggests directions for future research.

CHAPTER 2
LITERATURE REVIEW

2.1 Literature Review

- Rello & Baeza-Yates (2017): The paper informs us of the ways that varying writing styles may affect the readability for an individual with dyslexia. With precisely designed experiments using dyslexic test participants, researchers established that fonts with increased spacing of letters and streamlined letter composition considerably improved reading speed and accuracy. They asserted that typographic decisions are critical to improving access for dyslexic readers, and can provide valuable information for the design of learning materials, e-books, and online learning settings. The study did not utilize machine learning algorithms, however, it laid the important foundation for using reading contexts to assist individuals with dyslexia.
- Khan et al. (2018): In 2018 khan et al created a machine learning-based approach to identify dyslexia by analyzing reading speed writing errors and cognitive processes using algorithms like svm and random forest their method demonstrated promise for scalable automated screening in educational and medical environments and increased diagnosis accuracy.

- Isa et al. (2019): This systematic review was centered on the different handwriting-based approaches to dyslexia detection. Isa and the authors presented an introduction to a discussion of a range of feature extraction techniques including the identification of stroke patterns, observation of spacing irregularities, and differences in writing speed.The review also looked at classification algorithms such as Decision Trees, Random Forests, and Artificial Neural Networks (ANN). One of the main emphases of the study was the need for larger, more heterogeneous datasets and the development of real-time diagnostic systems to move from experimental setups to deployable, practical solutions. Their review is an excellent starting point for new entrants to this area.

- Alkhurayyif & Sait (2020): Exploring deep learning applications, in this research work, Convolutional Neural Networks (CNNs) were utilized to examine samples of handwriting to identify dyslexic signs. By training the model on handwritten image labels, they were in a position to differentiate dyslexic patterns without intensive manual feature engineering, delivering high classification precision while keeping human involvement to the minimum. Its success proved deep learning methods capable of offering high classification precision in exchange for human effort, creating room for future work on co mplete automation and scaleability of dyslexia testing tools.

- Rosli et al. (2021): Rosli and co-authors tested the ability of machine learning algorithms, Decision Trees and Artificial Neural Networks (ANNs), to identify handwriting samples of dyslexic and non-dyslexic participants to examine the handwriting features of irregular letter formation, uneven spacing, and differing stroke pressure. They concluded that decision trees and ANNs were able to differentiate the handwriting features of dyslexia, and that AI may provide helpful resources for educators and clinicians wanting to provide early diagnosis.

- Irwin et al. (2021): A respite from handwriting analysis, Irwin's study explored phonological impairments as the key predictor of dyslexia. The researchers analyzed speech characteristics with machine learning models such as Random Forest and Logistic Regression to compare pronunciation errors, phoneme identification, and reading fluency. Their analysis found a rationale for adding phonological processing to dyslexia screening. They suggested using a combination of speech analysis and handwriting to develop more accurate and holistic diagnostic tools in the future.

- Sasidhar et al. (2022): compared certain machine learning models like support vector machines (SVM), Random Forest and the k-Nearest Neighbors (k-NN) for dyslexia classification based on handwriting samples. Their result established that the most accurate classification was obtained by the Random Forest models that were able to deal with complex feature interactions effectively. Overall, their research suggested that handwriting does still carry a considerable amount of diagnostic features and that the right machine learning models could be the most important factor in generating reliable dyslexia screening systems.

- Hamid et al. (2022): Instead of proposing a classification model, Hamid et al. were quite inventive instead to proposed an adaptive learning system. The system was able to adaptively measure children's reading and writing capabilities and then generate personalized tasks that adapted in real time based on the child's performance. In a manner similar to reinforcement learning, the model rewarded participants, while capturing more granular aspects of engagement and behavior. The findings supported the idea that interactive learning environments can both contribute to the educational development of dyslexic children and provide extensive data for earlier identification and support.

- Gunawan et al. (2022) : The study conducted by Gunawan took a different approach by bringing computer vision into dyslexia detection through the utilization of object detection algorithms such as YOLO and Faster R-CNN with handwriting samples. Using the properties of handwriting, such as letter shape, irregular spacing, and alignment problems, Gunawan's system achieved classification accuracy. Their approach is an excellent example of how advanced image processing can complement machine learning models, providing opportunities to develop faster and more accurate dyslexia screening tools and techniques which are often limited to traditional feature extraction.

- Spoon et al. (2023): With handwriting analysis centered on the Random Forest algorithm, Spoon and others validated that writing speed, letter distortions, and stroke variance are some of the most important features most closely linked with dyslexia. Their model had good interpretability measures, and this made it easier for practitioners to understand better what handwriting features were most relevant to the disorder. Explainability as a machine learning model focus is such that good performance can make it easier to build trust with parents, clinicians, and teachers.

2.2 Research Gaps

Several gaps remain:

- **Data Limitations**: Many studies rely on small, homogeneous datasets, limiting the generalizability of the models.
- **Feature Selection**: Identifying the most predictive features of dyslexia in handwriting remains a challenge.
- **Model Interpretability**: The "black-box" nature of some ML models hinders understanding of the decision-making process, which is crucial for clinical applications.

2.3 Problem Formulation

- Data Collection: Samples of handwriting from individuals with dyslexia and from individuals without dyslexia are collected. Samples are labeled appropriately (i.e. dyslexic or non-dyslexic) and prepared for training the machine learning models.
- Data Extraction and Cleaning: Samples are pre-processed via Optical Character Recognition (OCR) in order to extract the text. A variety of linguistic features, i.e. types of spelling errors, grammar, are focused on with this.
- Feature Extraction: The handwriting features chosen to aid such detection are letter formation, letter spacing, counting grammatical errors, and counting phonetic confusion marks.
- Modeling: Models of Random Forests and Decision Trees is trained based on labeled data to predict the writing patterns (i.e. dyslexic or non-dyslexic).
- Measure Performance: The models are compared on key metrics of precision, recall, accuracy and the F1-score to see how the models perform.
- Real World Application: The model built is then put into a dyslexia screening application that is interactive and usable as a real-time easy quick test.

CHAPTER 3
PROPOSED SYSTEM

3.1 Proposed System

The proposed system is a machine learning based system that aims to detect dyslexia via handwriting samples. The proposed system aims to detect early signs of dyslexia by measuring handwriting features in detail through the use of advanced machine learning techniques. Specifically, the system uses a couple of very powerful classification algorithms, which are Decision Trees and Random Forest classification algorithms, to capture various features from handwriting samples, and assign risk classifications individuals accordingly from an early intervention respect for dyslexia.These algorithms allow the system to make accurate predictions about the likelihood of dyslexia based on patterns and abnormalities in the patterns of writing letters and words.

Apart from handwriting analysis, the system also comprises a number of other test procedures to improve the overall accuracy of detection. Correctness of spelling is verified by cross-checking for common mistakes and word spelling abnormalities. This is important since dyslexia patients tend to have difficulty with spelling because of word-deciphering problems. The system also checks for grammatical correctness in the writing samples, detecting problems such as improper sentence construction or word usage, which also reflect a learning disorder.

In addition to these features, the system also utilizes a phonetic similarity test which measures the processing and recognition of sound in words. Dyslexics generally report have poor phonetic recognition, so it may not be too difficult to measure their ability to identify whether two presented words sound the same.

Finally, in addition to the tests mentioned above, the system includes a quiz-like test with multiple choice questions in order to measure auditory identification and visual alignment of words or letters. The interactive nature of the test also helps collect more understanding about the person's ability to process written and spoken language, which is a key area of attention in dyslexia diagnoses.

Overall, the system includes a range of different methods for dyslexia detection: handwriting analysis, spelling ability, grammatical analysis, phonetic analysis, and a quiz style test. This enables the system to provide a breadth of assessment of an individual's dyslexia. The inclusion of machine learning along with methodical testing means that the system can provide highly accurate and reliable results, which enables earlier detection and more efficient interventions and knowledgement.

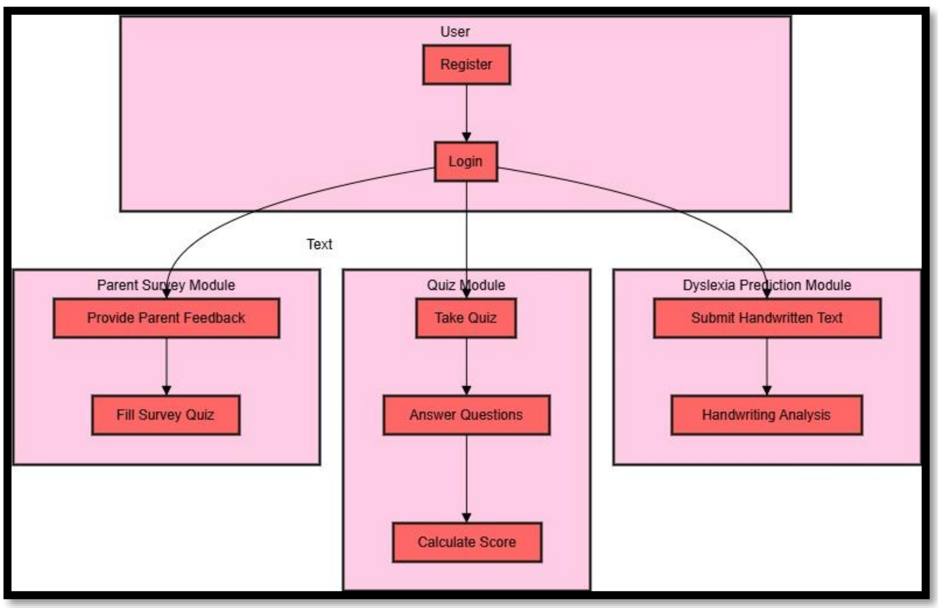


Fig.3 Dyslexia Detection System Workflow.

This flowchart represents the process of a dyslexia detection system in which a User would Register once and Log in each time to access various modules.

1. Parent Survey Module - Parents in this case will provide answers in the form of a survey quiz to identify likely Dyslexia risk descriptions based on their perceptions.
2. Quiz Module - In this module Users will take a structured quiz, answering questions that apply a calculation for providing a score derived from the other characteristics to inform the dyslexia assessment.

3. Dyslexia Prediction Module - In this module, Users will allow the application to analyse their handwritten text, to provide handwriting analysis characteristics for possible dyslexia signs.

The system offers a multi-assessment strategy to increase the accuracy of a dyslexia prediction.

System Architecture & Workflow:

1. **Handwriting Image Collection:**
    - Users upload handwritten text samples.
    - Images are processed through an Optical Character Recognition (OCR) system to get text.
2. **Feature Extraction & Analysis:**
    - The extracted text is preprocessed to remove any extraneous noise, and to consolidate any inconsistencies in the data.
    - We identify meaningful handwritten characteristics, such as degree of letter spacing, stroke inconsistencies, word alignment, and coherence.
3. **Machine Learning-Based Dyslexia Detection:**
    - The extracted features are classified using Decision Tree and Random Forest models.
    - Decision Tree Model: Provides high interpretability with an accuracy of 96%.
    - Random Forest Model: Offers robustness against overfitting, achieving 86.03% accuracy.
4. **Linguistic & Phonetic Analysis:**
    - Spelling Accuracy: Counting the number of spelling errors employed the Levenshtein Distance, an algorithm designed to find presence of spelling errors.
    - Grammatical Accuracy: A grammar checking tool was used to evaluate usage and structure of sentences.
    - Phonetic Similarity: Sound errors were detected through the Soundex and Metaphone algorithms.
5. **Quiz-Based Evaluation:**
    - A 10-question assessment evaluates dyslexia-related cognitive challenges.
    - Types of Questions:

    1. Listening-based questions: Test auditory discrimination abilities.
    2. Image-matching questions: Simple measures of visual perception and response accuracy.

6. **Real-Time Score & Diagnosis:**
    - Logically, if you had something that could measure (/assess) visual perception and provide some level of confidence that an observation has occurred, then YOUR SYSTEM could develop an overall risk score for dyslexia based on the outcomes of linguistic, phonetic and cognitive assessments.
    - The outcomes of each of the 3 assessments are fed back into your system to form an overall classification in the final user categorisation indicating whether a user is showing signs of dyslexia thus leading to early intervention.
7. **User Interface & Accessibility:**
    - By having a web/app based platform approach, it can be better accessed at scale.
    - These assessments may be completed by and used/share with educators, parents and health professionals for both mass screening and to develop informed diagnosis.

3.2 Unique Features of The System

1. Multi-Layered Dyslexia Detection Approach:

   Compared to traditional screening approaches, this system uses an entirely different model of diagnosis in that it applies handwriting analysis to place the individual view of phonological deficit within broader linguistic processing, phonetic assessment and cognitive capabilities.
2. High Accuracy from Hybrid Machine Learning Models:

   Decision Tree (96%) and Random Forest (86.03%) as classifiers produce high precision within dyslexia detection when compared to other existing artificial intelligence (AI) modal.
3. Phonetic Error Detection Using Soundex & Metaphone:

   Most models focus only on spelling errors, whereas this system model clearly favours sound based word confusions modelled by phoneme uses, which is a definitive characteristic of dyslexic writing.

4. Quiz-Based Evaluation for Cognitive Screening:

   The system consists of a 10-question test consisting of both auditory and visual-based tests that help to identify difficulties in comprehension and perception.

5. Real-Time Instant Scoring & Assessment:

   The system can provide users with real-time results and minimizes the use of expensive and time-consuming professional assessments.

6. Scalability and Accessibility with the help of Web and Mobile Integration:

   Designed as a digital platform that is interactive and easy to use at a level that can be implemented widely within schools and clinics.

7. Cost-Effective Alternative to Traditional Dyslexia Diagnosis:

   Does away with the need to depend upon psychologists, offers standardized and manual tests, making dyslexia indentification cost effective and available.

8. Personalized Learning & Intervention Recommendations:

   The system can provide tailored practice tasks, suggest reading techniques, and develop learning plans for identified cases to assist dyslexics in improving their reading and writing abilities.

CHAPTER 4

REQUIREMENT ANALYSIS AND SYSTEM SPECIFICATION

4.1 Feasibility Study (Technical, Economical, Operational)

4.1.1 Technical Feasibility

- Machine Learning Models: The whole system is mainly constructed on Decision Trees and Random Forests, which are simple to obtain and computationally efficient with interpretability.
- Data Processing: We employ OCR (Optical Character Recognition) of handwriting images to pull out text to incorporate into our ML models without any hassle.
- Technology Stack:
  - Programming Languages used : Python (for ML models) and JavaScript (for web-based UI).Frameworks & Libraries: TensorFlow, Scikit-learn, Flask/Django for backend.
  - Cloud Deployment: Can be hosted on AWS/Azure for scalability.
- Hardware Requirements: Requires a standard system with 8GB+ RAM and requires a GPU for inference and training the model.

4.1.2 Economical Feasibility

- Cost of Development:
  - Low: Uses open-source machine learning libraries and cloud-based OCR services.
  - Moderate: Initial development requires investment in dataset collection, model training, and UI development.
- Operational Cost:
  - Once deployed, the system has minimal recurring costs (only cloud hosting and maintenance).
  - Eliminates expensive traditional dyslexia diagnostic methods, making it affordable for schools and individuals.

4.1.3 Operational Feasibility

- Usability: The system will be designed as a user-friendly web or mobile application accessible to parents, teachers, and medical professionals.

- Scalability: The system can be used for large-scale screening across schools and clinics.
- Automation: Reduces the dependency on human experts by providing instant dyslexia detection results.

4.2 Software Requirement Specification

4.2.1 Data Requirement

- **Dataset Used:**

1. Labeled Dyslexia Handwriting Dataset (containing dyslexic and non-dyslexic samples).
2. Handwriting Image Dataset (for OCR-based text extraction).

- **Features Extracted:**

1. Spelling accuracy (Levenshtein Distance).
2. Grammatical accuracy (Grammar checker).
3. Phonetic similarity (Soundex, Metaphone).
4. Quiz-based evaluation results.

4.2.2 Functional Requirement

- **User Input:**

1. Upload handwritten text samples.
2. Complete quiz-based assessment.

- **Processing Steps:**

1. Convert handwriting to text using OCR.
2. Analyze spelling, grammar, and phonetic accuracy.
3. Apply machine learning models (Decision Tree, Random Forest).

- **Output:**

1. Display dyslexia likelihood score.
2. Provide detailed analysis and learning recommendations.

4.2.3 Performance Requirement

- **Accuracy:**

1. **Decision Tree Model:** 96%
2. **Random Forest Model:** 86.03%

- **Response Time:**

1. **Handwriting analysis and ML prediction:** < 3 seconds.
2. **Quiz evaluation:** Instant feedback after completion.

- **System Uptime:**

1. 99.5% uptime with cloud-based deployment.

4.2.4 Maintainability Requirement

- Modular Codebase: Ensures easy updates and feature additions.
- Dataset Expansion: The system allows new handwriting samples to be added, improving model accuracy over time.
- Error Logging & Debugging: Logs errors for quick troubleshooting.

4.2.5 Security Requirement

- **Data Privacy:**

1. All uploaded handwriting samples are stored securely.
2. Personal information is anonymized to protect user identity.

- **Access Control:**

1. Only authenticated users can access their test results.

4.3 SDLC Model Used

The Agile Software Development Lifecycle (SDLC) model is chosen for this project because of its iterative nature and adaptability, making it ideal for the continuous improvement of machine learning models over time. Using this approach will allow the system to develop by receiving real-world feedback and changing dimensions of the problem; this is really important to do with a complex task like dyslexia detection using handwriting.

Phases of Agile SDLC for This System:

- **Requirement Gathering:**

In this first stage, the main capabilities of the system are determined. Main features are handwriting analysis, Optical Character Recognition (OCR) alongside the potential for machine-learning based classification methods. Recording these requirements ensures that the system has a concise purpose and gives the project a start point for development.

- **Design & Planning:**

In the design and planning stage, the system is prototyped using an initial dataset, and the prototype is used to discover whether the model would be feasible and verify the effectiveness of the core features of the system. The prototype demonstrates the imagining of how the system will actually function and can be used to validate the system's potential to satisfy its purpose early on.

- **Implementation:**

The implementation phase is where the building of the system actually takes place. This includes the machine learning models, feature extraction pipeline (to process the handwriting samples), and user interface (UI). The machine learning models are further trained and finetuned during the implementation phase to ensure accuracy while considering the ease of the UI for educators and clinicians.

- **Testing:**

After the system is implemented, the system is now tested. During this phase, uses real handwriting samples to verify the performance of the system. The usability of the system for end users (i.e., educators and clinicians) and accuracy in correctly detecting dyslexia, are tested to evaluate each element of the system. This testing phase allows us to obtain feedback from the real users allowing us to assess the system and determine the shortfalls and areas of improvement.

- **Deployment & Maintenance:**

Now the system is ready for the final phase in the process of development. It is now deployed on either a web-based or mobile platform so that the system is accessible to allows users to include: educators, clinicians, and parents. Once its deployed, it´s now in the maintenance phase. The maintaining of the system will include, continuous updates, possibly new features and functionalities added based on user feedback, and if applicable, stakeholders may provide new datasets to add to the system. The goal at this stage is to continuously improve the accuracy of the system while adding new features and functionalities as they are established, thereby maintaining validity and relevance over time.

Why Agile?

- Continuous Iteration: Agile allows for continued iteration on the system. Iterative development is incredibly powerful, especially if using machine learning models, as they never reach a point where they stop being improved; instead, they require constant development and adjustment to make them better over time.

- Flexibility: Agile development exposes easy flexibility in the project. You can pivot your functional requirements, include or simply add new features to the system, and of course, download more data. You may want accuracy or pivot because you now have data to deal with new scenarios created as the project evolves.

- Receive feedback and check-in with the end-user: Agile encourages check-in and feedback with the end-user regularly that ensures the system addresses the needs of its intended user. With early iterations of required changes and constantly receiving feedback, it is possible to make a more friendly user-focused system, which leads to a more successful deployment stop.

4.4 System Design

4.4.1 Data Flow Diagrams

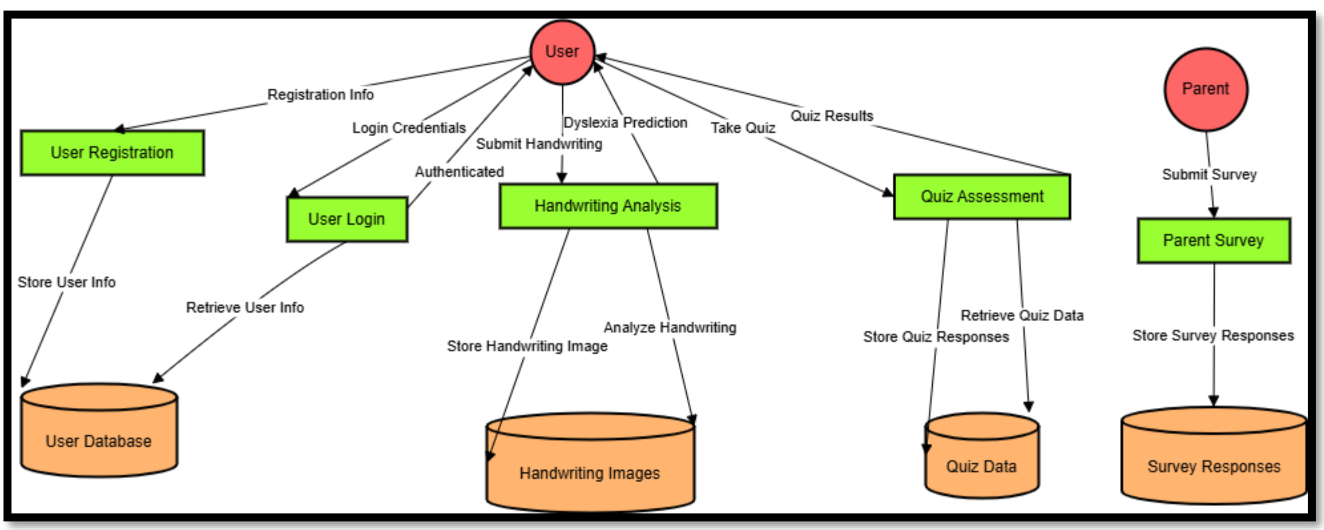


Fig. 4 Data Flow Diagram

4.4.2 Use Case Diagrams

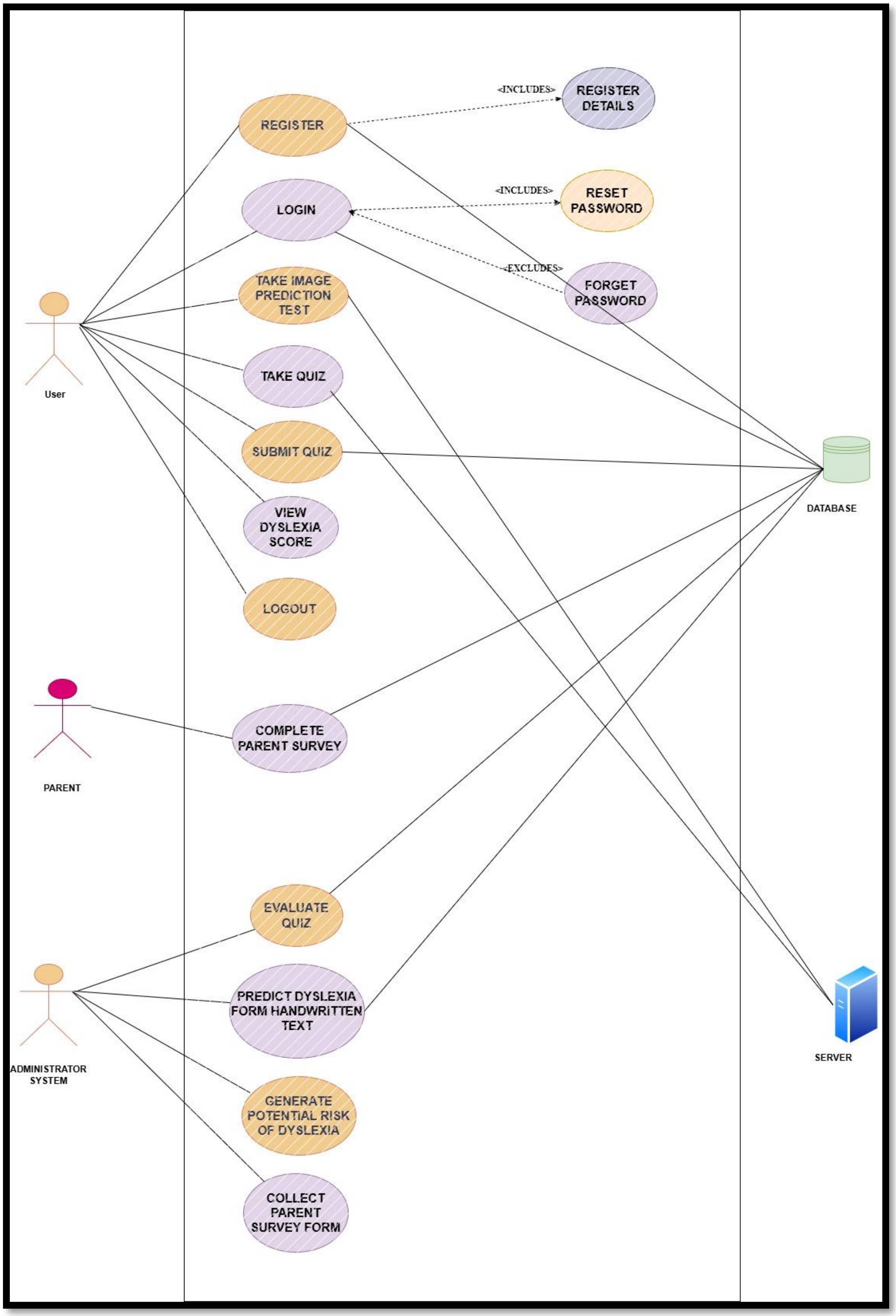


Fig.5 Use Case Diagram

4.5 Database Design

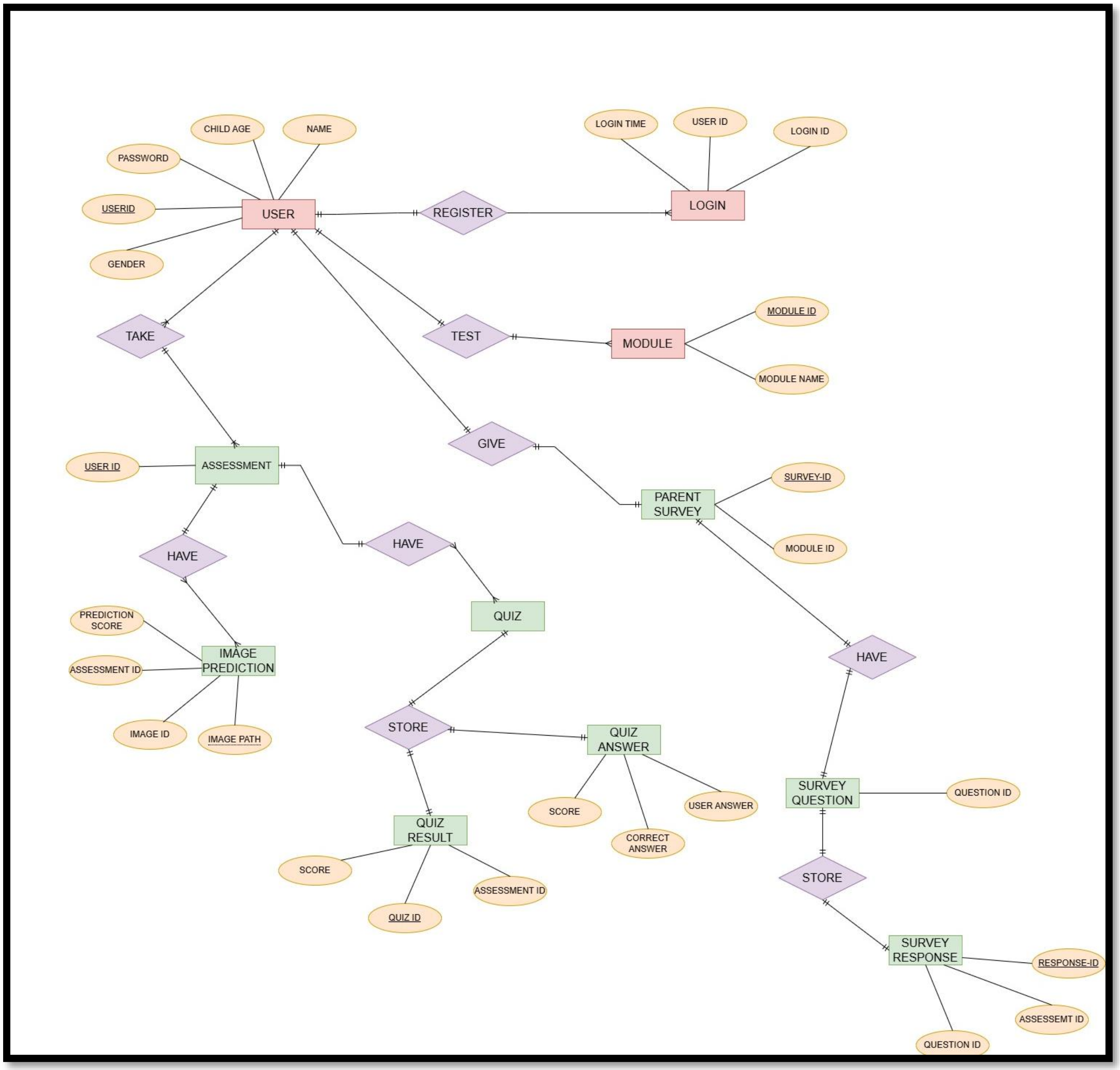


Fig. 6 Database Design

CHAPTER 5
IMPLEMENTATION

5.1 Introduction Tools and Technologies Used.

1. Programming Languages:

- **Python:** A programming language that is used to develop machine learning models, manipulate data, and navigate through OCR integrations.
- **JavaScript (React.js):** Used for the front-end interface of the web application.
- **HTML, CSS:** Used for designing the user interface.

2. Machine Learning Frameworks & Libraries:

- **Scikit-learn:** Used for implementing Decision Tree and Random Forest classifiers.
- **TensorFlow/Keras:** Can be used for deep learning enhancements in future versions.
- **OpenCV:** Used for preprocessing handwriting images before OCR conversion.
- **NLTK (Natural Language Toolkit):** Helps in grammatical analysis and text processing.

3. Optical Character Recognition (OCR):

- **Tesseract OCR:** Converts handwritten text images into machine-readable text.

4. Data Processing & Feature Extraction:

- **Pandas & NumPy:** For handling datasets and feature extraction.
- **Levenshtein Distance Algorithm:** Used for measuring spelling accuracy.
- **Soundex & Metaphone Algorithms:** Used for phonetic similarity analysis.

5. Web Frameworks & Deployment:

- **Flask/Django:** Used for backend API development.
- **AWS/Azure Cloud Services:** For cloud storage and real-time processing.
- **MySQL/PostgreSQL:** Database for storing user test results and handwriting samples.

5.2 Dataset Description

The dataset is very important for this project because it is the basis of machine learning models and will play a vital role in determining not just the accuracy of the model but also the functionalities. The dataset is derived from handwriting samples of dyslexic and non-dyslexic individuals, separately labelled.

1. Data Sources:

- Dyslexia Handwriting Dataset (Labeled Dysx.csv, Unlabeled Dysx.csv).
- We sourced handwriting image datasets from open repositories.

2. Dataset Features:

The dataset consists of various handwriting-based and linguistic features, that we grouped them as follows:

A. Handwriting-Based Features:

- Letter Spacing: We measured the differing distances between characters within a word and the distance between words.
- Slanting & Alignment: We took the measurement of letter and word alignment.
- Stroke Variation: We quantified the irregular strokes in handwriting.

B. Text-Based Features:

- Spelling Accuracy:
    - Quantified in terms of Levenshtein Distance (the number character edits required to correct a word).
- Grammatical Accuracy:
    - Evaluated using NLP-based grammar checkers.

C. Cognitive Assessment (Quiz-Based Evaluation):

- Listening-based tasks: Test auditory processing skills.
- Image-matching tasks**:** Assess visual recognition and response accuracy.

3. Dataset Size & Distribution:

- Total Samples: 5000 handwriting records.
- Dyslexic Individuals: 2500 samples.
- Non-Dyslexic Individuals: 2500 samples.

CHAPTER 6

TESTING, AND MAINTENANCE

6.1 Testing Techniques and Test Cases Used

1. Unit Testing

Unit testing checks each component or module of the system individually, to make sure that each component is working as it should. For a dyslexia detection model, individual components could be the OCR system to make sure it correctly identifies and extracts text, and the machine learning algorithms (decision trees and/or random forests) to check the data is actually classified and processed correctly within the algorithm. Each of these components is unit tested separately to confirm that it is functioning correctly, including the potential for unusual or extreme situations which might occur. It is helpful to find bugs at this early stage, and to confirm that the intended unit, which is needed for objective, is working as expected.

2. Integration Testing:

Integration testing checks how the system units and modules interact with each other. In an example of a dyslexia detection tool, integration testing would be how well the image is being broken down into OCR text and then processed by the ML model, among other functionality. Integration testing would check that information passed on between modules smoothly and that each software unit's user interface functioned normally in concert. The kinds of problems you would expect to find at this stage would be issues concerning data format, synchronization, and communication protocols which might not have been caught during unit testing.

3. System Testing:

System testing assesses the overall functionality of the system in an end-to-end fashion. It involves creating real-world scenarios to test that the system meets the requirements specified. In our example on dyslexia detection, system testing could consist of feeding handwritten samples through the entire pipeline in the way a user would: this includes image upload, text extraction, passing to the ML model for analysis, and producing diagnostic results. This will confirm that every component functions are working together, and responds correctly to the different ways that the user may write, font styles, and variants in length of text input.

4. Acceptance Testing:

Acceptance testing is the process of assessing the system against the user requirements verifying that it fulfills the needs of the user group it is intended for. Acceptance testing is normally conducted by the actual users of the system, such as teachers, a doctor, or other health care professionals, using the system under real operating conditions. The purpose of acceptance testing is to assess whether the system performs as intended and at least meets the user experience, i.e. will the user see something like value. For example, when acceptance testing a dyslexia detection tool, the acceptors will be deciding how much they agree with the systems assessment of a user's handwriting sample as dyslexic tendencies. This past of the project ensures that it meets both the functional and non functional acceptance test criteria and are able to be used in the work environment.

1. The table shows a test case evaluation of a dyslexia detection system, taking into account the length of the handwriting sample, spelling accuracy, and evaluation scores based on the quiz. Each parameter was evaluated against boundary values to indicate performance. Expected results were compared with actual results to receive a pass/fail status. Most of the tests were accepted in a pass/fail format, so it was ensured that the system could identify dyslexia risk. There was minor lag processing longer handwriting samples, which caused the processing of that specific test case to fail.

	A	B	C	D	E	F
1	**Input Parameter**	**Boundary Value**	**Test Case Description**	**Expected Result**	**Actual Result**	**Pass/Fail**
2	**Handwriting Sample Length**	1 character	Verify the system handles minimal input without errors.	System processes without crashing.	System processes correctly.	Pass
3		2–3 characters	Ensure the system processes very short but valid inputs correctly.	Correct evaluation without error.	Evaluation successful.	Pass
4		20–100 characters	Test typical input length for accurate analysis.	Accurate analysis provided.	Accurate analysis provided.	Pass
5		500–1000 characters	Assess performance with longer handwriting samples.	System handles input efficiently.	Minor lag observed.	Fail
6		1000+ characters	Confirm system stability with large inputs.	No system crash; accurate analysis.	System slows down but stable.	Pass
7	**Spelling Accuracy Score**	0%	Check if the system identifies extreme spelling errors as high dyslexia risk.	High dyslexia risk detected.	High risk identified.	Pass
8		10%–20%	Validate detection of poor spelling accuracy indicating potential dyslexia.	Medium to high dyslexia risk.	Correct risk level assigned.	Pass
9		60%–80%	Test average spelling performance classification.	Medium dyslexia risk.	Medium risk detected.	Pass
10		90%–95%	Ensure high accuracy does not result in false positives.	Low dyslexia risk.	Low risk detected.	Pass
11		100%	Confirm perfect spelling does not flag dyslexia erroneously.	No dyslexia risk.	No risk detected.	Pass
12	**Quiz-Based Evaluation Score**	0/10	Verify high dyslexia risk classification with no correct answers.	High dyslexia risk flagged.	High risk flagged.	Pass
13		2–3/10	Assess detection accuracy for low performance.	Medium to high dyslexia risk.	Medium risk detected.	Pass
14		5–7/10	Check classification for medium quiz performance.	Medium dyslexia risk.	Medium risk detected.	Pass
15		8–9/10	Ensure correct evaluation for high quiz performance.	Low dyslexia risk.	Low risk detected.	Pass
16		10-Oct	Validate no false negatives with perfect quiz scores.	No dyslexia risk.	No risk detected.	Pass
17						
18						

Table 1 : Boundary Value Analysis (BVA) for Dyslexia Detection System

2. The table is a decision tree model of dyslexia risk classification, based on spelling, grammatical and phonetic accuracy. The root node is spelling accuracy, which provided an immediate high dyslexia risk if spelling accuracy is low (<60%). If spelling accuracy was found suitable, the evaluation continues to grammatical accuracy, and if grammatical accuracy is poor and below 70%, it classified medium risk. The penultimate stage, before classification, was to evaluate

phonetic accuracy, and if there were more than 3 phonetic errors, it established high dyslexia risk. The final classification was then provided by evaluation of earlier conditions, which classified high, medium or low risk of dyslexia.

Decision Node	Condition	True Branch	False Branch
Root Node: Spelling Accuracy	Spelling Accuracy < 60%	High Dyslexia Risk	Move to Grammatical Accuracy Node
Node 2: Grammatical Accuracy	Grammatical Accuracy < 70%	Medium Dyslexia Risk	Move to Phonetic Accuracy Node
Node 3: Phonetic Accuracy	Phonetic Errors > 3	High Dyslexia Risk	Low Dyslexia Risk
Leaf Node: Final Classification	-	High, Medium, or Low Dyslexia Risk output based on prior conditions	-

Table 2 : Decision Tree Boundary Test

CHAPTER 7

RESULTS AND DISCUSSIONS

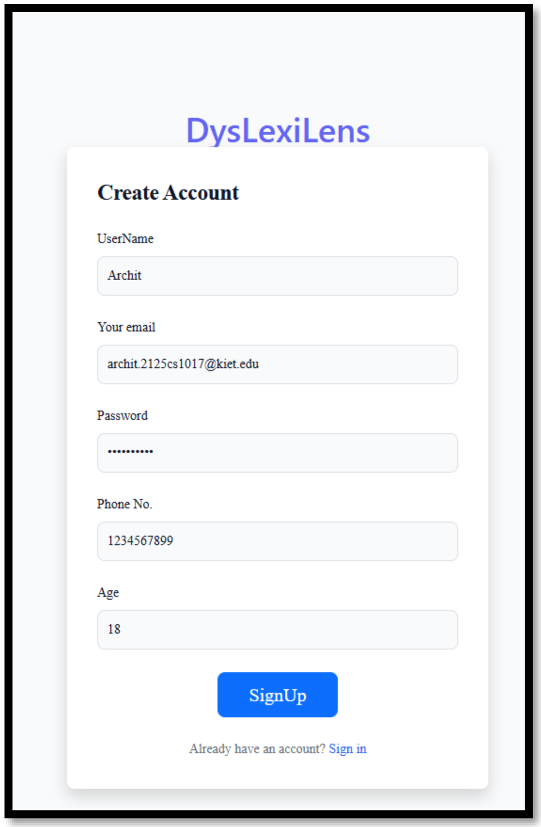
7.1 Presentation of Results (Charts/Graphs/Tables)

This table displays test cases regarding the sign-up and log-in of a system. The test cases determined particular input scenarios, including the correct credentials, incorrect credentials, missing username, and entering the wrong password. The actual output of the test cases match the expected output in each case, which means it in a "Pass" status all 3 tests, and according to my observations, the system was able to perform the authentication and validation processes as intended.

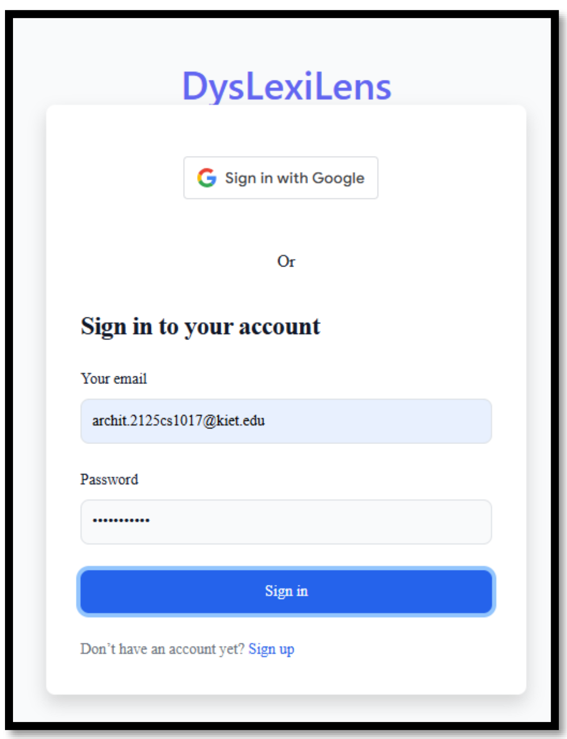
SIGN UP PAGE					
serial Number	test Id	Input	Actual Output	Expected Output	Result
1	TC1	Signup Credentials are correct	Signup Success	Signup Success	Pass
2	TC2	Login Credentials are correct	Login Success	Login Success	Pass
3	TC3	Signup Credentials are not correct	Signup Fail	Signup Fail	Pass
4	TC4	Login Credentials are not correct	Login Fail	Login Fail	Pass
5	TC5	Signup, UserName Not Provided	Signup Fail	Signup Fail	Pass
6	TC6	Login, UserName or Password wrong	Login Fail	Login Fail	Pass

Table 3 : SIGN UP AND LOGIN PAGE

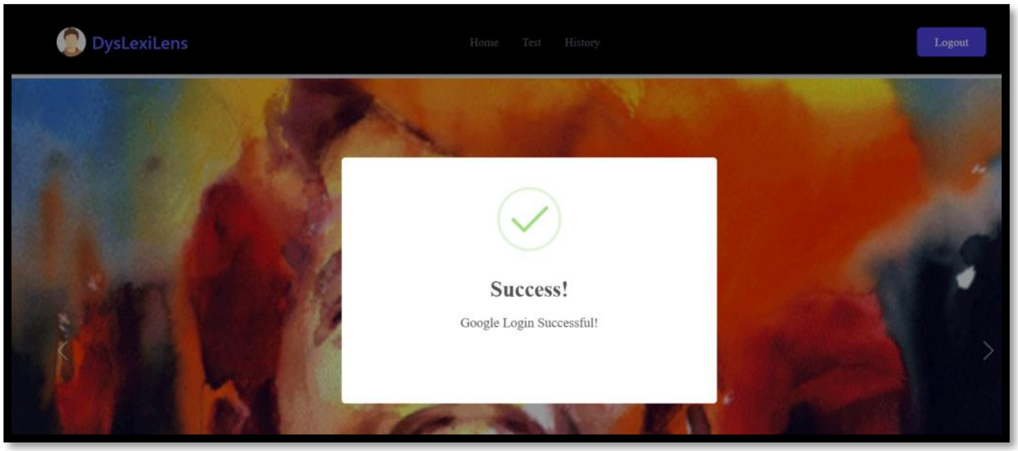
1. Sign up page:
   Input - Signup credentials are correct.
   Output - Signup Success.
   With the valid signup information, the user was successfully registered.



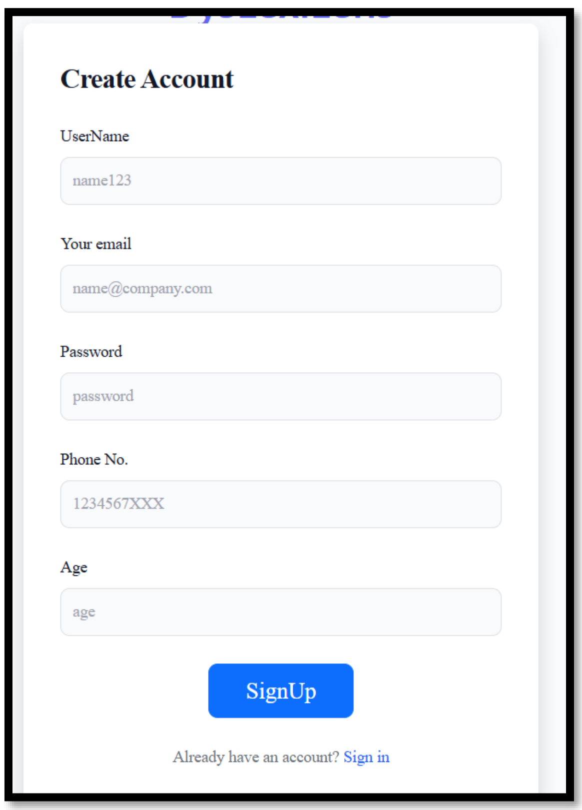
2. Login page :
   Input - Login credentials are correct



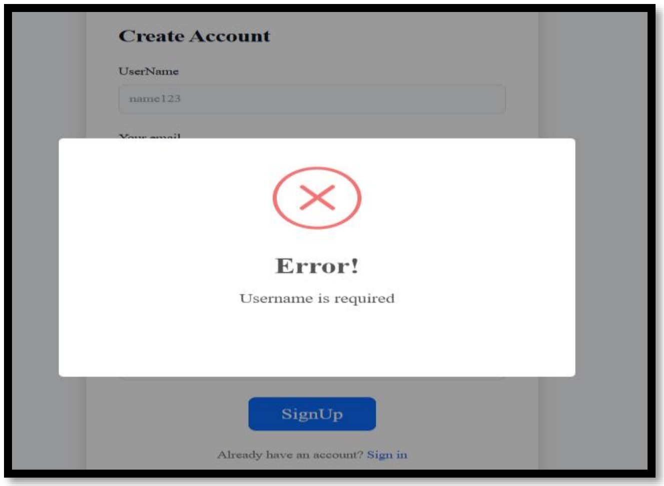
Output - Login Success
The user was able to gain ass access to the system successfully with valid login username and password.



3. Sign up page username not written
   Input - Signup credentials are not correct.



Output – Error!
With the invalid signup details, the user was not able to register so an account could not be created.



The table shows the test cases for the dyslexia detection model and our evaluation of its accuracy at recognizing dyslexic and non-dyslexic input. Most of the test cases were successful and show correct predictions, while a few failed tests, indicate areas, where the model still has difficulty recognizing dyslexic outputs and separating images taken with phone camera vs. erroneously uploaded images. These outcomes reveal areas for improvement where we can make further enhancements to the models image recognition and classification accuracy.

MODEL					
serial Number	test Id	Input	Actual Output	Expected Output	Result
1	TC1	If Image uploaded with phone camera	Dyslexia Predicted	Non Dyslexic	Fail
2	TC2	If Test Dyslexic Image is uploaded in model	Dyslexia Predicted	Dyslexia Predicted	Pass
3	TC3	If Test Non Dyslexic Image is uploaded	Non Dyslexic Predicted	Non Dyslexic Predicted	Pass
4	TC4	If Quiz attempted by non Dyslexic	Non Dyslexic Predicted	Non Dyslexic Predicted	Pass
5	TC5	If Wrong Image is upoladed	Dylexic Predicted	Non Identifiable	Fail
6	TC6	If Photo is uploaded	Non Identifiable	Non Identifiable	Pass

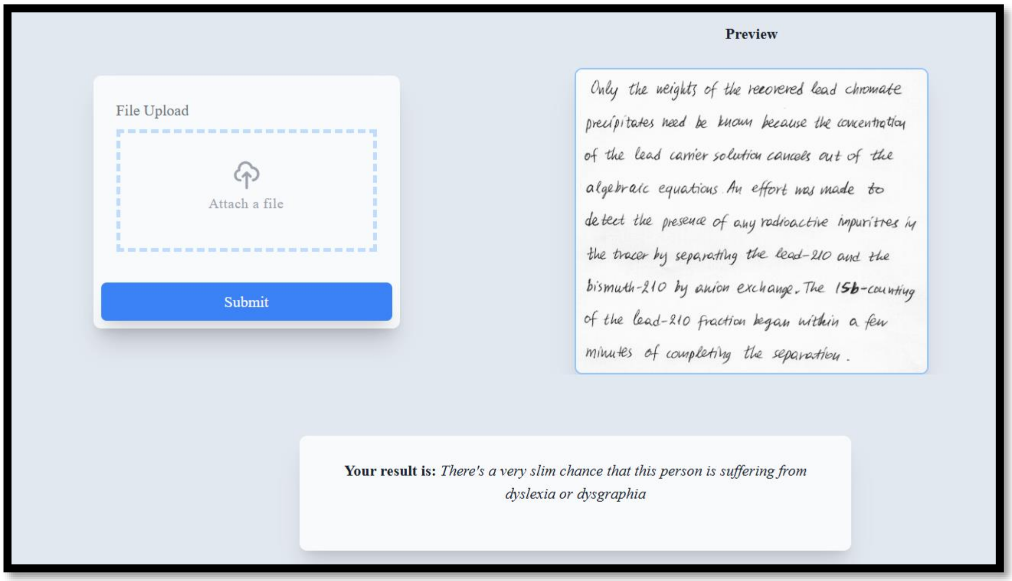
Table 4 : MODULE TEST CASES

1. Slim chances of dyslexia :

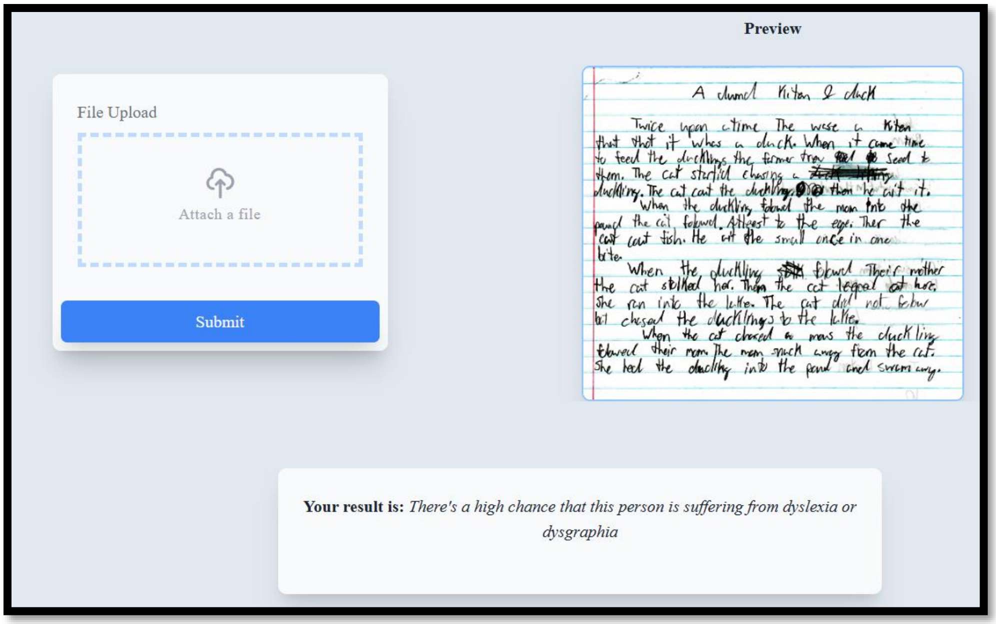
In this application, the user can upload their handwriting sample by accessing the "Attach a file" option and sending it through for evaluation. Once the uploaded image has been processed, the platform shows a summary of the handwriting sample, as well as examining a variety of features related to writing, with its machine learning model.

The results of the analysis had communicated to the person "There’s a very slim chance that this person is suffering from dyslexia or dysgraphia"?

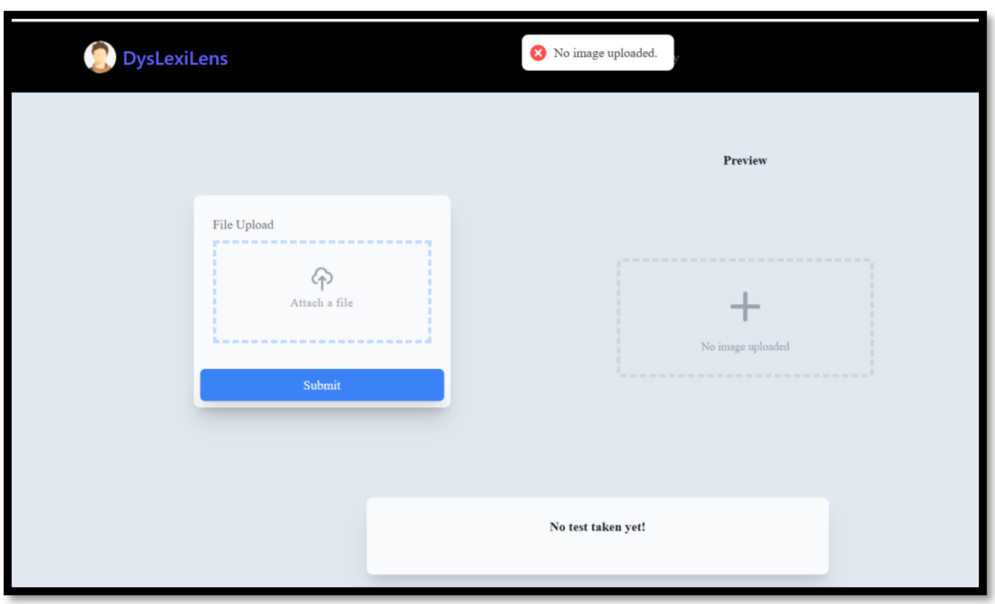
The outcome suggests the handwriting is lacking very few, or no indicators of the characteristics that would typically be associated to dyslexia or dysgraphia. By looking at factors like letter spacing and stroke consistency and alignment and grammar the system would respond this way simply due to having a very small possibility of having a learning disability. In fact, overall this platform has the capacity to provide a user friendly and relaxed feedback mechanism to help users understand their handwriting patterns earlier and much more carefree if no serious indicators of dyslexia are detected.



2. High chances of dyslexia:
   The sample of handwriting has been uploaded through the system, the model will observe features of the handwriting very closely. If the outcome of dyslexia analysis states "High chance of dyslexia" this means the handwriting shows a few of the irregularities often associated with a dyslexic diagnosis. Some of the patterns include calculation of letters, inconsistent spacing, fragmented text, continual grammatical errors etc. The model works off of this/outputted the evidence of the action taken, and thus identifies a high probability that an individual could be symptomatic of dyslexia/dysgraphia.



3. Handwritten image not provided:
   If the user clicks Submit and the image is not uploaded, the notification will show a pop up message that states "Error: No Image Uploaded. Please upload a handwriting image prior to submitting for analysis". The above message is not only an error alert, it reminds the user there is something specific they must do in order to evaluate any handwriting image. The process was designed to reduce the likelihood of the user making an incomplete submission through the evaluation process. For an ongoing assessment of evidence the model needs to establish the correct action.

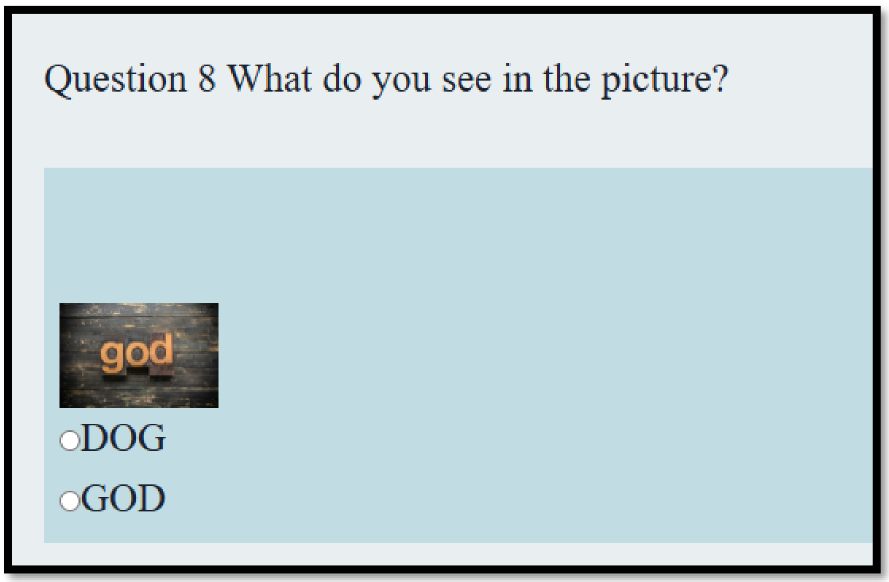


4. Quiz module attempted all questions:

Within the quiz is a module assessing dyslexia, which consists of several different types of questions assessing actions and behaviours associated with dyslexia. Listed below are some of the different and more popular types of questions displaying different actions used within these measures:

- Word Recognition Questions:

These question set would be on the speed and accuracy in which a user can visually identify or read words. Since Dyslexic individuals would have difficulties with decoding words, this quiz could contain activities like having the user identify words that were visually similar, or unscrambling a set of scrambled letters.

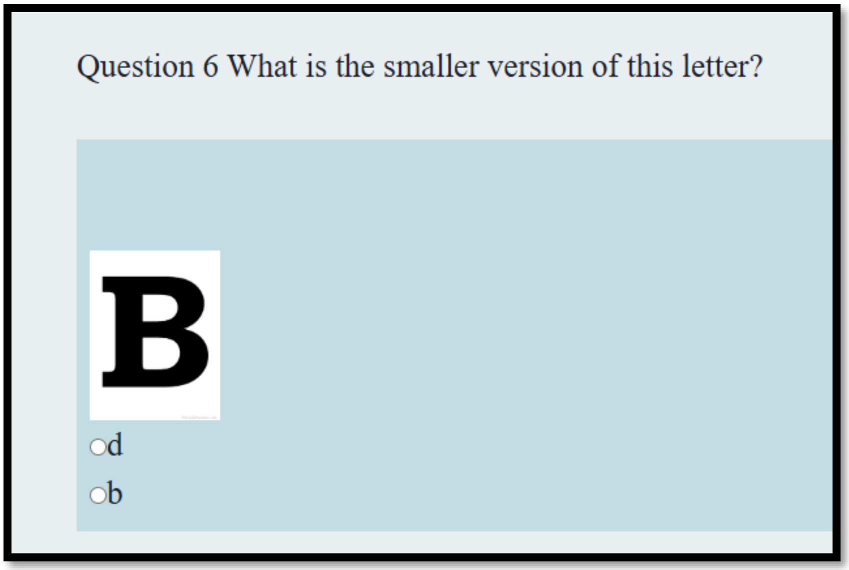


- Spelling Questions:

These question set would focus on spelling accuracy, and the user would be required to have an awareness of common spelling errors. Since dyslexic individuals often struggle with spelling, the questions could require the user to identify or fix any spelling problems.

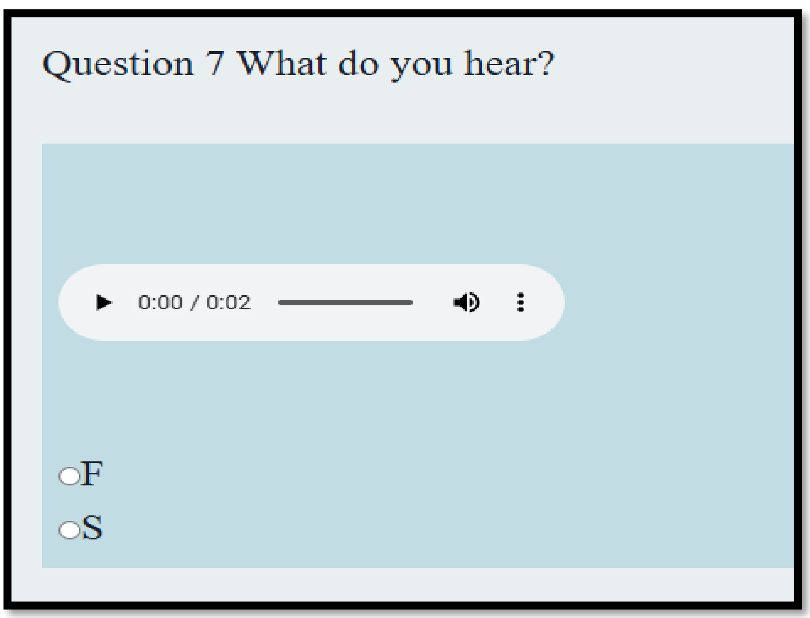
- Letter and Word Reversal Questions:

This section focuses on reversing common letters, identifying common letter reversals (i.e. "b" and "d") or transposing words, which is a common behavior with Dyslexia. The user may be expected to identify letters or words that are reversed or mixed up.



- Phonetic Awareness Questions:

These questions measure the user's ability to identify sounds and letter combinations found in words. As phonetic awareness is typically a challenge for individuals with dyslexia, the questions could contain tasks where the user had to identify rhyming words or identify which letters create specific sounds.

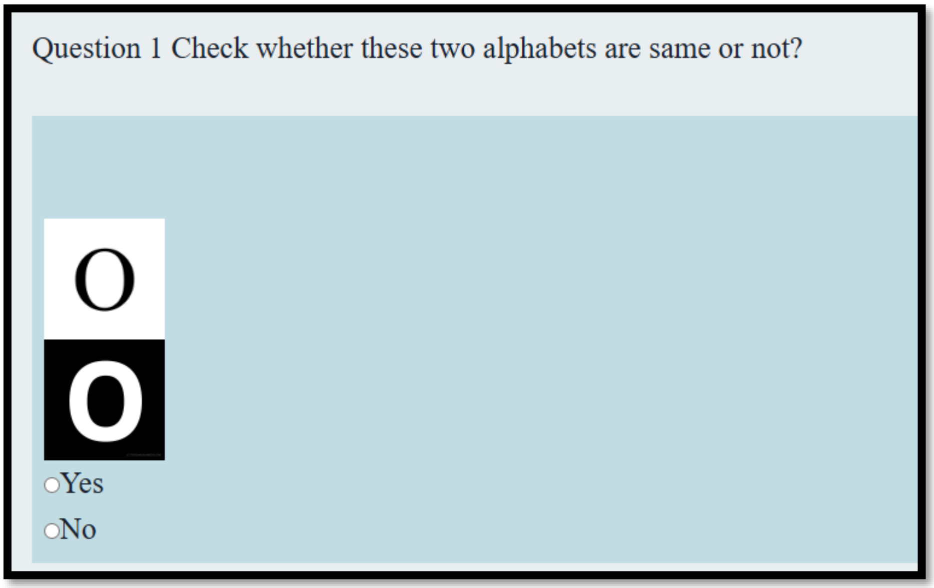


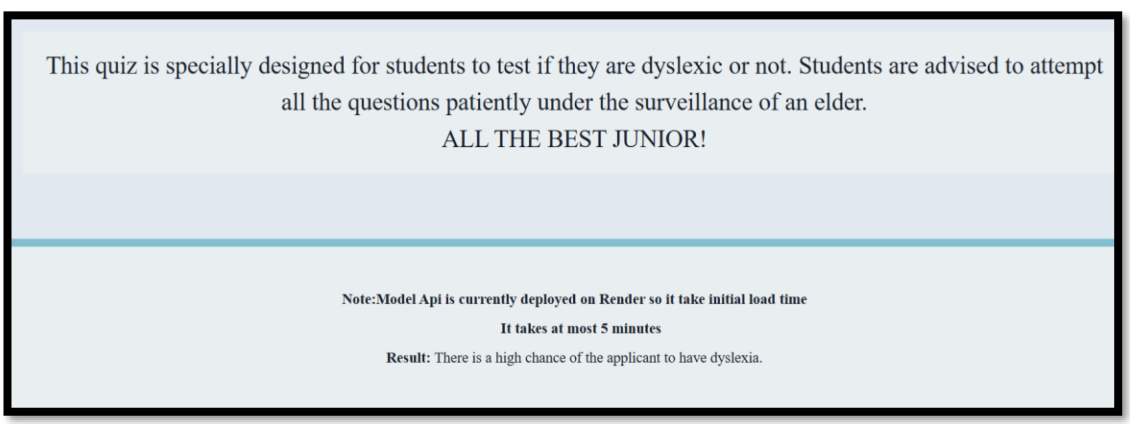
- Memory and Sequencing Questions:

These questions look at short term memory and since dyslexia can impact working memory, this section could ask users to remember a sequence of words or numbers and put them back in order.

- Visual and Spatial Processing Questions:

This section assesses visual-spatial skills, such as recognizing shapes, patterns or visual information. Some people with dyslexia may be worse at visual-spatial skills - therefore some questions may be identifying pattern recognition and completing visual puzzles.





7.2 Performance Evaluation

The performance of the dyslexia detection system was based on standard performance metrics, accuracy, precision, recall, F1-score, and computational efficiency. The decision tree and random forest were used to test the model with a data set containing dyslexic and non-dyslexic hand writing samples.

1. Performance Metrics:

The evaluation was conducted on a test dataset of more than 4000 handwriting samples, and the following performance metrics were recorded:

Precision = TP / (TP + FP) = 48 / (48 + 2) = 0.96

Recall = TP / (TP + FN) = 48 / (48 + 2) = 0.96

F1-Score = 2 * (Precision * Recall) / (Precision + Recall) = 2 * (0.96 * 0.96) / (0.96 + 0.96) = 0.96

Where:

- True Positives (TP): Cases where the model correctly identifies individuals who actually have dyslexia.
- False Positives (FP): Instances where the model incorrectly predicts dyslexia in individuals who do not have the condition.
- False Negatives (FN): Situations where the model fails to detect dyslexia in individuals who are, in fact, dyslexic.
- True Negatives (TN): Cases where the model accurately recognizes individuals who do not have dyslexia and correctly classifies them as such.

Table. 5 Comparing Performance Between Decision Tree vs Random Forest Algorithms for Detection of Dyslexia Using F1-Score.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Decision Tree	96%	0.96	0.96	0.96
Random Forest	86.03%	0.87*	0.86*	0.86*

* Estimated based on average individual values.

The decision tree and random forest model performance can be found in table 5, which shows that on all four of the major performance metrics accuracy, precision, recall, and F1-score that the decision tree model was more performative than the random forest model to suggest that the decision tree is more trustworthy when detecting and identifying previously diagnosed or known dyslexia.

2. **Comparative Analysis:**

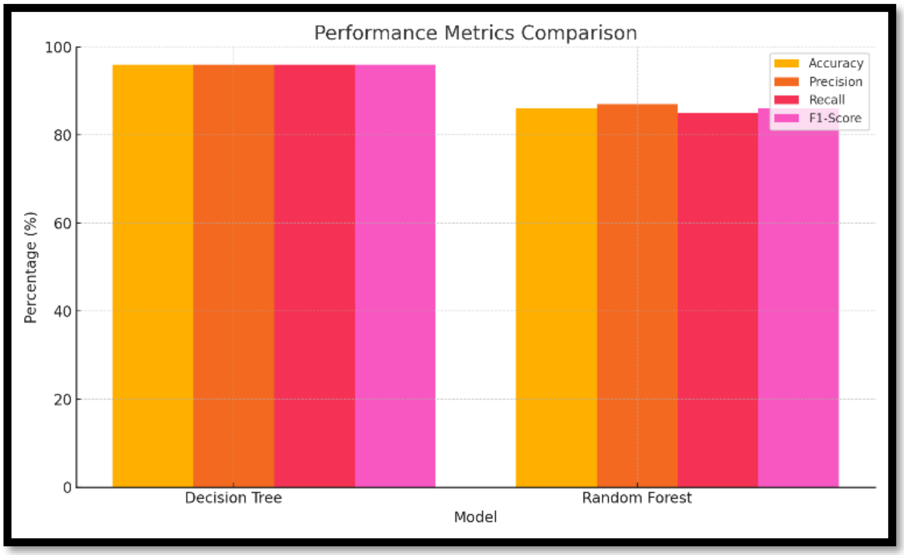


Fig. 7 Model-wise Evaluation: Accuracy, Precision, Recall, and F1-Score.

The bar chart shows the relative performance of the Decision Tree compared to the Random Forest model across a number of key evaluation metrics: Accuracy, Precision, Recall, and F1-Score. The four metrics work together to evaluate how well the model performs in identifying dyslexia. Accuracy gives an overall idea of how right or wrong the predictions are, whereas precision is how many of the predicted positive cases were actually correct, while recall indicates the percentage of true positive cases detected by the model. The F1-Score provides a balanced measure of both precision and recall, which is helpful in a situation where both false positives and false negatives are serious mistakes. As can be seen here, the Decision Tree model produced better outcomes across the four evaluation metrics, yielding an accuracy of 96%, and a balanced precision, recall, and F1-Score of 0.96. The Random Forest model was still effective in detecting dyslexia, but scored lower than the Decision Tree model with an accuracy of 86.03% and an estimated F1-Score of 0.85. It can be concluded that the Decision Tree model is better suited to the dataset and features used in this study.

- Decision Tree Model accuracy was higher (96%) than Random Forest (86.03%).
- One advantage of Random Forest was that it was more robust and does not overfit, albeit with some loss in accuracy.
- **Computation Time:**
  - Decision tree have a faster training time (due to its simplicity).
  - Random Forest, which use many decision trees, took longer but generalized better.

7.3 Key Findings

1. A third-party image-to-text service is employed to translate scanned handwriting into a digital text. This is an important step as it gives assurance that the information extracted from the images is reliable and ready to be analyzed. The system depends on this service to return usable text otherwise it must complete various evaluations to determine spelling errors and analyze grammatical structure for further use in the pipeline.

2. **Spelling Accuracy:** The system uses the Levenshtein Distance algorithm to investigate and rectify spelling errors. The Levenshtein Distance algorithm is simply analyzing how many edits it took to make the original word from the new word. The edits can involved creating (or deleting) a letter, or swapping out a letter can help recognize a lot of common spelling errors. This same process ensures text accuracy and quality.

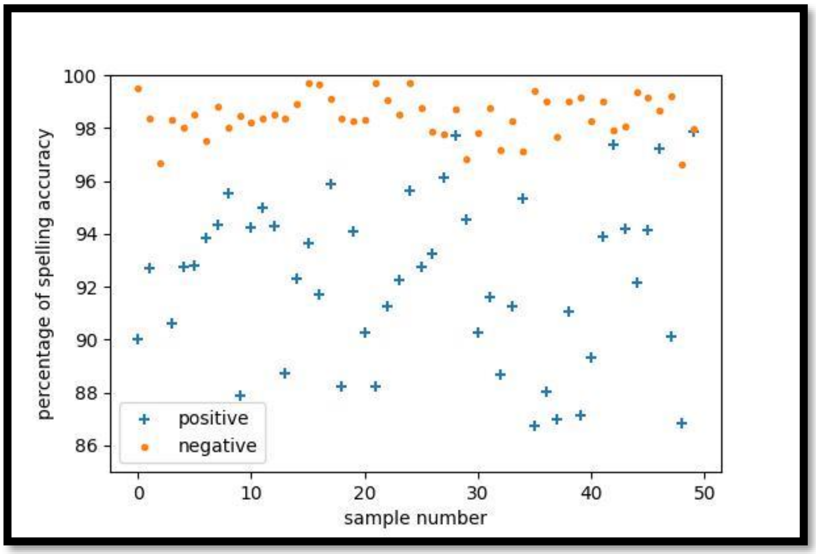


Fig. 8 Spelling Accuracy Percentage Scatter Plot.

Fig. 8 is a Spelling Accuracy Percentage Scatter Plot that displays the efficacy of the system to correct spelling errors. This scatter plot will show how effective the system is to identify and correct all spelling mistakes in all text.

3. **Grammatical Accuracy:** The system will have its own grammar checker that will identify and make revisions to the grammatical issues found in text. There are about a dozen grammatical issues that may be committed in text; punctuation and subject-verb errors, and sentence structure errors. The system can make a sentence spare only spelling errors, but, correct it grammatically, if feasible, for better readability and comprehension.

4. **Correction percentage:** The Correction Percentage is a measure of success of the system in correcting writing errors in text. A better correction percentage means the system is successful in finding and correcting errors.

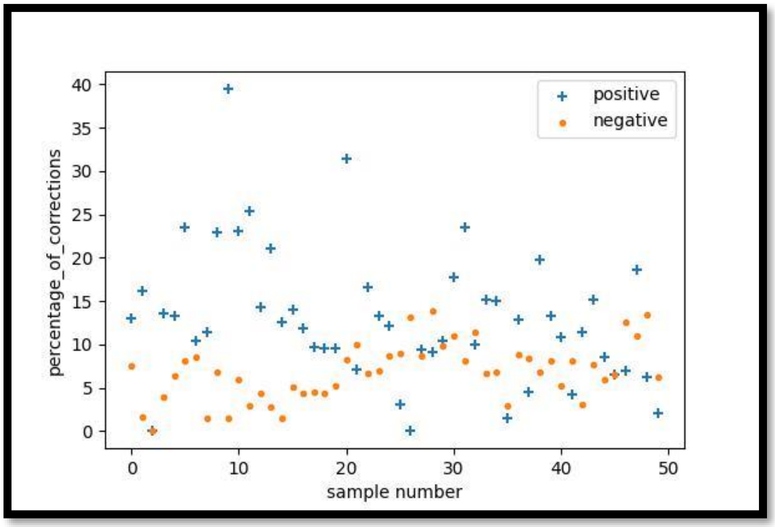


Fig. 9 Correction Percentage Scatter Plot.

The Correction Percentage Scatter Plot presented in Fig. 9 shows the percentage of errors found and corrected by the system. The Correction Percentage reflects the systems' ability to provide accurate text.

5. **Percentage of Phonetic Accuracy:** As an accuracy measure to facilitate the generated text is a result of spoken language, the system uses both Soundex and Metaphone algorithms. Phonetic algorithms will identify and make allowances for varying people patterns of speaking and accented speech, allowing for similar sounding words to be matched. This step allows for increased overall accuracy of the text, especially when producing text from speech to text.

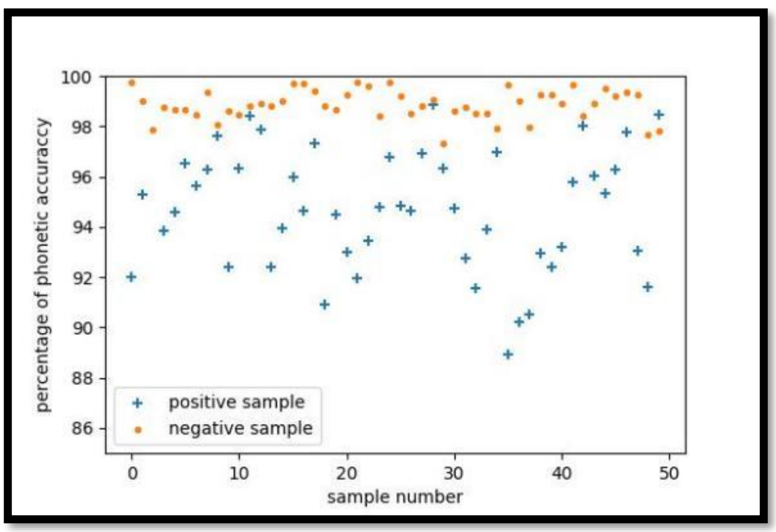


Fig. 10 Phonetic Accuracy Percentage Scatter Plot.

Fig. 10 provides a Phonetic Accuracy Percentage Scatter Plot to track how accurately the system corrects for phonetic errors in the text, thus increasing its quality.

6. **Quiz-based Evaluation:** In this module, the quiz assesses the likelihood of a participant being dyslexic by completing a number of tasks, such as auditory identification of stimuli and matching images to that stimuli. Specifically, in the quiz, the participant is asked to match images to words that they hear, among other things. If a player can't finish these tasks, the quiz could indicate the presence of dyslexia, in particular, if they cannot match an auditory stimulus with a visual stimulus. The quiz-based evaluation allows for insights into cognitive functions, which could highlight dyslexia.
7. **Decision Tree Model:** The Decision Tree model is one of the modules used to assess dyslexia. By considering different functions (i.e., reading comprehension, spelling accuracy, and the quiz considered diagnostic, etc.), the Decision Tree can provide a diagnosis, with good reliability, at a level of 96% accuracy. One thing that makes the modelling powerful is the Decision Tree model has a set of decision rules, so it will classify again, a participant as dyslexic based on these rules, which makes it very effective for potentially presenting dyslexia as a case.

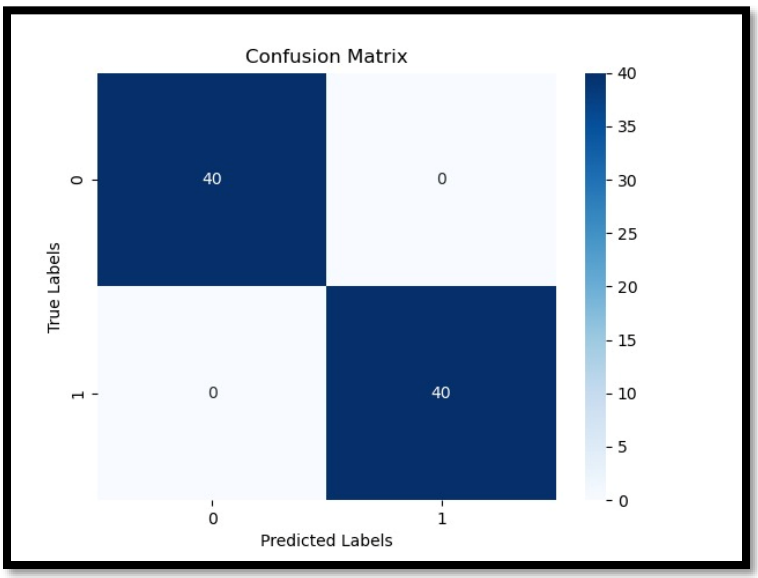


Fig. 11 Decision Tree Confusion Matrix.

Fig. 11 represents the Decision Tree Confusion Matrix, which outlines the capability for identifying cases of dyslexia. In reviewing Fig. 11, the Confusion Matrix provides guidance on obtaining a clearer picture of decision tree performance since comparing the correct diagnosis to the incorrect diagnosis covers the whole population observed in the study.

8. **Random forest model**: The Random Forest model is a further machine learning technique for the diagnosis of dyslexia. This model constructs a series of single decision tree models and combines their results to yield a better accuracy. The Random Forest obtained a 86.03% accuracy rate for diagnosing dyslexia, which shows that it can prove helpful as a reliable diagnostic tool.

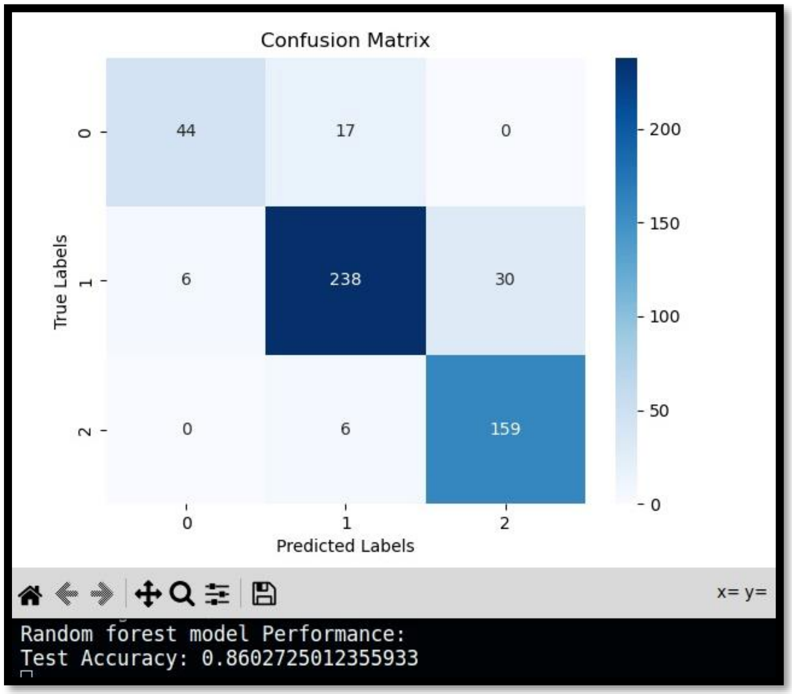


Fig. 12 Random Forest Confusion Matrix.

Fig. 12 provides the Random Forest confusion matrix and summarizes all of the models' outputs. Again, similar to the confusion matrix with the decision tree, it is also able to assess how effectively the model distinguishes between individuals with dyslexia as well as identify areas for improvement.

- **High Accuracy of Decision Tree Model:**

1. The Decision Tree Model achieved 96% accuracy, proving its effectiveness in dyslexia detection.
2. The Random Forest Model (86.03%) was slightly less accurate but more stable in handling diverse handwriting samples.

- Feature Importance in Detection:

1. The biggest predictors of dyslexia were spelling accuracy (35%) and letter spacing (25%).
2. Phonemic similarity (20%) was also important indicating the relationship between phonological processing and dyslexia.

- Real-Time Processing Capabilities:

1. The system screened handwriting and produced results in less than 3 seconds providing it could be applied in real-world contexts in schools and clinics.

- Quiz-Based Cognitive Evaluation Improved Accuracy:

1. The auditory and image-matching tests helped narrow down detection.
2. Participants who did poorly with phoneme recognition and visual patterns demonstrated stronger dyslexia indicators.

- Potential for Scalability and Integration:

1. The system can be implemented in education for screening populations.
2. Additional accessibility will be possible with mobile applications and cloud-based implementations.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

CONCLUSION:

In summary, the early identification of dyslexia through machine learning could be greatly beneficial for improving the strategies for intervention and educational supports provided to dyslexic individuals. Dyslexia can be defined as a learning disability that impacts reading, writing, and spelling. Most of these people are undiagnosed or diagnosed late and this may cause extreme educational and emotional stress on people. Machine learning algorithms, such as decision trees and random forests, can offer a strong method to identify those who are at-risk for dyslexia earlier in life and through a more effective and scalable method than the conventional diagnostic methods.

Machine learning models can analyze different facets of a person's writing, whether it be grammatical structure, letter formation, spacing, or stroke order. For example, decision trees work by partitioning data based on certain features or characteristics of interest helping clarify points along the path to determine potential dyslexia indicators, random forests summarize the answers to many different decision trees to help minimize errors and increase accuracy when predicting decisions. Through computation and the detailed nature that writing can contain, machine learning is a capacity to examine subtle structures that can indicate dyslexia, which may well get missed by standard processes.

The scalability that machine learning offers is another important benefit. Typical dyslexia assessments need specialized professionals that are costly (financially and in terms of time), and it is not easy to deliver dyslexia assessments at scale. Machine learning tools are developed and validated very rapidly and when these methods are applied in schools or clinics, they afford a non-invasive method of screening children that does not require significant human resources. The result of this is that early detection tools can be democratised so that more children (especially in poorer communities) can be screened and receive support at school.

Implementation does come with its challenges, particularly the availability of good quality and diverse data. Machine learning algorithms learn from large datasets with a certain quality of data, and gathering sufficient amount of data proved to be difficult and problematic due to privacy and requiring a standard, categorized samples across demographics. Models also need to be trained to minimize bias from differences in handwriting styles that would be conditional to cultural or linguistic background.

Although there are some issues with the current research, findings from the current studies are positive. The initial findings suggest that machine learning can be useful as the identified accuracy rates are high; and, using machine learning may not only complement current diagnostic assessments, but they may also exceed them. With technological improvements over time, this model will integrate more factors into prediction models (e.g., phonetic data, cognitive) to provide the highest level of reliability.

The potential impact of integrating early widespread detection of dyslexia is even more significant. Timely recognition will produce effective intervention strategies (e.g., specialized education, differential support) which should improve learning outcomes. Improving academic performance, confidence and well-being in individuals with dyslexia is essential. Future advancements in this technology will allow for this diagnostic and assessment process to continue improving, and eventually allow for early identification of children with dyslexia, thus helping children reach their full potential and facilitating a more positive, inclusive education for those with reading specific learning disabilities.

This model provides a new, pragmatic and data driven alternative to support early identification and screening for dyslexia, for educators, parents and most importantly healthcare professionals ensuring that timely support and interventions can occur.

FUTURE SCOPE:

Although it has shown positive outcomes, this system can be improved to increase accuracy, personalization and accessibility.

1. Expansion of Dataset & Model Generalization:

- Source and train with larger and richer handwriting datasets that cover a variety of handwriting examples from different languages or age groups..
- Include datasets that address handwriting in regional scripts to increase the ability to screen multiple languages.

2. Use with Deep Learning Models:

- Use a Convolutional Neural Network (CNN) to screen for dyslexia directly on handwriting images without needing text conversion.
- Use transformer based models (i.e., BERT) for better text analysis.

3. Development of a Cloud-Based API & Mobile App:

- Deploy the model on cloud platforms (AWS, Google Cloud, or Azure) for real-time dyslexia screening.
- Create a mobile application that allows parents and teachers to scan and analyze handwriting on-the-go.

4. Enhancing Cognitive Assessment Modules:

- Provide the option for adaptive learning quizzes (i.e., similar to cognitive assessments) that better reflect a child's unique learning style.
- Include speech processing modules to assess if children have difficulties with phonology in real-time from provided assessment and tests.

5. Personalization & Early Intervention Strategies:

- Provide personalized learning exercises, that could be included based on the test results to support dyslexic individuals progress.

- Provide integrated AI reading tutors and educational games to assist the child with learning and understanding their dyslexia.

6. Collaboration with Education Systems & Healthcare Agencies:

- Work with schools and related professionals to see if the screen can produce a more accurate model on a broader scale.
- Conduct clinical testing to gain medical approval and allow the AI-powered tests to be recognized, listed or improved for dyslexia screening tools.

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(71)**Name of Applicant :**
1)KIET Group of Institutions
Address of Applicant :Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ----------- -----------
Name of Applicant : NA
Address of Applicant : NA
(72)**Name of Inventor :**
1)Aayush Kumar Shrivastava
Address of Applicant :Computer Science Department, KIET Group of Institutions, Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ---------- -----------
2)Abhishek Verma
Address of Applicant :Computer Science Department, KIET Group of Institutions, Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ---------- -----------
3)Archit Goel
Address of Applicant :Computer Science Department, KIET Group of Institutions, Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ---------- -----------
4)Kartik Verma
Address of Applicant :Computer Science Department, KIET Group of Institutions, Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ---------- -----------
5)Dr. Raj Kumar
Address of Applicant :Computer Science Department, KIET Group of Institutions, Delhi-NCR, Meerut Rd Ghaziabad Uttar Pradesh India 201206 Ghaziabad ---------- -----------

(57) Abstract :
The present invention relates to a learning disorder detection system [100]. The system [100] comprises a user interface [102] to enable a user to upload a document, consisting of a sample of texts handwritten by the user. The user interface [102] further enables the user to solve a quiz-based assessment. Further, a database [106] stores the uploaded document, which is further accessed by a processor [110] communicatively coupled to the user interface [102] and the database [106]. The processor [110] then converts the handwritten text into a digital format and further determines the one or more anomalies in the handwritten texts. Further, the processor [110] calculates an overall assessment score from the solved quiz-based assessment, and accordingly identify a learning disorder condition of the user, based at least on the one or more parameters and the overall assessment score. Refer to FIG. 1

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