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Detection of Learning Disabilities Such as Dyslexia, Dysgraphia, and Dyscalculia in Kids at Early Stage

Prof. N. G. Pardeshi[1], Landage Rutuja[2]

Mehetre Shraddha[3], Mahajan Vaishnavi*[4], Nagpure Latikaben[5]

[1,2,3,4,5] Department of Computer Engineering

[1,2,3,4,5] Sanjivani College of Engineering, Kopargaon, Maharashtra, India

Email: vismahajan555@gmail.com

https://zenodo.org/record/7950218

Corresponding author: Mahajan Vaishnavi

Abstract:

Neurological processing issues called learning impairments can prevent youngsters from learning. Reading, writing, spelling, and even simple arithmetic are all tough tasks for someone with learning disabilities. About 10% of people worldwide are affected by this, making early diagnosis essential for effective treatment and prevention. Disabilities in learning, including dyslexia, dysgraphia, dyscalculia, and others. Interfere with academic performance but also have long-term effects that extend beyond the academic period. Children must complete a series of exams to determine whether they have such disabilities in their early years. These exams are scored by human experts who then determine, based on the results, whether the students need a certain educational approach. The evaluation may be expensive, time-consuming, and emotionally taxing. In this study, we explore how automating this assessment might be aided by artificial intelligence. In order to analyse the differences between dyslexic/dysgraphia and standard readers/writers and to build a model, we collect a dataset of hand-written text images and audio recordings from both standard children and from children who are dyslexic and/or dysgraphia. The model is trained using basic features discovered through analysis of the images and audio recordings. On the dataset we used, our prototype solution displays relatively high performances. This implies the potential for accurate non-invasive dyslexia and dysgraphia screening once sufficient data are available.

Keywords:

Learning Disabilities, Dyslexia, Dysgraphia, Dyscalculia, CNN.

1. Introduction:

A significant portion of the global population is afflicted with learning disorders like dyslexia, dysgraphia, and dyscalculia. These diseases have the potential to have far-reaching effects on a person's academic achievement, social relationships, and quality of life as a whole. Even though there are now available techniques for identifying and evaluating various learning problems, these procedures frequently call for specialised tools, qualified personnel, and a lot of time and money. When a student or instructor has a learning disability like dyslexia, dyscalculia, or dysgraphia, it may be difficult for everyone involved. It might be difficult to get an accurate diagnosis because early symptoms of these disorders are typically minor. Traditional physiological and psychological tests are unable to detect many illnesses in their early stages, preventing early intervention and effective treatment. Furthermore, there aren't many digital tools available to help kids with these problems learn better.

This study aims to close the gaps by suggesting a comprehensive platform that uses digital technologies to recognize and treat learning problems, particularly dyslexia, dyscalculia, and dysgraphia in their early stages when symptoms are moderate and more tolerable. In this study, we suggest a novel method for detecting and evaluating dyslexia, dysgraphia, and dyscalculia by combining machine learning, deep learning, computer vision methods and voice-assisted examinations. All users of this system, regardless of age or background, will find it easy to use, non-intrusive, and available. Three components make up the suggested system: dyslexia identification using CNN and handwriting images, dysgraphia evaluation using voice-assisted assessments, and dyscalculia assessment using simple arithmetic problems. A standard dataset was utilised for the development and testing of the dyslexia detection system; this dataset included 78275 normal class pictures, 8029 corrected class images, and 52196 inverted class images. Datasets were gathered from three different sources: the “NIST Special Database 19” for uppercase letters [11], the “Kaggle Dataset” for lowercase letters [12], and some datasets for testing from dyslexic students at “Seberang Jaya Primary School in Penang, Malaysia”. 75% of the images that were reversed were used to train the model, and the remaining 25% as well as the user's scribbled images were used to test it. With regard to dysgraphia, we created a voice-assisted exam that assesses accuracy by contrasting the user's response with the right response. We developed a collection of fundamental arithmetic problems in MCQ format for dyscalculia.

For those with learning difficulties, the suggested method has the potential to significantly enhance early identification and intervention. For quick and precise examinations of dyslexia, dysgraphia, and dyscalculia, it can be utilised in schools, clinics, and other contexts. In addition to presenting the findings of our studies, this paper also describes the methodology used to create and test the system, as well as prospective uses and system limits. The method described in this study uses computer vision techniques and voice-assisted exams to identify and evaluate dyslexia, dysgraphia, and dyscalculia. People of various ages and backgrounds can access the system, which is made to be user-friendly and non-intrusive. We built a voice-assisted test for dysgraphia and a set of multiple-choice questions (MCQs) for dyscalculia, and we tested the system using a standard dataset for dyslexia identification. The suggested system, which is adaptable for usage in clinics, schools, and other settings, has the potential to enhance early detection and intervention for learning difficulties. The approach utilised to create and test the system, the findings from our tests, the potential uses and restrictions of the suggested system, as well as the methodology's methodology are all presented in this document.

2. Literature Review:

According to the research [1], Concept Classification utilising SVM and CNN (2020), the SVM model that used a very small dataset obtained an accuracy of 93%; nonetheless, despite the fact that SVM is a very potent technology, reaching the aforementioned extreme veracity was still an anomaly. By employing dossier improvement, the dataset's size was additionally increased and SVM was continuously used, the accuracy was increased to 82%. On the static dataset, CNN performed well and achieved a veracity of 93.57%. Due to CNN's higher veracity, it is determined that utilising it over a big, enhanced dataset of countenances is preferable to using SVM.

Paper[2] shows a client-server web-based software system that can operate on modern devices like tablets and smartphones. It uses state-of-the-art JavaScript APIs and frameworks as well as industry-standard algorithms for multiple hand gesture detection. This algorithm is known as the Dynamic Time Warping algorithm and was specifically designed to recognize complex gestures. The software tools give users the option of carrying out groups of various activities of various types, structured at various levels, starting with merely connecting the dots to finish a word writing and ending with comparison of writing completed with a reference maintained by an expert. The software application aids in diagnosing, researching, and rehabilitating dysgraphia handwriting by giving quick feedback based on objective factors and a comprehensive collection of data recorded in both JSON and INKML structures.

In a publication [3], the handwriting and comprehension of children between the ages of 5 and 8 were correlated with the production of the ILT, a simple activity for developing graphomotor skills. The ILT has been used for research. Children's handwriting (speed and legibility) was evaluated in conjunction with the ILT during Phase I of this study. The following year, Phase II evaluated understanding and handwriting. The results show that there was a strong correlation between understanding and handwriting in the ILT presentation.

In paper [4], different handwriting metrics are taken into account, including whole time, per character time used, "in-air time," and handwriting speed. It has been observed that those who experience issues typically do poorly on writing activities and may need more "in-air time," or time spent with the pen tip away from the paper surface, than average writers.

3. Existing System:

The paper [5] proposes a decision tree-based screening tool for early diagnosis and identification of specific learning impairments (SLD). Web application development is the technology used in the tool. The test consists of detailed examination questions pertaining to several forms of learning disabilities, such as dyslexia, dysgraphia, and dyscalculia. The process entails gathering and utilising a decision tree algorithm to analyse data from the quiz. The decision tree algorithm was chosen for its clarity and capacity to mirror human decision-making. The algorithm estimates the presence of learning difficulties based on the quiz results from the students and how long it took them to complete the questions.

The research [6] suggests a technology and approach for automating the dysgraphia testing procedure which makes use of a convolutional recurrent neural network-based model. The model examines typographical errors that people make while copying corpus texts, such as letter additions, deletions, and reversals. Based on the overall number of errors, a risk factor is calculated, and in order to determine how seriously the user is affected, specific findings are provided, including the total number of often mistaken letters, the characters that were correctly identified, and the character error rate. A 73% accuracy rate was attained by the model after it was trained on the IAM dataset.

In order to develop a diagnostic model for dyscalculia, researchers [7] employ machine learning techniques. Specifically, they compare four supervised machine learning algorithms (Support Vector Machines, Simple Logistic Regression, Naive Bayes, and Random Forest). The study intends to automate the dyscalculia screening procedure. The model attempts to deliver precise and quick diagnosis, particularly at early stages of screening, by utilising machine learning's self-learning capabilities. Based on the data, it's clear that Simple Logistic Regression is the most effective method for identifying dyscalculic children between the ages of 6-7. Its 99% accuracy makes it particularly well-suited for this purpose. The study stresses the value of early diagnosis and suggests mandating dyscalculia screening at the school level, along with suitable occupational therapy for affected children.

The study [8] uses an intelligent system using Raspberry Pi for detecting dyscalculia in school-age children. The approach uses a series of assessments to evaluate students' proficiency in counting, geometrical ideas, and fundamental maths skills. It measures how long it takes children to respond to questions, assesses their performance relative to children who are usually developing, and finds whether dyscalculia is present. The technology offers mobility, simplicity of use, and the capacity to give parents feedback in real-time. The method uses early screening to determine whether kids are at risk for dyscalculia and to assess mathematical aptitude through the use of particular exams. The method intends to make early detection and intervention more convenient, providing focused support and better academic results for kids with dyscalculia.

A gamified smartphone software for screening and intervention of certain learning impairments as dyslexia, dysgraphia, and dyscalculia is developed in the study [9] using deep learning and machine learning approaches. Within the application, convolutional neural networks are trained to recognize spoken, written, and numerical characters. In order to identify learning disorders, the outputs from these networks are then used in machine learning models like support vector machines, random forests, and k-nearest neighbours. For primary-age children between the ages of 6 and 7, the application is made to give reliable screening results and integrated intervention, with a focus on Sinhala - language primarily spoken by the Sinhalese people of Sri Lanka.

4. Methodology:

4.1. System Architecture:

1. **User:** A user can be anyone recruited from schools and educational centres in the local community. People who have been labelled as having a learning disability such as dyslexia, dysgraphia, or dyscalculia based on their academic performance or past evaluations are included.

2. **Data collection for dyslexia:** Users were asked to write a standardised paragraph using a pen and paper. These handwriting samples were then collected and digitised for analysis using a convolutional neural network (CNN). The handwriting samples were obtained from the Dyslexia Image Database (DIB), which includes images of handwriting samples from individuals with dyslexia as well as control participants. The dataset contains normal, corrected, and reversed images of handwriting samples. 75% of the reversed images were used for training the CNN model, and the remaining 25% were used for testing the model. The model was also tested on participants' handwritten images for dyslexia detection.

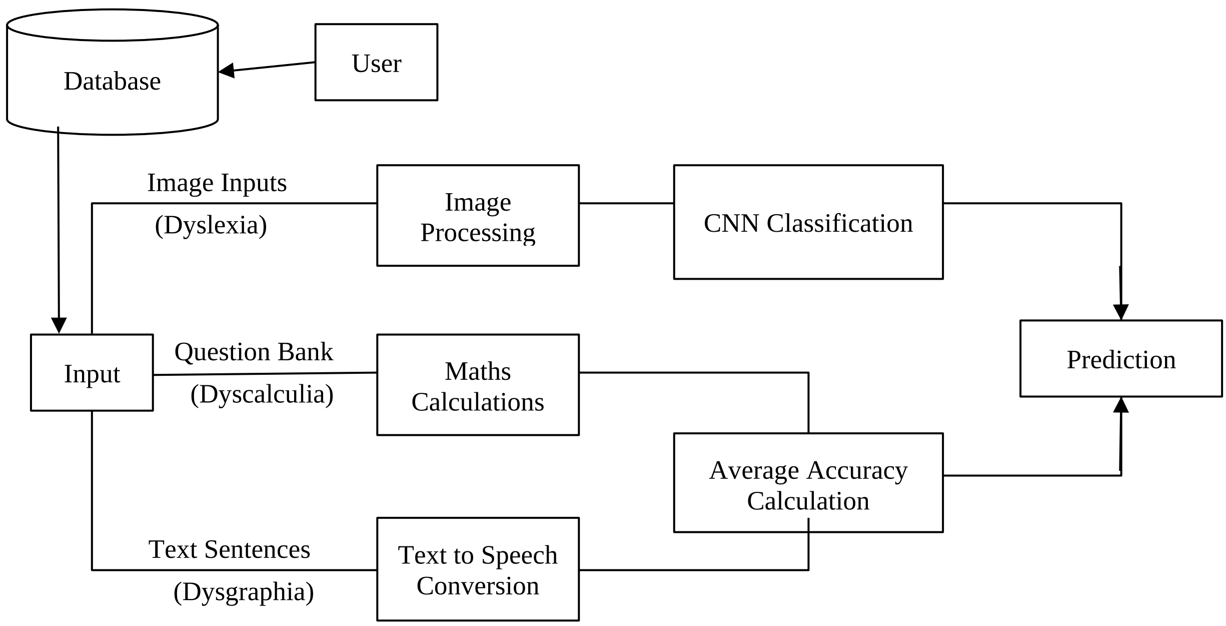


Figure. 1: System Architecture

3. **Data collection for dysgraphia:** Users were asked to complete a voice-assisted typing test. The test consisted of a series of sentences that were read aloud to the participant, who then had to type the sentence accurately using a computer keyboard. The test was designed to assess the user's ability to understand and type accurately and efficiently.

4. **Data collection for dyscalculia:** Users were asked to solve a set of basic mathematical problems. The problems consisted of addition, subtraction, multiplication, and division questions with single-digit numbers. The test was designed to assess the participant's ability to perform basic mathematical operations.

5. **Data analysis:** The CNN model was evaluated on the testing set of handwriting samples to determine its accuracy in detecting dyslexia. For the voice-assisted typing test and the maths problems, accuracy and response time were recorded and analysed to identify patterns and potential indicators of dysgraphia and dyscalculia.

4.2. Proposed System Approach

1. **Data Acquisition:** It involves collecting data that is required for detecting these diseases. For Dyslexia, dataset images are used as well as handwritten image files taken as input from the user. For Dyscalculia, we have provided a set of questions in a question bank along with the correct answers which further gets selected randomly and displayed to the user. For Dysgraphia, a set of English sentences are provided.
2. **Pre-processing:** Necessary preprocessing is performed for all the inputs of the system. For Dyslexia, the images are converted to grayscale images, bounding box technique is used on the image to extract the required part of the image and morphological operations such as dilation and erosion are performed.
3. **Text-to-Speech Conversion:** Text-to-speech (TTS) conversion is the process of converting written text into spoken words. It is a technology that can be used to assist people with visual or reading impairments, as well as to create natural-sounding audio for voice assistants, audiobooks, and other applications.
4. **Levenshtein Distance Calculation:** Among other names, the distance between two strings is known as the Levenshtein Distance or the Edit Distance. It is the smallest set of insertions, deletions, or substitutions that may be made from one string to another.

```
def levenshtein_distance(s, t):
    m = len(s)
    n = len(t)
    d = [[0] * (n + 1) for i in range(m + 1)]
    for i in range(m + 1):
        d[i][0] = i
    for j in range(n + 1):
        d[0][j] = j
```

```
for j in range(1, n + 1):
    for i in range(1, m + 1):
        if s[i-1] == t[j-1]:
            d[i][j] = d[i-1][j-1]
        else:
            d[i][j] = min(d[i-1][j] + 1, # deletion
                          d[i][j-1] + 1, # insertion
                          d[i-1][j-1] + 1) # substitution
return d[m][n]
```

5. **Segmentation:** Segmentation is a technique used in image processing that involves chopping up a picture into smaller pieces that each represent a different feature or item. Image segmentation is a fundamental task in computer vision.
6. **Feature Extraction:** Image size, edges and character shape from the image is extracted using morphological operations.
7. **CNN Classifier:** One kind of deep learning algorithm used for such tasks is the Convolutional Neural Network (CNN) classifier. It is designed to automatically learn features and patterns from images, and then use those features to classify new images into different categories.
8. **Detection & Accuracy:** The trained models work accordingly to detect the disease for the real time inputs provided by the user. The system gives accuracy (%) for the detected disease along with the timestamp.

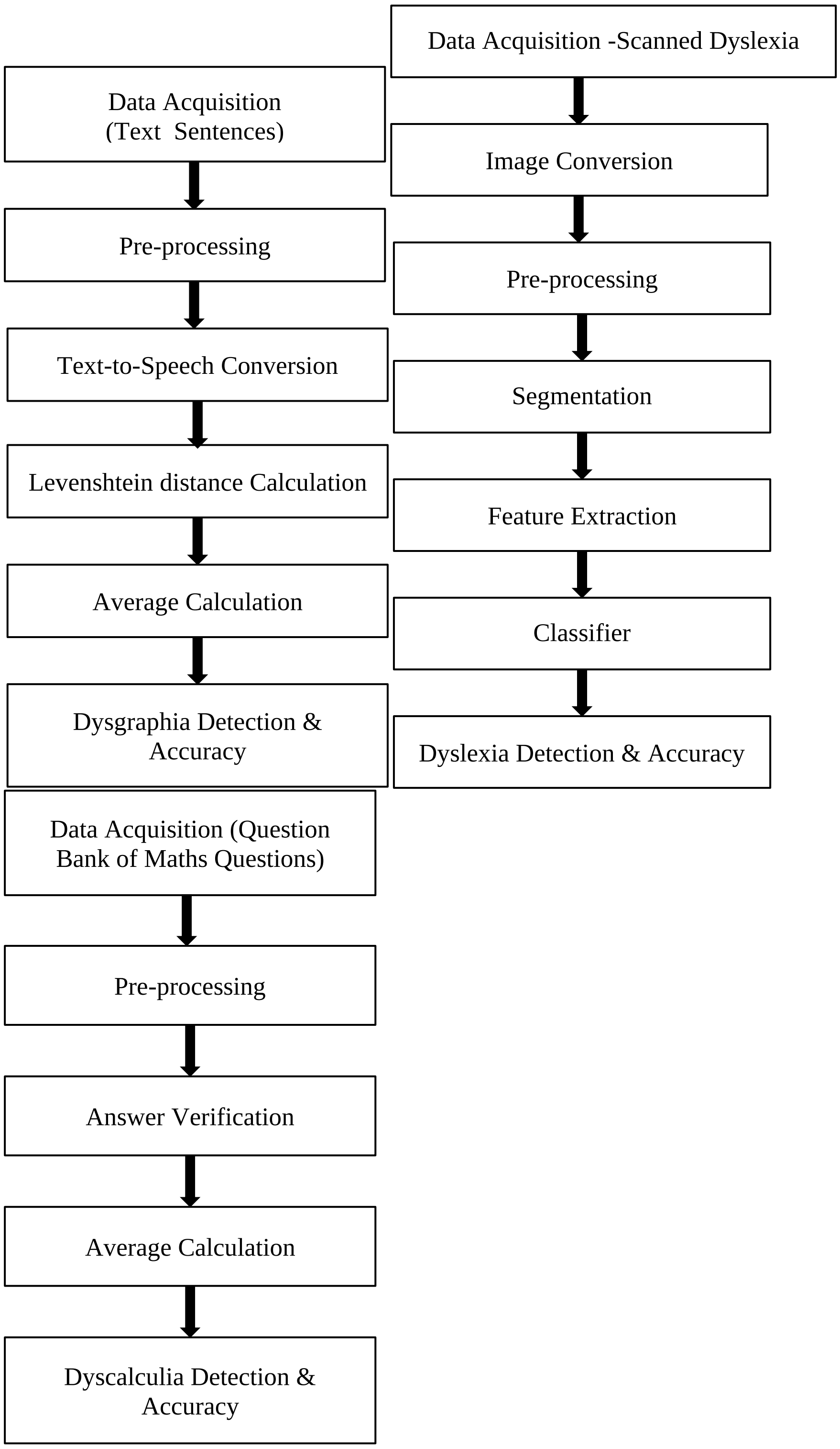


Figure. 2. Disease(s) Detection Approach

4.3.Proposed System:

The proposed system uses a combination of image processing and user reaction analysis to identify dyslexia, dysgraphia, and dyscalculia. Dyslexia identification, dysgraphia assessment, and dyscalculia assessment are the three primary elements of the system's graphical user interface (GUI). The user must first register by completing a registration form. The user can use their credentials to log into the system after registering.

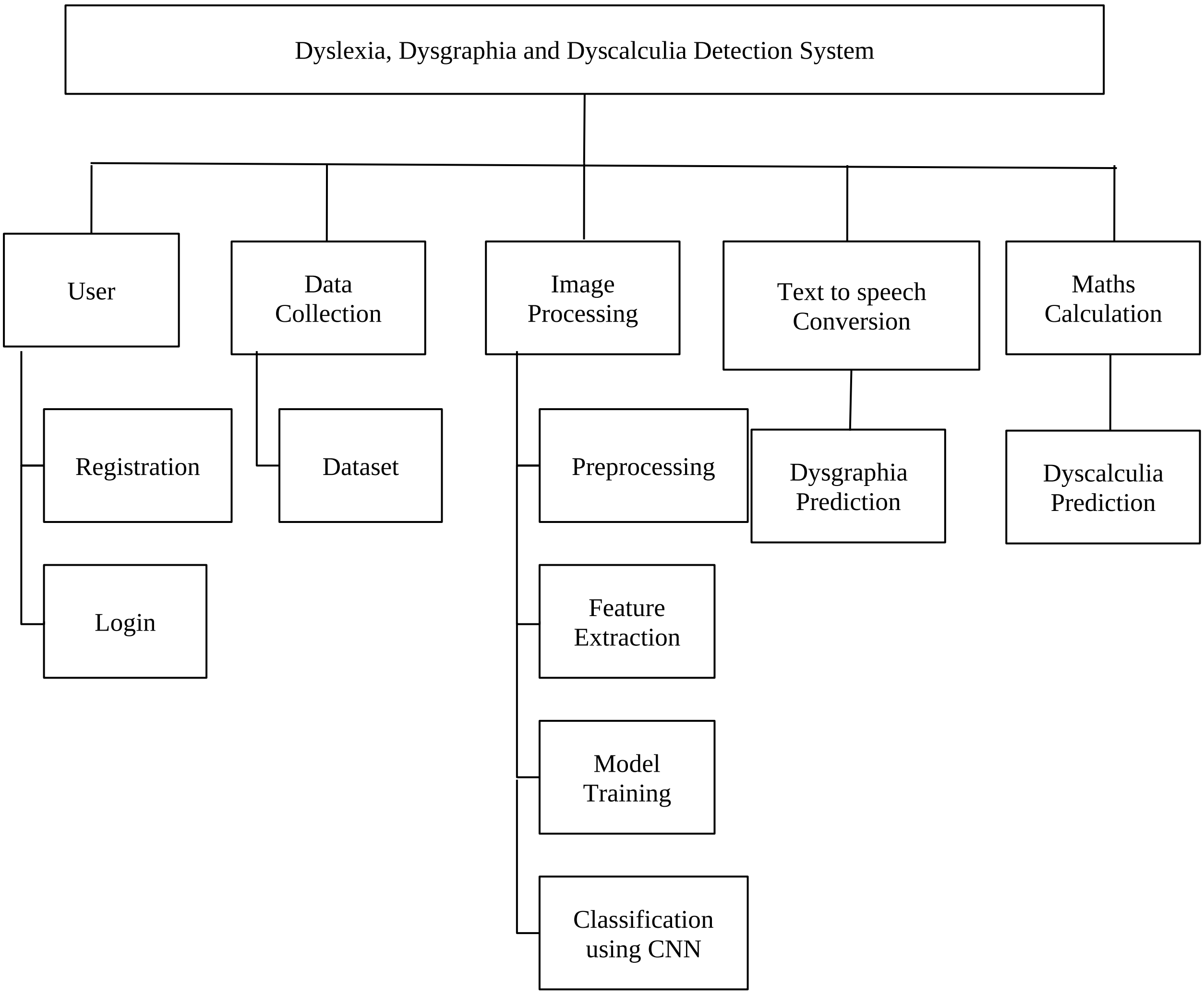


Figure. 3: System Breakdown Structure

The user is taken to the home page, where they can access the three main parts, after logging in. The user can upload a scanned image of their handwritten text to the dyslexia detection section. A convolutional neural network (CNN) is used to process the image after it has been converted to grayscale and trained on a dataset of normal, corrected, and inverted handwriting images. The system outputs both the likelihood that dyslexia will be found and the likelihood that it won't. A voice-assisted test is used in the dysgraphia assessment part to gauge the user's writing skills. Sentences are given to the user to write, and the system reads them out. The system asks the user to type the statement, and then analyses their input to determine whether it is accurate. Each response's accuracy is output by the system as a percentile. The user is presented with a number of simple mathematical multiple-choice questions in the dyscalculia testing portion. For each inquiry, the user must select the appropriate response. When the user has finished the test, the system reports the percentage of questions successfully answered and offers commentary on erroneous responses.

Overall, by combining image processing and user response analysis, the suggested system offers a thorough method for identifying dyslexia, dysgraphia, and dyscalculia. With an easy-to-use GUI, the system is made to be accessible and user-friendly.

System Breakdown -

1. ***Registration Module***
   - Registration form
   - User database
2. ***Login Module***
   - Login form
   - User authentication
3. ***Dyslexia Detection Module***
   - Image input field
   - Image preprocessing (RGB to grayscale)
   - Convolutional Neural Network (CNN) model
   - Dyslexia detection output (probability of dyslexia detection and probability of no dyslexia detection)
4. ***Dysgraphia Assessment Module***
   - Voice-assisted test form
   - Sentence presentation and voice playback
   - User response analysis
   - Dysgraphia assessment output (accuracy of each response as a percentile)
5. ***Dyscalculia Assessment Module***
   - Mathematical questions form
   - Multiple-choice question presentation
   - User response analysis
   - Dyscalculia assessment output (number of questions answered correctly and feedback on incorrect answers)

6. ***Results Module***

- Display of dyslexia detection, dysgraphia assessment, and dyscalculia assessment outputs

7. ***GUI Module***

- Main page layout
- Navigation between modules

8. ***System Administration Module***

- User management (add, edit, delete users)
- System settings (configuration, data backup, restore)

5. Results and Analysis:

The proposed system achieved an accuracy of 83% in detecting dyslexia using convolutional neural networks (CNN) and handwriting images. This is a promising result that shows the potential of applying computer vision techniques for early detection of dyslexia. The algorithm was able to correctly differentiate between handwriting styles associated with dyslexic people and those without the disease by training the model on a dataset containing normal, corrected, and reversed images. A different collection of reversed images and user-generated scribbled images were used to test the model, and the results showed the reported accuracy.

For dysgraphia evaluation, the system employed a voice-assisted assessment that compared the user's response with the correct response. This method allows for an objective evaluation of the accuracy of the user's writing. By converting the written sentence into audio and comparing it with the sentence written by the user, the system can identify deviations or errors in the user's writing by using levenshtein distance which is used to calculate the difference between two strings/sentences.

In the case of dyscalculia, the system utilised multiple-choice questionnaires (MCQs) to assess the user's ability to solve simple arithmetic problems. The user's answer was compared to the actual correct answer for each question. However, the system does not provide specific results or accuracy metrics for the dysgraphia and dyscalculia evaluation components.

5.1. Login & Homepage

Fig. 4.1(a) & 4.1(b) shows the Login page and Homepage for the user. User can login using the credentials for which he has registered previously. After successful login, the user can see the homepage as above, where he can take the tests for all three diseases namely Dyslexia, Dyscalculia & Dysgraphia.

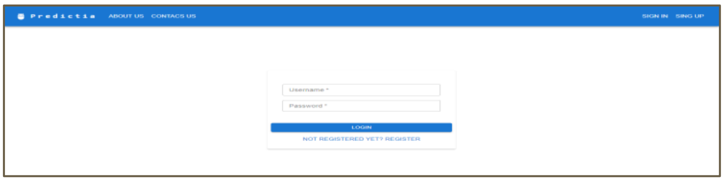


Figure. 4.1(a) Login Page

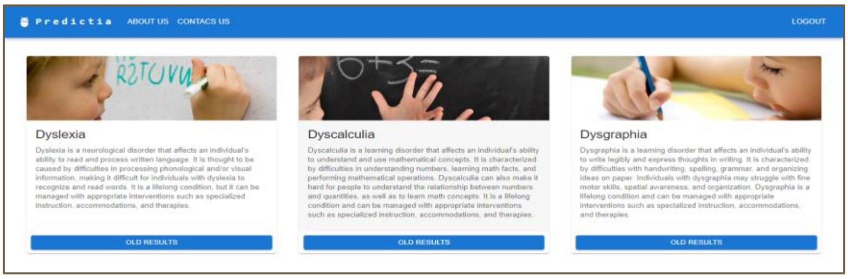


Figure. 4.1(b) Homepage

5.2. Dyslexia Prediction

Fig. 4.2(a) shows the view that a user can use to upload an image of a kid's handwriting which will be used for detecting Dyslexia by performing necessary processing on the image. Fig. 4.2(b) presents the result of the conducted test, which basically shows the percentage by which the kid is diagnosed by dyslexia and the count of characters scanned in the input image.

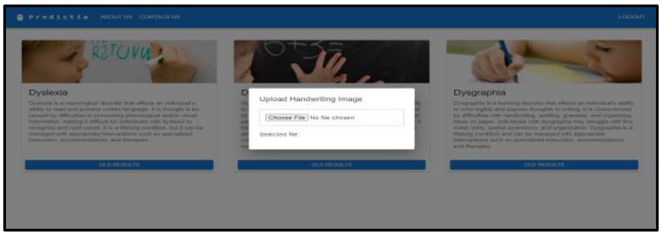


Fig. 4.2(a) Dyslexia Test

5.3. Dyscalculia Prediction

Fig. 4.3(a) shows the tests that users will carry out in order to predict Dyscalculia. It shows some mathematical questions that will check a kid's ability to understand & perform mathematical operations. Fig. 4.3(b) shows the accuracy for the test along with the given answer and the correct answer for the asked questions.

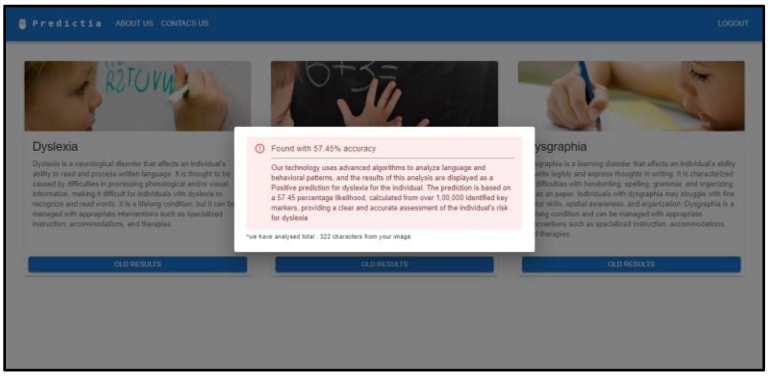


Figure. 4.2(b): Dyslexia Prediction

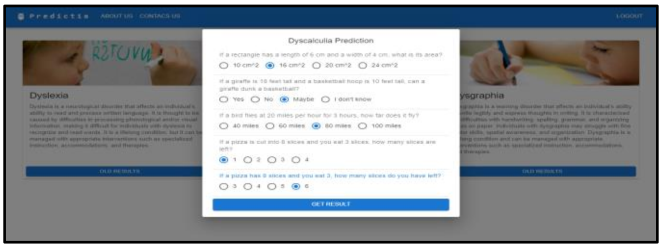


Figure. 4.3(a): Dyscalculia Test

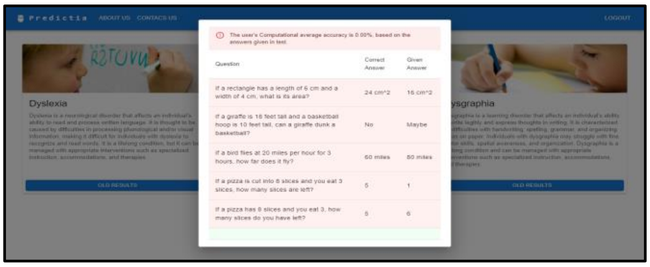


Figure.4.3(b): Dyscalculia Prediction

5.4. Dysgraphia Prediction

Fig. 4.4(a) represents the tests that users will carry out in order to predict Dysgraphia. It shows some audio inputs that will check a kid's ability to listen & and understand English sentences. It focuses on their listening skills. Fig. 4.4(b) shows the accuracy for the test along with the given (typed) text and the correct text for all the audio inputs.

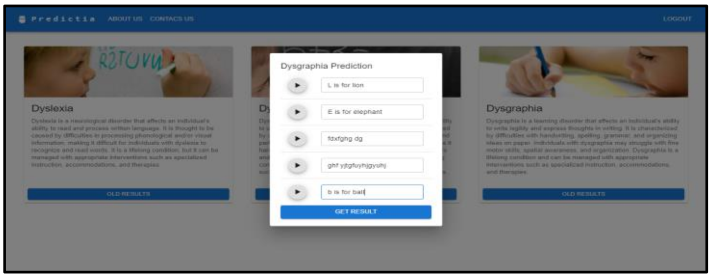


Figure. 4.4(a): Dysgraphia Test

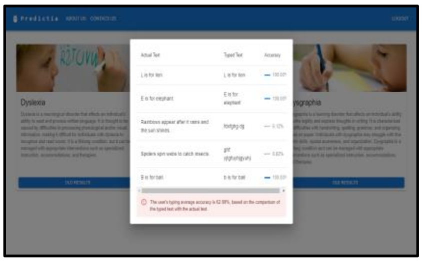


Figure. 4.4(b): Dysgraphia Prediction

5.5. Previously Executed Tests

Fig. 4.5(a), 4.5(b), 4.5(c) shows the old results of the tests that are carried out by a specific user for each of the diseases along with the prediction accuracy (%) and the timestamp.

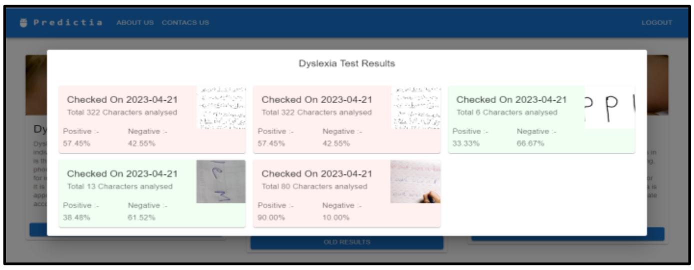


Figure. 4.5(a) Old Results of Dyslexia

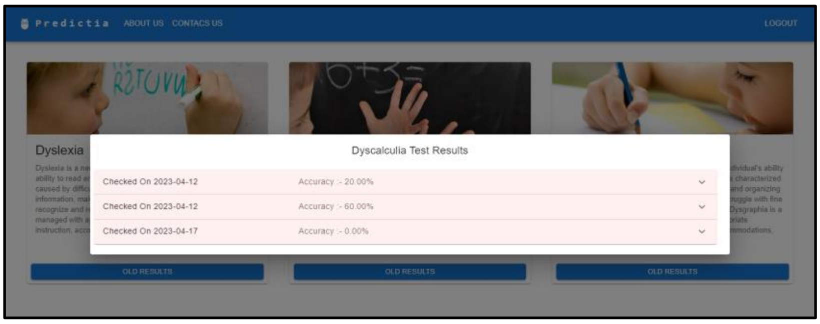


Figure. 4.5(b) Old Results of Dyscalculia

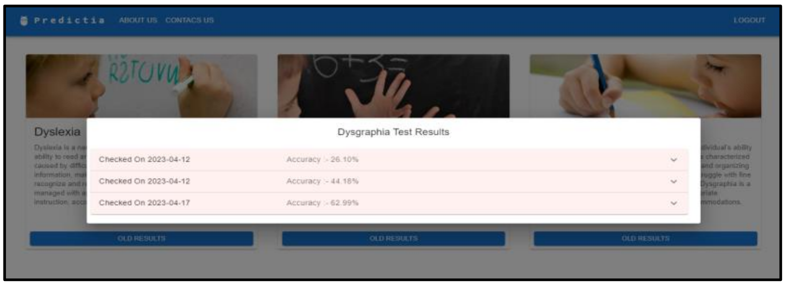
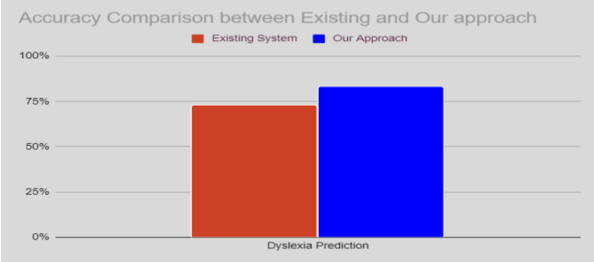


Figure. 4.5(c) Old Results of Dysgraphia

The graph above compares the accuracy of dyslexia prediction between the existing system and our approach. The existing system [6] achieved an accuracy of 73%, while our approach demonstrated improved accuracy at 83%.



The results highlight the effectiveness of our approach in accurately predicting dyslexia compared to the existing system. With a higher accuracy rate, our approach shows promise in early detection and identification of dyslexia, allowing for timely interventions and support for individuals with dyslexia.

6. Conclusion

Using this system, we are proposing a system that will detect the diseases like Dyslexia, Dysgraphia and Dyscalculia at an early age and early stage of the disease. As the disease will be detected at an early age and early stage the negative effects of the diseases can be mitigated. This will help the affected children to live a comfortable life. Paper presents a comprehensive system for the early identification and assessment of learning disabilities, specifically dyslexia, dysgraphia, and dyscalculia. To recognize and evaluate various learning impairments, the suggested system makes use of artificial intelligence techniques as convolutional neural networks (CNN), voice-assisted assessments, and multiple-choice questionnaires (MCQs). This method could help youngsters with learning disabilities by enabling early intervention and personalised support with further growth. The method has the potential to significantly improve the quality of life for kids who have dyslexia, dysgraphia, and dyscalculia by utilising digital technology. With an accuracy rate of 83%, the study's findings show promising accuracy in identifying dyslexia using CNN and handwriting imagery. While the research does not provide precise accuracy metrics for the dysgraphia and dyscalculia components, it does highlight the use of text-to-speech conversion, sentence comparison, and MCQs for dyscalculia evaluation.

The system's capabilities need to be improved and refined through additional research and development. To increase the system's precision and dependability, it is essential to collect additional information, broaden the dataset, and fine-tune the machine learning and deep learning models. For ongoing system improvement and modification to meet the changing requirements of affected children, cooperation with subject-matter experts and user feedback will also be crucial.

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