Framework for Dyslexia assessment, identification, analysis and personalized learning aid for Children

[1]Dr. Naveenkumar T. Rudrappa,

[2]Manoj P, Naveenraj N, Sanket S, Vilas B

[1]Assistantt Professor Department of CSE, KLS Vishwanathrao Deshpande Institute of Technology, Haliyal

[2]Final Year Students, Department of CSE, KLS Vishwanathrao Deshpande Institute of Technology, Haliyal

Abstract- Dyslexia is a widespread learning disability, unnoticed and undiagnosed, starting from a child's educational journey, leading to significant challenges in developing literacy skills. Seizing the efficiency of machine intelligence methods and machine intelligence approaches, the research has produced forward a skeletal outline for early disease, labeling and analysis of dyslexia injured infants through a systematic test of all-inclusive and concerning qualities not quantities factors in the way that education, writing, thinking and resolving attitude patterns with the help of various acting metrics. Discovering the dyslexia that can be used for implementing and adjusting the learning policies required to train each individual that facilities learning. The System has been developed has the significance of continuing privacy, attainable bias in Artificial Intelligence models, and demands mutual efforts of accompanying doctors accompanying coaches and software specialists from childhood through pre adulthood to effectively unify of the form into study hall environments. The rising demand contributes to the increasing machine-readable data within system of AI - automated teaching aids, advocating for effective resolutions that determine the required support for teenagers with dyslexia.

Keywords: Dyslexia, Machine Learning, Multisensory organs, Psychiatric, Education, Artificial Intelligence

I. Introduction

Dyslexia is learning disability that affects the reading and writing ability of a child. The word Dyslexia is derived from the Greek, “dys” means weak, poor or inadequate, and “lexic” means words or language. So, it mostly means weak with words or language. Dyslexic children find it hard to understand accent-based language, even when child is smart and have good hearing ability. They sometimes can’t remember what they have just read or heard, and also get confused with spoken and written words. Even when they try hard, they may jumble up letters like “b” and “d” or words like “was” and “saw”. It’s not a sickness but a brain difference in how it works with language. Some people call it "word blindness" before. It can be different from person to person. Some struggle more with reading fast, others with writing words, or sounding them out in their head. Additionally, visual processing issues, such as sensitivity to high- contrast text or difficulties with directional orientation (ex: confusion between left and right), are common. Most time, it starts to show signs at school. The effect of Dyslexia extends beyond the academic sphere into self-esteem and emotional adjustment. Left untreated, the Dyslexic individual can expect life-long difficulties in education, employment, and social integration. But with earliest possible detection and specific support, much can be gained. Traditional detection methods are normally integrated with full length testing by educational psychologists, which can be costly and inaccessible in low-resource regions such as rural India. This has led to the technological innovation, especially Artificial Intelligence (AI), to make diagnosis techniques very simple, automated and scalable solutions at rural and remote sites. Such resources integrated with educational tools with multisensory techniques and gamification have provided better and improved learning experiences in children with dyslexia Technological advancements in Artificial Intelligence has increased opportunities to revolutionize the medical diagnosis techniques and assist for Dyslexia learners. AI-powered tools can check behavior, language, and thinking patterns to detect signs of Dyslexia with increased accuracy and precision. Also, personalized learning tools and multisensory techniques can make learning easier, accessible, enjoyable and engaging for children with Dyslexia.

II. Literature Survey

1 Challenges [1]

In most of the cases Dyslexia is considered as a disability that affects learning the main problem is with careful and accurate reading, spelling, and writing. For the International Dyslexia Association (IDA), for them it is considered as neurobiological disorder that occurs due to lack of the learning aspect of language. Research estimates that 10% world's population is suffered, with different symptoms of dyslexia Researchers have always stated the neurological origin of Dyslexia, that its due to lack of intelligence and reading disability [2].

Conventional assessment procedures for identifying Dyslexia depends on assessment by educational psychologists, which frequently includes different part that includes reading ability, and memory holding capacity tests. Although these tests are valid, they are time-consuming and not available in low-resource environments [3]. Experts state that delayed assessment will increase the psychosocial issues for the individuals, promoting poor academic achievement, low self-esteem, and social integration issues.

2 Role of AI in Dyslexia Detection

2.1 Emerging Technologies in Dyslexia identification and diagnosis.

Technological developments in AI have created new pathways for identification and management of Dyslexia. AI-driven applications employ Machine-Learning-Algorithms (MLA) to process linguistic, behavioral, and cognitive patterns to provide more convenient and rapid diagnostic solutions. For example, software that tracks reading fluency and eye-tracking data proved to be highly accurate in the identification of Dyslexic characteristics [4]. Such applications can democratize access to diagnosis, especially in underprivileged regions.

2.2 Educational Interventions, Gamification and Multisensory Learning

Educational approaches for Dyslexia learners have evolved significantly, with a growing emphasis on multisensory methods that engage visual, auditory, and kinesthetic learning pathways. The Orton-Gillingham approach [5], which integrates phonics-based instruction with multisensory activities, remains the current research trend. Furthermore, the incorporation of gamification into educational tools has been shown to enhance engagement and motivation among dyslexic students. Studies highlight the power and capabilities of digital world that combines gamified elements with personalized feedback to improve learning outcomes [6].

2.3 Ethical Considerations in AI environment

AI based tools are promising but their widespread adoption raises important ethical considerations. Security and safety parameters like data privacy, algorithmic bias, and the need for over-reliant on automated systems must be addressed. Additionally, experts caution against viewing AI as a replacement for traditional diagnostic and intervention [7] methods, advocating a broader framework for support.

2.4 Integrating Medical and Engineering viewpoints

Psychiatrists and educationalists emphasize on a multidisciplinary approach to Dyslexia management. Experts are of the opinion that while technological advancements are invaluable, they must be complemented by teacher training, parental support, and awareness campaigns to create an inclusive environment for Dyslexia learners.

III. III.System Architecture

Figure 1 shows the system architecture of the Dyslexia Identification System (DIS), where the data of more than 100 people with and without disability are given as input to the system. The system detects the presence or absence of the ailment and provides the tailored learning mechanisms.

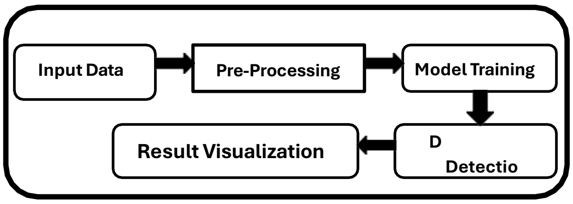

Fig. 1: System Architecture

Step 1: Dataset Collection and Preparation (Input data)

Machine learning [8], the model completely depends on the quality and quantity of a dataset, which are used for training and for model evaluation so that both dyslexic and non-dyslexic children ensure good performance.

Step 1.1: Sources Of Data

- Public Dataset: It is well Established datasets, from “Kaggle”, which will serve as a foundational source.
- Custom Data: The Data is collected in collaborations with schools, institutions and clinics having Dyslexia affected children. The collection will strictly follow the guidelines and contains informed consent from the participants.
- Data Collection Types
  - Text Dataset: Includes sample data of reading, writing exercises, focusing on errors, grammar, and reading speed.
  - Audio Dataset: Includes data such as speech patterns to assess phonological capability and pronunciation precision.
  - Behavioral Dataset: Contain data that can track eye movements, mouse pointer behavior and touch interactions during learning activities.

Step 2: Collected data Pre-processing

Requirement collection phase consists of gathering input data that includes both textual and speech samples from children, categorized into affected and non-affected groups. This data is sourced from a publicly available Kaggle dataset related to Dyslexia

- Textual data is normalized by removing unnecessary symbols and formatting errors.
- Audio data undergoes noise removal and segmentation to isolate relevant speech segments.
- Behavioral data is cleaned to remove outliers, and it is structured accordingly for machine learning compatibility.

The pre-processing stage is critical to ensure that the raw data is transformed into a structured, clean and meaningful format suitable for training the models.

It consists of data cleaning to remove any irrelevant noise, extracting of key speech features, and normalization of textual data to ensure consistency.

Step 3 : Model Training

Training phase consists of utilizing several of ML [9, 10] methodologies like Convolutional (CNN), Recurrent (RNN) Neural Networks, Natural Language Processing (NLP), Deep Learning [11] and the Random Forest Algorithm (RFA), to build a hybrid classification model with added advantages.

After training, the model outputs a prediction that identifies whether a child is Dyslexia affected or not. To visualize the results obtained, an interactive dashboard provides a better display of the results for easy understanding.

Step 4: Dyslexia Detection Module (DDM)

Dyslexia identification calls for the need to design a machine learning model capable of processing multimodal data inputs like text, speech, and behavioral patterns. Figure 2 shows the detailed block diagram of Dyslexia Detection module .

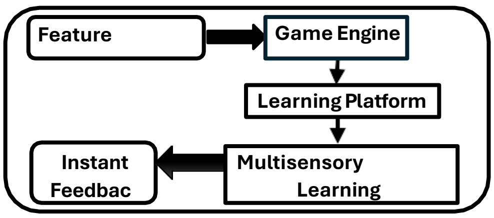

Fig. 2: Insights of Dyslexia Detection Module

Step 1: Feature Selection:

The model considers traditional characteristic qualitative parameters like as reading fluency, speech accuracy, phoneme articulation, and gaze stability. These are identified through existing literatures. Dyslexia behavioral traits include inconsistent mouse movements or prolonged fixation on a specific screen area.

Step 2: Game Engine:

Textual data is passed through various NLP techniques, having tools such as Bidirectional Encoder Representations from Transformers (BERT) to evaluate grammar, syntax and reading fluency. Audio data is analyzed by speech recognition models to evaluate pronunciation and phonological errors, using CNN and RNN. Behavioral data is modeled using Attention-Based-Neural- Networks (ABNN) to detect significant patterns for a homogeneous set of people.

System Integration:

The detection model is coupled into an interactive educational platform, where data from the child's interactions is analyzed in real-time to identify Dyslexia tendencies. Graphical User Interface allows educators and parents to view detection results along with actionable recommendations for further activities.

Step 3: Learning Platform

Phase 3.1:

Child Interaction: Child is provided with a series of educational tasks, such as interactive exercises, quizzes, and puzzles, designed to make learning enjoyable. The platform creates an immersive and engaging experience, where the child actively participates in tasks that motivate learnability through playful gestures.

Phase 3.2:

Adaptive Learning System: Utilizing AI, the system continuously calibrates the difficulty level of activities like reading comprehension, debate, group discussion or speech enactment activities that ensure appropriateness for the child's skill development.

Step 4: Multisensory Learning Approach:

Visual aids like images or videos and auditory components like voice guidance and musical patterns are coupled into the developed system that caters to different learning styles and understanding levels like slow, average and fast learners.

Step 5: Instant Feedback:

The platform provides immediate parallel feedback as the child works through tasks, offering real-time insights to help improve reading, understanding and speech generation skills in a supportive manner.

Dyslexia Detection Module Training Phase:

Labelled datasets are divided into testing and training subsets to evaluate the model's performance. Metrics such as accuracy, precision, recall and F- score are computed to gauge the model's effectiveness. Figure 3 shows Knowledge Feedback Cycle for Performance Improvement in Dyslexia Detection Module abbreviated as (KFC for PI in DDM)

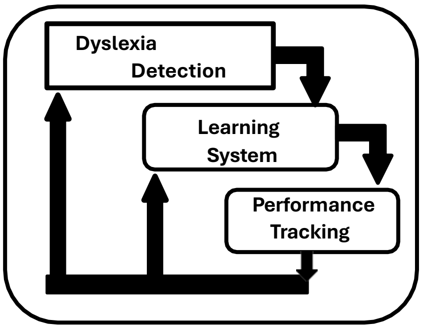

Fig. 3: KFC for PI in DDM

Step 1: Learning System:

The learning aid aims to create an engaging, adaptive environment for Dyslexia children, incorporating gamification and multisensory techniques to ensure increased concentration, coherency, inclusivity and effectiveness.

- Gamification with Points and Rewards: Children are incentivized to complete tasks with a point-based system that activates an emotional feeling of success like milestone achievement and motivation.
- Gamification with Levels and Challenges: Learning Content is broken into manageable levels, progressively increasing in difficulty to match the learner's improvement.
- Leader boards and Social Interaction: Encourage healthy competition among peers, enhancing collaboration, confidence and improved performance tuning.
- Visual Enhancements: The interface includes vibrant visuals, dynamic animations, and adjustable themes to cater to children with visual sensitivities. Ex Yellow color on a bus indicates that it is related to academic institutions, red color indicates danger, White indicates peace, and Green indicates growth.
- Audio Integration: Phonics-based sounds, clear verbal instructions, and interactive storytelling will help children improve language comprehension. Ex Siren of an Ambulance, Fire-Engine, vehicle horn etc.
- Gaming Activities: Interactive tasks, such as tracing letters or completing puzzles, will aid in tactile memory and fine-tune motor skill development. The multisensory approach ensures that all sensory organs of a child are working in coordination, creating an inclusive learning environment.
  - Word-Building Games: These activities challenge children to construct words using phonetic clues, improving phonological awareness.
  - Sequencing Challenges: Focus on enhancing organizational and cognitive skills through interactive puzzles.
  - Choose-Your-Own-Adventure Stories: Allow children to explore dynamic narratives, building vocabulary and reading comprehension.

Step 2: Performance Tracking

Dashboards for parents and educators provide detailed progress reports, highlighting strengths and areas that need improvement. Learning paths are dynamically calibrated depending on the child's performance to ensure effective growth.

Step 3: Continuous Improvement

The output results obtained after performance tracking are continuously injected back into the KFC module that follows structured pipeline to assess reading and speech patterns effectively.

IV. Data Sources and Implementation

Data Collection Sources:

Relevant datasets, including those from Kaggle and academic sources, are gathered. These datasets are made up area speech recordings, reading samples, and linguistic markers, which will be then pre-processed to remove noise or irrelevant data and make them align according to the requirements for next step.

Dyslexia Detection Model Implementation:

It is built using Keras, Tensor-Flow, and NLP techniques that analyze the already processed input to determine dyslexia -related speech and reading patterns.

The learning system:

It includes gamification and multisensory learning strategies to improve user engagement and skill development.

Performance Tracking:

This functionality is built using SQLite and Flask which is a lightweight python framework for backend processing, allowing for personalized learning experience to each user. It makes sure that child gets continuously better. This structured arrangement provides a dossier-compelled and AI-powered approach to dyslexia evaluation, seamlessly including discovery, learning, judgment and accomplishment. This section specifies how the system is built to achieve the above-mentioned objectives, focusing on the core architecture and technologies used that can find Dyslexia by considering reading and speech patterns, followed by the personalized learning paths. At the core of the system, DDM makes use of advanced algorithms like NLP for reading assessments and speech recognition models to evaluate speech accuracy. This model helps differentiate whether the child might have dyslexia based on reading speed, errors, and phonological awareness. Once we find potential signs of Dyslexia our system provides personalized, gamified learning games- built games to maximize reading skills and speech accuracy, followed by a multisensory approach. Real-period response is provided to the kid all throughout education sessions, accompanying an instrument panel usable for educators and people to track progress and offer ideal learning tools.

Implementation Complexity:

The proposed system mandates the need to couple Machine Learning, Web-Development, and Gaming technologies for a better identification, assessment and diagnosis of Dyslexia.

- ML [12] and AI [13]: The system uses algorithms such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), both ideal for sequential data analysis. NLP libraries like SpaCy and NLTK are used for reading assessments, while Google Cloud Speech API is utilized for speech-to-text conversion and speech recognition tasks for dyslexia detection.
- Gaming: To escalate learning experience, Unity 3D, Godot software are employed for gamification tasks that engage children and help them improve and escalate their reading and speech skills.
- Web Development: Progress monitoring and interaction with personalized learning content, needs React.js for frontend development. Node.js handles the backend services, with HTML5, CSS3, and JavaScript used for creating responsive, engaging and interactive User Interfaces.
- Speech Recognition and NLP [14]: Tools like Pyaudio, Google Cloud Speech API and Deep Speech are used to transcribe and evaluate the child's spoken words during assessments. This helps in identifying pronunciation errors and phonological awareness issues.
- User Interface Design: The UI's cater to both children and educators with a seamless experience. A centralized dashboard for Parents and Educators is in place where educators and the child's performance on reading fluency and speech accuracy. Graphical trends in reading speed, accuracy and phonological skills are displayed, offering valuable insights into the child's progress.
- Interactive Learning Activities: These activities focus on improving reading and pronunciation skills. For example, children are provided with word-building exercises, phonics-based games and interactive story books to assess reading fluency, concentration and interpretation capabilities.
- Personalized Feedback: During the interaction between child and the tool through tasks, real- time feedback is provided to rectify mispronunciation, reading mistakes and behavioral changes simultaneously offering suggestions for improvement.

Integration of Dyslexia Detection Model (DDM) with the Personalized Learning System (PLS)

DDM and PLS are fully integrated, ensuring that the child's learning experience is calibrated dynamically. The explanation below justifies how the modules interact.

1. Real-Time Input Data Collection: Once the child finishes reading and speaking. data is collected in from these activities in real-time. Which includes audio recordings and keyboard input that assess the reading and typing fluency.
2. Audio and Text Pre-processing: Both audible and textual data are transformed. For example, speech is transcribed into text, and noise is filtered out from both audio and textual data.
3. Detection Process: DDM evaluates the processed data to identify any markers that suggest the child might have dyslexia. For instance, if speech recognition indicates poor phonetic awareness, the model flags it.
4. Personalized Learning: Only if dyslexia is detected, the system switch to provide a personalized learning content. These tasks are designed to focus on improving reading fluency and speech accuracy with dynamic calibration to increase or decrease difficulty levels based on individual performance.
5. Audible Feedback: Audio feedback is continuously provided to the child to ensure that any issues are addressed immediately. Parents and educators can keep an eye on the progress through the provided dashboards.

6 Continuous Improvement: The system's adaptive learning model keep track of records regularly. Tracking performance over time i.e weekly, monthly or yearly the system dynamically adjusts the difficulty level of tasks to keep the child engaged without overwhelming them. This method also encourages better focus and participation by using tools like eye-tracking for visual attention and mouse movement analysis to incorporate interactive elements into the learning process.

7 Performance Monitoring: Real-time analytics and report generation show trends in the child's progress. These insights can guide parents and educators in offering targeted support.

Figures 4 and 5 display the 2 different data flow diagrams, one from administrator view point and the other refers to the end user view point of the prototype

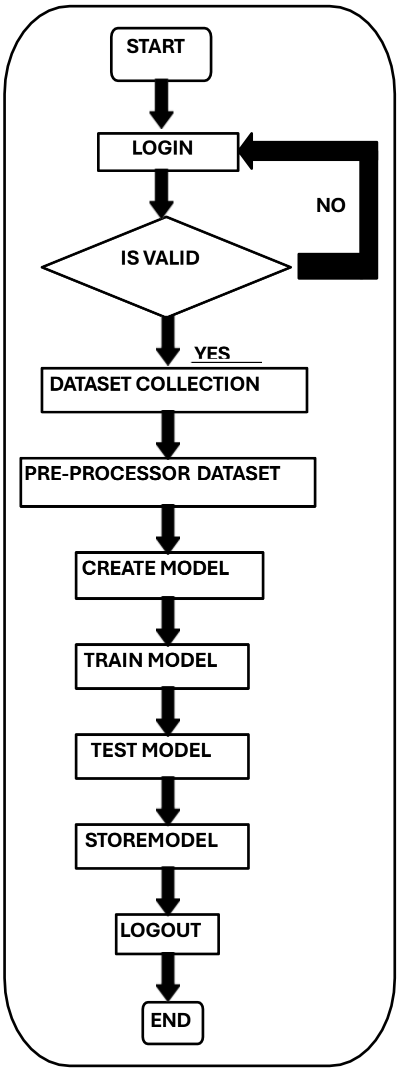

Fig. 4: Administrator Data Flow Diagram

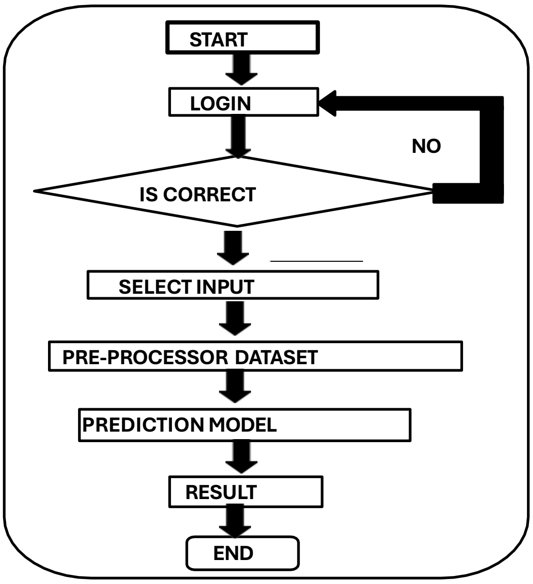

Fig.5: End-User Data Flow Diagram

V. Results and Discussion

This section focuses on the outcomes of the proposed dyslexia detection system, including the evaluation of model performance and the impact of the multisensory learning aids. The goal is to analyze the efficiency and accuracy of the dyslexia detection model, assess the personalized learning aids, and discuss how the system contributes to the understanding and support of dyslexic learners. Figure 6 shows the home page of the landing window when it is searched.

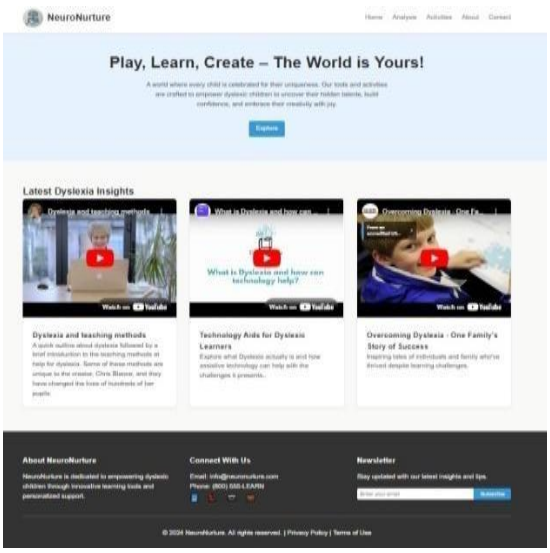

Fig. 6: Screenshot of Neuro-Nurture Landing Window

DDM Performance Evaluation

Several performance metrics were used in the evaluation of DDM. These metrics are key indicators of the model's ability to correctly identify Dyslexia in children based on their reading, speech and behavioral data. The metrics computed are as elaborated below-

1 Accuracy: Ratio of correct predictions made by the

model relative to the total number of predictions. High accuracy indicates the model's general effectiveness in detecting Dyslexia.

$$\frac{(True\ Positives + True\ Negatives)}{(True\ Positives + True\ Negatives + False\ Positives + False\ Negatives}*100$$

Computed Accuracy= 92.5%

2 Precision: This metric determines how many of the predicted Dyslexia cases were truly positive. A high precision value minimizes the chances of false positives.

$$\frac{True\ Positives}{(True\ Positives + False\ Positives)}$$

Computed Precision= 88.7%

3 Recall: It is also known as Sensitivity, and measures how well a model identifies all the relevant positive outcomes. It focuses on how many actual positive instances were correctly identified out of all possible positive instances. A high recall rate justifies that most dyslexia individuals were properly identified by the system.

$$\frac{True\ Positives}{(True\ Positives + False\ Negatives)}$$

Computed Recall= 90.1%

4 F1-Score: The harmonic meaning of precision and recall, provides a balanced measure of the overall system performance. It is particularly useful when the class distribution is imbalanced. A high F1 score indicates that the model is highly good at detecting True Positives and avoiding False Positives, for example when there are more non-Dyslexia cases than dyslexic cases or vice- versa.

$$2 * \left[\frac{Precision * Recall}{Precision + Recall}\right]$$

Computed F1-Score=89.4%

DDM experimented on a large dataset, consisting of both text and audio samples, gathered from Dyslexia and Non-Dyslexia children. The model's performance was assessed using k-fold cross-validation, ensuring that the results are robust and generalizable.

Above computed results show that the model demonstrates a strong potential in dyslexia detection, with high accuracy and recall, ensuring that most Dyslexia children can be accurately identified. Figures 7 and 8 show the screenshots of the assessments carried out.

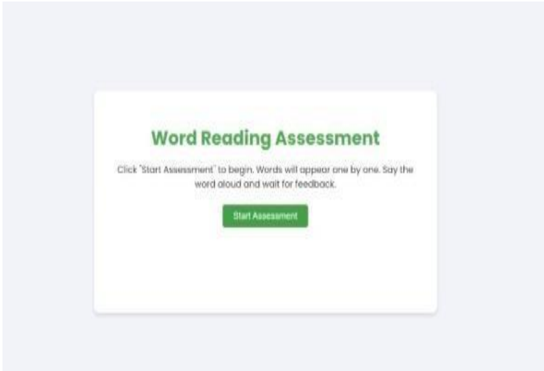

Fig.7: Screenshot of Reading Assessment Window

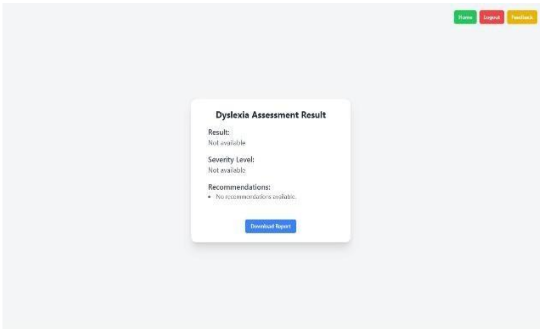

Fig.8: Screenshot of Assessment Result Window

DDM Multisensory Learning Aid Evaluation

In addition to the detection model, the personalized learning aid system was evaluated for its effectiveness in helping Dyslexia children improve their reading and speech skills. The evaluation focused on the engagement level of the children with the gamified elements, the efficacy of the multisensory learning techniques, and the overall user experience.

➢ **Engagement and Motivation:**

The gamified elements, such as points, rewards, levels, and leaderboards, contributed significantly to increased engagement and motivation. Children reported feeling more motivated to complete tasks due to the reward system, and the leader board fostered healthy competition, encouraging them for continuous improvement.

➢ **Effectiveness of Multisensory Learning**:

The combination of visual, auditory, and kinesthetic learning approaches were particularly beneficial in addressing the diversified needs of dyslexia children. The use of vivid visuals, phonetic-based audio, and hands-on activities like tracing letters supported the development of reading and writing skills. Feedback from both parents and educators indicated that children showed improvement in phonological awareness, reading fluency, and hand-writing quality after consistent utilization of the platform.

DDM+MLA with User Feedback Evaluation: The interface and system design were also evaluated based on ease of use, accessibility and overall satisfaction. Parents and educators found the platform easy to navigate and real-time progress tracking allowed them to closely monitor a child's development. The personalized learning paths that adapt to the child's learning pace were praised for their flexibility and effectiveness.

The combination of gamification and multisensory learning strategies resulted in a positive and engaging learning experience for the children, making the process more enjoyable and less stressful. Figures 10 show the screenshots of actual learning strategy carried out by a test set having more than 100 children.

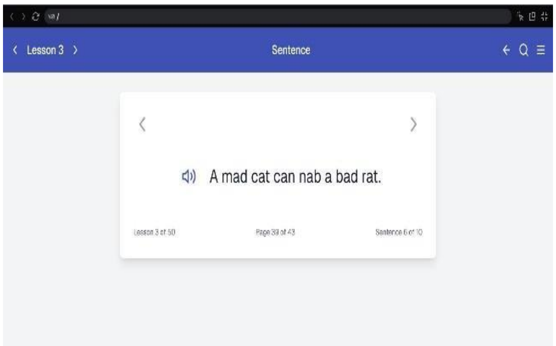

Fig.10: Screenshot of Personalized Learning Window

Medical Impact of tool usage on Dyslexia Learners

Prototype of DDM with PLA module had a measurable positive impact on the participants like:

1 Improvement in Reading and Speech Skills: After providing the platform for several weeks, children showed significant improvement in reading speed, accuracy, and pronunciation clarity. This is very important for reading smoothly and understanding what they read.

2 Increased Confidence: The game like nature of learning activities made children feel more confident.

3 Feedback from Guardian and Teacher: Guardians reported that the system provided them with meaningful observation into their child’s progress. Educators found the tool to be useful for providing the proper teaching facilities to each child. Real time feedback is helpful for the educators and the guardians to provide on time and ensure that the children do not lack in the learning journey.

Real Time Assessment of 100 Children under Study

Figures 11, 12 and 13 show the graphs plotted which is generated output of the prototype once the assessment was completed by a group of children. To support further prediction. we have categorized the children under 3 categories where group 1 had only children of age 8, group 2 had only children of age 9 and group 3 had only children of age 10 years.

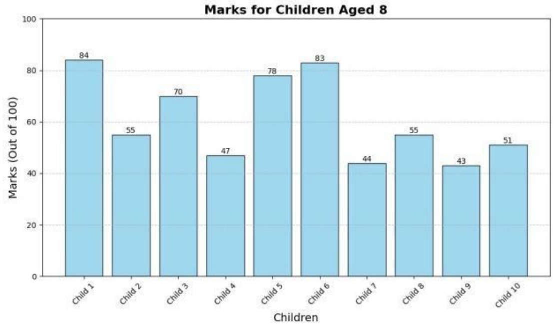

Fig.11: Bar graph of group 1 with age 8 years

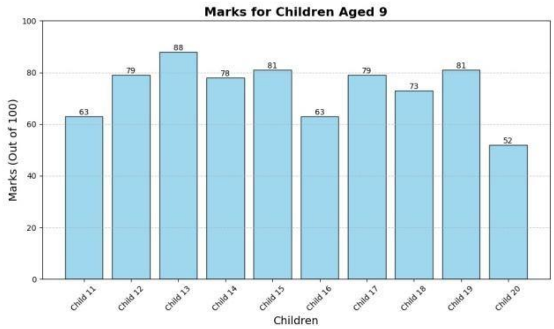

Fig.12: Bar graph of group 2 with age 9 years

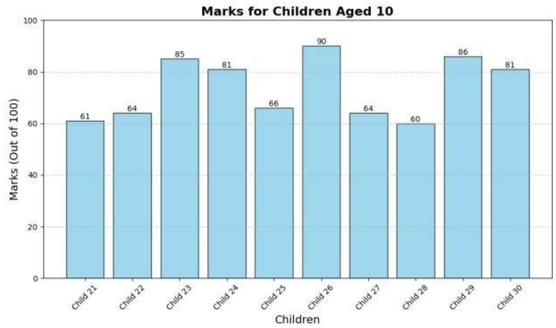

Fig.13: Bar graph of group 3 with age 10 years

Calculations performed by developed prototype

Step 1: Each parameter is given a Score

If a student reads 150 words per minute and the best score is 200, their reading score is (150/200) × 100=75

Step 2: Decide how important each parameter is

Some things matter more than others. For example:

- Reading speed: 30%
- Spelling: 25%
- Memory: 20%
- Survey answers: 25%

Step 3: Add All the above 4 parameters.

Multiply each score by its importance value and add them together. For example:

- Reading speed: 75 × 30% = 22.5
- Spelling: 80 × 25% = 20
- Memory: 70 × 20% = 14
- Survey answers: 85 × 25% = 21.25

Conclusion:

Total Marks obtained by child 5 in group 1 having age 8 years = 22.5 + 20 + 14 + 21.25= 77.75 ~78. The prototype performs real time calculation for each child only after the child has completed assessment. During the assessment dynamic audible feedback is continuously provided to the child for ON-THE-FLY calibration thereby improving multisensory learning capabilities in real learning environments.

LIMITATIONS

Despite of the promising results, several pros and cons were observed like:

1 Data Quality: Dataset used in the training phase was comprehensive; there were instances of noisy and incomplete data that marginally affected model accuracy. Ensuring high-quality, annotated data is mandatory for improving the model's performance.

2 Individual Differences: Dyslexia manifests differently in each individual, which means that a ONE- SIZE-FITS-ALL approach may not always be effective. The system has a capability to adapt for a unique learning need in a future, but more work is needed to improve the adaptive learning path accomplish wider variety of Dyslexia profiles.

3 Scalable: The current version of system can be further developed to scale it for larger populations. Even though it has been tested for smaller group of challenges and that can be related to server load and processing speed need to be addressed for expanding.

VI. CONCLUSION AND FUTURE SCOPE

The proposed system for Dyslexia detection and identification among children is by both machine learning algorithms and personalized learning aid, developed for social benefits that can be combined with the psychiatrist who treat dyslexia and a team of Software Developers. The data such as assessing reading, speech, and behavioral traits among children of different age groups can be used for research purpose. The Dyslexia detection model performed well.

identifying risk of dyslexia with high accuracy, precision, and recall. Additionally, integrated gamification that helps the children to learn more interactively and get engaged in learning.

Enhancement of model: Adding new data such as video or neuroimaging data the model can be improved that help is more accurately tuning the results. exploring the other machine learning algorithm such as deep learning, transfer learning we can analyze individual results and enhance the model functionality.

Gamification Enhancement: The detection model can be further improved by providing exceptional features like multiplayer modes and/or interactive story- based games that could further increase engagement and learning outcomes.

Academic Impact: The detection model can be used as a regular assessment tool for a long-term impact for visualizing children's academic progress and overall well-being. Tracking progress weekly, monthly over a set of years would provide valuable insights for platform improvement and additionally enriching Dyslexia learners.

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