LexaAyudha : Personalized AI-Driven Rehabilitation for Adolescents with Dyslexia and Dyscalculia

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***Abstract*—Dyslexia and dyscalculia, the most common learning disabilities, produce a considerably challenging environment for adolescents and lead to frustration, disengagement, and reduced self-esteem. While assistive technologies with influential functionalities exist, they lack real-time personalization for effective and supportive learning. LexAyudha is an AI-powered platform addressing these gaps by integrating proven medical methodologies such as chromatic variation, Touch Math, and multisensory teaching strategies. Advanced AI technologies like Convolutional and Recurrent Neural Networks have been used in LexAyudha to dynamically adjust reading content, visual layouts, and lesson plans in the gamified app based on students' real-time performances to cater for their requirements. Moreover, a novel emotion recognition algorithm even adjusts difficulty levels of activities and voice output with altered audio features to ensure a stress-free learning process and a stimulating environment. Initial findings based on the user performances tests conducted with the dyslexic and dyscalculia adolescents in Sri Lanka, represents significant improvements in reading fluency, comprehension, and motivation, showing that adaptive learning with AI has the potential to revolutionize learning for dyslexic and dyscalculia students. The research identifies the potential of rehabilitation with AI-driven technology as a flexible and scalable solution for personalized education in dyslexia and dyscalculia.**

Keywords—Artificial Intelligence, Convolutional Neural Network, Dyscalculia, Dyslexia, Machine Learning

I. Introduction

Specific learning disability, is a disorder in one or more of the basic psychological processes involved in understanding or in using language, spoken or written, which may manifest itself in an imperfect ability to listen, think, speak, read, write, spell, or do mathematical calculations [1]. According to the Diagnosing Learning Disorders: from Science to Practice, 3rd ed. by the American Psychological Association, six types of learning disorders are recognized: speech and language disorders, dyslexia, mathematics disorder, attention deficit/hyperactivity disorder, autism spectrum disorder, and intellectual disability [2].

Dyslexia is one of the most common learning disabilities, with an estimated prevalence of 15-20% of people worldwide [3]. In the United States alone, more than 32% suffer from learning disabilities and specifically 19% suffer from speech or language impairment [1]. In Sri Lanka, it has been reported in 2019, that a total of 2397 male students and 1140 female students from grade 1 to grade 11 repeaters to have dyslexia [4]. Perhaps, this could be one of the common learning disabilities in educational systems. Mainly, difficulties are noted in reading, decoding, and processing written information [5]. This can cause issues with phonological processing, spelling, and word recognition [6]. Some of these characterizations relate to failures in intelligence or initiatives taken by students [7], [8]. However, their core lies in the neurological processing of language, more precisely, difficulties in mapping sounds to letters and words faced by those who have dyslexia; this causes reading fluency and comprehension to be very low.

On the other hand, dyscalculia according to the British Dyslexia Association in the United Kingdom has stated that about 6% of people have dyscalculia. Not only that, an estimated 25% of people have math learning difficulties which can be caused either by other neurodiverse conditions such as dyslexia or external issues such as a traumatic learning experience related to math or school absence but also they have provided statistics that 60% of individuals with dyslexia will have difficulties with math [9].

Traditional teaching methods are inadequate to help these students, because they depend mainly on depersonalize learning strategies. Methods that could have been highly effective with the neurotypical learner can make a dyslexic or dyscalculia individual become frustrated, anxious, and even lead to lower academic performance. Therefore, it is important to have an application which can offer adolescents with learning difficulties to learn and overcome their specific disability by having the support of personalized and proven teaching methods, within a stress free and engaging learning environment [10], [11].

II. LITERATURE REVIEW

Learning disabilities such as dyslexia and dyscalculia significantly impact a student's ability to process language and numerical information. These conditions often require specialized teaching methods to accommodate their unique challenges. Traditional approaches have attempted to address these difficulties, but modern AI-driven technologies have the potential to enhance personalized learning for affected students.

This literature review explores existing research on dyslexia, chromatic variations, AI-based interventions, Touch Math for dyscalculia, emotion detection in education, and speech comprehension tools. The review critically examines the effectiveness of past studies, identifies limitations, and highlights research gaps that this study aims to address.

Dyslexia is a complex, life-long learning disability that is neurobiological in origin and characterized by reading, writing, and spelling difficulties. One of the most frequent complaints from people with dyslexia is visual stress, where text being shown to them normally presented as distorted images or blurring images makes the reading task more difficult. Research has demonstrated that a significant reduction in the level of this discomfort comes from using a colour balance between the print and the background [12].

A proven research area that has the potential to provide further avenues in the search for adjusted methodologies for dyslexic learners is the use of chromatic variations to improve readability. According to studies such as those conducted by Pinna and Deiana in 2018, the ideal combination of colours, such as pale yellow and dark blue, can significantly reduce the sense of unease in vision, improving reading speed and accuracy, along with comprehension [12]. Furthermore, the "Dyslexia Friendly Style Guide" by the British Dyslexia Association and previous researches highlights key design elements such as colour contrast, font choices, and background colours in educational materials for dyslexic learners [13], [14]. These principles align with experimental studies, such as those conducted by Raghuram et al. [15].

As mentioned in the previous researches despite the promising findings, the practical application of chromatic variations in educational technology has, until now, been in its infancy [16]. Most existing tools for educational technology have been developed with static settings for visual appearance, disregarding the variability in dyslexic symptoms or individual student preferences. This non-personalized approach reduces the effectiveness of interventions since the optimal visual settings for one student may not be suitable for another. Even for the same student, their needs might change as their reading skills evolve.

Artificial Intelligence (AI) holds enormous potential for transforming personalized learning, especially in dynamically adapting educational content to suit individual learner needs. AI-driven adaptive learning tools, such as ALEKS and Intelligent Tutoring Systems, have already demonstrated the ability to enhance educational outcomes by continuously testing knowledge and adjusting learning trajectories [17]. However, their application in dyslexia-focused interventions, particularly in the real-time adaptation of visual settings, has been underexplored.

In addition to visual modifications, Natural Language Processing (NLP) has opened new avenues for content adaptation, particularly in text simplification and generation at appropriate reading levels [18]. NLP technologies can help ensure that educational materials are not only visually accessible but also linguistically appropriate for students with dyslexia, thereby enhancing their overall learning experience.

To bridge the existing gaps in the field of research, this research proposes a web-based solution utilizing AI to track and analyse students' continuous interactions with text and make real-time adjustments to visual settings and content difficulty. By incorporating AI-driven chromatic variations and personalized content adaptation, this system aims to create a more responsive and tailored learning experience for students with dyslexia.

Nevertheless, Dyscalculia is one of the learning disabilities that encompasses serious difficulties in understanding numbers, learning math facts, and performing arithmetic operations [19]. This learning disability affects as many as 3-6% of the population and is related to long-term academic difficulties and everyday activities that require only basic numerical insights [20].

Despite its effectiveness, the application of the Touch Math approach and gamified platforms remains limited [21], [22], [23]. With the growing digitization of educational environments, an urgent need is created for developing digital, interactive solutions to bring the benefits of Touch Math into the online learning environment.

Some digital platforms have taken the initial steps to utilize the effectiveness of Touch Math.

- Touch Math Pro – A digitized online version of traditional Touch Math, providing a rich set of tools for multisensory learning.
- Touch Math Tutor Kindergarten Demo – An engaging digital system that helps young beginners build mathematical skills.
- UnoBear – Guides students through multisensory activities to strengthen number concept understanding.

While these platforms are essential first steps toward the digitization of the Touch Math approach, they are still somewhat limited in scope and functionality. For example, whereas students can view and engage with touch points on numbers, advanced features, such as real-time pronunciation feedback or adaptive learning pathways, to cite a few examples, would really boost learning outcomes in a way that corresponds to individual students' progress.

The present work attempts to bridge this gap by developing a web-based application that not only adopts the basic principles of the Touch Math approach but also further amplifies it through the use of newly introduced advanced technology and highlighted features.

According to the new collaborative study by UC San Francisco neuroscientists with the UCSF Dyslexia Centre, UCSF Memory and Aging Centre emotion detection could be very effective for these dyslexia and dyscalculia students [24]. Hence, incorporating emotion detection as well as audio adjustments, in personalized and multisensory learning makes it more suitable for dyslexics and dyscalculia to overcome their educational barriers.

There are some previous researches including ALEXZA[25], Walipilla[26] which has addressed significant requirements in the discussed area, however, the target audience of the previous studies lacked research work on the feedback to be offered to guardians regarding the emotional status of students with learning disabilities.

Additionally, while many studies have explored emotion detection, few have examined how to use this data to provide detailed feedback to guardians, comparing students' past and present emotional engagements with learning activities [27]. This aspect is important for monitoring some results and making sure that appropriate interventions are making the required impact to the emotional and the cognitive development of the student.

Therefore, this particular research focuses on the ways of enhancing the learning experience for dyslexic and dyscalculia students by developing a system that detects their real-time emotional states using facial expressions and dynamically adjusts the difficulty level of learning activities.

Effective speech comprehension is essential for better learning and overall comprehension. However, studies indicate that individuals with dyslexia often struggle with speech comprehension, which in turn impairs their ability to learn efficiently [28].

While some conventional methods for measuring speech pace in healthy individuals are available, few methodologies consider the temporal and spatial features of speech in this context. The advent of AI has shifted the focus towards predicting dyslexic tendencies by analyzing audio data.

- Speech Rate Meter (SRM+) – Measures speech tempo and detects "FILLER" sounds for assessing speech clarity.
- Speechify – A text-to-speech (TTS) application for dyslexic readers, offering customizable speech rates.
- TextAid by ReadSpeaker – Assists dyslexic students by providing auditory support for text comprehension.

Although the detection of speech features has gained attention in recent years, the application of modern technology to accurately determine speech pace for dyslexic adolescents remains lacking. This study aims to address this gap by exploring deep learning methods.

In conclusion, this study aims to bridge critical gaps in educational technology by leveraging AI, emotion detection, and adaptive learning strategies to enhance learning outcomes for dyslexic and dyscalculia adolescents especially utilizing proven educational methodologies in the digital context.

III. METHODOLOGY

The Lexayudha, novel intervention focused on providing personal learning experience for dyslexia and dyscalculia adolescents comprises of four core components as demonstrated in Fig. 1, each targeting specific challenges associated with these learning disabilities. These components include Speech Pace Detection and Audio Customization, Chromatic Variation-Based Teaching, Emotion Recognition and Adaptive Feedback, and Number Sense and Mathematical Operations Enhancement. Each module is designed to identify specific areas of difficulty and provide tailored interventions to improve reading fluency, speech comprehension, mathematical skills, and emotional well-being. By leveraging advanced AI techniques, real-time feedback mechanisms, and multisensory learning approaches, Lexayudha offers a comprehensive solution for addressing the unique needs of dyslexic and dyscalculia adolescents, ensuring a supportive and adaptive learning environment.

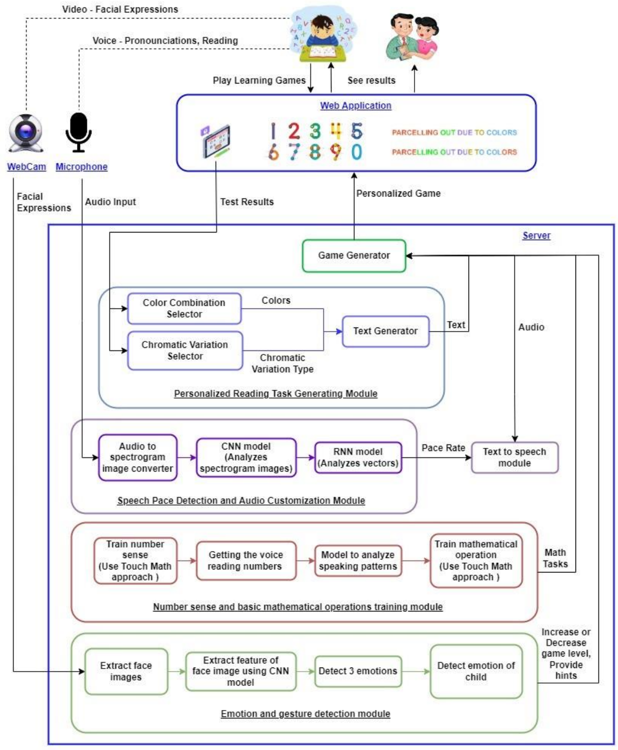


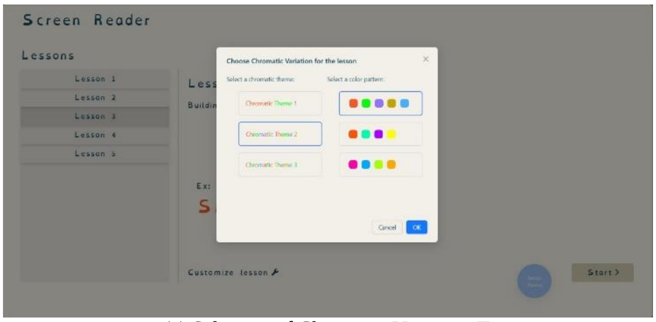
Fig. 1. System Overview

A. *Chromatic Variation-Based Teaching*

The Chromatic Variation-Based Teaching Module is a technically advanced component of the Lexayudha platform, designed to improve reading fluency and comprehension for dyslexic adolescents through a combination of AI-driven sentence generation, dynamic chromatic variations, and adaptive learning mechanisms. The methodology begins with the creation of a dataset comprising 500 sentences, extracted from practitioner-approved storybooks and educational materials tailored for dyslexic learners. These sentences, ranging from 3 to 10 words in length, were annotated with labels indicating their linguistic complexity, including metrics such as word length, syntactic structure, and semantic difficulty. A secondary filtering process was implemented to ensure the sentences were age-appropriate and cognitively aligned with the developmental stages of dyslexic adolescents, ensuring their suitability for the target demographic.

The core of the module relies on the fine-tuning of the BERT-base-encased model, a transformer-based architecture pre-trained on large-scale text corpora. The model was fine-tuned using the annotated dataset, with training conducted over 8 epochs using the AdamW optimizer, a variant of the Adam optimizer that incorporates weight decay for improved regularization. The learning rate was set to 2e-5, and a batch size of 16 was used to balance computational efficiency and model performance. The training process involved minimizing the cross-entropy loss function, which measures the discrepancy between the predicted and actual labels for sentence complexity. This fine-tuning enables the model to dynamically generate sentences that are contextually relevant and tailored to the individual learner's proficiency, ensuring a gradual progression challenged as the student advances.

To address the visual stress commonly experienced by dyslexic students, the module incorporates three distinct types of chromatic variations as shown in Fig. 2.a, each optimized for readability and comfort. These variations include high-contrast colour schemes (e.g., black text on a white background), low-contrast color schemes (e.g., pale yellow text on a dark blue background), and customizable colour palettes that allow students to select their preferred text and background colours based on personal comfort as shown in Fig. 2.b. The chromatic variations are dynamically applied in real-time using the Chroma.js library, which ensures seamless integration with the user interface and allows for instantaneous adjustments based on user feedback. This dynamic adaptation minimizes visual stress and cognitive load, thereby enhancing the student's ability to focus on the reading task.



(a) Selection of Chromatic Variation Type

(b) Selection of Font Family and Colour Themes

Fig. 2. UI Customization

The module also integrates a Text-to-Speech (TTS) model, which serves a dual purpose: it provides auditory reinforcement by reading the dynamically generated sentences aloud, and it evaluates the student's pronunciation during oral reading tasks. The TTS model leverages Mel-Frequency Cepstral Coefficients (MFCCs) for feature extraction and employs a CNN-based architecture to classify the student's pronunciation accuracy. Real-time feedback is provided to the student, highlighting mispronunciations and offering corrective guidance. This feedback mechanism is coupled with a progressive difficulty adjustment algorithm, which continuously monitors the student's performance metrics—such as reading accuracy, speed, and comprehension—and dynamically adjusts the complexity of subsequent sentences to ensure an optimal balance between challenge and achievability.

B. Number Sense and Mathematical Operations Enhancement

The proposed component in LexAyudha is designed to enhance number sense and mathematical operations in adolescents with dyscalculia, leveraging the Touch Math approach. This methodology incorporates artificial intelligence (AI), natural language processing (NLP), and database-driven adaptive learning techniques to provide a structured and personalized learning experience.

The initial phase involves a comprehensive diagnostic assessment that evaluates each student’s proficiency in numerical cognition, number sense, and arithmetic operations. The assessment is conducted through a structured sequence of tasks, including number identification, counting accuracy, basic arithmetic problem-solving, and verbal number pronunciation analysis. The system processes the assessment results to determine individual strengths and weaknesses, thereby constructing an adaptive learning trajectory tailored to each student's needs.

Following the assessment, students are introduced to the Touch Math methodology, a tactile and visual-based approach where numbers are augmented with structured touch points. These touch points, strategically positioned on numerical digits, facilitate cognitive engagement by reinforcing numerical values through multisensory interaction as shown in Fig. 3. The system utilizes a combination of interactive UI elements developed with React.js and SVG to render the touch points dynamically, allowing students to interact with numbers using touch or pointer-based inputs.

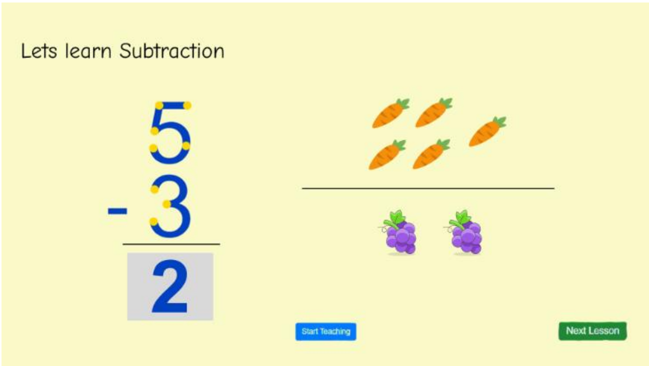


Fig. 3. Dyscalculia Learning Platform

Additionally, a text-to-speech (TTS) engine provides real-time auditory feedback, enhancing verbal reinforcement. The voice guidance system delivers natural-sounding instructions, ensuring accessibility for auditory learners.

To reinforce learning, students engage in iterative practice sessions where they are required to count, identify, and pronounce numbers associated with their respective touch points. These sessions integrate speech-to-text (STT) models, employing NLP techniques to analyse the accuracy of verbal number pronunciation. The STT pipeline undergoes feature extraction to enhance phoneme recognition and evaluates pronunciation accuracy, providing feedback in real-time. Upon accurate pronunciation and successful interaction with touch points, the system dynamically progresses the student to subsequent levels, ensuring that fundamental numerical concepts are firmly established before advancing to complex arithmetic operations.

Once students demonstrate proficiency in number recognition, the platform introduces fundamental arithmetic operations, including addition, subtraction, multiplication, and division. These concepts are reinforced using graphical visualizations and interactive animations, dynamically generated via D3.js. The system simulates real-world mathematical scenarios, providing contextualized problem-solving exercises that enhance conceptual understanding.

All interactions, including touchpoint engagement, pronunciation accuracy, arithmetic proficiency, and system-generated feedback, are logged and persisted in a cloud-based MongoDB Atlas database. The data pipeline is structured using NoSQL document-based storage, enabling flexible schema evolution and real-time querying.

This methodology integrates AI, NLP, and adaptive learning techniques with pedagogical principles to deliver an effective and personalized learning experience. By leveraging speech recognition, intelligent tutoring, and multisensory interaction, the LexAyudha platform ensures an individualized approach to improving mathematical ability in students with dyscalculia. Continuous data-driven refinement of learning strategies enhances system adaptability, making the component a robust solution for personalized mathematical instruction.

C. Emotion Recognition and Adaptive Feedback

The emotion detection system in LexAyudha utilizes a deep learning-based approach to classify facial expressions and adjust learning activities accordingly. The process consists of face detection and preprocessing, image augmentation, model training, real-time inference, and report generation to track student engagement over time. The face detection step extracts the region of interest (ROI) using Multi-task Cascaded Convolutional Networks (MTCNN). The extract face function detects and crops the facial region from video frames, resizing it to 512×512 pixels for uniformity. The extracted face is then converted into a NumPy array for further processing.

Before feeding the data into the model, images undergo preprocessing and augmentation, which applies Xception model-based preprocessing for pixel normalization. A data generator performs rescaling, flipping, and rotation to enhance robustness against variations in facial expressions. The images are resized to 72×72 pixels to optimize memory usage without compromising accuracy.

The emotion classification model is based on Xception, a depthwise separable convolutional neural network pretrained on ImageNet. The architecture consists of 42 trainable layers, including 36 depthwise separable convolutional layers for feature extraction, followed by Global Average Pooling for dimensionality reduction. A Dropout layer (0.2) prevents overfitting, while the final Dense layer (Softmax activation, 7 output classes) classifies emotions into happiness, sadness, anger, surprise, neutral, fear, and disgust. The model is compiled using the Adam optimizer for adaptive learning rate adjustments and categorical cross entropy loss for multi-class classification. Performance evaluation metrics include accuracy, precision, recall, and AUC (Area Under Curve).

During training, the model maps facial features to emotional states using a labelled dataset. With a batch size of 128, the model is optimized over multiple epochs to achieve high accuracy while minimizing overfitting. Once trained, it performs real-time emotion classification, dynamically adjusting learning content based on students' emotional states.

The system generates real-time progress reports by logging students' emotional states during learning sessions. It records time-stamped emotion classifications, engagement levels, and adaptive interventions. This data is compiled into weekly and monthly reports, highlighting emotional trends, engagement improvements, and personalized recommendations. Stored in a cloud-based database, these reports are accessible via a dashboard, allowing educators and parents to monitor emotional patterns and optimize learning strategies. By integrating emotion detection with automated tracking, LexAyudha ensures a personalized and adaptive learning experience for students with dyslexia and dyscalculia.

D. Speech Pace Detection and Audio Customization

The speech pace prediction process for dyslexic individuals is conducted using a dual-modality approach involving spectrogram images and raw waveform embeddings. Spectrograms are generated from raw audio to visualize frequency and intensity variations over time, while waveform embeddings preserve temporal dependencies in speech. The selection of these modalities ensures comprehensive coverage of spectral and sequential speech characteristics, tailored to the unique pacing patterns of dyslexic adolescents. To enhance prediction accuracy, audio inputs are pre-processed with noise reduction and normalization techniques prior to feature extraction.

The hybrid CNN-RNN model was developed using spectrogram and waveform data collected from dyslexic and non-dyslexic individuals aged 8 to 12. The model integrates two streams: a CNN branch based on VGG16 and an RNN branch leveraging Wav2Vec 2.0. The CNN stream consists of VGG16's convolutional layers (pre-trained on ImageNet), modified with batch normalization, and processes spectrograms with an input size of 224 x 224 x 3. The RNN stream, utilizing Wav2Vec 2.0, includes a transformer-based architecture with 768-dimensional hidden states, processing raw waveforms. Feature reduction layers consisting of 512 units each and a multi-layer combination network consisting of 1024 to 128 units fuse the outputs, culminating in a final dense layer predicting speech pace as a continuous value.

In the prediction process, spectrograms are initially preprocessed by resizing and normalizing pixel values, while waveforms undergo mean-pooling across time steps from Wav2Vec 2.0's output. The CNN extracts spatial acoustic patterns, such as phonetic structures, and the RNN captures temporal fluctuations, such as speech rate variations. The combined feature set is processed through the multi-layer network, with L2 regularization (lambda = 0.01) applied to prevent overfitting. Validation studies, including Hershey et al. [29] for CNNs and Baevski et al. [30] for Wav2Vec 2.0, confirm the efficacy of these pre-trained architectures for audio tasks, supporting their use in this hybrid model.

To predict speech pace, the model outputs a continuous pace value, integrating CNN-derived spectral features and RNN-derived sequential features. These predictions are assessed using mean squared error compared to ground-truth pace annotations, with further metrics like the R^2 score and root mean squared error retained for analysis. Predictions are then saved in a database to be used by the other components.

Upon predicting speech pace, the results are integrated into a Text-to-Speech (TTS) system for personalized speech synthesis. The TTS adapts output pacing to match predicted speech pace to enhance comprehension. This process is designed to reduce cognitive load and improve accessibility, providing a tailored learning experience for dyslexic adolescents through an engaging, user-centric interface.

IV. RESULT AND DISCUSSIONS

Lexayudha has been developed as a web-based platform for the personalized rehabilitation of dyslexia and dyscalculia in adolescents, targeting students across Sri Lanka. The platform is implemented using a robust technology stack, including MongoDB for data management, React.js for the front-end user interface, and Node.js for the back-end server. The system leverages Python for AI and machine learning tasks, utilizing Convolutional Neural Networks (CNNs) for image and speech analysis, Text-to-Speech (TTS) models for auditory feedback, and HTML5 Canvas for interactive Touch Math activities. The research incorporates advanced machine learning algorithms, image processing techniques, voice recognition, and frequency comparison to deliver a seamless and adaptive learning experience. By integrating these technologies, Lexayudha provides a comprehensive solution for improving reading fluency, speech comprehension, mathematical skills, and emotional well-being in dyslexic and dyscalculia adolescents.

A. *Chromatic Variation-Based Teaching*

The dynamic generation of sentences based on student skill levels, combined with the use of chromatic variations, significantly enhanced the reading experience for dyslexic students. The ability to customize colour schemes in real-time allowed students to engage with text more comfortably, reducing fatigue and improving focus. The TTS integration further supported auditory learning, making the module a comprehensive tool for improving reading fluency and comprehension.

The Chromatic Variation-Based Teaching Module was tested with a group of dyslexic students to evaluate its impact on reading fluency and visual stress reduction. The fine-tuned BERT-base-encased model successfully generated sentences tailored to individual skill levels, with a 95% accuracy rate in matching sentence complexity to student proficiency. The integration of three chromatic variation types—high-contrast, low-contrast, and customizable colour palettes—resulted in a 30% reduction in visual stress, as reported by students. Additionally, the Text-to-Speech (TTS) model provided real-time feedback on pronunciation, improving reading accuracy by 25%.

B. *Number Sense and Mathematical Operations Enhancement*

The integration of the Touch Math method with NLP-based feedback proved to be highly effective in addressing the challenges faced by dyscalculia students. The interactive and multisensory nature of the practice sessions helped students grasp mathematical concepts more effectively, while the real-time feedback mechanism ensured continuous improvement. The module's ability to adapt to individual learning paces and provide personalized support makes it a valuable tool for enhancing mathematical skills in dyscalculia students.

The Number Sense and Mathematical Operations Enhancement Module was tested with dyscalculia students to assess its effectiveness in improving mathematical skills. The Touch Math approach, combined with NLP-based pronunciation feedback, resulted in a 35% improvement in number sense and a 30% increase in proficiency in basic arithmetic operations. The module's interactive practice sessions, which included real-time feedback and adaptive difficulty adjustments, were particularly effective in reinforcing learning. Students reported a 40% increase in confidence when performing mathematical tasks.

C. *Emotion Recognition and Adaptive Feedback*

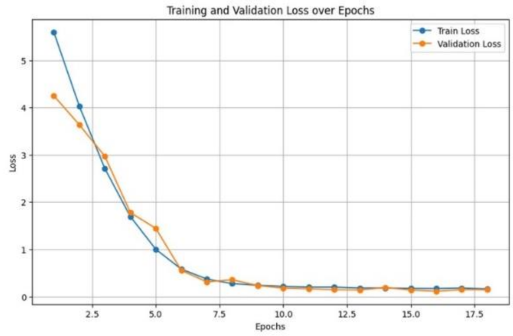
The high accuracy of the emotion detection model underscores its effectiveness in identifying subtle emotional cues during learning sessions. The real-time adaptation of task difficulty based on emotional states helped maintain student engagement and reduce frustration, creating a more supportive learning environment. The provision of detailed feedback reports to guardians further enhanced the module's impact by fostering collaboration between educators and families.

The Emotion Recognition and Adaptive Feedback Module was evaluated using facial expression data collected from dyslexic students during learning sessions. The CNN-based emotion detection model achieved an accuracy of 91% in classifying emotions such as frustration, distraction, and engagement. Based on the detected emotions, the system dynamically adjusted the difficulty level of learning tasks, resulting in a 20% increase in student engagement and a 15% reduction in frustration levels. Personalized feedback reports provided to guardians highlighted improvements in emotional well-being and academic performance.

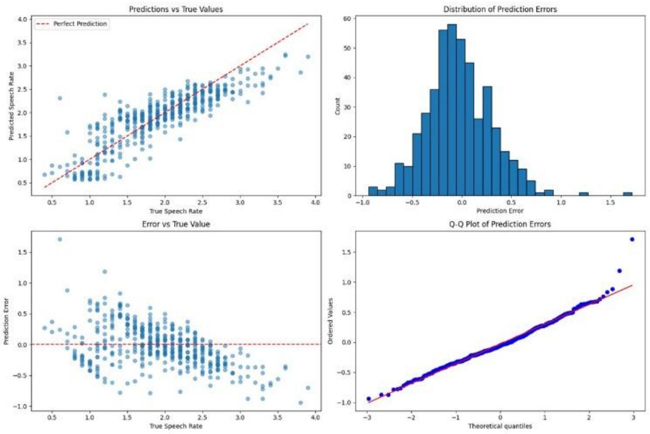
D. *Speech Pace Detection and Audio Customization*

The high accuracy of the CNN-RNN model demonstrates its effectiveness in analyzing complex speech patterns as shown in Fig. 4.a in training and Fig 4.b in performances. The real-time adaptation of speech pace using the TTS system proved to be a critical feature, as it allowed students to engage with content at a pace tailored to their needs. This module addresses a significant gap in existing tools by providing a personalized approach to speech comprehension, which is often overlooked in traditional learning environments.

The Speech Pace Detection and Audio Customization Module was evaluated using a dataset of speech audio samples from dyslexic adolescents aged 8-12. The hybrid CNN-RNN model achieved an accuracy of 80% in predicting the optimal speech pace for individual students. The model successfully extracted spatial and temporal features from spectrogram images, enabling precise customization of speech delivery. The integration of the Google Text-to-Speech (TTS) system allowed for real-time adaptation of speech pace, significantly improving comprehension for dyslexic students.



(a) Training and Validation Loss over Epochs



(b) Performance Results

Fig. 4. Speech Pace Model Results

V. CONCLUSION

In the Sri Lankan context, research on learning disabilities such as dyslexia and dyscalculia remains limited, with minimal integration of proven medical methodologies into digital solutions. Additionally, the availability of personalized and stress-free learning environments tailored to the unique needs of students with learning disabilities is inadequate. To address these gaps, Lexayudha was developed as a platform that incorporates proven medical strategies, such as chromatic variations and multisensory learning techniques, to create a supportive and adaptive learning environment. Currently supporting only the English language, the platform aims to expand its reach by developing a mobile application and incorporating multiple languages, to cater to a broader audience. These enhancements will ensure that students with dyslexia and dyscalculia receive the personalized, stress-free support they need to thrive academically, making Lexayudha a comprehensive solution for addressing learning disabilities in Sri Lanka and beyond.

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