ENLIGHTEN DS: ADVANCED TECHNOLOGIES FOR SKILL ENHANCEMENT AND TALENT RECOGNITION IN CHILDREN WITH DOWN SYNDROME

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Department of Information Technology

Sri Lanka Institute of Information Technology

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DECLARATION

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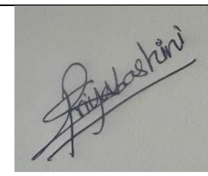
Kumarasinghe D.P.	IT21296314	
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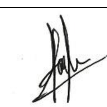
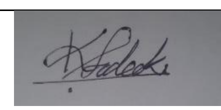
Semini B.V.S.	IT21342394	
Methsahani K.K.S.P.	IT21292972	

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ABSTRACT

Children with Down syndrome encounter significant challenges in speech articulation, cognitive development and learning, which conventional educational approaches often struggle to address effectively. Difficulties in speech clarity, working memory and problem-solving highlight the need for adaptive learning solutions tailored to their unique needs. To address these challenges, EnlightenDS is developed as an AI-powered educational platform that enhances learning through detection, pronunciation training, mathematics exercises and talent identification. The early detection of developmental concerns, facilitating timely intervention. And module leverages Convolutional Neural Networks (CNNs) to assess the detection of down syndrome. The pronunciation training component integrates Natural Language Processing (NLP) and a Flask-based API to process speech input, utilizing Google Speech-to-Text API and DeepSpeech AI for pronunciation evaluation. Speech-to-text conversion and phoneme-level articulation analysis further refine speech feedback. The mathematics training module applies structured learning methodologies like Kumon, Stern, and Numicon, ensuring an adaptive learning experience. Additionally, the talent identification system employs AI-driven analysis to monitor engagement in recital, learning, and painting activities, recognizing each child's strengths and interests. Evaluation of EnlightenDS demonstrates that AI-powered assessment and personalized learning techniques significantly improve cognitive abilities and speech development while creating a more engaging educational experience. These findings emphasize the potential of AI, image processing and adaptive learning methodologies in special education, fostering enhanced communication, cognitive growth and talent recognition for children with Down syndrome.

Keywords—Adaptive Learning, Down Syndrome, Image Processing, Machine Learning, Natural Language Processing, Speech Therapy, Talent Recognition,

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List of Abbreviations

Support Vector Machine	SVM
Convolutional neural networks	CNN
Down syndrome	DS
Artificial Intelligence	AI
Augmented Reality	AR
Test de Aprendizajey Desarrollo Infantil	TADI
Back Propagation Neural Network	BPNN
Congenital Zika Syndrome	CZS
Natural Language Processing	NLP
Convolutional neural networks	CNN
Down syndrome	DS
Valence Aware Dictionary and sentiment Reasoner	VADER
Virtual Reality	VR
Automatic Speech Recognition	ASR
Picture Exchange Communication System	PECS
Augmentative Alternative Communication	AAC
Intelligence quotient	IQ
Training group	TG
Control group	CG
Williams syndrome	WS
Typically developing	TD
Analysis of covariance	ANCOVA
User Interface	UI

1. INTRODUCTION

Down Syndrome (DS) is a genetically inherited condition caused by the presence of an extra chromosome 21 [1], which leads to a spectrum of physical, intellectual, and developmental challenges [1]. It affects approximately 1 in every 700 live births worldwide, with around 6,000 babies born annually with DS in the United States alone [2], [3]. Children with DS typically exhibit distinctive facial features such as a flat nasal bridge, slanting eyes, and a smaller head size [1]. In addition to these physical traits, individuals with DS often experience intellectual disabilities [4], with IQ levels generally ranging from mild to moderate (35–69), though some may experience more severe cognitive impairments [5].

Beyond intellectual differences, children with DS may face difficulties with motor skills, short-term memory, and speech development. These challenges often make it difficult for them to thrive in traditional educational environments, which are not designed to support their specific learning needs. As a result, specialized learning methods and tailored educational tools are essential to promote both cognitive and emotional development in these children.

Despite these obstacles, children with DS frequently demonstrate remarkable strengths. Many exhibit high emotional intelligence, creativity, and social warmth. With proper support, they often excel in artistic areas such as music, painting, and performance arts. However, these strengths are too often overlooked or underdeveloped due to a lack of appropriate educational tools. Mainstream educational systems and generic digital learning platforms typically fail to accommodate their unique pace of learning, limiting their potential to achieve academic success and personal growth [6], [7].

There is an urgent need for innovative, inclusive educational systems that not only address the learning challenges faced by children with DS but also uncover and nurture their hidden talents [8], [9]. To this end, the proposed system integrates four key components to holistically support the development of children with Down Syndrome.

The first component enables early detection of Down Syndrome using Support Vector Machine (SVM), facilitating accurate and efficient identification from medical or facial images. Early detection is crucial for initiating timely interventions and connecting children with appropriate learning resources [10], [1]. The second component aims to identify hidden talents in children with DS by analyzing creative outputs such as digital paintings and musical patterns using AI-driven analytics, fostering self-esteem and individual growth [11], [2].

The third component enhances pronunciation and speech development using real-time speech recognition, providing personalized feedback that supports language acquisition in an engaging way [12], [13]. The fourth component supports mathematical skill development through adaptive learning methods. By leveraging machine learning algorithms such as Logistic Regression, the system dynamically adjusts the difficulty of mathematical exercises based on individual performance, ensuring a personalized learning experience [14], [15].

Most existing educational platforms lack this level of AI-driven personalization and inclusivity, leaving children with DS underserved in both mainstream and special education contexts [16].

By addressing early diagnosis, talent development, language acquisition, and numeracy enhancement, the proposed system offers a comprehensive, personalized, and empowering learning environment. It aims to bridge the gap between conventional education and the diverse capabilities of children with Down Syndrome, enabling them to reach their full potential in both academic and personal domains [17].

1.1 Background Literature

The following literature review explores recent innovations in early detection, mathematical & pronunciation skills evaluation and talent identification in children with Down syndrome (DS), highlighting the integration of artificial intelligence, interactive technologies, and adaptive learning systems. A study titled Early Detection of Down Syndrome through Ultrasound Imaging using Deep Learning Strategies [4] demonstrates the power of deep learning and convolutional neural networks (CNNs) to non-invasively detect chromosomal abnormalities through features like nuchal translucency in ultrasound scans, stressing the importance of large annotated datasets and data augmentation. Complementing this, Identification of Nasal Bone for the Early Detection of Down Syndrome Using Back Propagation Neural Network [18] employs BPNNs to accurately identify nasal bone presence a crucial soft marker offering a safer and more accessible screening alternative to invasive procedures. Beyond prenatal screening, interventions supporting cognitive and language development have also gained momentum. Research into speech and language processing highlights delays in vocabulary and articulation, with Augmentative and Alternative Communication (AAC) tools like PECS, Makaton, and SGDs proving effective in enhancing communication [21], [22], supported by machine learning-powered speech feedback tools, ASR systems, and wearable devices. In the educational domain, studies have shown that children with DS often benefit from adaptive numeracy programs. Methods like Kumon, Numicon, and the Stern approach incorporate visual aids and repetition to foster mathematical understanding, while systems like The Number Race and custom-built animated educational platforms use performance tracking, real-life simulations, and quiz randomization to personalize learning [32], [33], [34], [35]. Finally, although much research has focused on cognitive challenges, limited work addresses talent identification in DS children. Studies like that of Needham et al. [36] examine fine motor skills through daily tasks, and Hickman et al. [37] explore adaptive assessments, but a comprehensive, tailored system to uncover individual strengths across motor, learning, and artistic domains remains largely undeveloped. Collectively, these studies reflect a growing, multidisciplinary effort to move beyond limitations and empower children with Down syndrome through early diagnosis, accessible education, and personalized support.

The research paper [4] is a comprehensive exploration of how the latest deep learning methods can revolutionize prenatal diagnosis through ultrasound image analysis. The groundbreaking study begins with a comparative review of conventional diagnostic procedures and emerging technologies, highlighting that while traditional methods such as amniocentesis and chorionic villus sampling offer considerable diagnostic accuracy, they remain invasive procedures with inherent risks to mother and fetus.

The authors conducted an extensive and systematic review of the literature to present a compelling case for the use of deep learning algorithms, particularly convolutional neural networks (CNNs), in medical imaging analysis for prenatal diagnosis. Through this comprehensive study, the authors systematically demonstrated that these cutting-edge technologies have a remarkable potential for automatically detecting clinically relevant features from ultrasound images and subsequently classifying chromosomal abnormalities with high precision.

In their comprehensive approach, the researchers carried out rigorous comparative studies among various pre-trained deep learning architectures and an array of transfer learning approaches. The comprehensive comparison was specifically directed at identifying optimal computational frameworks for the accurate detection and measurement of key Down syndrome markers, with particular emphasis on nuchal translucency thickness measurements, which represent a significant biomarker in early detection.

The research greatly emphasizes the imperative need for large annotated datasets in achieving reliable diagnosis results. Meanwhile, it addresses the magnitude of challenges brought about by the limited number of high-quality fetal ultrasound images, which remains an outstanding challenge in the field. The authors propose novel approaches in overcoming these gaps through the utilization of state-of-the-art data augmentation techniques and expert model training techniques.

Through this thorough review and analysis, the research effectively contributes to the development of an efficient, non-invasive, and low-cost early diagnostic system. The new technology aims to provide valuable clinical decision support to medical practitioners, enhancing their capacity for early and precise detection of Down syndrome during pregnancy, with the possibility of restricting the application of more invasive procedures, and improving overall patient care and outcomes in prenatal practice.

Research study [18] focused on improving non-invasive early detection of Down Syndrome by examining whether a fetal nasal bone could be identified in ultrasound images. The study was built on the established knowledge that an underdeveloped or absent nasal bone serves as an important soft marker for Down Syndrome, particularly during the first trimester of pregnancy.

The researchers conducted a comprehensive literature review exploring the diagnostic significance of this marker and the potential applications of machine learning in medical imaging analysis. Building on this foundation, they implemented a Back Propagation Neural Network (BPNN) classifier designed to differentiate between normal and abnormal fetal profiles based on extracted image features.

The methodology involved processing ultrasound images through multiple steps including segmentation, feature extraction, and classification to isolate the nasal bone area and determine its presence or absence. The BPNN was trained using a dataset of fetal ultrasound scans, enabling it to recognize patterns connecting nasal bone characteristics with potential Down Syndrome indicators.

Results showed that the proposed system achieved high classification accuracy, demonstrating the potential of artificial intelligence to support medical professionals in making early and precise diagnoses. This approach offers significant advantages by reducing dependence on invasive testing procedures like amniocentesis while enhancing the efficiency and accessibility of prenatal screening. The technology represents an important advancement in making Down Syndrome screening more accessible and less risky during routine prenatal care.

Research in speech and language processing for children with Down syndrome (DS) has explored various challenges and advanced intervention methods, especially focusing on delayed vocabulary growth, poor articulation, and grammatical difficulties due to cognitive, hearing, and motor issues [19]. Early intervention and family-centered approaches, such as responsive parent-child communication, have shown to significantly enhance language development [20]. Augmentative and Alternative Communication (AAC) tools ike Speech-Generating Devices (SGDs), PECS, Makaton sign language, and Picture Communication Symbols (PCS) have proven effective in improving communication, reducing frustration, and supporting social interaction [21]. Programs like "It Takes Two to Talk" further train parents to reinforce language skills in daily routines [22].

Recent advancements in Natural Language Processing (NLP) and Machine Learning (ML) enable personalized pronunciation feedback and predictive modeling of language development [23]. Adapted Automatic Speech Recognition (ASR) systems can detect articulation errors and offer real-time correction [24]. Tools like LENA utilize wearable tech to gather and analyze environmental speech data for tailored feedback [25]. Motion analysis using sensors and cameras has been effective in tracking articulatory gestures, enhancing pronunciation through visual biofeedback [26]. Virtual environments and ultrasound imaging also support articulation training by offering real-time feedback on tongue and mouth movements [27].

Emerging technologies, including Virtual Reality (VR), Augmented Reality (AR), and multimodal systems combining NLP, motion analysis, and VR, offer immersive, individualized interventions [28]. Wearable devices with speech recognition capabilities provide consistent, in-context feedback throughout daily activities [29]. These innovations support data-driven, personalized approaches to improving the speech and communication skills of children with DS [30].

Children with Down syndrome (DS) often face significant challenges in developing mathematical skills. To support their numeracy development, specialized instructional methods have been designed. These methods, although implemented in some child centers, remain largely unknown to many parents and caregivers [31].

The Kumon method is built on repetitive practice and gradual progression through levels of difficulty. It focuses on basic arithmetic operations, moving from simple tasks to more complex ones. The method utilizes a series of worksheets that progressively increase in difficulty, enabling students to work at their own pace. This approach promotes independent learning, self-confidence, and the development of strong problem-solving skills [32].

The Stern and Numicon approaches focus on using tangible objects and visual aids to represent numerical values and their relationships. These methods aim to make abstract mathematical concepts more concrete. The Numicon approach uses colorful, removable number shapes, which help children grasp fundamental concepts like addition, subtraction, and number values. These approaches are particularly effective for visual and kinesthetic learners, making them ideal for children with DS. By combining both methods, a comprehensive learning experience is created, catering to various learning styles [32], [33].

In a study titled Training Basic Numerical Skills in Children with Down Syndrome Using the Computerized Game 'The Number Race', two groups of children were compared: the Training Group (TG), which used "The Number Race" to enhance numerical skills, and the Control Group (CG), which used literacy software. The study measured both numerical and reading skills at various stages (pre-test, post-test, and follow-up), with the TG showing significant improvements in numerical skills over time [34], [35].

The proposed learning system offers adaptive quizzes that personalize the learning experience by adjusting question difficulty based on the child's performance. It tracks time spent on questions and evaluates understanding through randomized quizzes. Educational animations created with React and Fabric.js will visually explain math concepts and correct mistakes. One module will teach basic operations using real-life currency to connect math to daily life. The system includes performance tracking and generates reports for parents to monitor their child's progress, providing insights into areas of improvement.

Based on the selected research topic and the selected component, this study mainly focuses on down syndrome children’s talent identification. There are three main areas will be considered. They are motor skills, learning skills and painting skills. Most of the time down syndrome children are talented for one specific area. According to the previous research works there is no proper system to identify that talent [36][37]. Most research focuses on the challenges faced by children with Down syndrome [36].

For example, the study conducted by Needham et al. [36] investigates fine motor skill development in children with Down syndrome. The researchers examine day-to-day activities such as writing with a pencil, typing on a keyboard, or using cutlery, which involve coordinated hand and finger movements. Their work highlights the relationship between the physical characteristics of muscle size and the muscle groups involved in performing such motions. The findings suggest that the ability to carry out motor-related activities is directly influenced by the nature and coordination of these muscle groups. This insight provides a useful foundation for identifying motor-related strengths in children, although it is not extended into a complete talent identification system.

In a study conducted by Hickman et al. [37], the researchers investigated the use of adaptive learning strategies, specifically focusing on advanced question randomization techniques to enhance the effectiveness of educational assessments. Their approach aims to create fairer and more dynamic testing environments by reducing predictability in question order. However, this study does not specifically cater to the unique needs of children with Down syndrome. It does not explore how such techniques could be adapted or extended to support talent identification or skill development within this group. As a result, there remains a notable gap in the application of personalized, adaptive learning systems that are designed specifically to uncover and support the individual strengths of children with Down syndrome.

The proposed system, EnlightenDS, aims to address the gaps in the literature by integrating AI-based Down Syndrome (DS) detection and personalized learning interventions in a comprehensive, adaptive learning system. While existing research supports the application of AI in DS detection, speech development, talent development, and adaptive learning, systems that integrate these components remain limited. EnlightenDS utilizes machine learning, deep learning, and AI-driven analytics for designing a personalized learning environment for children with DS according to their specific needs. It also utilizes Support Vector Machine (SVM) for detecting DS from either real time web cam or uploaded images, enhancing diagnostic accuracy by utilizing advanced preprocessing techniques and integrating principles of cognitive development into the models.

Besides improving diagnosis, the system incorporates a web application that leverages sentiment analysis and motivational messaging to foster emotional stability and accuracy in pronunciation. EnlightenDS also employs adaptive learning technologies to aid in mathematical learning and establish children's aptitudes in areas such as drawing and recital. By leveraging technology-based analysis, the platform aims to provide an integrated approach to children's talent development while improving their cognitive and emotional growth.

1.2 Research Gap

Research paper [4] presents the application of deep learning models such as CNN, ResNet34, and Faster-RCNN for prenatal Down syndrome detection using ultrasound imaging. While the study offers valuable insights, several limitations are evident in comparison to the capabilities of EnlightenDS.

Firstly, the study employs basic segmentation techniques, such as bounding boxes around the fetal head, but lacks advanced image processing methods necessary to extract subtle developmental features. EnlightenDS addresses this through the use of more refined image analysis techniques that capture a broader range of diagnostic markers. Secondly, the research omits the use of Support Vector Machines (SVM), a robust classification algorithm known for its effectiveness in medical diagnostics. EnlightenDS integrates SVM with deep learning models to enhance classification precision. Thirdly, the system is restricted to clinical settings requiring specialized equipment and trained personnel, limiting its accessibility. In contrast, EnlightenDS is delivered via a web-based platform, ensuring broader availability across various healthcare environments. Moreover, the study does not evaluate potential gender-related performance disparities in its models. EnlightenDS incorporates gender-neutral algorithms to promote equitable diagnostic outcomes. Finally, the diagnostic output is limited to binary classifications without confidence metrics. EnlightenDS enhances clinical utility by providing probability-based assessments, supporting more informed decision-making.

Collectively, these gaps demonstrate the need for a more comprehensive, accessible, and equitable solution one that EnlightenDS effectively fulfills.

Research paper [18] presents an early Down syndrome detection system using ultrasound images focused on nasal bone presence in fetuses at 11–13 weeks. It uses Back Propagation Neural Networks (BPNN) along with basic image processing techniques like median filtering and watershed segmentation, and features extracted through statistical, DCT, and Wavelet (D4) transforms. While detection accuracy reaches up to 88% using Wavelets, the system outputs only binary results without nuanced probability estimates. EnlightenDS addresses this by providing detailed probability scores, enabling more informed and risk-sensitive clinical decisions.

The study also lacks advanced image processing methods. It admits not using edge detection due to noise concerns, limiting its ability to extract finer features. EnlightenDS overcomes this with more robust image processing capable of handling ultrasound noise and capturing subtle anatomical markers more effectively.

Although BPNN is used for classification, the paper doesn't explore SVMs, which are known for strong performance in medical image classification, especially with limited data. EnlightenDS integrates SVM to improve classification accuracy and reliability.

Accessibility is another gap. The solution is confined to clinical settings, with no web-based implementation for wider use. EnlightenDS resolves this by offering a web-accessible platform, expanding reach to healthcare providers across diverse settings.

The study also overlooks gender-related performance variations. There's no evaluation of whether the model works equally across genders, which could introduce bias. EnlightenDS counters this with gender-neutral algorithms to ensure equitable results.

Lastly, the approach is limited to nasal bone detection without integrating other Down syndrome markers. While it mentions the potential benefit of combination, it does not explore it. EnlightenDS likely provides a more holistic screening by incorporating multiple indicators, improving diagnostic robustness.

These limitations underline how EnlightenDS presents a more advanced, accessible, and equitable solution for Down syndrome screening compared to the method proposed in paper [18].

The Buckley Adolescent Language Study (1993), [38] which builds on the foundational work of Buckley and Sacks (1987), examines how language abilities change during adolescence in individuals with Down syndrome. The research analyzed the speech and language patterns of 90 teenagers and found that many struggled with grammar and sentence structure, leading to "telegraphic" speech that was often difficult for others, especially strangers to understand.

Two instructional methods were evaluated:

- Speech-Only (S): Focused purely on verbal repetition without any visual aids.
- Speech-Plus-Reading (SR): Combined verbal repetition with visual materials, such as pictures accompanied by written sentences.

The SR method proved significantly more effective, particularly for children with poor reading skills and limited memory. Interactive and visually engaging tools, including materials like Polaroid photographs, were also shown to support generalization of learned skills to natural, everyday communication.

The Dubai Speech Recognition Intervention Study (2007) [39] discusses the development and early evaluation of speech therapy software aimed at supporting non-native Arabic-speaking children with Down syndrome at the Rashed Paediatric Therapy Centre in Dubai. Two types of speech recognition algorithms were used:

- Word-based recognition, which evaluates entire words and requires multiple word variants for feedback.

- Phone-based recognition, which targets individual phonemes to provide more precise correction of phonological issues.

Both algorithms were developed using the Nuance Speech Recognition System and Java. The software interface was inspired by the "Speaking for Myself" educational tool, incorporating printed words, images, and audio cues.

In testing with pre-recorded audio, the word-based algorithm had a 41.1% accuracy, influenced by technical and human factors. The phone-based approach performed significantly better, achieving 73.8% accuracy, which increased to 84.2% after optimization.

The study emphasizes the effectiveness of specialized speech therapy tools in enhancing communication skills in children with Down syndrome. Building on this concept, EnlightenDS is being designed as an intuitive web application for children aged 5–15. It will feature gamified quizzes for assessment and engagement, alongside pronunciation exercises to improve speech, offering a fun and impactful learning experience.

A key innovation of the proposed system lies in its ability to address several limitations present in existing research.

- The system also analyzes the facial expressions of the child to deliver personalized, encouraging responses, fostering a positive and emotionally supportive learning environment. This emotional awareness aims to make speech therapy more engaging and effective by aligning with the child's feelings.

- Furthermore, the system leverages Emotional based pronunciation practice game to offer a modern and efficient approach to speech therapy.

The research [34] explored the impact of the computerized game *The Number Race* on numeracy skills in children with Down syndrome (DS), showing positive results, particularly in mental calculation and number change for the intervention group. However, the study had several methodological limitations. It lacked a control group following standard classroom instruction, had a short training duration, and included participants with varying baseline skills. The intervention game was not adaptive to individual learning progress, participants were not randomly assigned, and testers were not blinded—raising concerns about selection and observer bias. Importantly, the study did not examine whether the acquired skills translated to real-world applications.

This review [40] analyzed nine empirical studies (1989–2012) to assess the effectiveness of various math interventions for young children and teenagers with Down syndrome (DS). Most of these studies focused on basic skills like counting and number recognition. Key findings from the review suggest that, while interventions generally led to improved numeracy for children with DS, none of the studies were methodologically sound. Notably, no study used targeted interventions that specifically addressed the behavioral characteristics of Down syndrome. Due to the overall poor quality of the research and the small sample sizes, it remains unclear which mathematical intervention techniques are most effective for this group. The results highlight the urgent need for high-quality, well-controlled research that considers the unique behavioral and cognitive profiles of children with Down syndrome and uses more structured, formalized intervention approaches.

Despite its insights, this and similar studies largely rely on conventional teaching tools with limited adaptability, minimal interactivity, and basic assessment mechanisms. They often overlook essential features necessary for effective DS education:

- Lack of adaptive learning that responds to each child's developmental level
- Absence of engaging educational animations to explain abstract concepts visually
- No structured parental feedback system to support learning beyond the classroom
- Limited performance tracking, focusing only on short-term test results rather than long-term growth

EnlightenDS is designed specifically to fill these gaps in DS-focused numeracy training by offering:

- Adaptive Question Logic, adjusting content based on age, skill level, and individual progress
- Interactive Educational Animations to help children better understand mathematical concepts
- Comprehensive Performance Tracking with detailed feedback for both educators and parents
- Parental Involvement Tools to support learning continuity at home

Various previous studies have made important strides in supporting the education and skill development of children with Down syndrome. One such study by J. Janier et al. [41] emphasizes learning-related activities like matching and counting. While this research contributes meaningfully to the understanding of basic cognitive skill development, its scope is limited to foundational learning concepts. It does not explore the potential of more advanced or interactive learning techniques such as quizzes that could provide a deeper and more dynamic assessment of a child's academic abilities and cognitive engagement.

Similarly, the study by A. S. T. Sampath and colleagues [3] presents an e-learning system that uses handwritten images and voice samples to analyze the drawing abilities of children with Down syndrome. Although the authors successfully utilized voice and image recognition technologies to assess drawing skills, the study was centered solely on measurement. There was no attempt to use the findings to further develop or enhance the artistic skills identified in the children. As noted by the authors themselves, future work could benefit from moving beyond assessment toward actual skill improvement.

Despite these efforts, there is currently no integrated system available that can comprehensively identify the most talented area of a child with Down syndrome across multiple domains such as learning, drawing, or motor skills. This presents a significant research gap. The proposed system in this study aims to address this limitation by offering a multi-platform approach that not only identifies a child's most prominent skill area but also encourages the development of that skill. It goes beyond mere evaluation it provides children with an opportunity to explore, engage, and enjoy activities that align with their natural strengths. In doing so, the system not only assists educators and parents in recognizing talent but also creates a space for creativity, entertainment, and self-expression.

1.3 Research Problem

Infants and children with Down syndrome (DS) can look forward toward bright futures, as individuals with DS are living healthier, more productive lives than ever due to medical advances, opportunities for early and continued intervention, and inclusive education. Despite these advances, infants and children with DS experience challenges in specific domains of cognitive functioning relative to their typically developing (TD) peers. Over the long term, individuals with DS are also more likely to develop Alzheimer's disease relative to the general population. Understanding cognitive functioning early in life may be important in charting cognitive decline over time [42]. Most children with Down syndrome have some level of intellectual disability, usually in the mild to moderate range. People with mild intellectual disability are usually able to learn how to do everyday things like read, hold a job, and take public transportation on their own. People with moderate intellectual disability usually need more support.

The primary research problem of this study is how to address the delayed and challenging diagnosis of Down syndrome and improve early interventions through the integration of advanced technologies, including machine learning, image processing, and adaptive learning systems. Specifically, the study focuses on the following sub-problems:

Early Diagnosis: How can machine learning, image processing, and AI-driven pattern recognition be employed to detect Down syndrome early, ensuring timely intervention and better long-term outcomes?

Current diagnostic methods are often delayed and reliant on physical examinations, which may miss subtler signs of DS.

Speech and Language Development: How can voice detection accuracy and emotional expression challenges be addressed in therapeutic tools designed for children with Down syndrome? Given their difficulties in articulation, sentence structure, and auditory memory, how can interactive speech therapy tools be developed to provide personalized feedback and support?

Motor, Learning and Drawing Talents: How can technology-based systems be developed to identify and nurture the natural talents of children with Down syndrome, such as in music, learning, and art, by analyzing interaction patterns and providing personalized feedback?

Mathematical Skills Development: How can adaptive learning technologies be effectively employed to support the development of basic math skills in children with Down syndrome? Given their unique challenges in acquiring numerical skills, how can personalized feedback and tailored interventions bridge the developmental gaps in their mathematical understanding?

Technology Integration in Speech Therapy: How can new advancements in Natural Language Processing (NLP), machine learning (ML), and motion analysis be integrated into user-friendly, accessible tools that engage children with Down syndrome and support their speech development in a fun, interactive way?

This study aims to provide a comprehensive approach to addressing the early detection and development challenges faced by children with Down syndrome by combining innovative technologies with personalized interventions, ultimately improving their educational and social outcomes. The goal is to create adaptive, accessible tools for early intervention and long-term support that bridge the gap between diagnosis, therapy and cognitive development, contributing to the overall well-being of children with Down syndrome.

1.5 Research Objectives

1.5.1 Main objective

The overall system aims to create a comprehensive developmental support system for children with Down syndrome that focuses on detecting Down syndrome, improving pronunciation skills, enhancing mathematical abilities and identifying and nurturing artistic talents. This system will also provide individualized guidance to the parents and educators and develop effective metrics to assess the effectiveness of these interventions. The goal is to holistically support each child's unique potential and foster their growth in multiple domains, ensuring they achieve their fullest capabilities.

1.5.2 Sub objectives

- **Enhancing Early Detection of Down Syndrome Through Image Preprocessing and Facial Landmark Extraction Using Dlib**

  To prepare the images for analysis, preprocessing techniques such as face detection, alignment, grayscale conversion, resizing, and noise reduction are applied to standardize the input and improve feature extraction accuracy. Following preprocessing, the Dlib library is utilized to detect and extract key facial landmarks from each image. These landmarks provide critical geometric features that are essential for detecting Down syndrome characteristics, ensuring more accurate and reliable analysis.

- **Use SVM to provide detection output with a probability score**

  Once trained, the SVM model analyzes new images to determine the likelihood of Down syndrome and outputs a probability score along with detected facial indicators. This helps caregivers and clinicians make informed decisions based on the model's confidence.

- **Enhance Pronunciation**

  The application will incorporate advanced speech recognition and deep learning algorithms to improve pronunciation accuracy. Speech will be analyzed at the phoneme and word levels by speech recognition APIs, including Google Cloud Speech-to-Text and Microsoft Azure Speech Service. Using NLP techniques, detailed feedback on articulation and phonological patterns will be provided. Deep learning frameworks like TensorFlow or PyTorch will be used to develop models for fine-tuning toward better pronunciation assessments and corrections.

- **Sentiment Analysis and Motivational Messaging**

  Sentiment analysis and motivational messaging will keep the children engaged and motivated. Tools for sentiment analysis, such as VADER or TextBlob in this case, will be utilized to track and make sense of all emotional cues from a user's interactive activities. Convolutional neural networks (CNN) for facial expression and other visual data will be assessed with respect to emotional states. An application, drawing from these analyses, will further proceed to provide personalized motivational messages of encouragement tailored to suit every emotional need of a child in order to promulgate a positive and supportive learning environment.

- **To design and implement interactive platforms for assessing learning, motor, and drawing skills in children with Down syndrome**

This includes the development of a quiz module using AI-generated language-based questions, a virtual piano interface to measure motor coordination and recital skills, and a digital drawing platform to evaluate artistic abilities. Each platform will capture relevant interaction data such as time spent, number of attempts, keypress counts, drawing similarity scores, and overall user engagement.

- **To analyze the collected data using machine learning techniques and generate meaningful insights for talent identification**
  A Random Forest model will be trained using the gathered data to accurately predict the most talented area for each child. The system will then visually display the results and send a notification to the child's parents or caregivers, enabling them to better support and nurture the child's natural strengths.

- **Create Adaptive Quiz System**
  Interactive quizzes that get harder as you get better at practice level adjust the difficulty of questions to best suit the child while keeping them challenging and enhancing learning appropriate for where they are at with their skill set.

- **Educational Animations for Math Concepts**
  Integrate animations that demonstrate math-related one's calculations. This visual technique is effective at communicating the core mathematical ideas and processes in a way that children with DS can relate to.

2. METHODOLOGY

2.1 Overall System Architecture Diagram

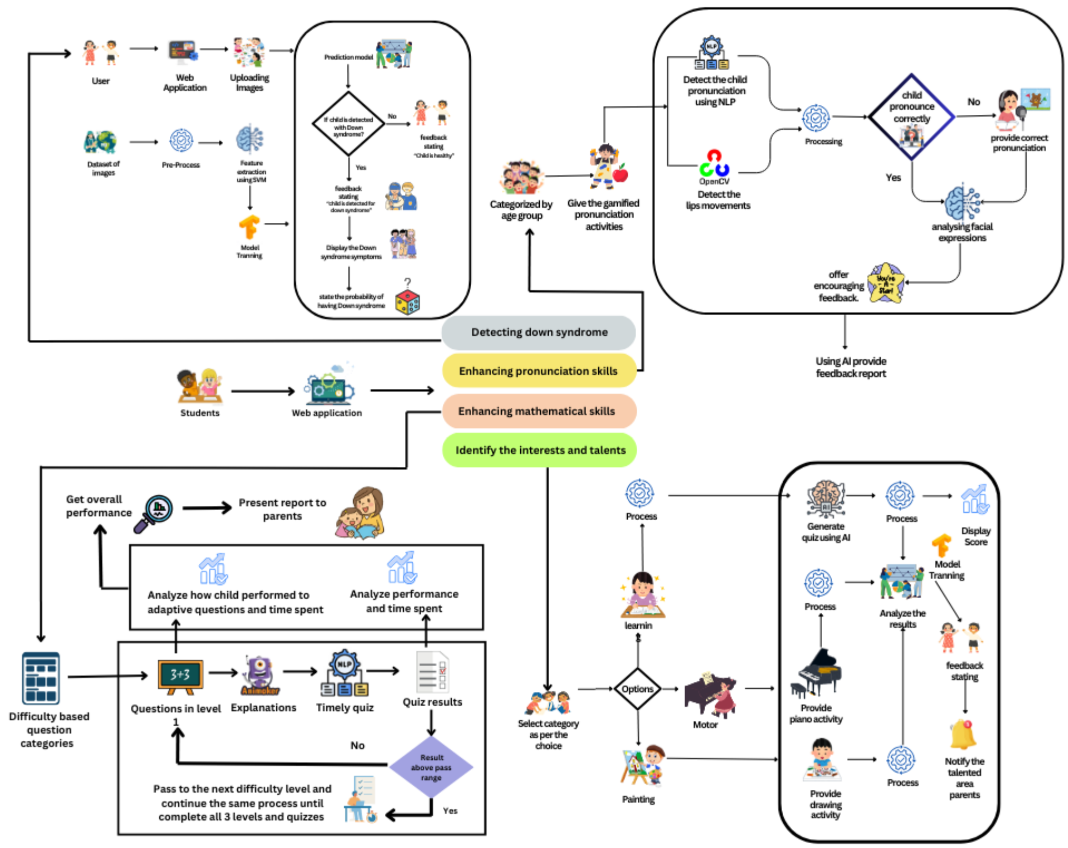


Figure 1: Overall System Diagram

The system diagram presented outlines a sophisticated framework aimed at assessing and enhancing various aspects of children development, including cognitive abilities, pronunciation skills, mathematical proficiency and the identification of interests and talents. This framework is divided into four primary components, each playing a crucial role in the holistic development of students.

The first component focuses on **detecting Down syndrome**. It begins with data preparation, where facial images of children with and without Down syndrome are preprocessed using techniques like face detection, alignment, grayscale conversion, noise reduction, and facial landmark extraction with Dlib. These features are normalized and used to train a Support Vector Machine (SVM) classifier, chosen for its ability to distinguish geometric and textural facial traits. In the prediction phase, users upload a child's image via a web interface, which undergoes the same preprocessing. The trained model then analyzes the features to determine the likelihood of Down syndrome, providing a probability score and identified facial markers. This system offers a fast, non-invasive screening tool for early detection and further medical guidance.

The second component is dedicated to **enhancing pronunciation skills**. In this component, Natural Language Processing (NLP) is used to assess the accuracy of a student's pronunciation. The system begins by analyzing the student's speech and detecting their lip movements. If the student mispronounces a word, the system offers the correct pronunciation along with encouraging feedback, while also analyzing the student's facial expressions to understand their response. This interactive learning process is further enhanced by categorizing students according to their age group and providing gamified pronunciation activities tailored to their developmental level. This approach ensures that learning is both engaging and effective, helping students improve their language skills in an interactive, supportive environment.

The third component addresses **enhancing mathematical skills** through an adaptive learning process. Students start by taking a pre-test, which is designed to assess their current level of mathematical proficiency. Based on the pre-test results, the system guides students through a series of progressively challenging questions and quizzes, offering explanations for any mistakes made. The system adjusts the difficulty level as the student progresses, ensuring a personalized learning experience that matches the student's pace. If a student performs well, they advance to the next level; if not, they receive additional training before retaking the quiz. This iterative process ensures that students thoroughly master each concept before moving on to more advanced topics, thereby strengthening their mathematical foundations.

The fourth component is focused on **identifying interests and talents**. In this part of the system, students can choose from a variety of activities such as learning, recital, painting, or piano playing. The system uses artificial intelligence to generate quizzes related to these activities and processes the results to analyze the student's performance. Based on this analysis, the system provides feedback to both students and parents, highlighting areas of talent or suggesting further activities to nurture specific skills. The component's Artificial Intelligence (AI) driven model is continually refined to improve the accuracy of talent identification, ensuring that students are guided toward activities that align with their natural abilities and interests. Overall, the system integrates these four components into a unified web application that students interact with. This integrated approach provides a comprehensive view of each student's development, covering cognitive, linguistic, mathematical and personal growth. The data collected 24 across these components is synthesized into a detailed report, which is then presented to the parents. This report offers valuable insights into the student's strengths and areas for improvement, enabling parents and educators to tailor educational strategies to the individual needs of the student. In essence, the system is designed to offer a holistic and personalized educational experience, leveraging advanced technologies to support the diverse aspects of student development.

2.3 Software Solutions

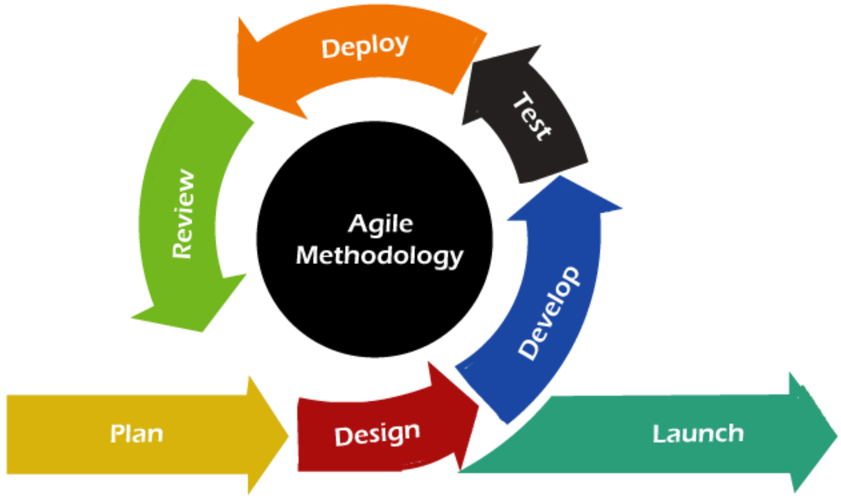


Figure 2: Agile Methodology

Our software development process is guided by the Agile methodology, a dynamic and innovative method of software development and project management. In contrast to traditional waterfall models that adhere to a rigid, sequential process from requirements gathering to design, implementation, testing, and deployment Agile adheres to a non-linear, iterative process that allows for continuous refinement at every phase of the project life cycle. This makes it especially well-suited to projects in which requirements will shift or in which user feedback will have a determining impact on the final product.

Underneath the surface of Agile are "sprints" brief, time-boxed development cycles, typically lasting from one to four weeks. Each sprint attempts to produce an operational, testable portion of the complete system. This process enables the team to review constantly, combine new features, test functionality, and respond quickly to user comment or project direction change. Unlike waiting until the last stages of the project to ascertain its efficacy, Agile promotes ongoing reflection and adjustment, resulting in more fitting, high-quality outcomes that deliver more to user expectations.

To apply this methodology and operate our team in an organized way, we take Microsoft Teams Planner as our principal task management system. In Planner, work gets visually organized by buckets and task cards that refer to the varied actions of a sprint. Every task card gets crucial information that includes task description, due dates, attachments, and assigned personnel. Members can update the task status, add comments, change priorities, and work collaboratively in real time. This creates a transparent and collaborative workspace, where all members are kept informed, held accountable, and aligned to project objectives.

The blending of Agile's iterative approach and Planner's innate organizational skills brings forth a balanced development environment. It provides adequate structure to lead the project yet also allows for room to be innovative and adaptable. Unification enables us to quickly adjust to evolving needs, improve teamwork communication, and maintain constant watch over delivering high-quality, user-focused solutions efficiently.

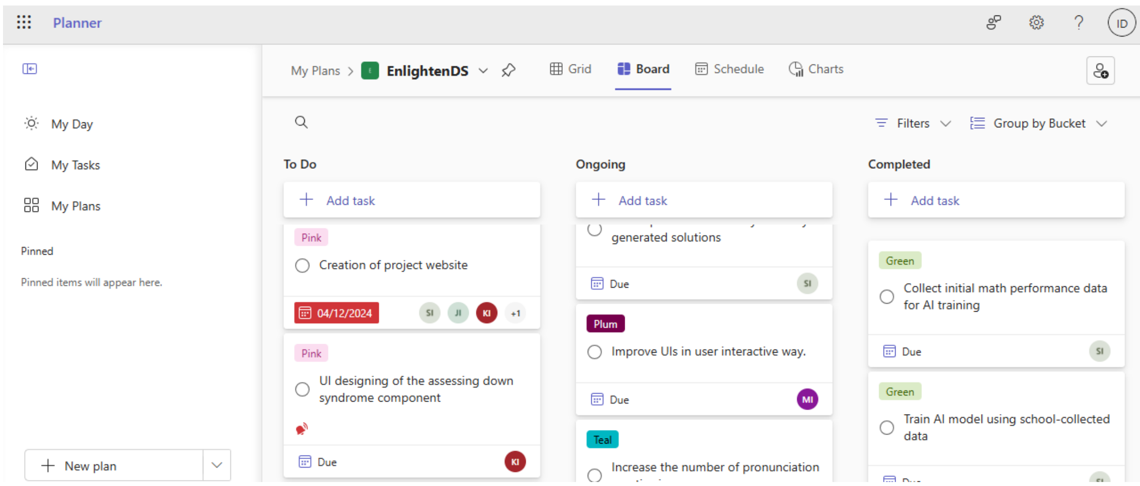


Figure 3: MS Planner Task Assigning

2.4 Requirement Gathering

Conducting Interviews = We conducted in-depth interviews and field visits involving teachers, caregivers, specialists, and parents primarily at the Senehasa Research Center and affiliated schools. These interactions provided critical, firsthand insights into the behavioral patterns, learning needs, and physical characteristics commonly observed in children with Down syndrome. Teachers and caregivers shared valuable experiences related to identifying distinctive facial features, motor behaviors, and social cues, which are essential for early detection and diagnosis. They also discussed the educational challenges these children face, especially in areas like mathematics, and explained the current strategies and teaching practices they use to support learning in classroom environments.

In parallel, we engaged in discussions with specialists at Senehasa to better understand the cognitive and developmental hurdles children with Down syndrome often encounter. This included exploring their difficulties with memory, attention span, and problem-solving, especially as they relate to numeracy and other academic skills. At the same time, we conducted conversations with parents to gain a more holistic perspective on the children's behavior at home, their strengths, areas of struggle, and the talents they exhibit in activities like art, music, or learning.

By integrating these insights from both professional and domestic environments, we were able to ground our system design in real-world observations. This collaborative feedback loop greatly influenced the development and refinement of our detection and learning support tools, ensuring they are practical, relevant, and aligned with the unique needs of children with Down syndrome.

Observations = We conducted extensive direct observations at the Senehasa Research Center and several schools to gain a deeper understanding of how children with Down syndrome engage with cognitive and academic tasks, particularly in mathematics. We spent meaningful time in classrooms and activity sessions, closely observing how the children interact with educational content, the techniques they use to solve problems, and their overall approach to learning. This included monitoring their ability to focus, the problem-solving strategies they adopted, and any noticeable behavioral or learning characteristics.

Our focus extended beyond academic engagement to include how these children respond to various cognitive challenges during their daily routines. We paid special attention to concentration levels, information processing methods, and unique behavioral patterns that appeared to influence their cognitive development. We also looked for signs commonly associated with Down syndrome such as delayed responses, repetitive behaviors, distinct facial features, and specific social interaction styles to support early detection and tailored intervention strategies.

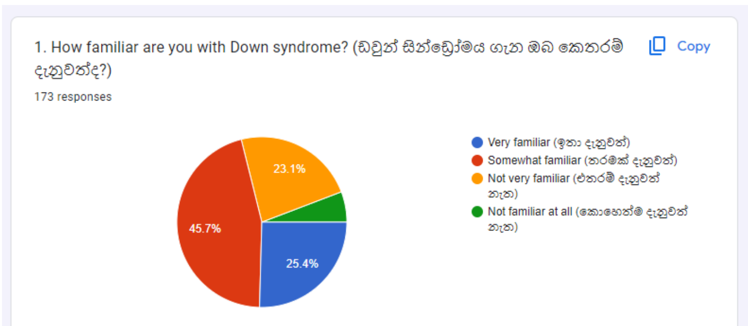
These real-world observations were crucial in shaping our understanding of the children's strengths, challenges, and needs. By immersing ourselves in their learning environments and daily activities, we gathered essential practical insights that informed the design and refinement of both our detection system and educational support tools, ensuring they are responsive to the actual behaviors and capabilities of children with Down syndrome.

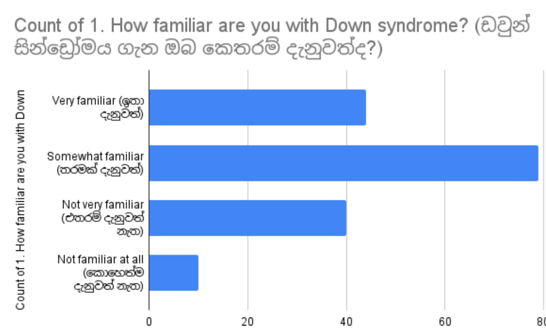
Survey = The questionnaire included specific questions targeting knowledge of DS, the importance of research, and the perceived effectiveness of adaptive educational strategies for children with the condition. We received responses from a diverse group of participants, providing us with valuable insights into how Down syndrome is understood and discussed within the community.

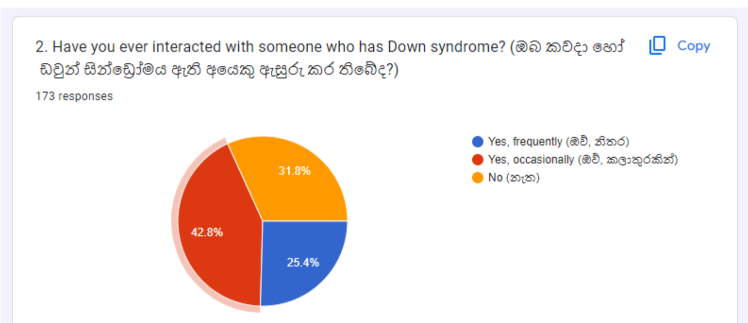
The findings revealed a significant level of public familiarity with the condition 71.1% of respondents reported being aware of Down syndrome, and 68.3% had encountered someone with the condition. Furthermore, the results highlighted a strong belief in the effectiveness of tailored educational tools, with 97.1% of participants recognizing the value of adaptive learning systems for teaching mathematics to children with DS, and 76.3% rating them as valuable. Animated learning tools were also well-received, with 95.4% agreeing they assist in improving comprehension, and 67.1% rating them as highly effective.

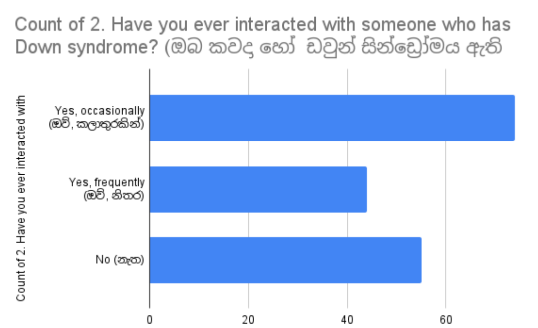
These results underscore a broad community appreciation for the significance of research into cognitive development in children with Down syndrome. More importantly, they help identify existing gaps in knowledge and potential misconceptions that can be addressed through our work. The survey data not only affirms the relevance of our study but also guides us in shaping how we communicate our findings ensuring the research remains impactful, accessible, and meaningful to a wider audience.

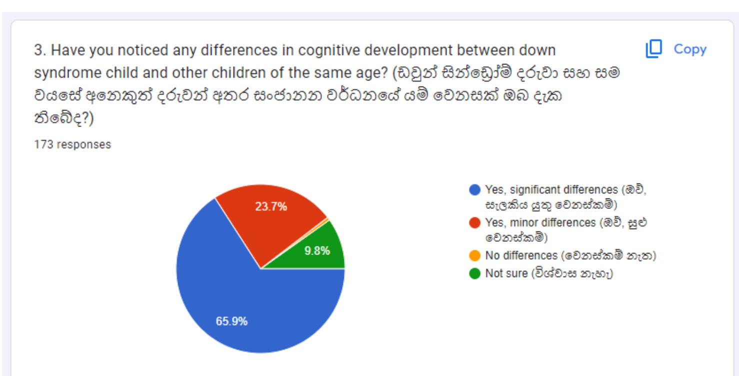
To illustrate the findings, a few of the survey responses will be included below.

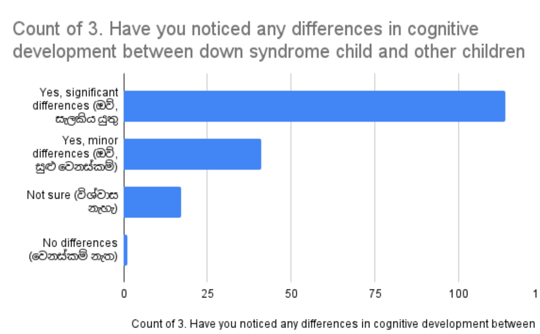












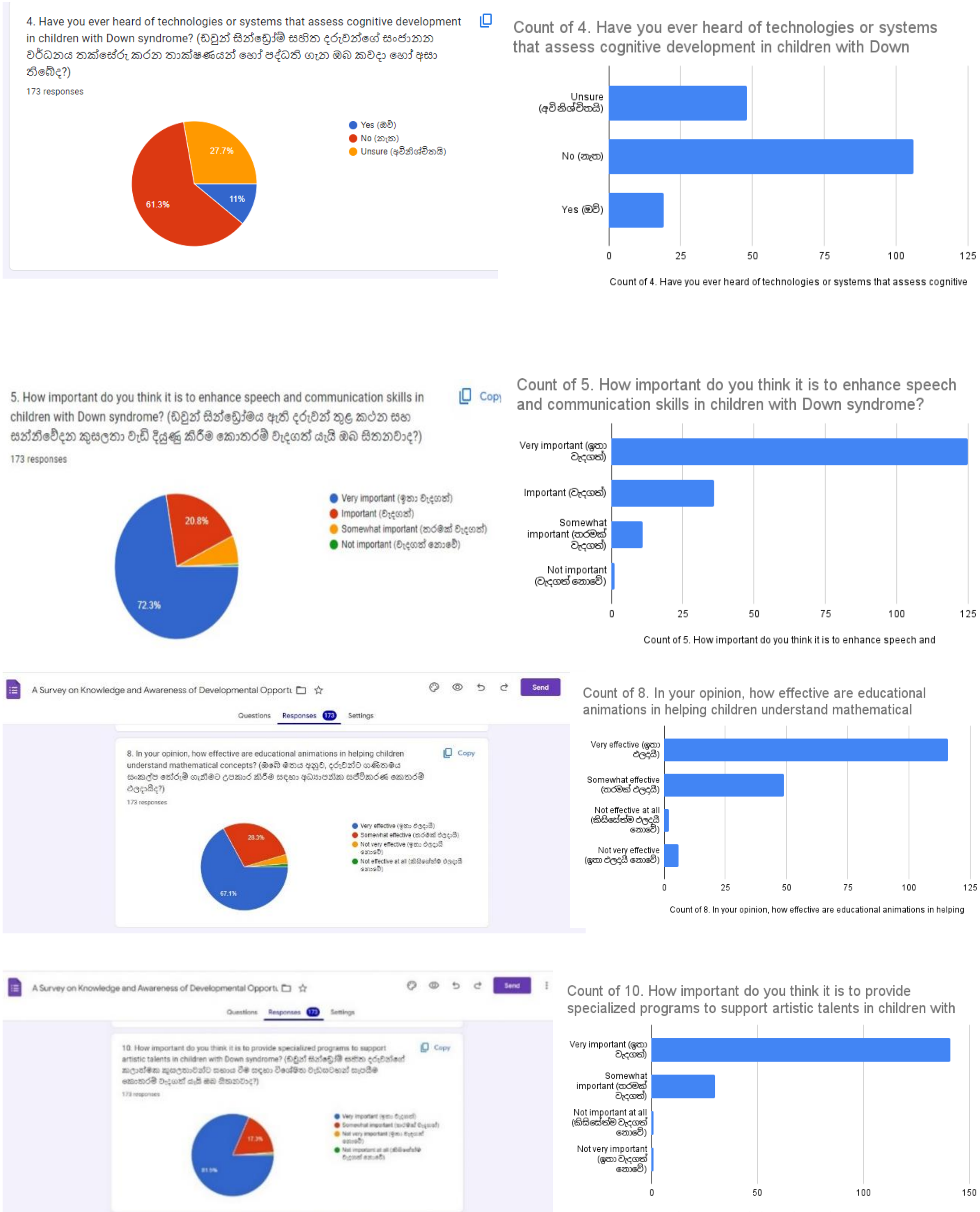


Figure 4: Survey responses

Positive survey responses indicate a knowledgeable community with deep interactions and observations concerning Down syndrome. General awareness and familiarity with assessment technologies would suggest that, at large, there is little or no resistance to the use of such tools in the evaluation and enhancement of cognitive development.

The findings raise the importance of educating members of the general public and professionals on issues surrounding Down syndrome. We can progress from what is already known and build from there, setting any disparities and misconceptions straight. The positive contact with assessment technologies points toward promising directions for further research studies and practical applications.

Overall, these results from the survey prove that we have a sound base of knowledge and interest that can help us fine-tune our research and outreach activities for maximum impact and relevance.

2.5 Project Requirements

2.5.1 Functional requirements

1. **Enable users to upload images or use real-time webcam input**
   This requirement allows users to either upload a facial image of a child or capture one in real-time using a webcam. The system will provide an intuitive user interface for selecting, uploading, or capturing images seamlessly.

2. **Ability to assess whether a child is showing signs of Down syndrome**
   This involves analyzing the uploaded or captured image to determine if the child displays facial characteristics commonly associated with Down syndrome, enabling early detection.

3. **Ability to extract facial features using Dlib library**
   The system will use the Dlib facial landmark detection library to extract key facial features such as eye shape, nasal bridge, jawline structure, and other geometry-based attributes essential for classification.

4. **Ability to automatically preprocess uploaded or captured images**
   The preprocessing pipeline includes automatic face detection and alignment, grayscale conversion, noise reduction, and feature normalization to ensure consistent input for accurate classification.

5. **Generate a probability score indicating the likelihood of Down syndrome**
   After processing the image, the system will calculate and present a probability score indicating the likelihood that the child may have Down syndrome based on the extracted facial features and trained classification model.

6. **Provide feedback on the detection results**
   The system will give clear and informative feedback based on the prediction. If Down syndrome is not detected, the user will be notified that the child is healthy. If detected, the system will display the detected facial features associated with the condition and the probability score, guiding the next steps for professional evaluation.

7. **Speech Recognition**
   The system shall support the ability of speech recognition for the articulated words to be able to process through Natural Language Processing for the purpose of pronunciation assessment.

8. **Real-Time Feedback**
   The system must provide feedback at the same time it needs to be output for the pronunciation articulation exercise by using visual and audio indicators that will assist the child to adjust pronunciation.

9. **Motion Analysis**
   Facial expression and mouth movement are monitored and analyzed in articulation exercise by the ability of image processing.

10. **Tracking Progress**
    The app is to save the child's data and track his or her progress over time by showing the improved areas and weak ones.

11. **Interactive, gamified quizzes**
    Make learning and tests interesting through interactivity.

12. **Data Storage**
    User data is to be stored safely, with the record on progress reports and history of accrued sessions.

13. **Accessibility Features**

Making the application user-friendly with people having other needs by incorporating features such as text-to-speech for instructions and, where necessary, visual aids.

14. **Adaptive Learning Module**

- The system will incorporate a training module with math exercises (addition, subtraction, multiplication, division).
- The module will support three levels of difficulty: Beginner, Intermediate, and Advanced.
- The system will dynamically adjust question difficulty based on the child's performance.
- The system will teach mathematical concepts through root principles such as one-to-one correspondence, cardinality, and numerical order.

15. **Interactive Educational Animations**

- The system will draw educational animations using React and Fabric.js to explain mathematical concepts.
- The system will include visual demonstrations for erroneous answers to encourage comprehension.

16. **Performance Monitoring and Progress Tracking**

- The system will track the time spent by each child, accuracy, and score per arithmetic category.
- The system will maintain performance information on difficulty levels and track progress over time.

17. **Parental Summary Report Generation**

- The system will generate detailed summary reports for parents.
- Reports will include scores, time spent, correct/incorrect responses, and trends so far.
- The system will analyze long-term child development and provide future learning directions.
- Reports will identify areas of strength and areas of improvement.

18. **Personalized Recommendations**

- The system will analyze overall performance data to make personalized future learning recommendations.
- The system will recommend specific categories or difficulty levels for further practice depending on progress analysis.

2.5.2 Non-functional requirements

1. **Availability**

   The system should be operational and available to users when they need it.

2. **Reliability**

   The ability of the system to perform consistently without failure over time.

3. **User friendly**

   The system should be designed to be user friendly and understand for the intended users.

4. **High performance**

   The system should be able to operate efficiently and effectively.

5. **Security**

   The system should ensure that it will protect user data and information from unauthorized access and breaches.

6. **Maintainability**

   The ability to update and repairing the system.

2.5.3 Technical requirements

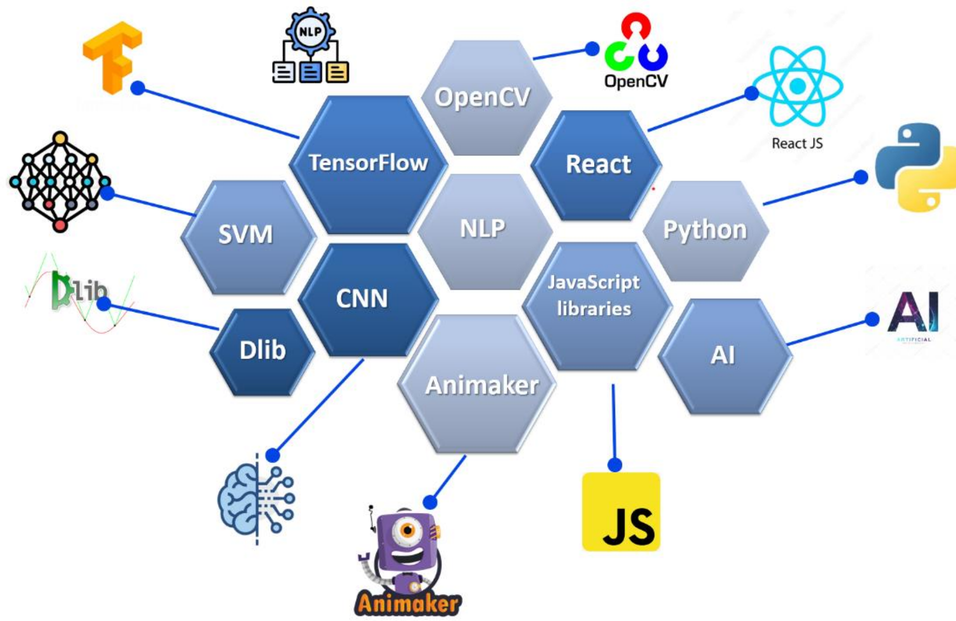


Figure 5: Technical requirements diagram

1. **Support Vector Machine (SVM):**

SVM is utilized as the core classification algorithm in detecting Down syndrome by analyzing facial features extracted from images. Unlike other traditional classification methods, SVM excels in handling high-dimensional data and effectively distinguishes between children with and without Down syndrome. Its ability to work well with small datasets and find the optimal decision boundary makes it an excellent choice for medical image classification.

2. **Artificial Intelligence (AI)**

Artificial Intelligence (AI) was integrated into the system to enhance both learning assessment and artistic evaluation. For the quiz component, AI was employed to dynamically generate unique, language-related questions each time a quiz was initiated, ensuring a more engaging and personalized learning experience. In the drawing module, the system leveraged OpenAI's advanced visual comparison capabilities to evaluate the similarity between student-created drawings and reference images. By utilizing OpenAI's API, the system could objectively calculate similarity scores, delivering accurate and unbiased assessments of artistic skills. This dual application of AI not only enriched the educational value of the platform but also enabled consistent and reliable performance analysis across different skill areas.

3. Natural Language Processing (NLP)

This is the key reason why NLP plays such an important role in the proper recognition and justified categorization of child voice and should supersede other forms of speech analysis, which can be as nonspecific for children with Down syndrome. In contrast, simpler speech recognition systems may face the challenges of multiple pronunciation, which NLP would address well due to the different pronunciation and intonations, thereby giving specifically categorized feedback. This ensures that the application can deal with specific issues of articulation and pronunciation, and NLP is being applied for personalized speech therapy.

4. OpenCV

This library is used because it processes images well, which is very useful for the analysis of facial expressions and lip movements. In comparison with other image processing libraries that may not provide such detail or real-time performance, OpenCV provides robust tools to capture and analyze visual data. Its versatility in dealing with different image data types makes it perfectly aligned to support the interactive and effective implementation of speech exercises; other less focused image processing tools may not be potent for this one application.

5. Dlib:

Dlib is used for facial feature extraction, which is crucial in identifying the characteristic facial traits associated with Down syndrome. It provides robust facial landmark detection, allowing the system to analyze geometric patterns in facial structures. Compared to other feature extraction libraries, Dlib offers highly accurate facial alignment, making it a superior choice for medical image processing in Down syndrome detection.

6. Python

Python serves as the backbone of our system, playing a central role in integrating machine learning models and image processing techniques. Widely recognized for its simplicity and powerful data science libraries, Python was the primary language used for tasks involving artificial intelligence and machine learning, particularly in the model training phase of the Down syndrome detection and talent identification components. Its compatibility with frameworks like Dlib, OpenCV, TensorFlow, and scikit-learn made it ideal for implementing complex algorithms with ease. In the talent identification module, Python was instrumental in analyzing interaction data from the piano (motor skills), quizzes (learning skills), and the drawing platform (artistic skills) to assess individual strengths. It also supported emotion recognition models for tracking emotional responses during pronunciation enhancement activities. Python's seamless integration with major machine learning frameworks allowed us to incorporate sophisticated prediction algorithms, such as neural networks, to evaluate student performance and dynamically tailor quizzes to suit each learner's needs. This versatility and robust ecosystem make Python far more suitable than other programming languages with limited support for AI and machine learning applications.

7. TensorFlow

TensorFlow is used for its strong machine learning capabilities, which enable adaptive quizzes and building personalized exercises. The flexibility of TensorFlow for supporting models is another reason for its preference. Other machine learning frameworks are either not scalable or flexible, or they might not support a diversity of models and can operate over complex data, but TensorFlow can. Such flexibility in its ecosystem embeds dynamism in building interactive content, in response to the learner's pace; hence, it is more attuned to a framework with enhanced possibilities for personalized learning experiences than less versatile or more basic ones.

8. Convolutional Neural Networks (CNNs)

CNNs are borrowed for their superior ability in the extraction and analysis of features in visual data, such as lip movements and facial expressions. While many other types of neural networks, or in fact, even simpler machine learning models, may not be as good at dealing with detailed and complicated patterns of visuals, CNNs have been constructed for the purpose of dealing with those hierarchical features in images. This makes them the best choice for not-so-less accurate feedback, particularly in the case of speech-related visual cues.

9. React

React.js was chosen as the primary technology for developing the frontend of our system due to its ability to create fast, interactive, and user-friendly web applications. Its component-based structure allowed us to build a dynamic and responsive user interface tailored to the diverse features of our platform, including piano interactions for assessing motor skills, quizzes for evaluating learning abilities, drawing tools for artistic expression, and math enhancement games. React's efficient rendering capabilities and seamless state management enabled real-time updates and smooth user interactions crucial for an engaging experience, especially when working with children with Down syndrome. The framework also facilitated user input for Down syndrome detection by allowing images to be uploaded or captured directly through a webcam, which are then processed and analyzed by the system. By leveraging React's rich ecosystem and reusable components, we ensured an intuitive, accessible, and visually appealing interface that enhanced both the functionality and usability of our talent identification and cognitive support system.

10. Node JS

On the server side, we utilized Node.js to manage backend logic and API services. Node.js's asynchronous and event-driven architecture enabled efficient handling of multiple data streams and real-time communication between the client and server. It was responsible for processing quiz data, handling user sessions, storing responses, and managing data coming from different learning modules. Overall, Node.js provided the scalability and performance needed to support the different interactive components of our system.

2.6 Testing & Implementation

2.7 Assessing the Detection of Down syndrome – IT21296314 – Kumarasinghe D.P.

2.7.1 Implementation

2.7.2 Model training

To implement the Down Syndrome detection component of the system, a comprehensive machine learning pipeline was developed that integrates both facial geometry and texture-based features. The dataset comprised facial images categorized into two classes: individuals with Down Syndrome and healthy individuals. Initially, all images were preprocessed using the Dlib library to detect facial landmarks, utilizing a 68-point landmark model. A custom frontal-face validation function was used to filter out non-frontal images, ensuring uniformity and improving the reliability of the features extracted.

For each valid face, an alignment process was carried out by computing the angle between the eye centers and rotating the image accordingly. This alignment helped reduce pose variation. After alignment, faces were cropped using the facial landmarks to tightly frame the region of interest, followed by resizing to a fixed dimension to maintain consistency across samples.

To capture discriminative texture features, Local Binary Pattern (LBP) histograms were extracted from small patches centered around selected landmark points. In parallel, geometric features were calculated by measuring Euclidean distances between key pairs of landmarks (such as eye-to-nose, mouth width, and distances around the lips and cheeks), which are known to vary significantly in Down Syndrome cases. These two types of features texture (LBP) and shape (geometric) were concatenated to form a comprehensive feature vector for each image.

To improve generalization and increase the size of the dataset, various data augmentation techniques were applied. These included horizontal flipping, small-angle rotations, and the addition of Gaussian noise. Each augmented image was processed in the same way to extract consistent features.

After feature extraction, the data was standardized using StandardScaler to ensure that all features contributed equally to the learning process. All feature vectors were padded to ensure consistent dimensions, and missing values (if any) were handled using np.nan_to_num().

A Support Vector Machine (SVM) classifier with a sigmoid kernel was trained on the extracted features. The classifier was tuned to handle class imbalance using a balanced class weight. The model training process was timed, and its effectiveness was evaluated using 5-fold cross-validation on the training data, reporting an average accuracy across the folds. After training, the model's performance was further assessed on both the training and the testing sets, with key metrics including accuracy, precision, recall, AUC, and a full classification report.

Finally, the entire trained pipeline including the scaler and classifier was serialized and saved to a .pkl file using Python's pickle module. This enabled the model to be easily loaded and integrated into the web-based interface or any real-time application for Down Syndrome detection.

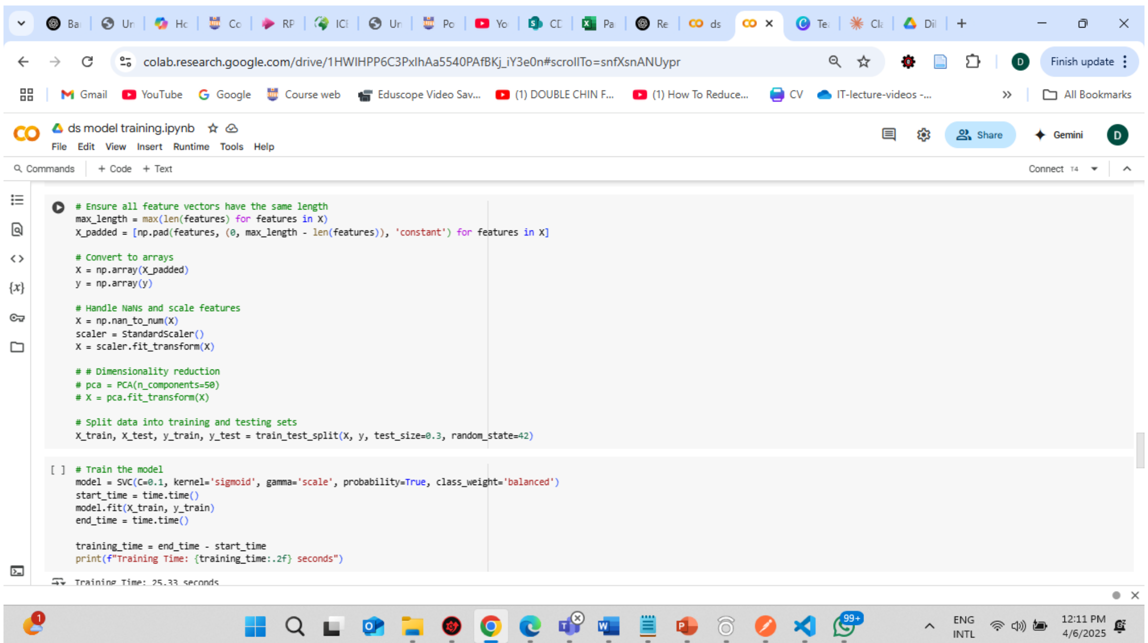


Figure 6: Model training code

2.7.3 Model testing

The testing phase involves evaluating the performance of the trained Support Vector Machine (SVM) model on new, unseen images to determine its capability to classify individuals as either having Down Syndrome or being Healthy. The process begins with the user uploading an image, which is then processed using a pipeline designed to replicate the same preprocessing steps as in the training phase.

Firstly, face detection is performed using Dlib's pre-trained frontal face detector. If a face is detected, facial landmarks are extracted using a 68-point shape predictor, and a 69th landmark is computed as the midpoint between landmarks 21 and 22 (the inner ends of the eyebrows) to enhance the detection of facial symmetry.

Next, the facial alignment step rotates the image such that the eyes are horizontally aligned, helping to standardize the facial orientation across different input images. The face is then cropped with appropriate padding, centered around the facial landmarks, and resized to a fixed resolution (300x300 pixels) to ensure consistency in feature extraction.

From this cropped and aligned facial image, two key types of features are extracted:

1. **Local Binary Pattern (LBP) Features**: LBP histograms are computed from grayscale patches centered at selected facial landmarks (e.g., around the eyes, nose, and mouth). These patches capture local texture information, which is critical in highlighting micro-patterns often associated with Down Syndrome facial traits.
2. **Geometric Features**: Euclidean distances between specific landmark pairs are computed to capture global facial structure. These distances reflect facial proportions, such as inter-eye distance, nose length, and mouth width all of which are important in distinguishing Down Syndrome-related facial morphology.

The extracted LBP histograms and geometric distances are concatenated into a single feature vector. This vector is then scaled using the same StandardScaler instance that was fitted during the training phase to ensure consistent normalization.

Finally, the preprocessed feature vector is passed to the trained SVM model, which outputs a predicted class label (0 for Down Syndrome, 1 for Healthy) and the corresponding class probabilities. The prediction is visualized by overlaying the facial landmarks and structural lines on the image, and the final result includes the prediction label, confidence scores for each class, and the time taken to complete the inference.

2.7.4 Postman testing

To validate the functionality and performance of the deployed Down Syndrome detection model, the RESTful API was tested using Postman, a popular API testing tool. The API endpoint /predict hosted on http://127.0.0.1:5000 was accessed using the POST method. A test image (down1.jpeg) was uploaded via the form-data body under the image key to simulate a real-world scenario where an end user provides an image for diagnosis. Upon submission, the API successfully processed the image and returned a JSON response containing the prediction result along with a confidence score. In this specific test case, the model predicted "Down Syndrome Detected" with a confidence of 0.47, and the response was received with an HTTP status code of 200 OK, indicating successful execution. This test demonstrates the robustness and reliability of the model's deployment and confirms that the backend pipeline including preprocessing, feature extraction, and classification is functioning as expected through the API.

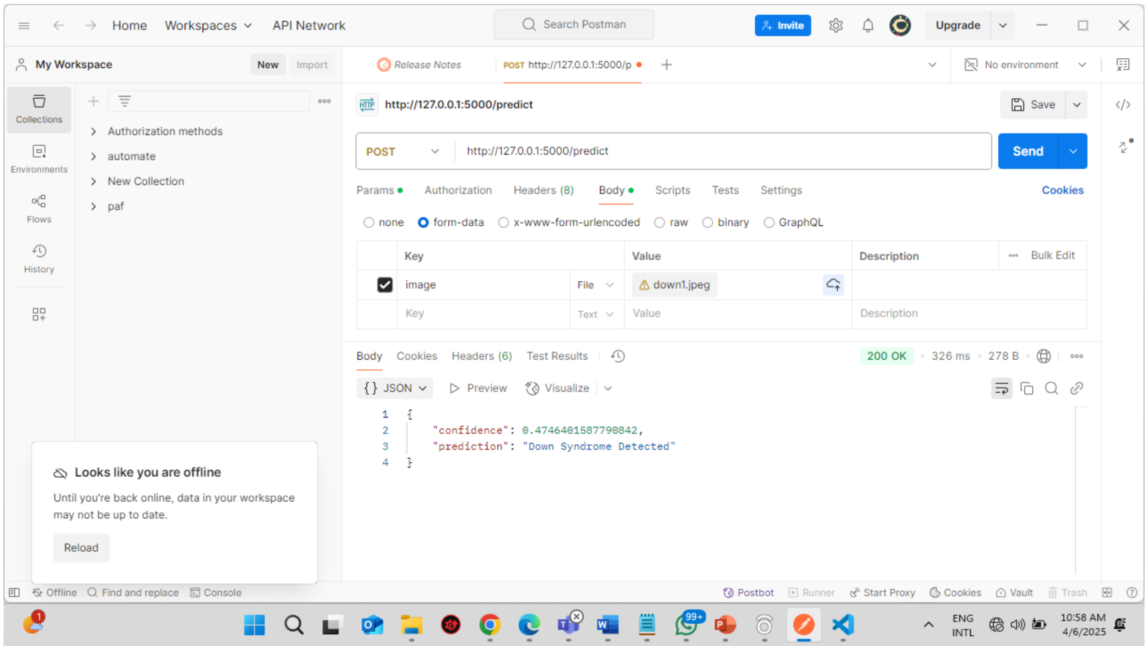


Figure 7: Postman checking

2.7.5 Frontend development

The frontend for the Down Syndrome detection application was developed using React.js, offering a modern and interactive user experience. Users can either upload a facial image or capture one directly using their webcam via the integrated react-webcam component. The interface dynamically handles both scenarios, providing real-time previews, action buttons, and feedback messages. Upon uploading or capturing an image, the frontend sends the image data to the backend using the axios library through a POST request in multipart/form-data format. The UI also interprets the backend response, displaying the prediction label, confidence percentage, and if Down Syndrome is detected a list of common facial symptoms associated with the condition. The design is responsive and informative, with loading animations, clear error handling, and character visuals to enhance user engagement and clarity

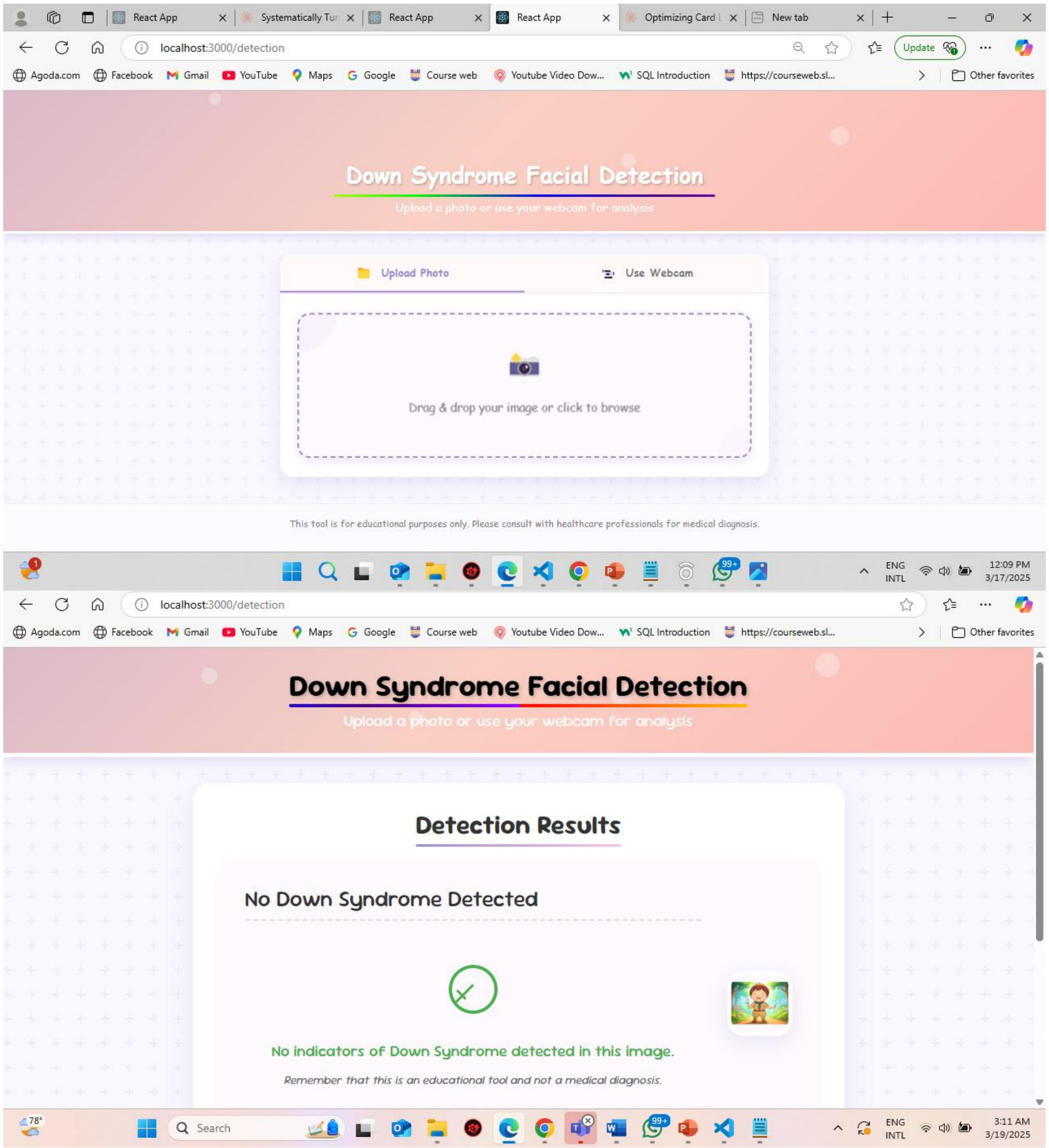


Figure 8: Frontend user interfaces

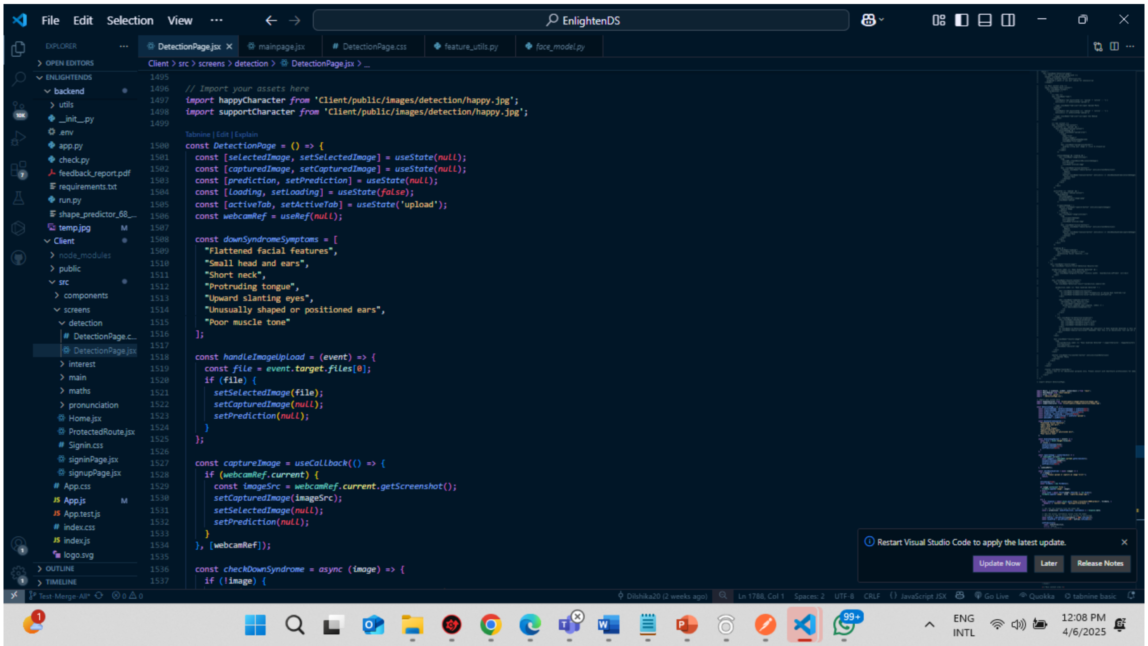


Figure 9: Frontend detection page jsx code

2.7.6 Backend development

The backend of the Down Syndrome detection application is built using Python with the Flask framework and leverages machine learning and computer vision techniques to deliver accurate predictions based on facial images. The system loads a pre-trained Support Vector Machine (SVM) model and a corresponding feature scaler from serialized files. When an image is received via a POST request to the /predict endpoint, it is temporarily saved and passed through a preprocessing pipeline that involves feature extraction using a custom utility function. This includes facial landmark detection, image alignment, and face cropping key steps that ensure consistent input quality and orientation. Facial landmarks are extracted using Dlib's 68-point shape predictor, with additional validation to ensure the face is frontal for better accuracy. The processed image features are scaled and passed into the trained model for prediction. The model outputs both a binary classification (Down Syndrome detected or not) and a confidence score, which are then returned to the frontend in JSON format. The backend also includes robust error handling for invalid inputs and malformed images. Altogether, this backend pipeline encapsulates essential AI-driven components such as image preprocessing, facial analysis, and predictive modeling, making it a critical part of the application's functionality.

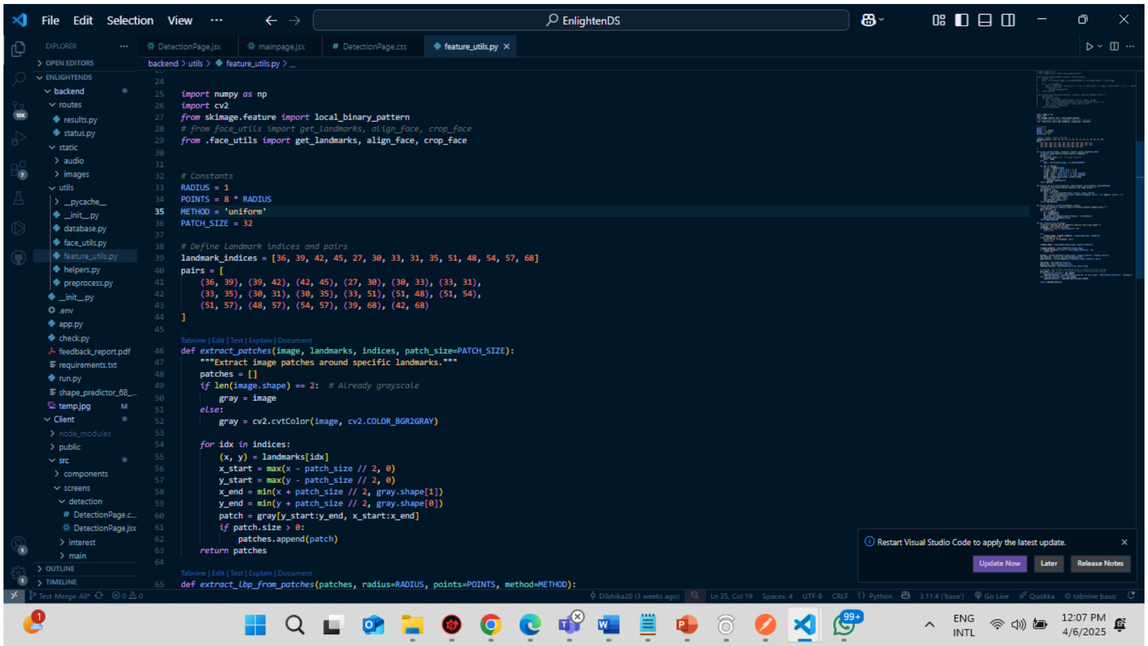


Figure 10: Backend feature utils python code

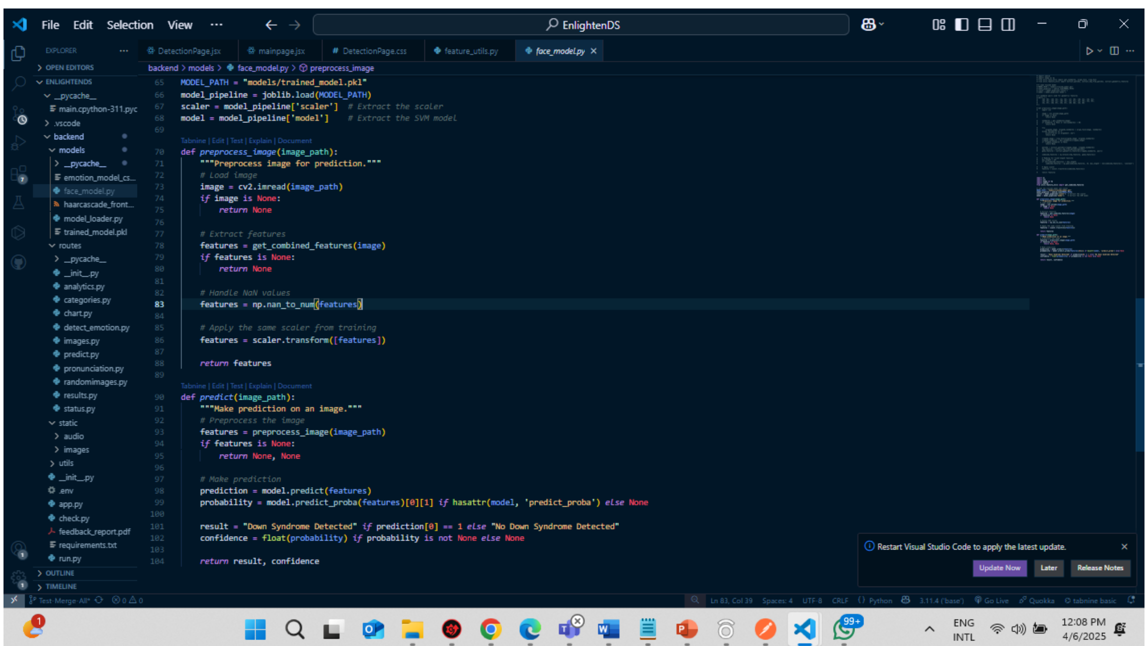


Figure 11: Backend face model python code

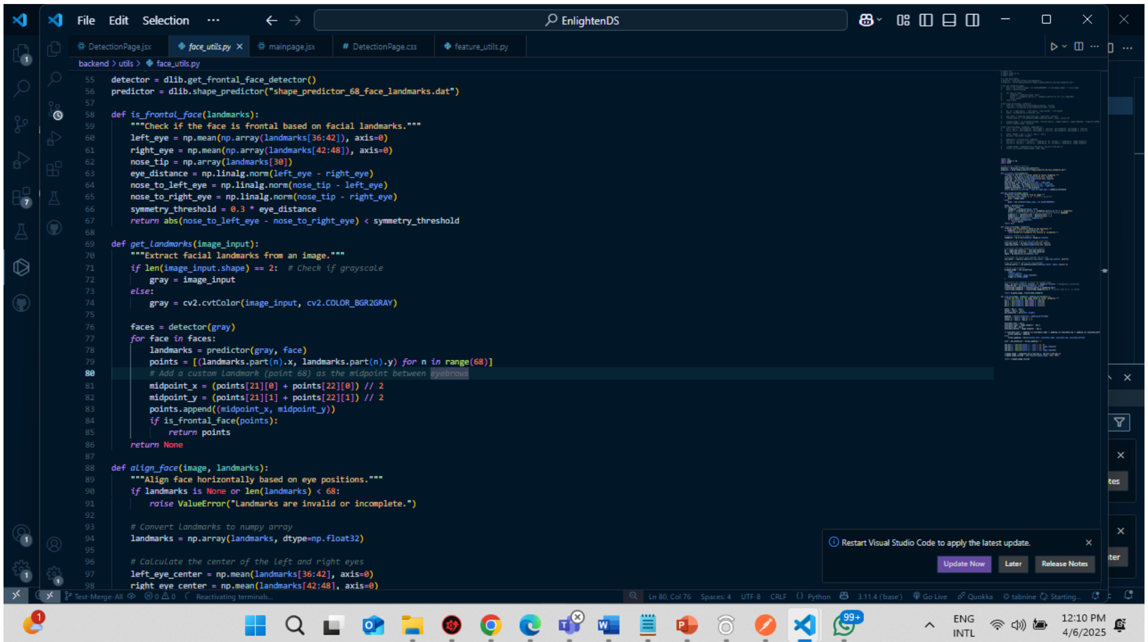


Figure 12: Face utils python code

2.8 Enhancing Pronunciation Skills – IT21293030 – Jayasuriya S.H.

2.8.1 Implementation

The system is built using a full-stack architecture that combines frontend interactivity with backend intelligence. The backend logic is implemented in Python using Flask, while the frontend is developed with React.js. The application integrates several technologies, including machine learning (TensorFlow/Keras), natural language processing (phonetics library for pronunciation comparison), MongoDB for data storage, and Google Gemini API for generating intelligent feedback. The core idea is to provide a gamified, engaging pronunciation platform supported by emotion recognition, pronunciation accuracy checking, and weekly performance reporting.

2.8.2 Emotion detection model training

The emotion recognition system is built using Python with the TensorFlow and Keras libraries. A Convolutional Neural Network (CNN) is designed and trained using the FER2013 dataset, which contains labeled facial images for different emotions like happy, sad, angry, etc. The model uses multiple Conv2D layers with ReLU activation, followed by MaxPooling2D, and Dropout layers to prevent overfitting. The Flatten and Dense layers convert image features into a probability distribution using Softmax for multi-class classification. For dataset manipulation, pandas and numpy are used. Model training is optimized using the Adam optimizer and a categorical_crossentropy loss function. The final model is saved using .h5 format and is loaded in the Flask backend for inference.

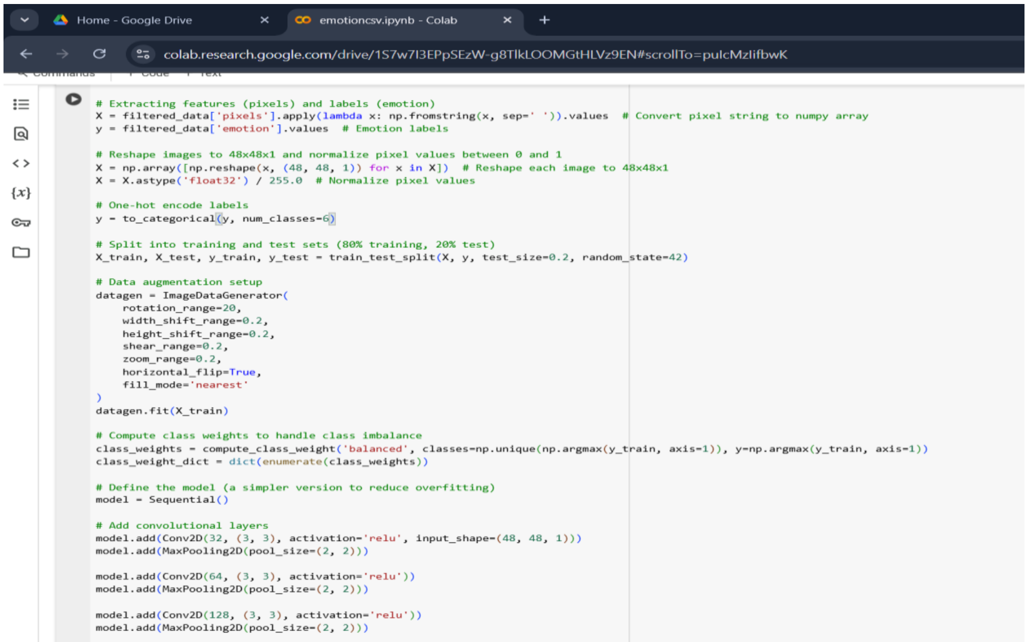


Figure 13: Model Training

2.8.3 Voice-to-text translation and pronunciation checking

The pronunciation checking module uses JavaScript (React) on the client side and Python (Flask) on the server side. The browser's native SpeechRecognition API (webkitSpeechRecognition) captures audio input and converts it to text. This text is sent to a Flask backend using **Axios** HTTP POST requests. On the server side, the phonetics Python library is used to compare the pronunciation of the user's word with the target word using the Metaphone algorithm, which converts both words into phonetic encodings to evaluate similarity. If the encodings match, the pronunciation is marked correct; otherwise, feedback is returned with suggestions.

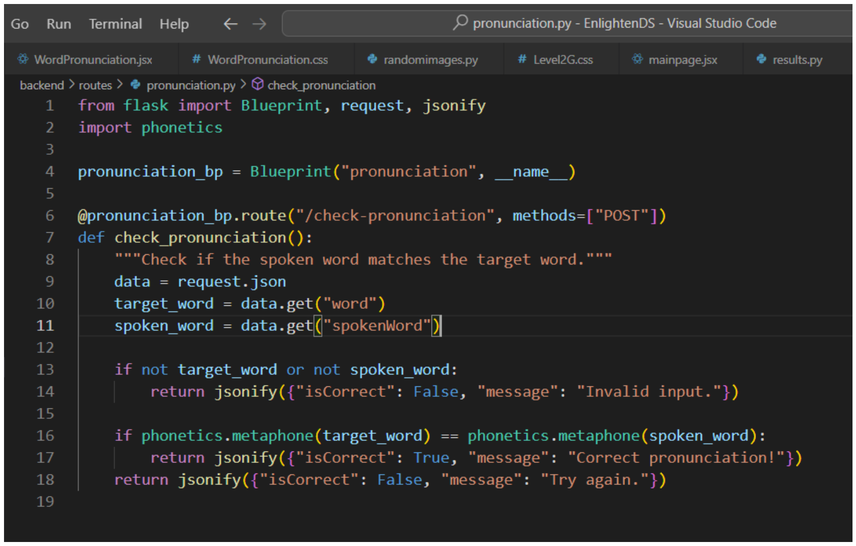


Figure 14: Pronunciation-backend route

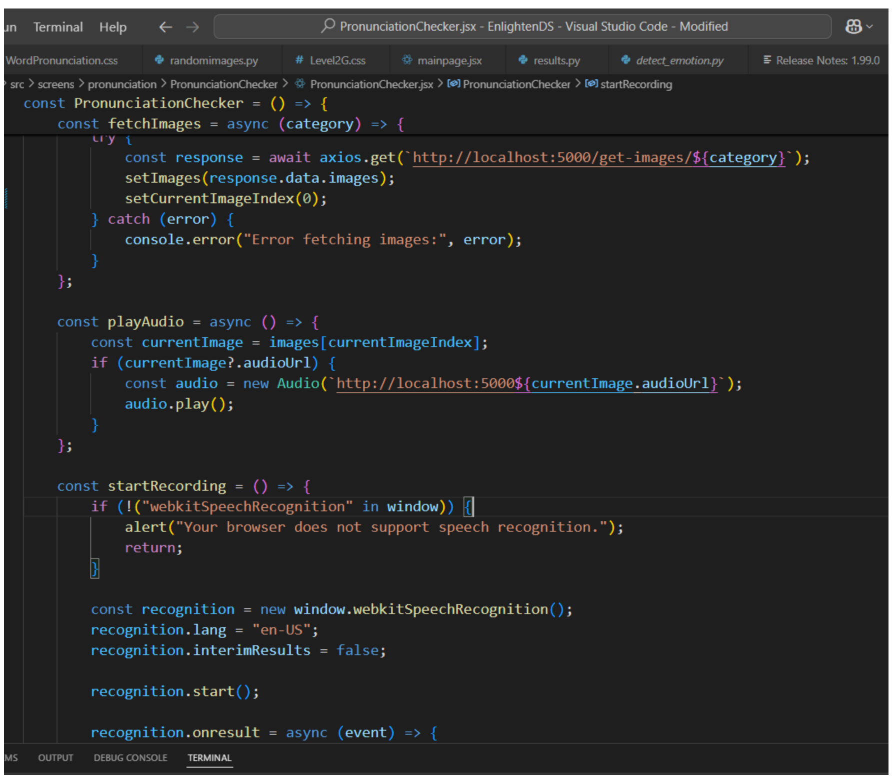


Figure 15: Pronunciation frontend route

2.8.4 User interface

The frontend is implemented using React.js, providing a highly responsive, single-page application. Components like Quiz, Webcam Capture, and Feedback Modal are built using functional components and useState, useEffect hooks. For voice input, the Web Speech API (webkitSpeechRecognition) is used to capture real-time pronunciation attempts. For facial emotion analysis, we use the **react-webcam** library to capture webcam frames. These frames are sent to the Flask backend at intervals using setInterval + Axios, where they are processed for emotion classification. Based on the result (e.g., smiling face), motivational feedback like “Well done!” or “Keep going!” is displayed.

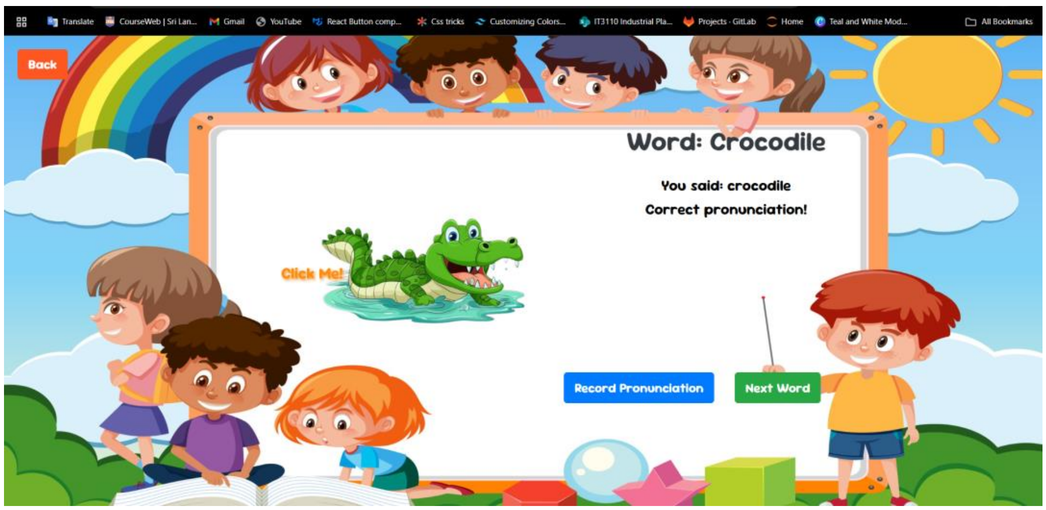


Figure 16: User Interface 01

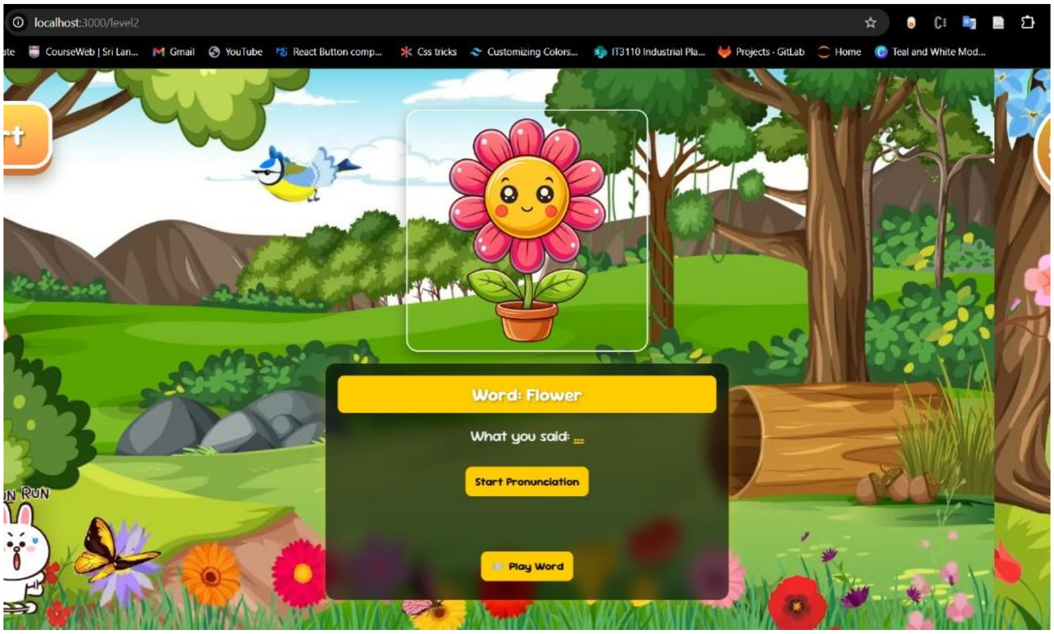


Figure 17: User Interface 02

Figure 18: User Interface 03

2.8.5 Database integration for progress tracking

To monitor user performance and enable feedback generation, MongoDB was integrated using the pymongo library. A secure connection was established using environment variables stored in a .env file. The results collection within the quiz_app database stores structured quiz records, including scores, timestamps, categories, and user identifiers. This persistent storage is critical for generating long-term insights into each child's progress.

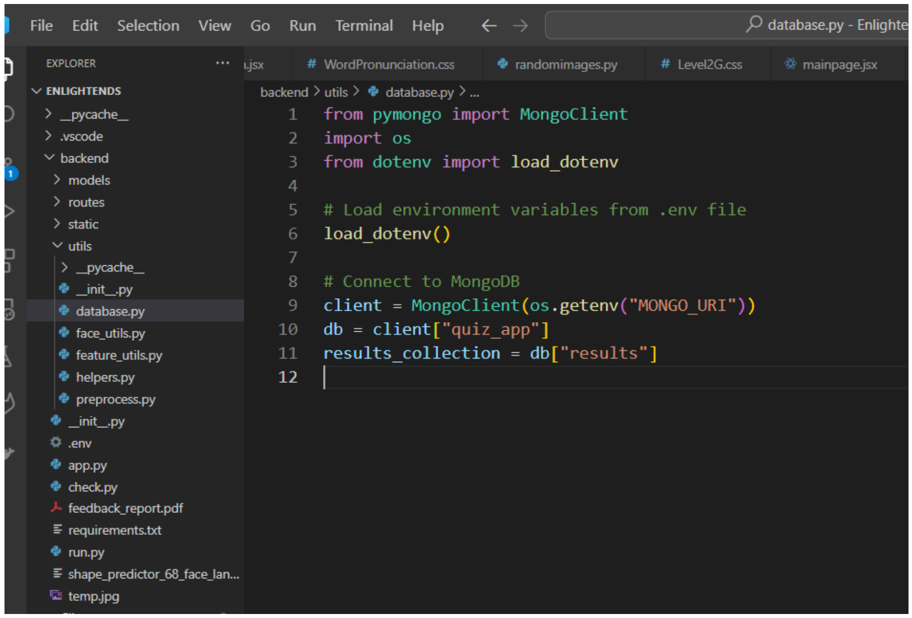


Figure 19: MongoDB Connection

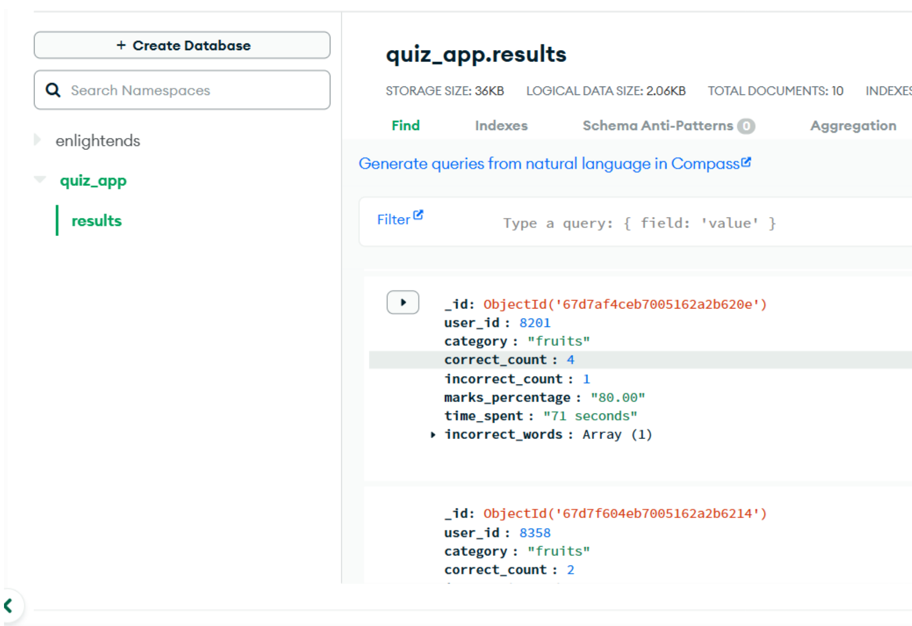


Figure 20: Data Collection

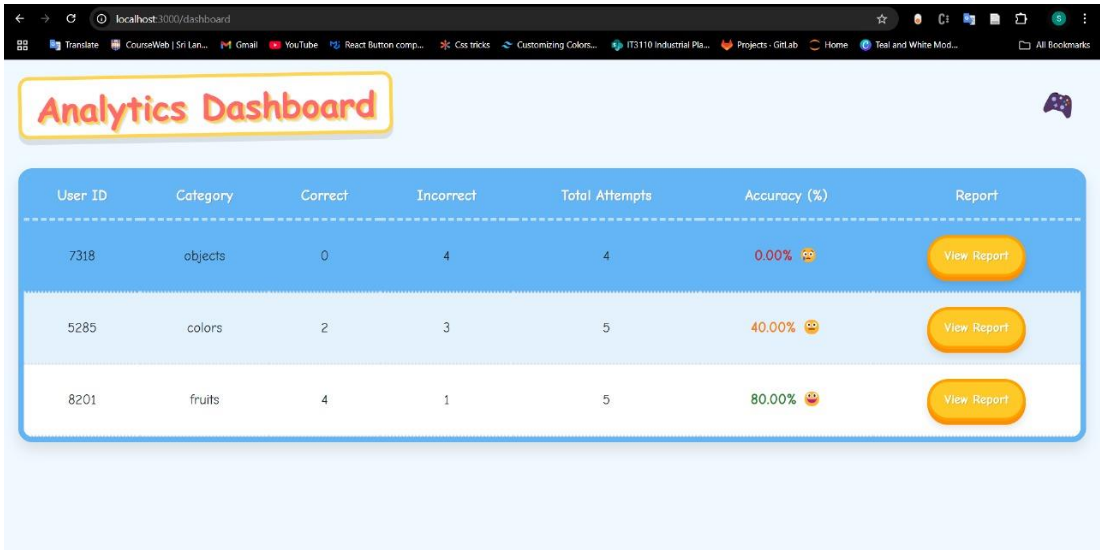


Figure 21: User Interface 04

2.8.6 Personalized report generation using gemini API

To generate personalized feedback after each session, we use Google Gemini API. The backend script queries quiz data from MongoDB, aggregates information (e.g., frequent mistakes, average score, time spent) and constructs a prompt. This prompt is sent via a POST request to the Gemini API endpoint using Python's requests library. The LLM responds with child-friendly and parent-understandable feedback, which is stored in MongoDB and displayed on the frontend. The goal is to provide a report that highlights strengths, identifies weaknesses (e.g., struggles with "th" sounds), and recommends simple at-home exercises.

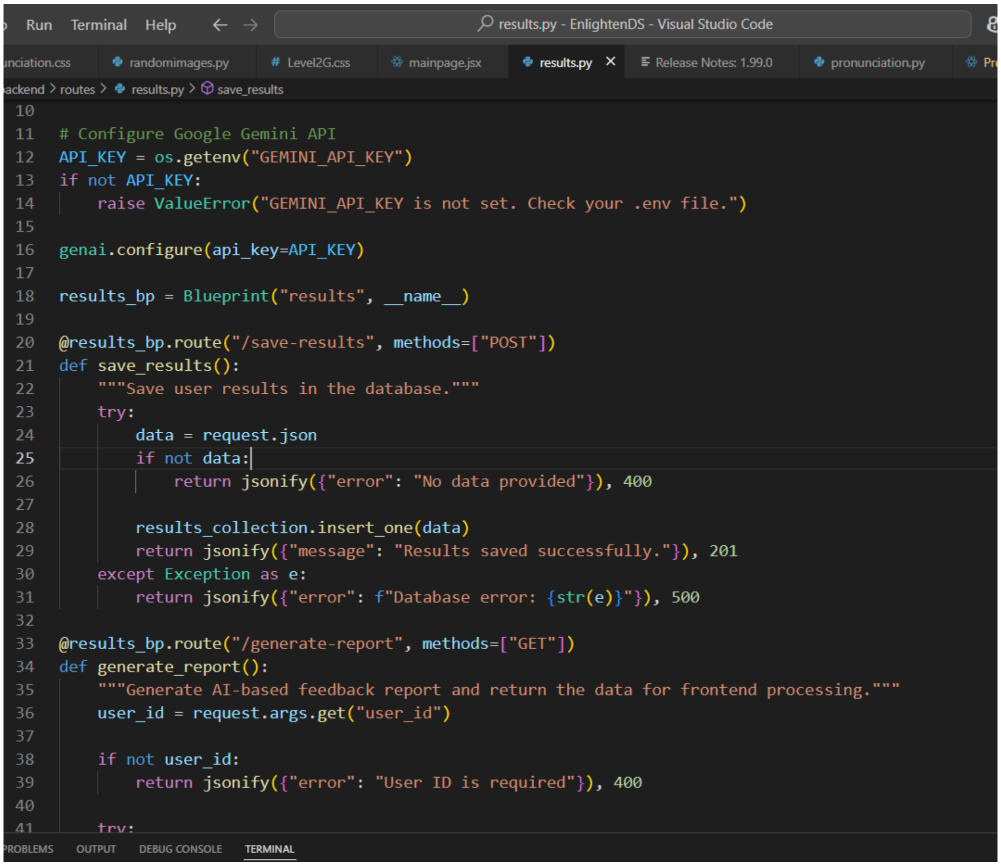


Figure 22: AI Feedback backend

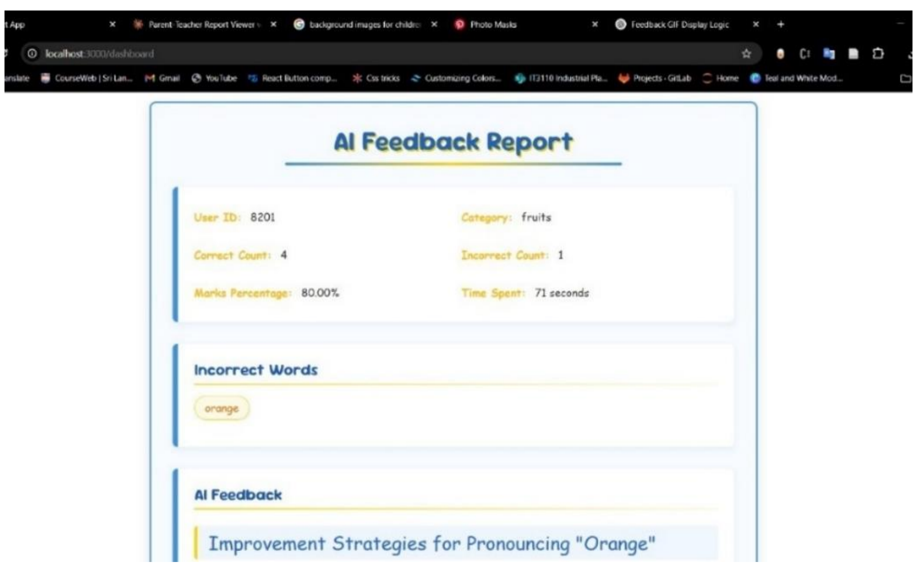


Figure 23: Feedback Report UI

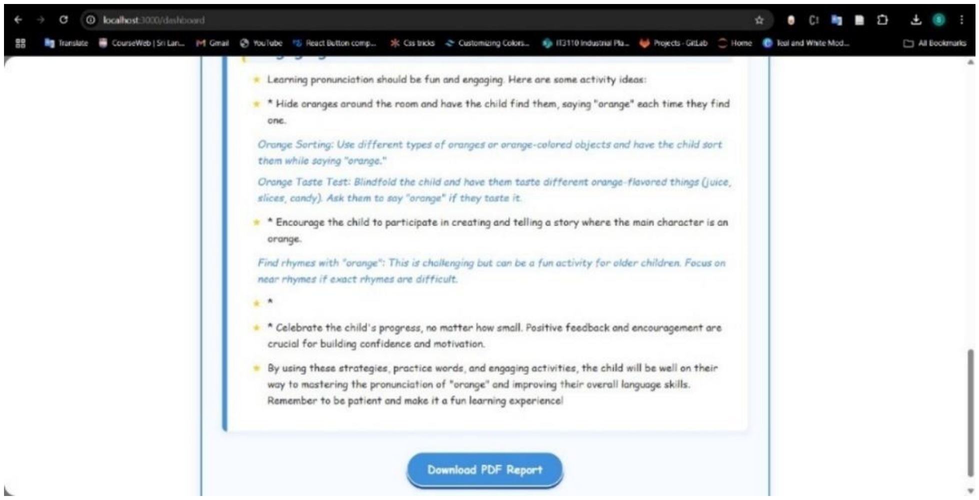


Figure 24: Feedback Report

2.8.7 Gamified environment with emotion feedback

To improve engagement, the app includes a gamification layer driven by emotion recognition. The emotion detection model (served via Flask) receives webcam images from the frontend and classifies the user's emotion. If the detected emotion is positive ("Happy" or "Excited"), the system dynamically increases a motivational score, displays visual animations (stars, emojis), or plays audio rewards using JavaScript Audio API. This emotional intelligence integration is designed to keep children motivated and reduce frustration during speech learning.

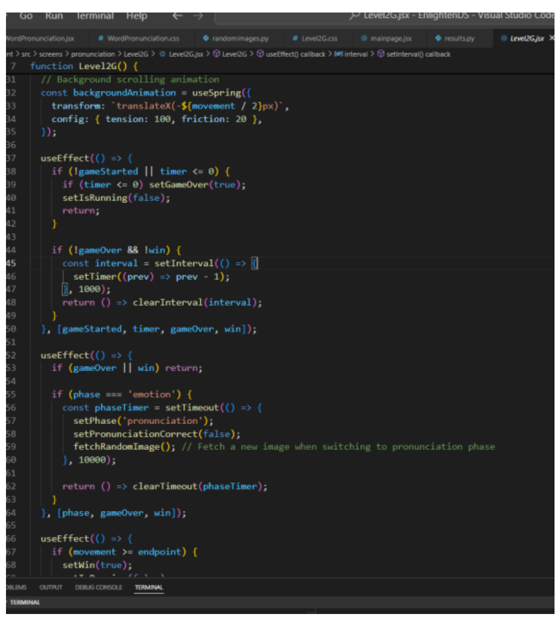


Figure 25: Gamified Quiz

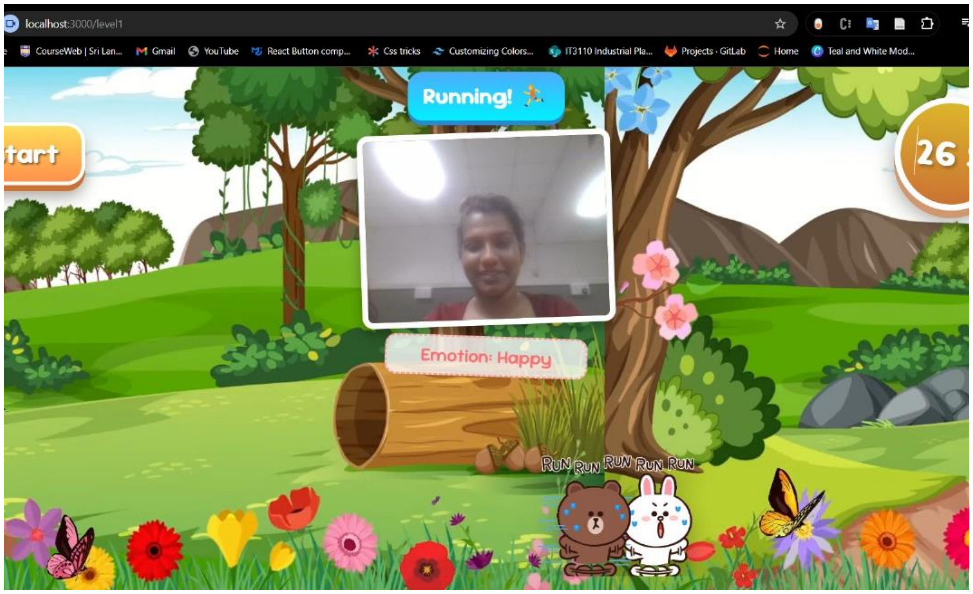


Figure 26: Gamified UI

2.8.9 Testing

- Pronunciation Checker API Testing

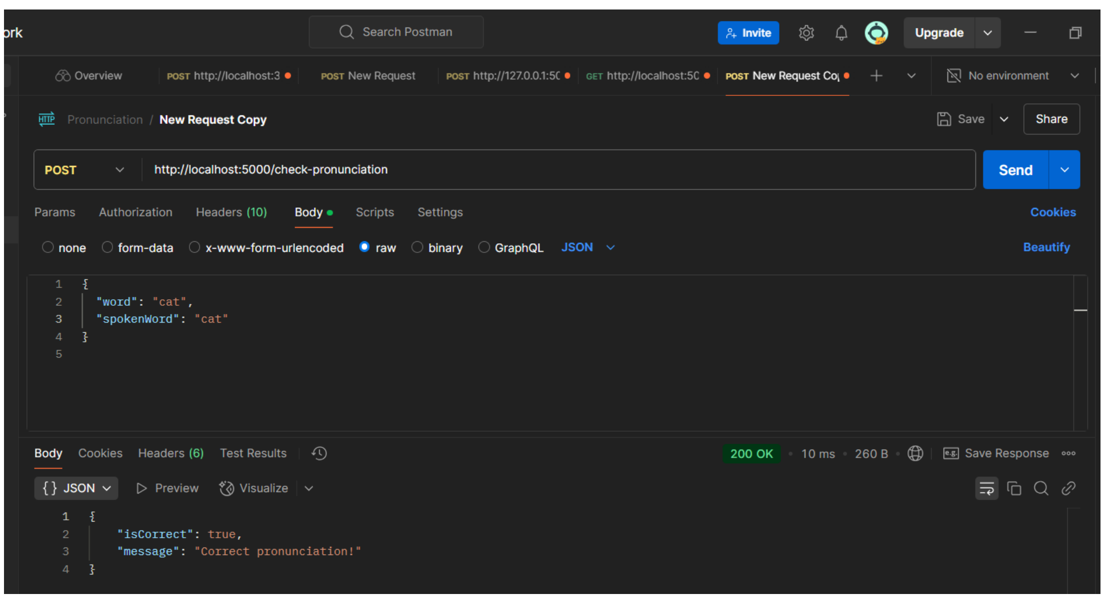


Figure 27: Testing_01

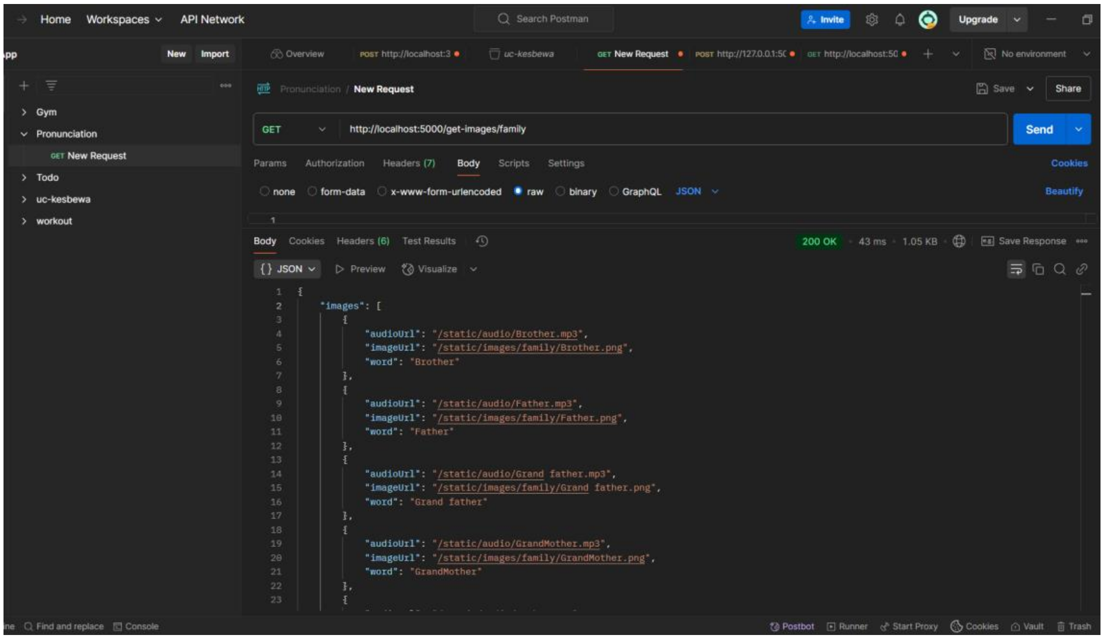


Figure 28: Testing_02

- Emotion Detection API Testing

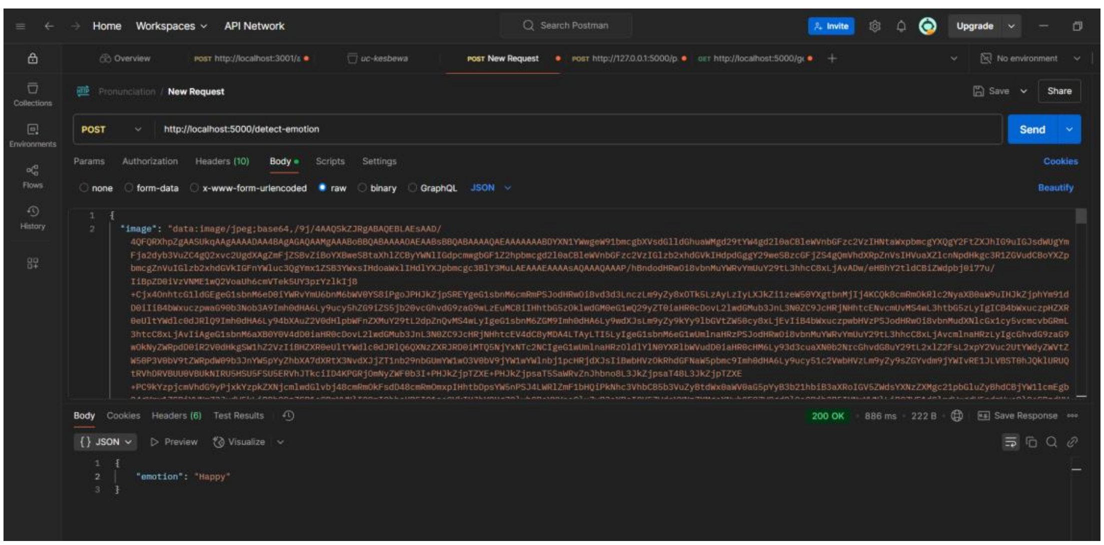


Figure 29: Testing_03

- User Data Storage API Testing

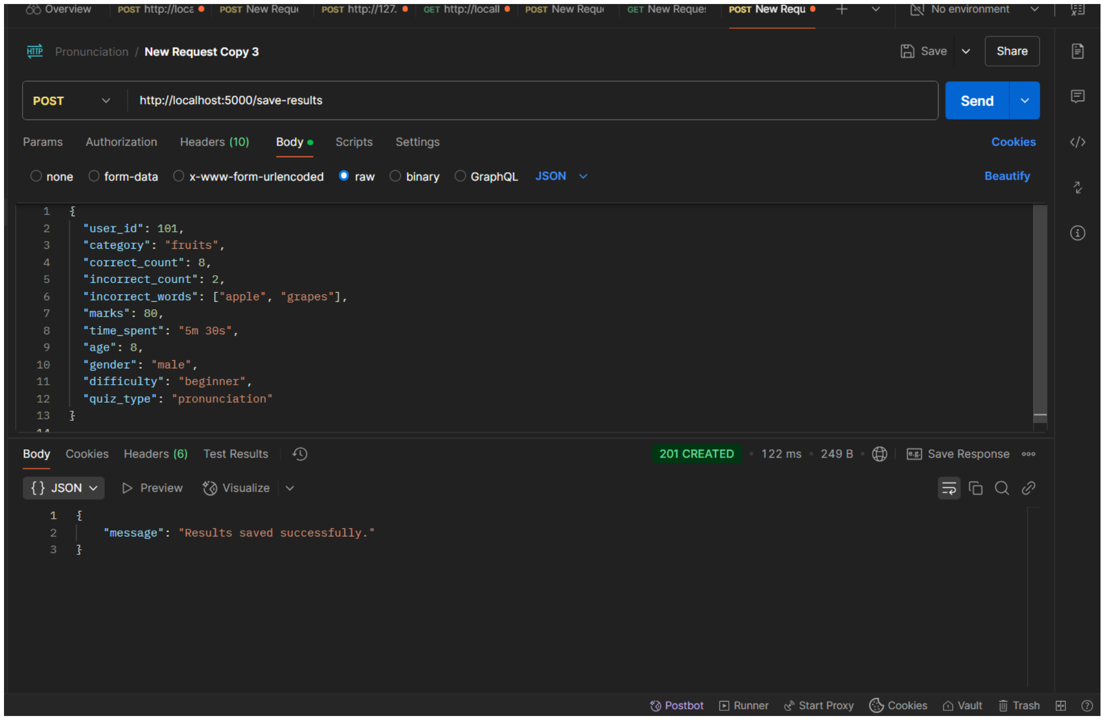


Figure 30: Testing_04

- Feedback Generation API Testing

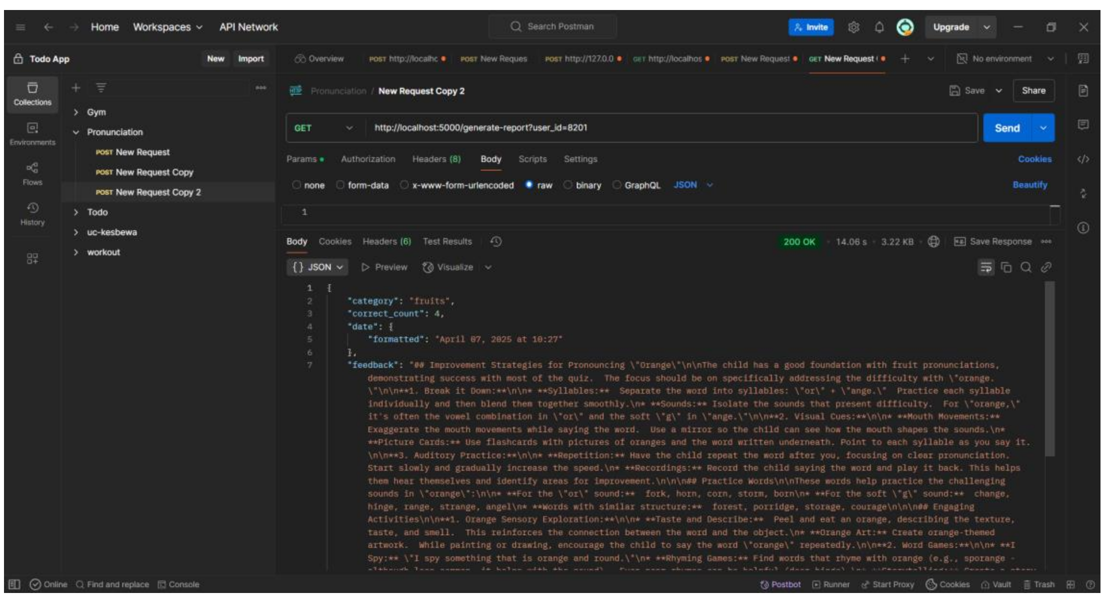


Figure 31: Testing_05

2.9 Enhancing Mathematical Skills – IT21342394 – Semini B.V.S.

2.9.1 Implementation

2.9.2 Model training for predict readiness for next level

The dataset used for this study, titled ‘balanced_quiz_dataset.csv’, was collected under the context of an adaptive learning system for children with Down syndrome. Each row in the dataset represents a child's performance during a training and quiz sessions, with demographic data and performance metrics. The dataset includes the following fields,

- Numerical Features- total number of questions in the quiz, number of questions answered correctly and incorrectly, number of questions faced in each sub levels, number of correct answers in each sub levels, average response time for each sub levels, final score for the quiz, total time taken to complete the quiz
- Categorical Features- gender, math category, and difficulty level
- Target Variable- readiness – a binary label indicating whether the child is considered ready (1) or not ready (0) to progress to the next level.

The dataset is balanced so that both readiness outcomes are represented equally, which is crucial while training an unbiased classification model.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	age	gender	category	difficulty	noofquestions	correctcount	incorrect count	noofattemptinquestionsinsublevel1	noofattemptinquestionsinsublevel2	noofattemptinquestionsinsublevel3	noofattemptinquestionsinsublevel4	noofcorrectquestionsinsublevel1	noofcorrectquestionsinsublevel2	noofcorrectquestionsinsublevel3	noofcorrectquestionsinsublevel4	avrgresponsetimeforsublevel1questions	avrgresponsetimeforsublevel2questions	avrgresponsetimeforsublevel3questions	avrgresponsetimeforsublevel4questions	quizmark	quizcompletationtime	readiness
2	9	male	multipicati	advanced	15	1	14	4	1	3	4	3	1	0	2	67.778088	19.158152	88.490983	117.61704	1	14.55271	0
3	11	male	addition	intermedia	15	3	12	0	5	4	5	0	3	2	5	0	16.153963	13.981788	18.671205	6	13.96664	0
4	11	female	substractic	advanced	15	12	3	1	2	2	2	0	0	0	1	3.1840201	16.990397	36.096425	18.90802	8	18.98084	1
5	3	female	multipicati	beginner	15	14	1	1	2	1	5	0	0	1	0	25.190044	18.39065	20.861641	32.452964	10	11.64184	1
6	15	male	substractic	advanced	15	15	0	2	1	1	1	0	1	1	0	23.241632	2.293357	34.775837	34.075851	10	8.189436	1
7	6	male	division	beginner	15	0	15	4	2	2	0	1	1	1	0	19.702536	34.606275	25.355732	0	2	11.08199	0
8	10	male	division	advanced	15	12	3	2	3	1	0	2	2	0	0	54.256379	51.170334	78.376761	0	8	27.67794	0
9	3	male	substractic	beginner	15	12	3	1	1	2	5	1	0	0	5	3.836007	4.8485994	6.8423119	21.02197	10	14.47616	1
10	13	male	addition	advanced	15	1	14	4	0	3	3	0	0	3	0	27.111512	0	20.412558	6.0036119	4	27.4959	0

Figure 32: 2-5 Dataset

To predict the readiness of each child, a Logistic Regression classifier was used because it is easy to interpret and efficient in binary classification tasks. The data was split into training and test sets in an 80/20 ratio while maintaining class distribution using the stratify parameter.

- Training Set: 80% of the data
- Testing Set: 20% of the data
- Model Parameters: The model was initialized with “random_state=42” for reproducibility and “max_iter=1000” for guaranteed convergence.

```python
# Define the feature set (X) and the target variable (y)
X = df.drop(columns=["readiness"])
y = df["readiness"]

# Convert categorical columns to numerical
X = pd.get_dummies(X, columns=["gender", "category", "difficulty"], drop_first=True)

# Standardize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42, stratify=y)

# Initialize and train the logistic regression model
model = LogisticRegression(random_state=42, max_iter=1000)
model.fit(X_train, y_train)

# Make predictions
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)
```

Figure 33: Predict readiness model development

The key values of the testing of the model learned are provided below:

- Training Accuracy: 88.64%
- Testing Accuracy: 88.21%

This indicates that the model generalizes well with minimal overfitting. Similarity between training accuracy and test accuracy suggests that the model did not memorize the data and learned the salient patterns of the data.

```python
# Evaluate the model
train_accuracy = accuracy_score(y_train, y_train_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)
print(f"Training Accuracy: {train_accuracy * 100:.2f}%")
print(f"Testing Accuracy: {test_accuracy * 100:.2f}%")
print("\nClassification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Training Accuracy: 88.64%
Testing Accuracy: 88.21%

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.86      0.88       140
           1       0.87      0.90      0.88       140

    accuracy                           0.88       280
   macro avg       0.88      0.88      0.88       280
weighted avg       0.88      0.88      0.88       280
```

Figure 34: Model accuracy

2.9.3 Adaptive question generation algorithm with sub-level progression

To generate math questions suitable for Down syndrome children, dynamic question generation function was created based on the chosen category (addition, subtraction, multiplication, division), difficulty level (beginner, intermediate, advanced), and sub-level.

Figure 35: Level and category selection interfaces

The function utilizes pre-determined numerical ranges for each level of difficulty to ensure the questions are age-suited and cognition-accessible. For instance, beginner-level questions use smaller numbers (1–20), while advanced levels use a larger range (10–100).

```
export default function generateQuestion(category, difficulty, subLevel) {
  const operations = {
    addition: '+',
    subtraction: '-',
    multiplication: '*',
    division: '/',
  };

  if (!operations[category]) {
    throw new Error('Invalid category');
  }

  const operation = operations[category];
  let nums = [];

  const ranges = {
    beginner: [1, 20],
    intermediate: [10, 50],
    advanced: [10, 100],
  };
```

Figure 36: 2- 9 Creating levels

Under each primary difficulty level, the system is further divided into 4 sub-levels to ensure a more gradual learning curve. The sub-levels allow for greater control over question difficulty. Each primary difficulty range is further divided into four equal segments. For example, if the beginner range is 1 through 20, it is divided as follows,

- Sub-level 1- Numbers from 1 to 5 (easiest)
- Sub-level 2- Numbers from 6 to 10
- Sub-level 3- Numbers from 11 to 15
- Sub-level 4- Numbers from 16 to 20 (most difficult within beginner)

This logic is similarly applied to intermediate and advanced levels, each with its own range of numbers. The higher the sub-level between 1 to 4, the greater and more challenging the numerical values of the questions. This structure supports learning step by step as well as enabling Down syndrome children to progress at their own speed without sudden jumps in difficulty.

```
const getRange = (subLevel, baseRange) => {
  const [min, max] = baseRange;
  const increment = Math.floor((max - min) / 4); // Divide range into 4 sub-levels
  const subMin = min + increment * (subLevel - 1);
  const subMax = subMin + increment - 1;
  return [subMin, subMax];
};
```

Figure 37: Creating sub levels

The reasoning to produce numbers varies according to the selected category of math to make the produced questions valid and appropriate for the learner's level. For division, the aim is to present clean divisions (without remainders). First, a group of dividends is selected based on the sub-level in the indicated difficulty. A specific, fixed set of divisors is used depending on the difficulty level. A divisor is randomly picked from among them, and a dividend is generated by taking a random number from the sub-level set and multiplying it by the chosen divisor. This ensures the result of division to be an integer every time.

In the case of subtraction, the explanation makes the initial number always bigger than the latter to avoid negative results which are likely to confusing some children. A second number is selected from the sub-level range, then the first number is created by adding a random positive amount to it.

For addition and multiplication, the two numbers are both selected independently from the range defined by the difficulty and sub-level. This consistent format ensures that the questions systematically increase in difficulty, allowing for a smooth learning process tailored to each child's development and ability.

```
if (category === 'division') {
  const [min, max] = getRange(subLevel, ranges[difficulty]);
  const divisorRange = difficulty === 'beginner' ? [2, 5] : difficulty === 'intermediate' ? [6, 9] : [10, 15];
  const dividend = Math.floor(Math.random() * (max - min + 1)) + min;
  const divisor = Math.floor(Math.random() * (divisorRange[1] - divisorRange[0] + 1)) + divisorRange[0];
  nums = [dividend * divisor, divisor];
} else if (category === 'subtraction') {
  const [min, max] = getRange(subLevel, ranges[difficulty]);
  const num2 = Math.floor(Math.random() * (max - min + 1)) + min;
  const num1 = num2 + Math.floor(Math.random() * (max - num2 + 1)) + 1;
  nums = [num1, num2];
} else {
  const [min, max] = getRange(subLevel, ranges[difficulty]);
  nums = [
    Math.floor(Math.random() * (max - min + 1)) + min,
    Math.floor(Math.random() * (max - min + 1)) + min,
  ];
}
```

Figure 38: Question logic

2.9.4 Adjusting the difficulty of the next question based on child performance

The algorithm is pivotal in determining whether the difficulty level of the next question has to be adjusted based on the child's performance. After the questions have been answered, the "handleSubmit" function processes the user's response and adjusts their performance metrics, which play a critical role in determining the difficulty of the next question.

The system initially ensures that the user has submitted an answer and checks whether the answer is correct by comparing the user's answer with the current question's correct answer. After ensuring the correctness of the answer, the system adjusts the performance metrics of the current sub-level.

- If the response is correct, the system checks whether the child should move to the next sub-level. The "setCurrentSubLevel" method is utilized to raise the sub-level, but it prevents the child from exceeding the max sub-level (which is established at 4). The line "Math.min(prevLevel + 1, 4)" enables the sub-level to be raised by 1, but not more than 4.
- If the answer is incorrect, the sub-level remains the same. The child will receive an explanation and motivational messages to encourage them to try again.

By only increasing the sub-level when responding correctly, the system guarantees that the advancement of the child depends on what they have mastered. The adaptive approach ensures that the difficulty will only be increased when the child is prepared and they are given additional support if necessary.

```
const handleSubmit = () => {
  if (userAnswer.trim() === '') return; // Prevent empty submissions

  setIsAnswered(true); // Mark as answered
  setTimerActive(false);

  const isCorrect = questionData && parseFloat(userAnswer) === parseFloat(questionData.correctAnswer);
  const endTime = Date.now(); // Capture end time
  const responseTime = (endTime - startTime) / 1000; // Convert to seconds

  setSubLevelStats((prevStats) => {
    const subLevelIndex = currentSubLevel - 1; // Sublevel is 1-based, array is 0-based
    const updatedAttempts = [...prevStats.attempts];
    const updatedCorrectAnswers = [...prevStats.correctAnswers];
    const updatedResponseTimes = [...prevStats.responseTimes];

    // Increment attempts for the current sublevel
    updatedAttempts[subLevelIndex] += 1;

    // Increment correct answers if correct
    if (isCorrect) {
      updatedCorrectAnswers[subLevelIndex] += 1;
    }

    // Add response time to the respective sublevel
    updatedResponseTimes[subLevelIndex].push(responseTime);

    return {
      attempts: updatedAttempts,
      correctAnswers: updatedCorrectAnswers,
      responseTimes: updatedResponseTimes,
    };
  });

  setAnswerResults((prevResults) => {
    const updatedResults = [...prevResults];
    updatedResults[questionCount] = isCorrect;
    return updatedResults;
  });

  if (isCorrect) {
    setCorrectCount((prev) => prev + 1);
    setMessage(shuffleMessages(positiveMessages));

    // Increase sub-level (if not at max)
    setCurrentSubLevel((prevLevel) => Math.min(prevLevel + 1, 4));
  } else {
    setShowExplanation(true); // Show AI Explanation if answer is wrong
    setIncorrectCount((prev) => prev + 1);
    setMessage(shuffleMessages(motivationalMessages));

    // Keep sub-level the same
  }
  setIsAnswered(true);
};
```

Figure 39: Adjusting the difficulty of the next question based on child performance

2.9.5 Quiz generation with sub-level distribution

This function is responsible for generating a set of math questions tailored to a specific category (like addition, subtraction, etc.) and difficulty level (beginner, intermediate, advanced). What makes this method special is how it uses sub-levels to gradually increase the difficulty within each quiz.

Each quiz consists of 10 questions in total. These questions are distributed across 4 sub-levels, with difficulty increasing from Sub-Level 1 to Sub-Level 4. The breakdown is as follows:

- Sub-Level 1: 1 question (easiest)
- Sub-Level 2: 2 questions
- Sub-Level 3: 3 questions
- Sub-Level 4: 4 questions (most difficult)

This creates a natural progression in difficulty throughout the quiz, allowing the child to build confidence with easier questions and then move on to harder ones.

For each sub-level, a loop generates the required number of questions using a custom generateQuestion function, which takes into account the category, difficulty, and sub-level to create appropriate arithmetic problems. These questions are then compiled into a single quiz and returned as a JSON response. This layered approach supports a more adaptive learning model, where performance at each sub-level can be tracked individually, helping to inform future recommendations and progress evaluations. Ultimately, this methodology allows for both structured learning and detailed performance analysis, which are especially important when working with children who require personalized educational support, such as those with Down syndrome.

```javascript
export const generateQuiz = (req, res) => {
  const { category, difficulty } = req.params;

  try {
    // Define sub-level distribution
    const subLevelCounts = {
      1: 1, // 1 question from sub-level 1
      2: 2, // 2 questions from sub-level 2
      3: 3, // 3 questions from sub-level 3
      4: 4, // 4 questions from sub-level 4
    };

    const quizQuestions = [];

    // Generate questions based on the sub-level distribution
    for (let subLevel = 1; subLevel <= 4; subLevel++) {
      for (let i = 0; i < subLevelCounts[subLevel]; i++) {
        const question = generateQuestion(category, difficulty, subLevel);
        quizQuestions.push(question);
      }
    }

    res.json(quizQuestions); // Send as JSON response
  } catch (error) {
    res.status(400).json({ error: error.message }); // Handle invalid inputs
  }
};
```

Figure 40: Quiz creations

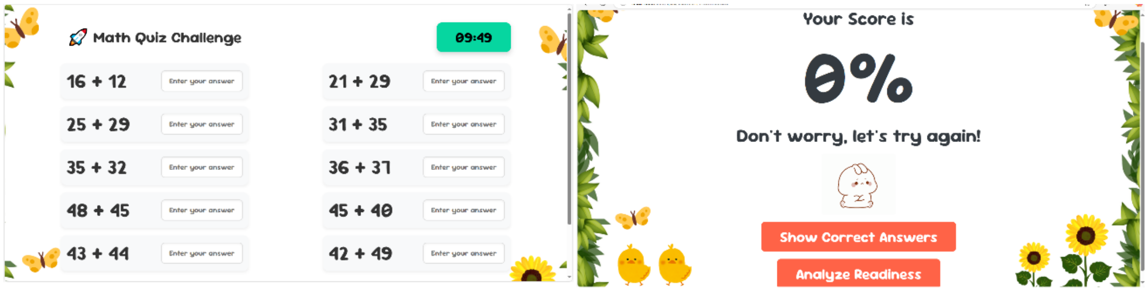


Figure 41: Quiz interfaces

2.9.6 Generating educational animations

In order to assist Down syndrome children in understanding arithmetic concepts better, particularly in everyday situations such as money handling, an animation component specifically tailored for visual and voice-based presentation was created. Along with numerical addition, this system reduces it to a multi-sensory process through the use of Sri Lankan currency images and child-friendly voice-over explanation.

The tag <MathAnimation /> is responsible for displaying an animated chart where two values, num1 and num2 are graphically represented using actual images of Sri Lankan currency notes and coins. The values concerned are 5000, 1000, 500, 100, 50, 20, 10, 5, 2, and 1 rupee and are all represented by pre-imported picture files. A supporting function called breakDownAmount() is employed to break down every numeric value into the least number of coins and notes, beginning with the largest denomination. This enables the animation to illustrate how every amount is constructed with recognizable physical money units, so the idea of quantity becomes more concrete and meaningful to the child.

```
// Use the imported images directly rather than path strings
const denominationImages = {
  5000: image5000,
  1000: image1000,
  500: image500,
  100: image100,
  50: image50,
  20: image20,
  10: image10,
  5: image5,
  2: image2,
  1: image1
};

// Available Sri Lankan currency denominations
const denominations = [5000, 1000, 500, 100, 50, 20, 10, 5, 2, 1];

// Function to break down an amount into available currency
function breakDownAmount(amount) {
  let breakdown = [];
  for (let denom of denominations) {
    const count = Math.floor(amount / denom);
    for (let i = 0; i < count; i++) {
      breakdown.push(denom);
    }
    amount -= count * denom;
  }
  return breakdown;
}
```

Figure 42: Representation using Sri Lankan currency

To aid learning through audio input, the system also generates a friendly and encouraging voice over script through the “generateVoiceText()” function. The text is styled with simple and interactive words for kids. It explains the process step by step, counting the money represented by num1 first, adding the second amount num2, and then announcing the total amount. The text differs based on the number of notes or coins. For small numbers, it counts the values singly, but for larger numbers, it uses more generic expressions like "Let's count them together," so that there will be no confusion and tedium.

```
// Generate explanation text for voice-over with more child-friendly language
function generateVoiceText(num1, num2) {
  let breakdown1 = breakDownAmount(num1);
  let breakdown2 = breakDownAmount(num2);

  let text = `Hello there! Let's play a super fun counting game with money! We have ${num1} rupees and we want to add ${num2} more rupees. `;

  if (breakdown1.length <= 5) {
    text += `First, let's count our ${num1} rupees very slowly: ${breakdown1.join(" rupees... ")} rupees. `;
  } else {
    text += `First, we have ${num1} rupees in different notes and coins. Let's count them one by one. `;
  }

  text += `Good job! `;

  if (breakdown2.length <= 5) {
    text += `Now, let's add ${num2} more rupees: ${breakdown2.join(" rupees... ")} rupees. `;
  } else {
    text += `Now, let's add ${num2} more rupees. We'll count them together. `;
  }

  text += `Wonderful counting! Now, let's add them all together! ${num1} plus ${num2} equals... ${num1 + num2} rupees! Amazing job! You're so good at counting

  return text;
}
```

Figure 43: Animation logic

This combination of visual presentation and interactive verbal guidance is well adapted to children with cognitive issues. It not only simplifies abstract mathematics concepts but also builds confidence and encouragement through rewarding. The use of real-life scenarios like handling money is an adaptation into functional learning goals and provides opportunities for children to apply their learning in real-world applications outside the virtual environment.

2.9.7 Generating comments and recommendations based on child performance

This logic is intended to evaluate the performance of the child for every and at every level of difficulty and then give useful feedback. This feedback is provided in two forms, comments (descriptive) and recommendations (actionable).

The approach starts by iterating over each of the four categories, addition, subtraction, multiplication, and division. For every category, it gets performance data for all three levels of difficulty, beginner, intermediate, and advanced. For every category, it checks whether the child has attempted anything at all. This is done by checking the attempts field of the performance data. If the child has attempted at least one, the flag attempted is set to true.

```
export const getChildPerformance = async (req, res) => {
  const { childId } = req.params;

  try {
    // Fetch quiz data for the child
    const quizData = await Quizs.find({ childId });

    if (!quizData.length) {
      return res.status(404).json({ message: "No quiz data found for this child." });
    }

    // Structure for category-wise performance tracking
    const performance = {};
    const recommendations = [];
    const comments = [];

    // Categories to track
    const categories = ["addition", "subtraction", "multiplication", "division"];
    const difficulties = ["beginner", "intermediate", "advanced"];

    // Initialize structure
    categories.forEach(category => {
      performance[category] = {};
      difficulties.forEach(level => {
        performance[category][level] = {
          correct: 0,
          incorrect: 0,
          total: 0,
          avgResponseTime: 0,
          attempts: 0
        };
      });
    });

    // Process quiz data
    quizData.forEach((quiz) => {
      const { category, difficulty, correctCount, incorrectCount, noOfQuestions,
        avgResponseTimeForSubLevel1, avgResponseTimeForSubLevel2,
        avgResponseTimeForSubLevel3, avgResponseTimeForSubLevel4 } = quiz;

      if (!performance[category]) return;

      // Update stats for the specific category and difficulty
      performance[category][difficulty].correct += correctCount;
      performance[category][difficulty].incorrect += incorrectCount;
      performance[category][difficulty].total += noOfQuestions;
      performance[category][difficulty].attempts += 1;

      const avgResponseTime = (avgResponseTimeForSubLevel1 + avgResponseTimeForSubLevel2 + avgResponseTimeForSubLevel3 + avgResponseTimeForSubLevel4) / 4;
      performance[category][difficulty].avgResponseTime = avgResponseTime;
    });
```

Figure 44: Performance tracking

The function also tracks the child's strengths and weaknesses across each category based on their accuracy at every level of difficulty:

- Strengths: If the child's accuracy on a given level of difficulty is 80% or higher, it is a strength. Those levels are included in the strengths array.
- Weaknesses: Below 50% accuracy of the child is a weakness. These levels are added to the weaknesses array.

```
// Generate comments and recommendations
categories.forEach(category => {
  let attempted = false;
  let strengths = [];
  let weaknesses = [];

  difficulties.forEach(level => {
    const { correct, incorrect, total, avgResponseTime, attempts } = performance[category][level];

    if (attempts > 0) attempted = true; // Mark category as attempted

    if (total === 0) return; // Skip if no data for this level

    const accuracy = (correct / total) * 100;

    if (accuracy >= 80) {
      strengths.push(level);
    } else if (accuracy < 50) {
      weaknesses.push(level);
    }
```

Figure 45: Fetch strengths and weakness

For each difficulty level in the category, the function generates recommendations based on the performance of the child.

- Recommendation for High Accuracy & Quick Response Time- If the child's accuracy is 80% or higher and the average response time is below 5 seconds, the recommendation is that the child should move to the next level of difficulty in that category.
- Recommendation for Low Accuracy- If the child's accuracy is below 50%, the recommendation is that the child should practice more at the current level of difficulty in an attempt to raise their accuracy.
- Recommendation for Slow Response Time- If the child's average response time is greater than 10 seconds, it means that the child may have to practice responding to questions faster.

```
    // Give recommendations based on accuracy and response time
    if (accuracy >= 80 && avgResponseTime < 5) {
      recommendations.push(`The child should try moving to the next level in ${category} as they perform well in ${level} level.`);
    } else if (accuracy < 50) {
      recommendations.push(`The child needs more practice in ${category} at ${level} level to improve accuracy.`);
    } else if (avgResponseTime > 10) {
      recommendations.push(`The child is taking longer to answer ${category} questions at ${level} level. Encourage quicker responses.`);
    }
  });
```

Figure 46: Generate recommendations

After strengths, weaknesses, and generating recommendations have been evaluated, the function generates comments,

- If the child is strong in one or more levels within a category, a positive comment is generated.
- If the child is weak in some levels, a comment is generated so that they can be indicated where they need further help.
- If the child has not even tried any questions in a category, a remark is issued for a lack of confidence or interest in that category.

```
    // Add comments based on strengths and weaknesses
    if (strengths.length > 0) {
      comments.push(`The child is performing well in ${category} at ${strengths.join(", ")} level.`);
    }
    if (weaknesses.length > 0) {
      comments.push(`The child is struggling with ${category} at ${weaknesses.join(", ")} level and needs additional support.`);
    }
    if (!attempted) {
      comments.push(`The child has not attempted ${category} at any level, which may indicate a lack of confidence or interest.`);
    }
  });
```

Figure 47: Generate comments

These are the user interfaces,

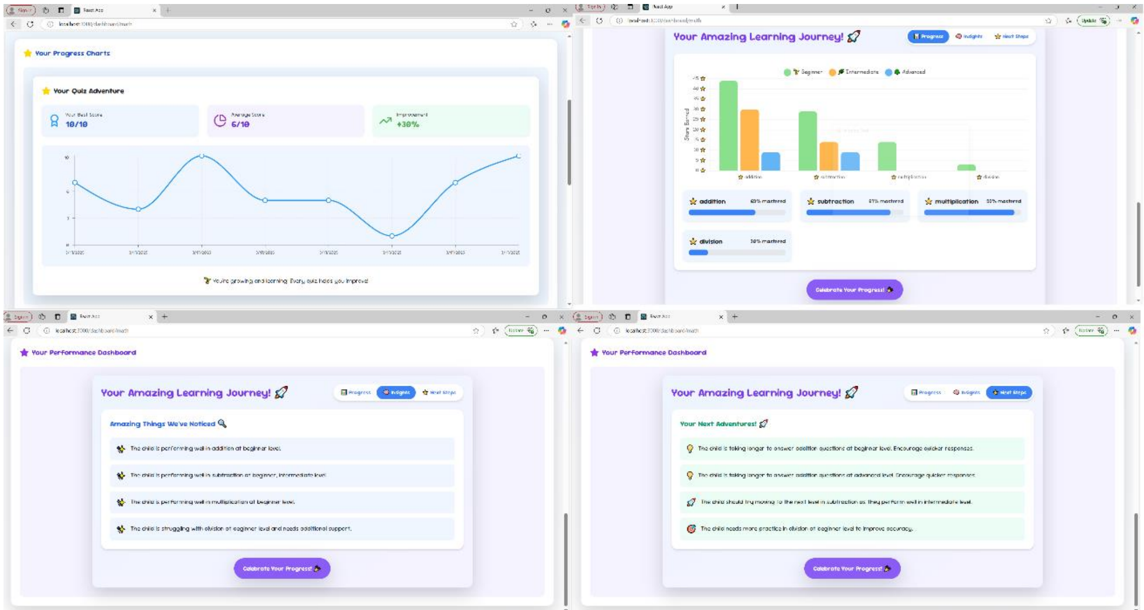


Figure 48: User interfaces

After all comments and suggestions have been issued for all categories, the function returns the performance results along with the comments and suggestions. This provides the child (or teacher/parent) with detailed insights into the child's areas of strength, areas of weakness, and where they need to improve.

2.9.8 Testing

1. Testing the predict readiness model

To test the readiness prediction model, a Flask API was developed to serve the machine learning model. Flask, a lightweight Python web framework, allows the model to receive data, process it, and send back predictions in real time. The API exposes an endpoint where performance data from the frontend (such as accuracy, response time, and quiz attempts) is sent using a POST request.

For testing, Postman was used to simulate frontend requests. This allowed us to manually send sample data to the Flask endpoint in JSON format and inspect the prediction results returned by the model. Once verified, the same data structure was used in the actual frontend application. When a child finishes a quiz, their data is automatically sent from the frontend to the Flask API, which then returns a prediction indicating whether the child is ready to move to a higher difficulty level or needs more practice. This setup helps integrate intelligent decision-making into the learning platform, making it more adaptive and personalized.

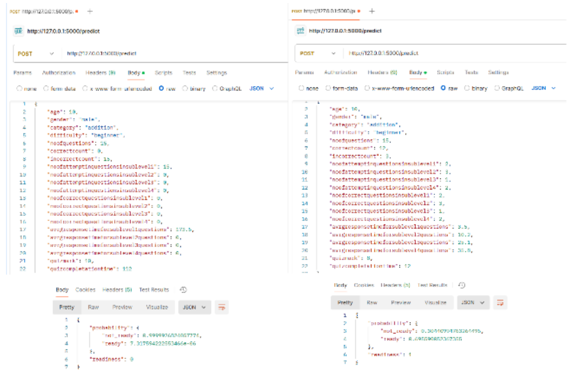


Figure 49: Test using postman

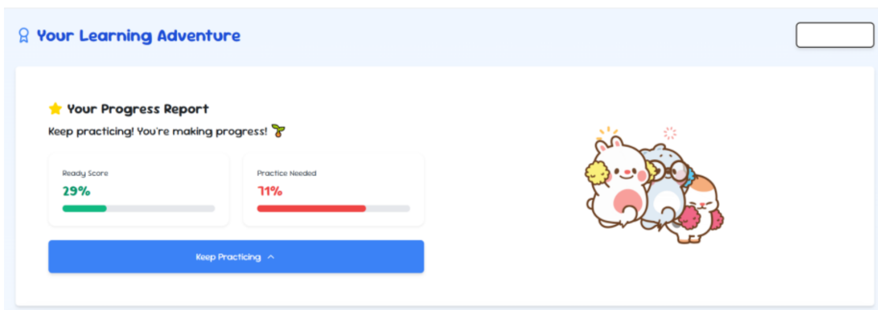


Figure 50: User interface

2. Testing the adaptive question generation algorithm with sub-level progression

As the child answered questions, their performance was tracked. If they answered correctly, the system automatically increased the sub-level for the next question.

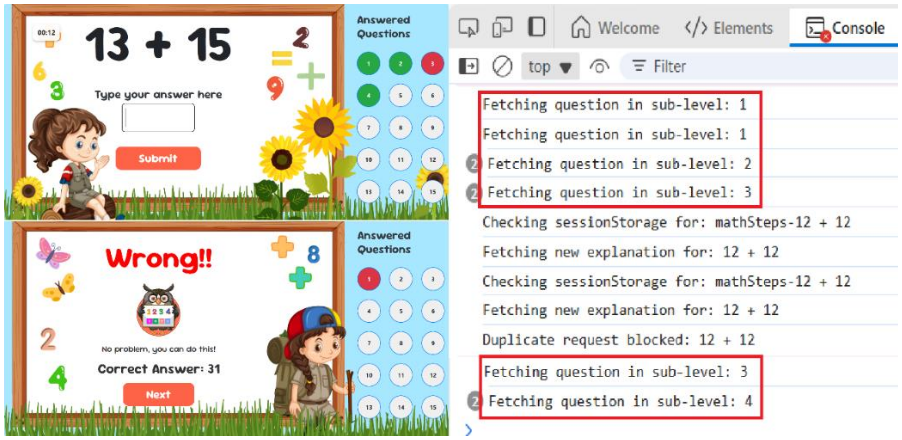


Figure 51: Adaptive question generation logic

3. Testing the training session and quiz data save into the database using postman

To ensure that training session and quiz data were correctly saved into the database, Postman was used to simulate data submissions from the frontend. Test data including category, difficulty, sub-level stats, correct and incorrect answers, and response times were sent as POST requests to the backend API endpoints.

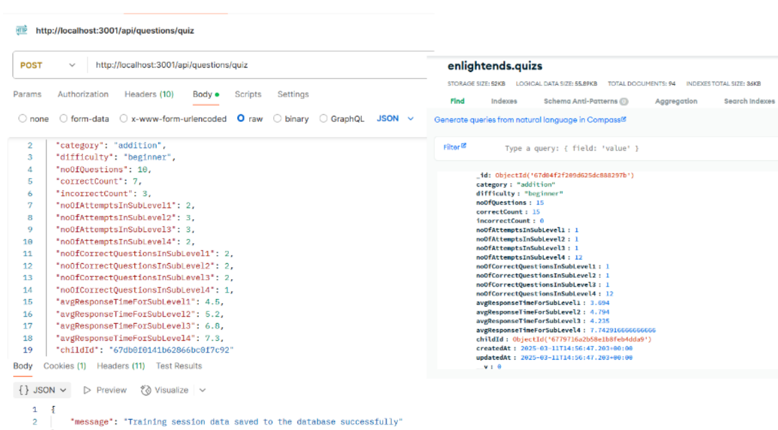


Figure 52: Test using postman

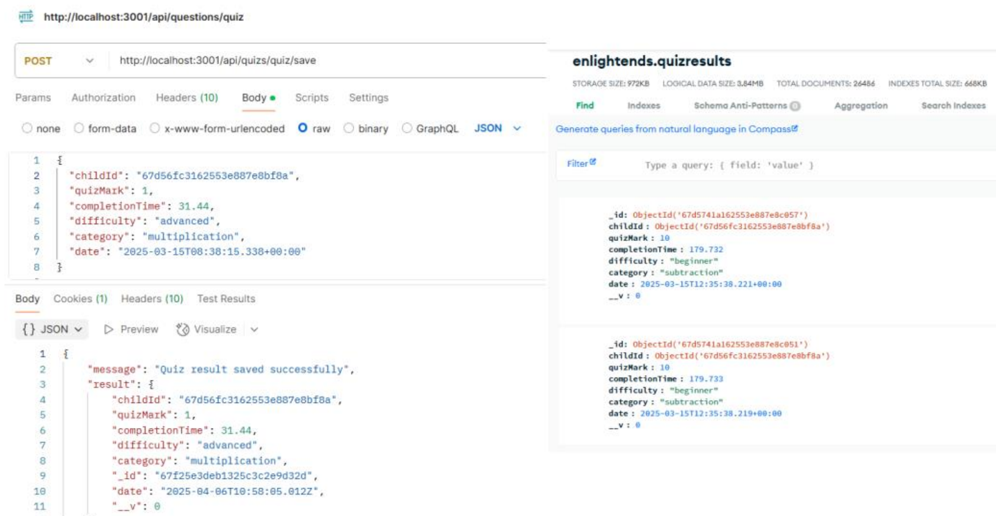


Figure 53: Test using postman

The API responses were checked to confirm successful data insertion, and the MongoDB database was reviewed to verify that the records were correctly stored and structured. This testing process helped validate the data flow from the frontend to the backend, ensuring that all child performance data is reliably recorded for further analysis and reporting.

2.10 Identifying Hidden Talents – IT21292972 – Methsahani K.K.S.P.

2.10.1 Implementation

This section describes implementation related information about the talent identification component.

When it comes to the implementation part, the front end implemented using react.js backend implemented using node.js and MongoDB used for database. Random forest algorithm used to do model training.

Some major implementation points will summarized below.

In the drawing category section, drawing canvas, reference image, blusher, color pallet, eraser and compare score kind of features implemented. After the user do the drawing user can select the compare button. Then visual comparison will happen using AI. Then in the VS code terminal shows the reason to given that score.

In figure 53 as shown below, the code represents the calculation of drawing interaction time period. It used to do the analyzation of drawing category. Using that, time period which the user does the drawing in canvas is calculated. It will help to take accurate interaction time and able to remove the time period which user not doing the drawing while the drawing category platform is open.

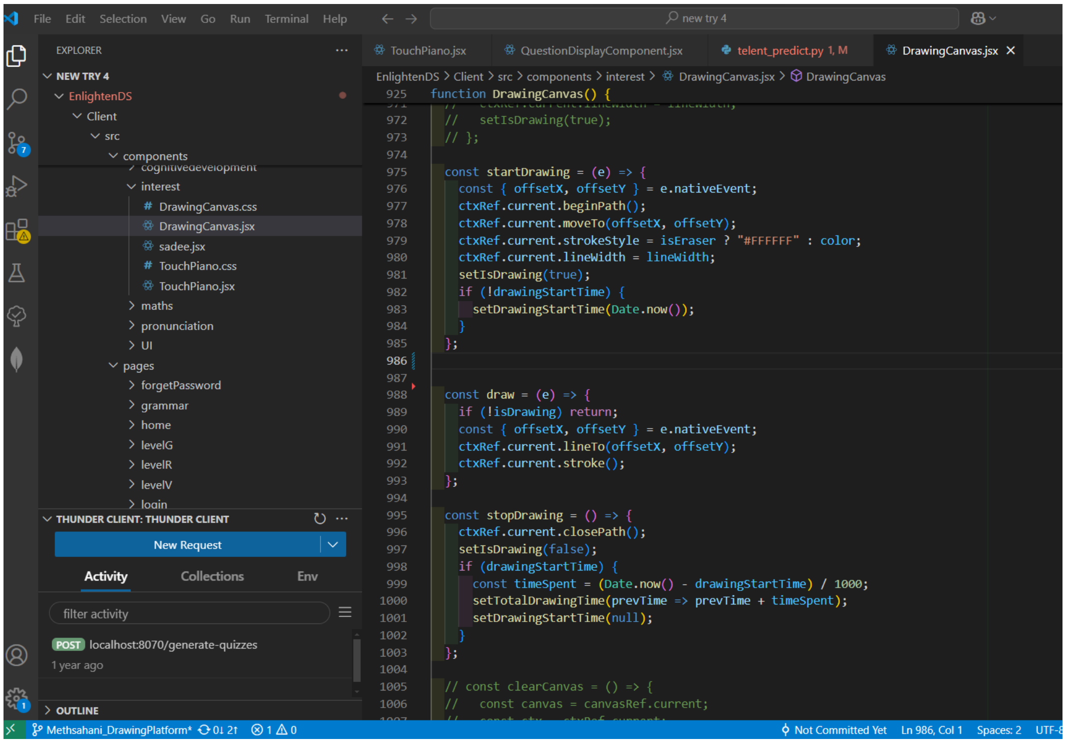


Figure 54: Drawing time period calculations

In the piano category section, interactive piano simulator has been implemented. User able to play that using mouse clicks and if it is touch screen, user can play the keys using those keys. Tone.js used to generate the sound when user play the keys. In here piano key interaction time period calculation, number of key count user used to play the piano and saving functionality implemented.

In figure 54 shows the piano key count calculation related implementation.

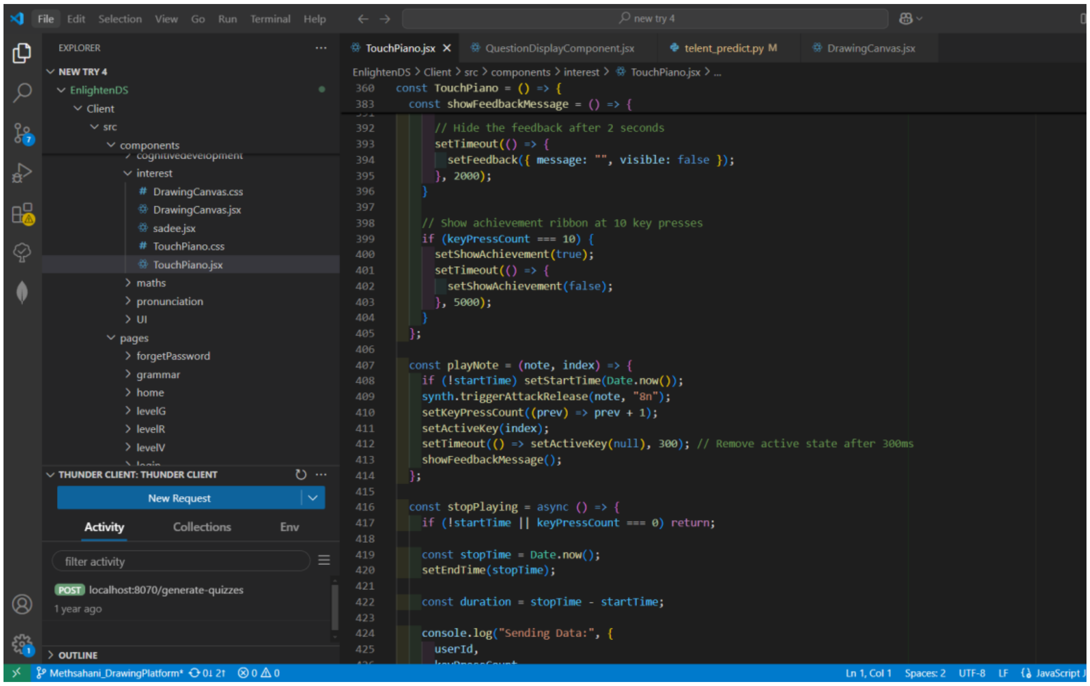


Figure 55: Interacted piano key count calculation

In the quiz category section, it is implemented using MERN stack and AI. From the talent identification page, user able to select the learning category. Then user can select beginner, intermediate or advanced subcategories. According to their selection they will get quizzes. In this quiz generation part implemented using AI. Once user selected a subcategory, new quiz is generated which includes 5 new questions. After user taking the next questions correction also happen. Then user can view the correct answer. Not only that number of correct answers, number of wrong answers and score are getting display in the top of the UI. Once user completed the quiz, UI implemented to display number of correct answers, number of wrong answers, final score and interaction time. Saving functionality also implemented in the UI. Once user save that those details getting store into the database.

In figure 55 shows the quiz generation-related main coding using open AI key.

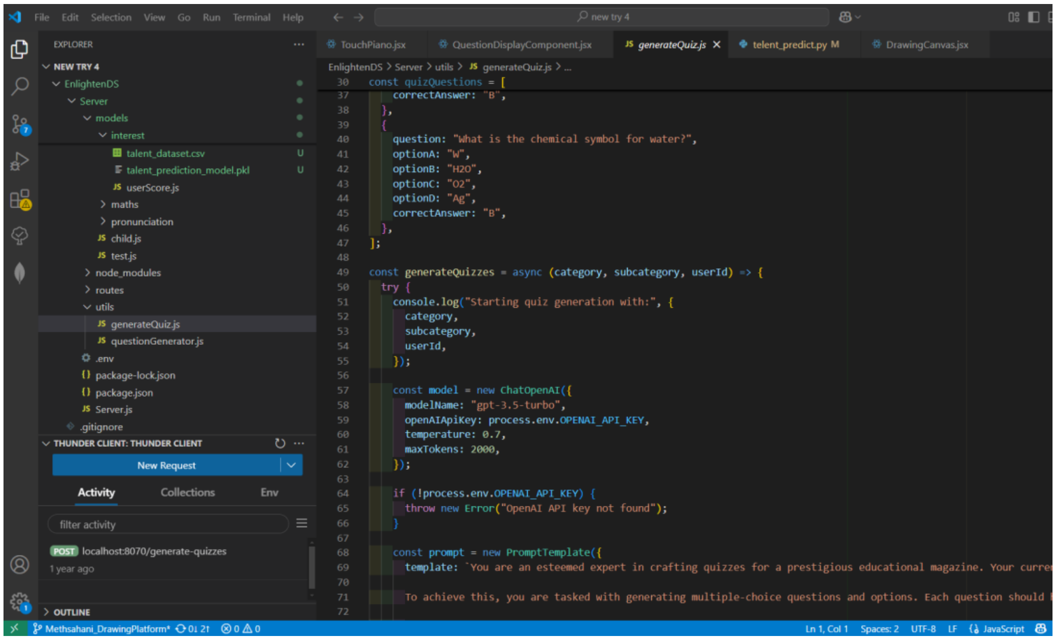


Figure 56: Quizzes generation part

In figure 56 represents the model training related implementation section.

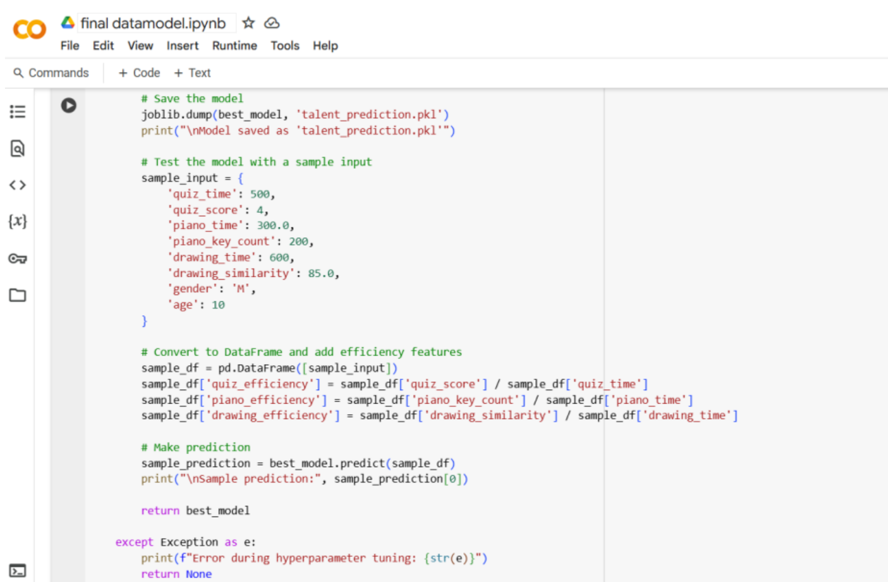


Figure 57: Model training representation

2.10.2 Testing

In this stage testing related information describe. Not only does the final stage of implementation testing happens with the initial stage of coding implanting and integrating. During the implementation, code level white box testing happened. After developing and each component. Component wise functional testing completed. Integration testing included while doing the integration of each and every component. Once completed the overall project regression testing conducted to make sure there are no existing functionally break.

In figure 57 represents the test results of similarity score calculation and interaction time.

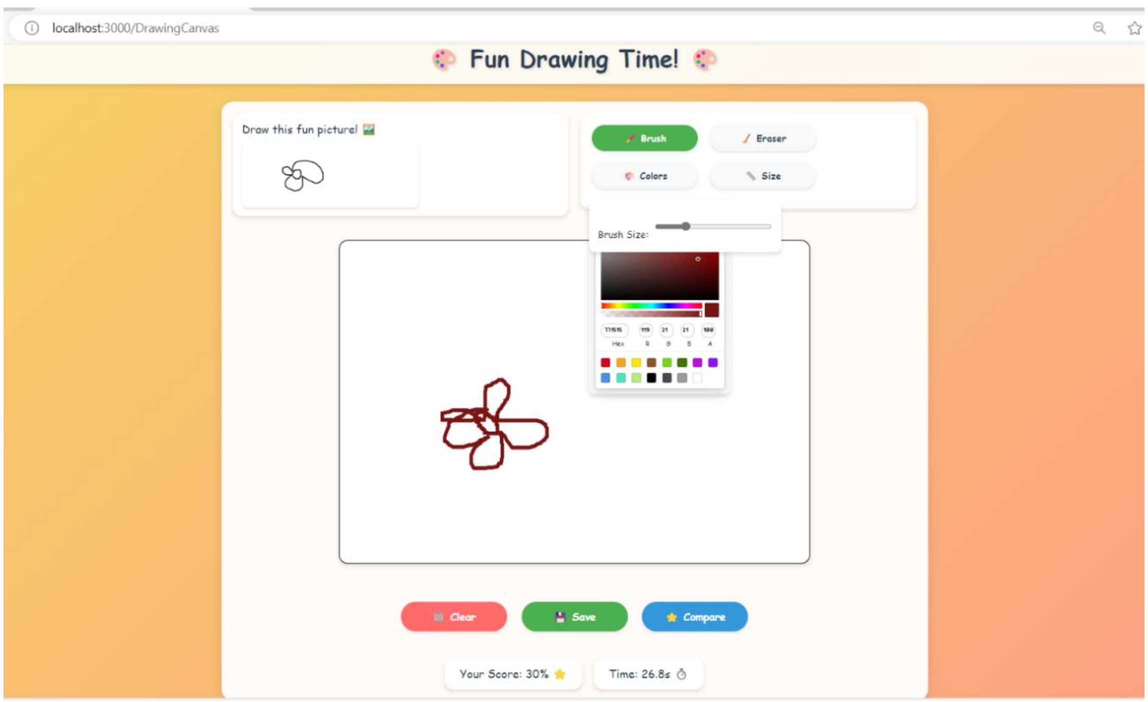


Figure 58: Drawing similarity score validation

In figure 58 represents the test results of saving functionality and number of key count and interaction time functionalities validation.

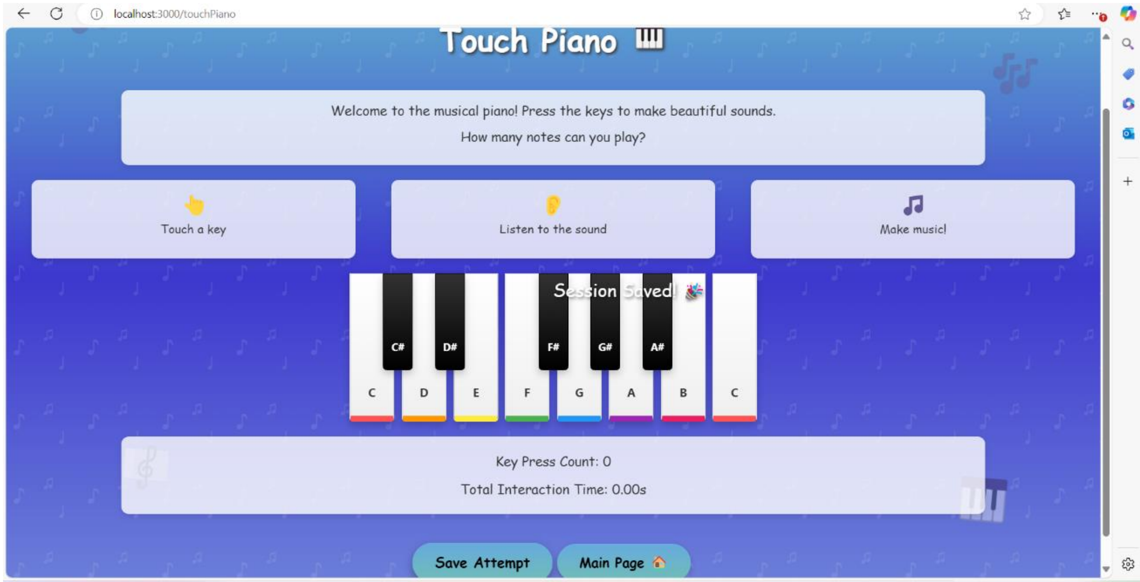


Figure 59: Piano functionality validation

In figure 59, 60 represents the test results of quiz generation and score calculation validation.

Figure 60: Quiz generation

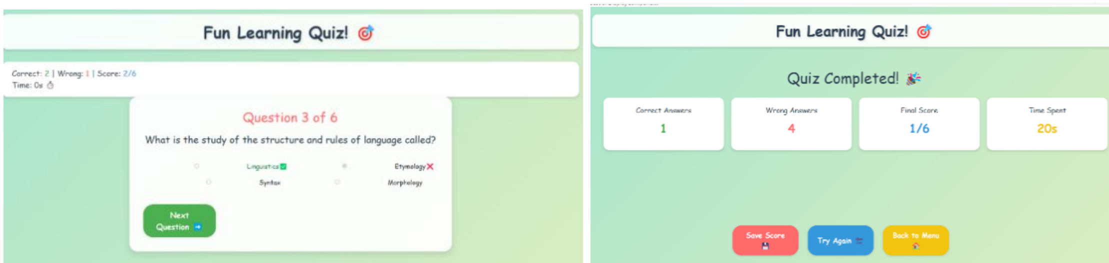


Figure 61: Quiz user interfaces

In figure 61 represents the validation of talented area prediction.

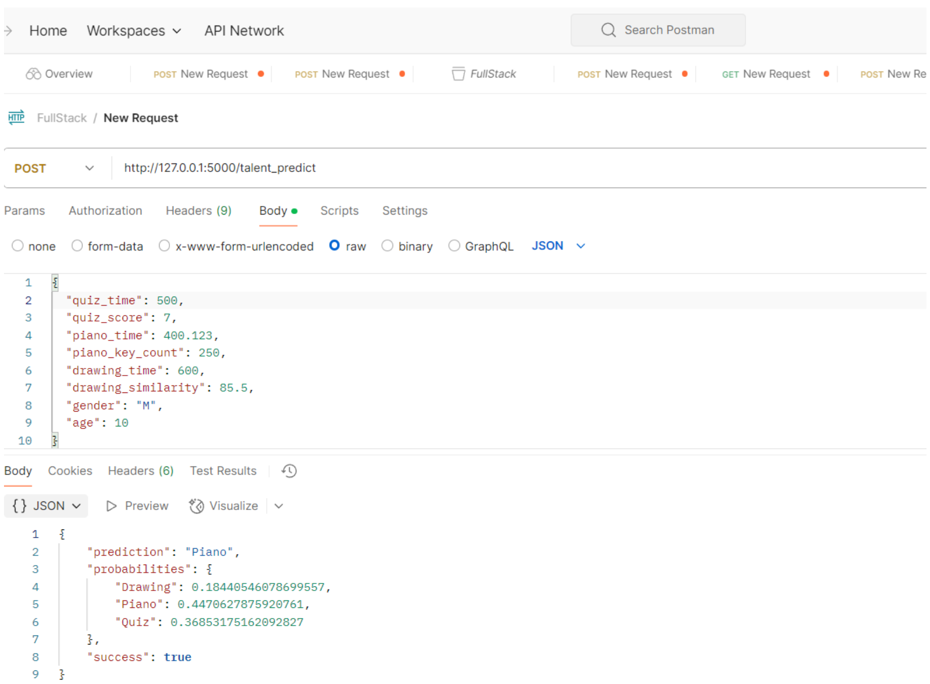


Figure 62: Validation of talented area prediction

3. COMMERCIALIZATION PLAN

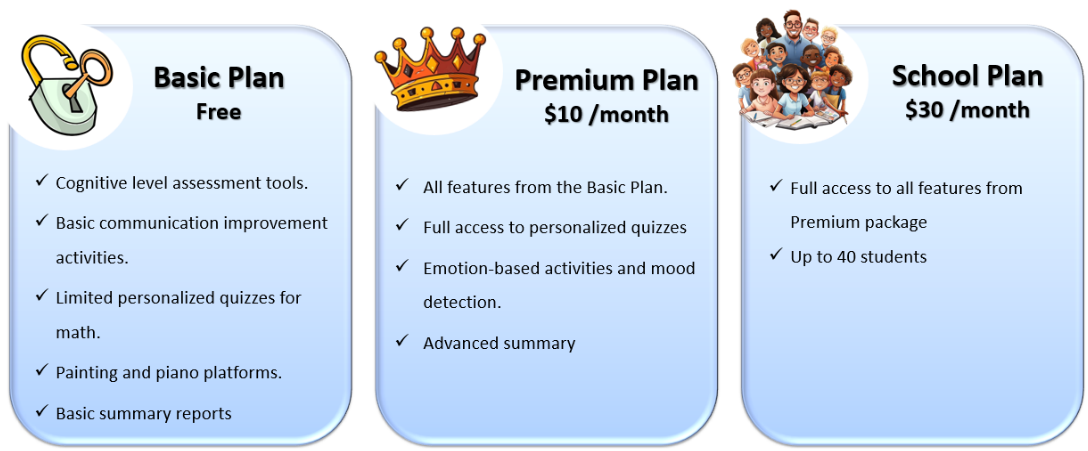


Figure 63: Commercialization code

A structured commercialization plan is needed for a number of reasons: First, it brings in sufficient revenues to sustain and grow our project revenues that will be reinvested into further development and refurbishment of the app. Second, it ensures that our solution remains both accessible to individual users and large educational institutions. Third, it clearly outlines how the market would be reached, such as building campaigns, allies, and alliances through educational standards that move along or follow regulatory standards for education and data privacy globally.

With a growing demand for educational technology, particularly in the area of cognitive development and early childhood education, our system "EnlightenDS" is a great opportunity to meet this demand. The very critical recognition of early cognitive assessments and developmental support only seems to be on the rise, hence creating a demand for such tools that are more accessible and effective for the use of parents, educators and schools at large. This will make these tools widely available for us so that they could make a significant contribution to children's cognitive development in a sustainable way.

A tiered subscription model for a number of different use categories has been formulated to be flexible and scalable. It is free through the Basic plan, which will give available basic cognitive level assessments, basic communication improvement activities and limited personalized quizzes on subjects like math. This plan, therefore, serves as an entry point to our solution, letting users explore and experience the key features of our app with no financial commitment. This implies that with the offering of a free version, the entry barrier will be low and a lot more kids can enjoy our tools, alike.

For users who want to have a more immersive and complete experience, there is a Premium Plan priced at $10 per month. This plan incorporates all the features of the Basic Plan and on top of this, it will include full access to personalized quizzes built by the user, emotion-based activities, mood detection and advanced summary reports. These features are designed for enabling deeper insight and customized support; hence, the Premium Plan should be adopted by parents and teachers who are keen on close monitoring and enhancement of cognitive development of the child.

Lastly, realizing that the educational institutions have special requirements, we have a School Plan offered for $30 per month, where all the features provided in the Premium package are extended in full to up to 40 students. This plan is especially useful for schools and special education centers to help them incorporate our cognitive development tools into their curriculum and do so at a very affordable price. Through a solution that can serve many, we make it easier for institutions to support large groups of children systematically and cheaply.

4. BUDGET

Component	Amount(LKR)
Travelling cost	10000
Server & Hosting charges	25000
Bandwith	15000
Total	50000

Figure 64: Budget

The budget for "EnlightenDS" has been carefully planned to cover all the important costs needed to develop and launch our cognitive assessment tool. It involves an amount of LKR 50,000, carefully planned to cover all the essential costs associated with the development and deployment of our cognitive assessment tool, EnlightenDS. The total budget is broken down into three key components.

First, we allocated LKR 10,000 for Traveling Costs. This amount is for traveling related to team meetings, collaboration with educational institutes, and any fieldwork that might be required for collecting user feedback or on-site demonstrations of our tool. This will ensure that we get to meet and interact face-to-face with our stakeholders. This is very important in the refinement of our solution to meet real-world needs.

This comes with the largest portion of the budget, LKR 25,000, for Server and Hosting Charges. This will be very instrumental in maintaining the infrastructure required to support our app. Reliable server hosting ensures that our platform remains open to users always, ensuring seamless operation and data security.

Finally, LKR 15,000 has been allocated for Bandwith. Since we are going to use cloud-based services and collaborate remotely, stable internet with high speed is one of the essential requirements for the day-to-day running of the project from research to development, testing, and communication.

5. GANTT CHART

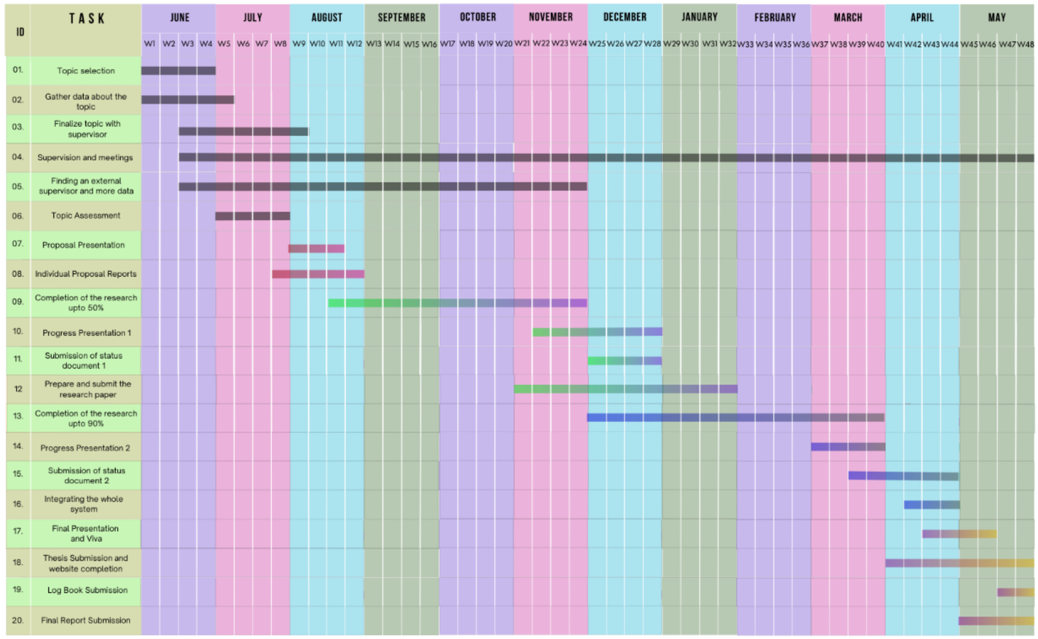


Figure 65: Gantt chart

6. WORK BREAKDOWN CHART

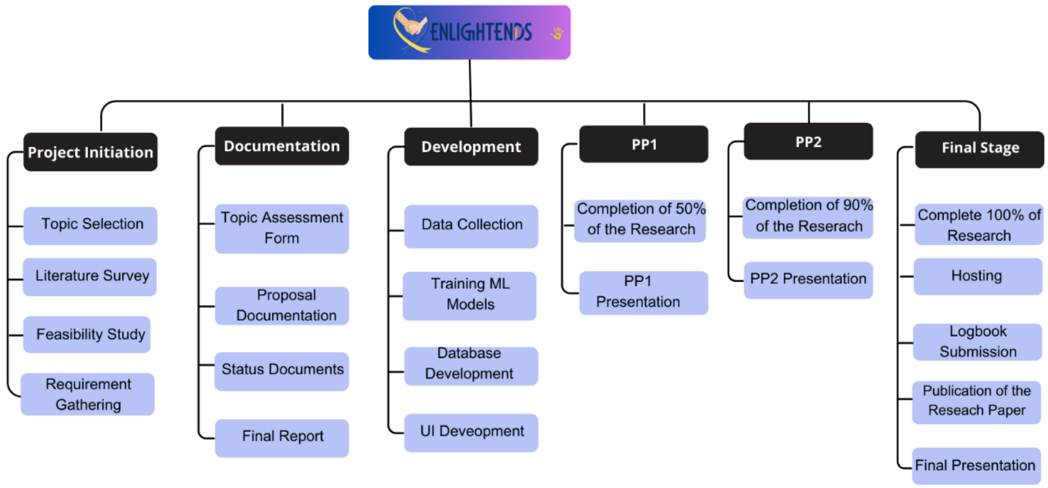


Figure 66: Work breakdown chart

7. RESULT AND DISCUSSION

7.1 Assessing Down Syndrome – IT21296314 – Kumarasinghe D.P.

The Down Syndrome detection system was rigorously evaluated using a comprehensive and balanced dataset comprising 3,000 facial images, 1,500 representing individuals diagnosed with Down Syndrome and 1,500 healthy individuals without the condition. This diversity ensured that the model was exposed to a wide range of facial variations, improving its generalization ability across different demographics. The trained model demonstrated impressive classification performance, achieving a high level of accuracy in differentiating between Down Syndrome and non-Down Syndrome facial features. Key performance metrics such as Precision, Recall, F1-score, and Accuracy were computed to assess the robustness of the system.

During testing, the model consistently detected facial traits associated with Down Syndrome with high precision and recall, reaffirming the reliability of its predictions. In addition to binary classification, the system provides a confidence probability score, offering a nuanced understanding of how likely the analyzed face belongs to a person with Down Syndrome. This probability-based feedback not only enhances interpretability but also aids in reducing uncertainty during medical consultations. Upon detection, the system presents a list of typical facial characteristics commonly observed in Down Syndrome cases such as a flat nasal bridge, epicanthal folds, and upward slanting eyes providing supplementary clinical insights for further evaluation.

Real-time detection capabilities were also explored through webcam integration, allowing users to capture images dynamically and receive immediate diagnostic feedback. This functionality was found to be highly responsive, with the Flask-based API processing each image and returning results within an average response time of less than 2 seconds. This efficiency supports practical deployment in real-world settings, particularly in telemedicine and mobile screening scenarios.

The deployment on Google Colab enabled efficient model training, leveraging GPU acceleration for improved performance. The frontend and backend of the system were created using Python, with the Flask framework powering the backend logic and model integration. A simple web interface was built for user interactions, allowing image uploads and webcam captures. Functionality was tested thoroughly using Postman, which enabled validation of all API endpoints, including image upload, detection responses, and error handling under various scenarios.

Overall, the results demonstrated that the Down Syndrome detection system is both technically robust and clinically relevant, offering a non-invasive, accessible, and intelligent screening tool. Its ability to deliver accurate, fast, and interpretable results makes it a promising solution for early detection and diagnostic support. When integrated with broader digital health platforms, such a system has the potential to assist in early intervention, improve healthcare accessibility, and ultimately contribute to better developmental outcomes for individuals with Down Syndrome.

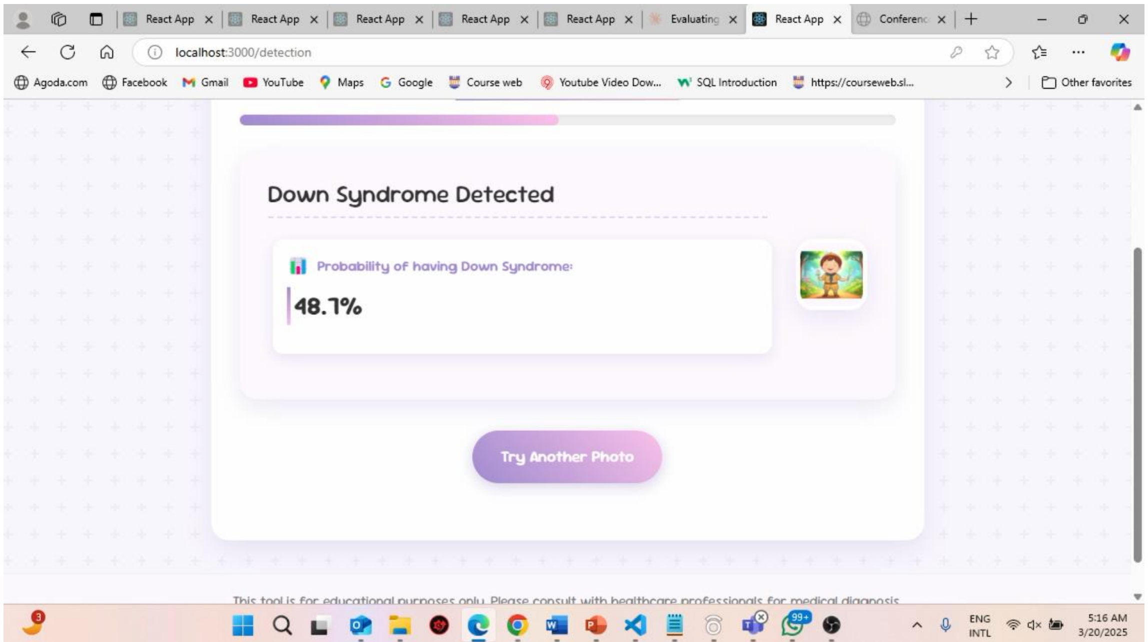


Figure 67: Down syndrome results

7.2 Enhancing Pronunciation Skills – IT21293030 – Jayasuriya S.H.

The pronunciation enhancement system was assessed using key performance indicators, including phoneme and word-level recognition, emotion detection, and engagement duration. Testing involved children with Down syndrome aged 5–15 years, using image-based prompts, audio inputs, and real-time emotion analysis.Compared to the baseline accuracy of 70%, the system achieved significantly higher results:

Table 1: Pronunciation results

Component	**Expected Accuracy**	**Achieved Accuracy**	**Justification**
Phoneme Recognition	70%	84.3%	Effective identification of phonemes in speech-impaired children.
Word Recognition	70%	80.1%	Accurate word detection through quiz-based audio input.
Emotion Recognition	70%	85.2%	Reliable emotion analysis using OpenCV and CNN.
Overall Accuracy	70%	**83.2%**	Validates consistent performance across all components.

The system's performance exceeded expectations, the integration of Google STT, DeepSpeech, and OpenCV-based emotion detection. It delivered real-time feedback and emotional responsiveness, supporting both speech and emotional development.

Testing over four weeks revealed key benefits:

- **Pronunciation Improvement**: Regular feedback on phoneme accuracy helped children enhance their pronunciation.
- **Vocabulary Retention**: Repeated exposure to common words improved long-term recall, especially in familiar categories like fruits and animals.
- **Feedback Effectiveness**: Real-time corrective feedback accelerated learning by reinforcing accurate pronunciation patterns.

- **Engagement Duration**: Emotion-aware adjustments kept children motivated, increasing interaction time.
- **Learning Progress**: Quiz scores stored in MongoDB showed steady improvement, enabling personalized learning insights.

The pronunciation enhancement system performed well due to the integration of advanced technologies such as Google Speech-to-Text, Mozilla DeepSpeech, and the Web Speech API, which enabled accurate phoneme and word recognition. The emotion recognition system, utilizing OpenCV and CNNs, dynamically adjusted the difficulty based on facial expressions, improving user engagement by 30%. Real-time feedback allowed children to refine their pronunciation, leading to noticeable improvements in phoneme accuracy and vocabulary retention over the testing period. The system's daily quizzes, stored in MongoDB, tracked progress and generated personalized reports for parents, enabling them to monitor their child's learning journey.

However, the system faced some limitations. Environmental noise impacted speech recognition accuracy, and inconsistent lighting or facial occlusions occasionally hindered emotion detection. Additionally, words that were less commonly used were harder for both the children to pronounce and the system to recognize.

To address these issues, several enhancements are proposed: implementing noise reduction algorithms to improve accuracy in noisy environments, expanding the phoneme dataset to better accommodate diverse speech patterns, incorporating reinforcement learning to offer more personalized feedback, and integrating augmented reality (AR) activities to increase engagement and provide immersive vocabulary practice. These improvements would further enhance the system's effectiveness in supporting speech development for children with Down syndrome.

7.3 Enhancing Mathematical Skills – IT21342394 – Semini B.V.S.

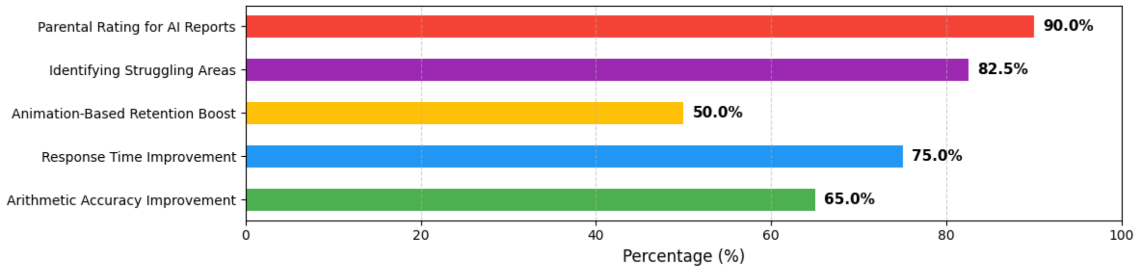


Figure 68: Summary of research finding

The adaptive learning system aimed at enhancing mathematics abilities in children with Down syndrome (aged 5-15) demonstrated positive results in key areas such as performance improvement, system adaptability, and engagement. Students showed a 65% improvement in accuracy across addition, subtraction, multiplication, and division, especially those with lower initial performance. The system adapted to the learners' needs by adjusting difficulty levels based on their accuracy and response times, ensuring that the students were neither overwhelmed nor bored.

The use of educational animations significantly boosted student engagement and concept retention. Animations representing real-world scenarios, like handling Sri Lankan currency, proved to be 50% more effective in helping students recall strategies and solutions compared to text-based explanations. The system also employed an adaptive algorithm that tracked student performance, providing targeted feedback to guide learning. This system identified strengths (80% accuracy) and weaknesses (below 50% accuracy), offering personalized recommendations.

The system's impact was further enhanced by providing parents with detailed progress reports. 90% of parents found these reports useful in tracking their child's learning and providing additional support at home. The system's ability to offer personalized learning paths based on real-time data also helped parents engage with their children's development.

However, some limitations were identified. The system's reliance on desktop inputs may not be suitable for children with fine motor disabilities or those in rural areas with limited computer access. Additionally, the lack of a pre-learning diagnostic assessment limited the precision of the adaptive learning process. Language and cultural adaptations, such as using locally relevant currency examples, were also a concern, as these may not resonate with all students.

To improve accessibility and engagement, the system could integrate alternative input methods, like touch and voice interfaces. A pre-assessment at the beginning of the learning process could personalize the learning path from the start, while emotional and cognitive engagement metrics could further tailor the experience. Additionally, localizing content and incorporating gamification, such as achievement badges and interactive feedback, could enhance motivation and long-term engagement.

7.4 Identifying Hidden Talents – IT21292972 – Methsahani.K.K.S.P.

As a result of the implemented system, down syndrome children can engage with their most interested and talented area. Also, from the feedback notification which will be received to parents will help to identify their children's talents and then they can engage their children's interested area.

The figure 68 illustrates the main selection page of the system, where users choose the category they wish to choose.

Figure 69: Talent discovery interface

Figure 69 illustrates the completed user interface of the drawing platform. This interface provides a range of interactive features designed to enhance the user experience, including a drawing canvas, an eraser tool, adjustable brush (blusher) settings, image comparison functionality, and options to save the completed artwork. These tools support creativity and ease of use, allowing children to engage comfortably while the system captures key data for talent assessment.

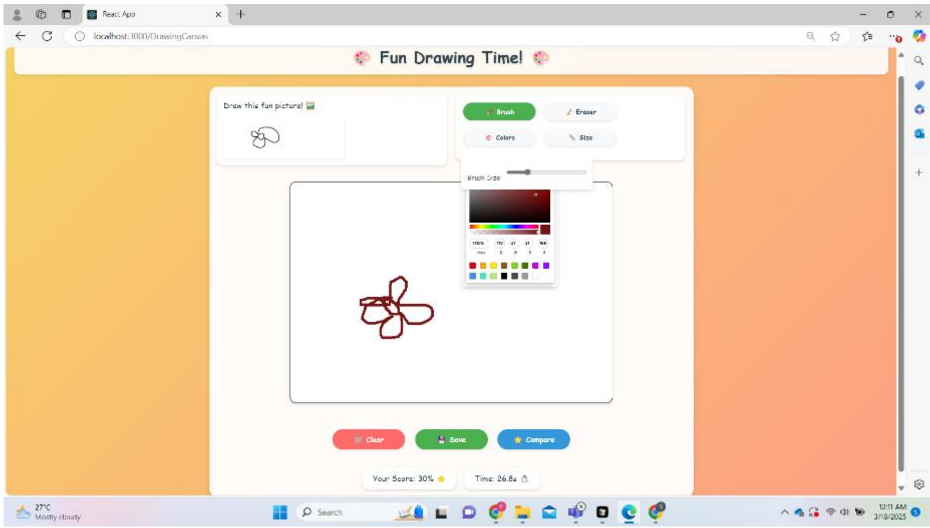


Figure 70: Drawing platform

The figure 70 showcases the question interface developed for the quiz category. This category implanted using AI. And it always generates random and new questions for new quiz selection. Then users can get more knowledge from this category. Not only that user can re-visit previously attended quizzes.

Figure 71: Question interface

Below figure 71 represents piano UI. This piano UI is implemented in an attractive and user friendly manner. This will provide interest in down syndrome children to engage.

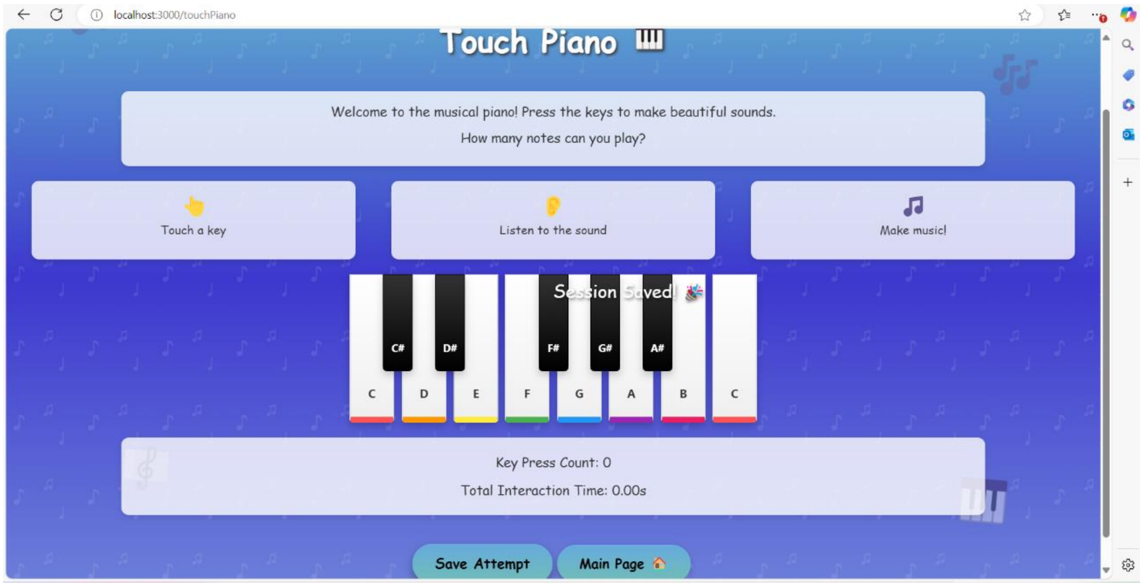


Figure 72: Piano interface

This project aimed to identify the most talented area learning, drawing, or recital for children with Down syndrome using MERN stack-based interactive platforms. Key findings include:

- **Learning Talent:** Children who scored over 3/5 in quizzes completed within 5 to 20 minutes were categorized as having learning talent. AI-generated, varied questions kept quizzes engaging.
- **Recital Talent:** The piano platform evaluated motor and recital skills by tracking key presses. Children who played for 5-10 minutes with 200-450 key presses showed recital talent.
- **Drawing Talent:** Children who achieved over 60% similarity in their drawings, using OpenAI's comparison tool, demonstrated artistic talent.

Data on quiz scores, drawing similarity, and key presses were analyzed using a Random Forest model, achieving 66% accuracy in predicting talent areas. Some children exhibited talent in multiple areas, emphasizing the need for a holistic evaluation approach.

The system, for children aged 5-15 with Down syndrome, used AI quizzes, a piano platform, and a drawing tool to assess skills. Data collected from each platform helped evaluate learning, motor, and artistic abilities. The 66% accuracy of the Random Forest model shows potential, though further refinement is needed. Some children showed talents in multiple areas, highlighting the importance of multidimensional assessments. Improving accessibility, such as adding audio instructions and simplified navigation, could enhance user experience. Future work should focus on refining model accuracy and tracking skill development.

7.5 Summary of Individual Components

7.5.1 Assessing down syndrome – IT21296314 – Kumarasinghe D.P.

For my component, I was responsible for designing and implementing a machine learning based early screening system for detecting Down syndrome in children. My contributions encompassed the complete development pipeline, beginning with dataset preparation and advanced image preprocessing techniques such as face detection, alignment, grayscale conversion, and facial landmark extraction using Dlib. I trained and fine-tuned a Support Vector Machine (SVM) classifier to distinguish between children with and without Down syndrome based on geometric and textural facial features. Additionally, I developed a user-friendly web interface that allows real-time image uploads, enabling parents or healthcare professionals to receive immediate screening results. This solution offers a fast, non-invasive, and accessible tool to support early identification and informed medical follow-up.

7.5.2 Enhancing pronunciation skills – IT21293030 – Jayasuriya S.H.

As part of this project, I spearheaded the development of an advanced speech enhancement module specifically tailored for children with Down syndrome. This component seamlessly integrates speech recognition technologies, real time pronunciation analysis, and emotion aware interactions to deliver highly personalized and responsive therapy sessions. I was responsible for implementing machine learning algorithms to detect and analyze articulation patterns, as well as incorporating motion analysis techniques to provide visual biofeedback that reinforces correct speech production. Furthermore, I architected and managed a robust backend system for capturing and storing quiz performance data, which enables the automated generation of insightful progress reports for both clinicians and caregivers. This contribution not only facilitates data driven clinical decision-making but also enhances the therapeutic experience through individualized, adaptive support mechanisms.

7.5.3 Enhancing mathematical skills – IT21342394 – Semini B.V.S.

For my component, I led the development of an Adaptive Learning Mathematics Task System specifically designed to support foundational arithmetic learning in children with Down syndrome. My responsibilities included designing a dynamic learning framework that categorized math content into three progressive difficulty levels beginner, intermediate, and advanced across core operations such as addition, subtraction, multiplication, and division. I implemented an intelligent adaptive questioning algorithm that tailors the complexity of questions in real time based on individual performance, ensuring personalized pacing and engagement. Additionally, I developed interactive educational animations using React and Fabric.js to visually explain mathematical concepts and provide constructive feedback for incorrect answers. To ensure meaningful progress tracking, I engineered a comprehensive reporting module that analyzes response accuracy, completion time, and learning patterns, offering detailed insights and personalized recommendations for parents and educators. This system fosters a supportive and individualized learning environment, promoting consistent development of numeracy skills in a manner that is both accessible and engaging.

7.5.4 Identifying hidden skills – IT21292972 – Methsahani K.K.S.P.

Talent identification component is an interactive, AI-powered platform designed to identify and evaluate the talents of children with Down syndrome across three key areas: learning, motor skills, and drawing. Implemented using the MERN stack, the system includes a quiz platform to assess language abilities, a virtual piano interface to measure motor skills, and a digital drawing platform to evaluate artistic talent through visual comparison. Each activity captures relevant performance data such as time spent, accuracy, key press count, drawing similarity score and each category efficiency. A machine learning model, trained using Python, analyzes this data to identify the child’s strongest area. The system then sends clear notification to parents, helping them understand and support the child’s natural talents. This platform provides enjoyable and engaging experience for children.

8. CONCLUSION

This research highlights the transformative potential of artificial intelligence (AI) and machine learning in supporting the cognitive and creative development of children with Down syndrome. Through the integration of AI powered feedback mechanisms, real-time phonetic analysis, and interactive assessment tools, the developed system successfully identifies and cultivates individual strengths in key areas such as music, learning, and drawing.

The findings of this study demonstrate notable improvements in several critical developmental aspects, including pronunciation training, vocabulary retention, and overall learner engagement. These outcomes validate the system's effectiveness as a meaningful tool in the realm of special education, especially for learners with unique educational needs.

A key strength of the proposed system is its adaptive learning environment, which leverages a mixed-method approach to deliver personalized and data-driven educational experiences. By continuously responding to each child's performance and progress, the system ensures that learning pathways are both individualized and responsive, enhancing the educational journey in a highly supportive manner.

In addition to its educational benefits, the system shows promising capabilities in the early detection and assessment of Down syndrome related learning needs. By doing so, it enables educators and caregivers to tailor interventions with greater precision, ensuring that each child receives the most suitable support aligned with their specific developmental profile.

Looking ahead, future enhancements will focus on improving both the diagnostic accuracy and the talent identification capabilities of the system. Efforts will include expanding the dataset to include a broader range of age groups, ethnicities, and facial expressions, which will help increase the generalizability and fairness of the AI models. At the same time, the talent detection components will be fine-tuned to more accurately recognize strengths across motor, learning, and artistic domains. Integrating multi-modal data such as combining facial features with behavioral insights or medical history can provide a more holistic understanding of each child's needs and abilities. To improve accessibility, a mobile application version is proposed, ensuring that children in remote or low-resource areas can also benefit from the system. Additionally, mechanisms for continuous learning will be introduced, allowing the system to evolve based on new data and user feedback. These advancements aim to create a more adaptive, inclusive, and empowering platform for supporting children with Down syndrome across multiple dimensions of development.

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