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Advanced Technologies for Skill Enhancement and Talent Recognition

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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 developed an artificial Intelligence system combined with educational technology that enhances learning through detection, pronunciation training, mathematics exercises and talent identification. The early detection of developmental concerns, facilitating timely intervention and module leverages support vector machine to assess the detection of Down Syndrome. The pronunciation training component integrates natural language processing and a flask-based API to process speech input, utilising 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 implementation and machine learning based analysis to monitor engagement in learning, drawing, and motor activities, recognizing each child's talents and interests. Evaluation of EnlightenDS demonstrates that AI-powered assessment and personalised 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

I. Introduction

Down Syndrome (DS) is a genetically inherited condition by having an extra chromosome 21 [1] and this leads to varied physical, mental, and developmental issues [1]. It affects approximately 1 in 700 live births worldwide, and around 6,000 DS babies are born annually in the United States [3], [6]. Children with DS typically possess typical facial features, such as a flat nasal bridge, slanting eyes, and a smaller head size [1]. Besides these physical characteristics, DS individuals typically possess intellectual disabilities [2] with IQ levels ranging from mild to moderate (35–69), although some may have severe cognitive impairments [5]. Children with DS may also struggle with motor skills, short-term memory, and speech development, which complicates their ability to engage in traditional educational environments. As a result, specialized educational tools and approaches are necessary to accommodate their unique learning needs.

Despite challenges, children with DS often show strengths in creativity, emotional intelligence, and social skills. Many excel in music, art, and learning when supported by individualized education. However, traditional schools often fail to meet their unique needs, hindering their growth [7]. Traditional teaching methods and generic digital learning tools do not account for the individual learning pace or challenges faced by children with DS, making it difficult to capitalize on their potential [8][9]. Therefore, there is a clear need for specialized educational systems designed to foster the abilities of children with DS and address their challenges [10], [11].

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The proposed system addresses these challenges by integrating four key components. The first component focuses on the early identification of DS using facial image analysis based on handcrafted features and Support Vector Machine classification. This enables preliminary screening from facial photographs, supporting timely access to specialized educational interventions while maintaining user privacy and clinical boundaries [12], [1]. The second component identifies the hidden talents of children with DS using AI-driven analytics to recognize patterns in creative outputs such as drawing and piano, thus fostering self-esteem and personal development [13], [3]. The third component enhances pronunciation skills by utilizing speech recognition technology that provides personalised feedback, supporting language development in a personalised manner [14], [15]. Lastly, the system focuses on improving mathematical skills in children with DS by utilizing adaptive learning methods [16]. It adjusts the difficulty of exercises based on the child's performance, using machine learning algorithms like Logistic Regression to personalize content [17]. Current educational platforms generally lack AI-driven personalization, failing to cater to the unique learning needs of children with DS [18]. By targeting early detection, talent recognition, speech, and math skills, the system bridges traditional education with personalized tools, fostering inclusive growth for children with DS [19].

II. Literature Review

This study examines AI-enabled DS screening through deep learning-based ultrasound assessment, with the hypothesis that CNN models yield superior diagnostic accuracy compared to conventional screening methods. AI-enabled ultrasound imaging should improve detection rates early, enabling timely intervention. Additionally, integrating DS screening with cognitive evaluation tools can enrich individualized support plans, supporting enhanced developmental progress in children with DS [20].

M. de Oliveira Braga Filho et al explores the use of touchscreen-based cognitive assessments to evaluate executive functions in children with DS related neurodevelopmental disorders. By developing interactive games for cognitive and psychomotor evaluation, the study hypothesizes that touchscreen interventions can enhance visuomotor accuracy, attention, and task persistence in affected children. Results indicate that DS children present lower precision and reaction times. These findings suggest that digital tools can enable early cognitive assessment and intervention procedures in children with neurodevelopmental disorders [21].

Research [20] used deep learning for DS detection via ultrasound but was limited by its clinical dependence, lack of probability estimates, and minimal accessibility. EnlightenDS addresses these gaps through a web-based platform that uses facial image analysis and Support Vector Machine (SVM) classification to provide accessible, probabilistic assessments. Similarly, [21] provides a novel approach to evaluating cognitive development in children with DS and ZVCS, it does not incorporate diagnostic probability metrics, advanced image processing, or machine learning models such as SVM. Additionally, its lack of a scalable, web-based platform and the absence of bias mitigation strategies further limits its scope. Our proposed system addresses these gaps comprehensively by offering a feature-rich, inclusive and technologically advanced solution for the early detection and support of DS.

Children with DS present serious challenges of speech and language development owing to cognitive delays, anatomical variation, and phonological processing problems. This examined two speech recognition-based techniques phone-based and word-based to assist children with DS to improve pronunciation. Their study validated the cell phone-based approach, seeking to correct a specific phonological error performed better than whole-word recognition. This research demonstrates the strength of speech recognition technology supporting speech intervention by offering immediate feedback and precise corrections [22][23].

F. Javadi et al. investigated the role of mobile applications in speech therapy for children with DS, demonstrating that interactive, game-based learning significantly improves pronunciation and vocabulary retention. Their study emphasized the importance of integrating speech processing algorithms into mobile platforms to create engaging and effective learning environments. The research concluded that mobile applications could complement traditional speech therapy by offering structured, accessible, and motivating exercises for children with DS [24].

The prior research has validated the effectiveness of both phone-based speech recognition techniques [22], [23] and mobile applications in improving pronunciation among children with DS [24], these systems often lack emotional responsiveness. Most focus on phonological correction or pronunciation learning without considering the child's emotional engagement or providing tailored feedback for ongoing support. This component bridges these critical gaps by introducing an emotion aware, gamified web application that dynamically adapts pronunciation activities based on the child's emotional state. Additionally, it delivers personalised feedback to both parents and teachers, fostering a more engaging, and responsive learning environment that promotes continuous improvement in speech development.

F. Sella et al. study evaluated the effect of the computer game 'The Number Race' on children with DS numeracy skills. 61 children were assigned randomly into two groups, 30 were assigned to play 'The Number Race'. The training of 10 weeks showed that the game had some positive effects on calculations [25] but it had limitations as it didn't adapt to different skill levels and lacked real-life application. Our research addresses both gaps by developing an adaptive quiz system that personalizes difficulty and includes real-world math scenarios.

Another study on math highlights key challenges in understanding basic numerical concepts such as quantity recognition, counting, and time and money. One major gap is that many children struggle to grasp number concepts [4]. To address this, our system integrates educational animations with Sri Lankan currency visuals and child-friendly voice-overs to explain each math question, making learning more relatable and easier to understand.

Based on research conducted by Nadeem et al. [26], they developed a correlation between muscle volume and muscle groups involved in various movements, such as writing with a pencil, typing on the keyboard, and cutting with a knife and fork. As an addition, their findings could be applied to enhance motor skills of DS children.

Based on the research conducted by F. Javadi et al. investigated [27], the authors studied programming evaluation methods and concluded that randomisation methods were better than shuffling questions. As a continuation of this study, the authors may work on adaptive question generation from individual-student responses, which would provide a more personalised learning experience.

Most of the literature available has only addressed the challenges of children with DS [26]. However, such a system to identify the specific talents of children with DS does not exist. The proposed component will fill this gap by helping identify the areas in which these children excel, thereby providing them an opportunity to nurture and enhance their talents. Without the vision of their strengths, it is difficult for the children with DS to access their potential. This aspect will form the core in discovering and developing their strengths.

The proposed system, EnlightenDS, aims to address the gaps in the literature by integrating AI-based DS detection, cognitive analysis and personalised 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 utilises machine learning, deep learning, and AI-driven analytics for designing a personalised learning environment for children with DS according to their specific needs. It also utilises SVM for detecting DS from 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. Furthermore, it establish children's aptitudes in areas such as drawing, learning and motor skills. In the learning category, all questions are new to users when they take a new quiz. To get new random questions, AI used 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.

III. Methodology

A. Data Collection

The dataset for DS detection was obtained from github [29], containing 1,500 images each in the 'Down Syndrome' and 'Healthy' categories, selected for their diversity and facial analysis suitability. This dataset supported the machine learning model used for early screening. Emotion detection data was obtained from a publicly available Kaggle dataset [28], containing labeled facial expressions across six categories: *happy, sad, angry, surprise, fear, and disgust*. The dataset was cleaned and pre-processed for training, including normalization and resizing images. Exploratory Data Analysis (EDA) was performed to examine class distribution and address imbalances through data augmentation techniques.

For mathematics and talent identification components, data collection followed ethical clearance and formal approval from the Zonal Education Office. Visits were conducted at selected schools. Mathematical assessments targeting Grades 1–5 was designed to evaluate understanding of core operations such as addition, subtraction, multiplication, and division across three levels of difficulty. Students' accuracy and response times were recorded to determine individual learning progression. Qualitative insights were obtained through structured interviews with teachers and classroom observations to understand common educational challenges. Interactive sessions including guided drawing tasks, skill-based questionnaires and keyboard-based simulations were conducted to evaluate motor coordination and areas of interest. Musical aptitude was assessed by recording and analyzing piano performances, interaction time period and hand coordination through key inputs.

This comprehensive data collection approach integrates facial recognition, speech analysis, mathematical performance, and talent identification, providing insights into learning patterns and cognitive abilities in children with DS.

B. Machine Learning Model and System Development

1) Detection of Down Syndrome

The DS detection component of the EnlightenDS platform leverages a hybrid machine learning approach that combines facial geometry and texture-based features for early detection. This system is explicitly intended as a preliminary screening tool and does not replace clinical diagnosis, which typically involves genetic testing and broader developmental assessments. Rather, this module facilitates early identification and selectively enables access to the platform's other components such as pronunciation, mathematical and talent identification only when the detection module yields a positive result.

The system utilises Dlib's 68-point facial landmark detector to extract key facial landmarks, ensuring accurate and consistent face alignment across all images. A custom validation function filters out non-frontal images, reducing the impact of pose variation and ensuring reliable feature extraction. Each image is aligned based on the angle between the eye centers and rotated accordingly, followed by cropping around facial landmarks and resizing to a standard size (300x300 pixels) for uniform feature processing.

Two primary types of features are extracted:

1. Texture Features (Local Binary Pattern - LBP): LBP histograms are computed from localized patches around critical facial landmarks such as the eyes, nose, and mouth. These features help capture subtle textural differences commonly observed in individuals with DS.
2. Geometric Features (Euclidean Distances): Distances between specific facial landmark pairs such as between the eyes, nose, and mouth are computed. These distances reflect morphological traits relevant to DS detection.

The extracted features are concatenated into a single feature vector and standardized using a StandardScaler. Data augmentation techniques, including horizontal flipping, small-angle rotations, and Gaussian noise, are applied to enhance the dataset's diversity and robustness. Classification is performed using a SVM with a sigmoid kernel, configured with class weights to address class imbalance. The model is evaluated using 5-fold cross-validation, reporting accuracy, precision, recall, and AUC to ensure comprehensive performance validation. The trained model and scaler are serialized using Python's pickle module for seamless integration into the platform's backend. When a new image is uploaded, the system processes it through the same preprocessing and feature extraction pipeline before classification. The output includes the predicted class, probability scores, and a visual overlay of detected facial landmarks. The frontend of the DS detection module is built with React.js, allowing users to upload or capture an image via webcam. It provides real-time previews and sends the image to the backend using axios. Predictions including class label, confidence score, and a list of facial features if DS is detected are displayed in an accessible, responsive interface enhanced with visuals and loading animations.Importantly, while the detection module offers high classification accuracy, its function is restricted to early screening. It cannot capture the full clinical context required for definitive diagnosis and is not intended to generate a list of clinical symptoms. Further evaluation by healthcare professionals is necessary to confirm any diagnosis.

The below Fig. 1 shows the DS diagnosis workflow.

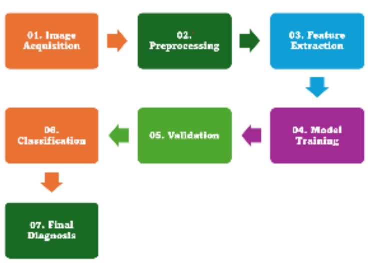

Fig. 1. Down syndrome Diagnosis Workflow

2) Enhance Pronunciation Skills

The Fig. 2 shows the emotion recognition model uses CNN-based architecture to classify facial expressions in children with DS. It incorporates convolutional layers with ReLU activation, max-pooling, and dropout (0.3 to 0.5) to prevent overfitting.

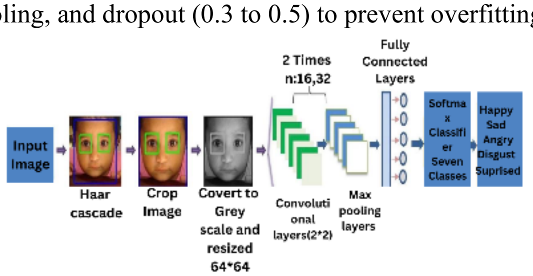

Fig. 2. CNN Architecture

Transfer learning with pre-trained models like VGG16 improves feature extraction. The dataset was sourced from Kaggle, providing a diverse collection for emotion detection. Training utilises the Adam optimizer (learning rate of 0.0001), early stopping, and hyperparameter tuning through Grid Search and Bayesian Optimization. The model achieves 80% accuracy, 78% precision, 76% recall, and a 77% F1-score.

A Flask-based API is developed for emotion detection, which receives an image input, detects faces using the Haar Cascade classifier, and applies a trained CNN model to predict emotions. The system, deployed with Cross-Origin Resource Sharing (CORS), integrates seamlessly with web applications. The frontend, built with React.js, ensures an interactive UI, with React-Webcam capturing facial expressions and React-Spring providing smooth animations. The Web Speech API enables speech-to-text for pronunciation verification, while Axios and Fetch API handle backend communication. React.js uses React Hooks (useState, useEffect, useRef) to manage state and side effects, and the UI is styled using HTML5, CSS3, and Tailwind CSS for a responsive, modular interface. The backend combines Flask (Python) and Express.js (Node.js), offering RESTful APIs for pronunciation verification and emotion detection. Google Speech-to-Text and DeepSpeech/Whisper AI are used for phoneme-level analysis, while TensorFlow/Keras and OpenCV handle emotion detection. Flask-CORS ensures secure communication, and Base64 encoding is used for image transmission. MongoDB stores data efficiently, and model performance is evaluated using accuracy, precision, recall, and F1-score, with the final model selected for both classification accuracy and performance efficiency.

The Gemini-1.5-Pro-Latest large language model was integrated into the system to generate personalised feedback reports for children with DS. These reports were based on real world user interaction data such as pronunciation attempts, quiz scores, incorrect word patterns, and time spent on each activity which served as the ground truth for evaluating progress and tailoring suggestions. The model generated customized activity recommendations for parents and teachers to support each child's pronunciation development. To ensure the system's reliability, the output generated by the AI was cross-checked against manually observed outcomes by speech therapists and educators.

3) Enhance Mathematical Skills

The collected data was analysed using machine learning algorithms to develop an adaptive learning framework that personalizes content difficulty based on student performance. A pre-test was initially administered to determine each child's starting skill level, and subsequent quiz responses were analysed to assess progression patterns. To classify students and predict whether they should advance or remain at their current level, three models called Logistic Regression, Decision Tree, and XGBoost were evaluated. Logistic Regression was the most effective due to its high interpretability, efficiency, and accuracy in making binary classification decisions and the below Fig. 3 illustrates the architecture of the logistic regrrssion model. Decision Tree and XGBoost were useful in analysing complex learning patterns, but Logistic Regression provided the most reliable results while maintaining computational simplicity. The adaptive learning system utilises Logistic Regression predictions to dynamically adjust question difficulty based on accuracy rates, response times, and error patterns. This approach ensures that learning pathways are optimized in allowing each child to progress at an appropriate pace while receiving tailored instructional support.

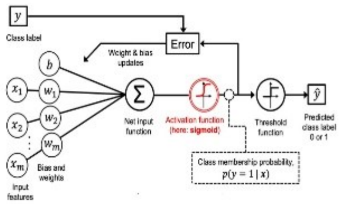

Fig. 3. Logistic Regression Architecture

To enhance learning, the system integrates educational animations using React and Fabric.js, focusing on visual and voice-based presentations to help children with DS understand arithmetic concepts, especially in real-life contexts like money handling. It employs Sri Lankan currency images and child-friendly voiceovers to create a multi-sensory experience for teaching numerical addition. A rule-based algorithm generates comprehensive parent reports that track the child's performance across different grade levels. These reports include details such as time taken, scores, accuracy, strengths, weaknesses, and personalised recommendations to support continued learning and development.

4) Identify the Interests and Talents

To create the proposed component, MERN stack, Artificial Intelligence (AI), and Machine Learning (ML) principles were primarily utilized. The front end of the application was created with React.js, and Node.js was utilized for creating the backend. MongoDB was used to database due to flexibility and scalability. Under the quiz category, LangChain, was included to handle open-ended responses, generating random questions. In this category, when user takes a new quiz each and every questions are new to user. Not only that, user can retake their previous quizzes again. LangChain preferred overrule-based implementations due to its greater ability to build dynamic interactions. Score calculation mechanisms and interaction time measurement of the user are also under this category.

Tone.js was utilized for the feature of piano simulation, as it enables real-time synthesis of sounds. From the chief parameters of the feature are played note count and interaction duration of the user interface side. A keyboard simulator was designed with React.js. On the drawing platform, the MERN stack was used to create a user-friendly interface. To enable saving functionality, the system stores drawings in MongoDB in Base64/Blob format. In drawing analysis, the original drawings created by children with DS were compared to refence drawing which provided by the system. This was achieved through visual comparison techniques using OpenAI API key, and the interaction time of the user was also considered.

Finally, the talent identification module employs data from all categories to assess the talent of the child. The assessment considers various factors such as interaction time, quiz results, piano key count, and drawing similarity. This analyzation happens using a model, which is implemented using random forest algorithm. To handle the request FLASK API used. Upon identifying a talent area, the system gives an alert to the user and presents insights to help the child further develop their talent.

Fig. 4 represetnts system diagram of talent identification component.

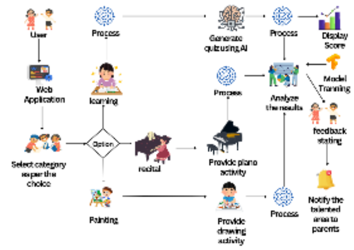

Fig. 4. Hidden Talents Identification System Diagram

IV. Results and Discussion

To evaluate the effectiveness and usability of the EnlightenDS platform, user testing was conducted with children with DS in real-world settings, The children engaged with all 4 components under the supervision of teachers. Observations revealed high levels of interest and active participation, particularly in gamified activities like pronunciation exercises and drawing tasks. These findings indicate that the platform is engaging, user-friendly, and holds potential to support the speech, emotional, and cognitive development of children with DS.

A. Detection of Down Syndrome

The DS detection model was trained and evaluated using a dataset containing 1,500 facial images each from individuals with DS and healthy individuals. Using a combination of Local Binary Pattern (LBP) texture descriptors and Euclidean distance-based geometric features, the system achieved a classification accuracy of 78%, with a precision of 76%, recall of 79%, and an AUC (Area Under Curve) of 0.84, as measured through 5-fold cross-validation and testing on a held-out set. The system was further tested via the integrated webcam interface, where it demonstrated consistent accuracy and responsiveness. The average response time from image capture to prediction was under 2 seconds, ensuring real-time feedback for users. All images passed through the same preprocessing pipeline, maintaining consistency between training and deployment environments. interactions. Score calculation mechanisms and interaction time measurement of the user are also under this category.

While the system demonstrates high classification performance using interpretable facial features, it is important to recognize its clinical limitations. DS diagnosis is multifactorial, typically requiring genetic testing, developmental assessments, and consultation with medical professionals. Facial analysis can support early screening but cannot capture the full clinical picture, including comorbidities or cognitive profiles. Therefore, this system is positioned as an educational and assistive tool that flags potentially at-risk individuals and selectively enables access to other related components. It serves as a gateway to a more personalised learning environment, particularly in under-resourced settings where early screening may be delayed. Ethical considerations include ensuring transparency about the system's role and limitations. It is explicitly stated in both the interface and methodology that the tool does not replace clinical evaluation, and users are advised to seek professional consultation if a positive prediction is returned. Additionally, for privacy and ethical reasons, images are not stored in any database, ensuring that personal data is not retained.

The system's reliance on facial images as a sole diagnostic criterion highlights the importance of recognizing its limitations in capturing the full complexity of DS diagnosis. While the model shows promising performance, it is critical to emphasize that facial analysis alone cannot generate a complete list of common symptoms for further evaluation, as DS diagnosis involves broader clinical context, including genetic and developmental assessments.

Future work will aim to enhance the system's generalizability by addressing potential dataset biases and expanding the dataset to include greater ethnic and age diversity. Additionally, incorporating multi-modal features, such as speech and behavioral cues, will help provide a more comprehensive assessment of individuals with DS. Finally, efforts to improve the interpretability of the model through feature attribution techniques will enhance its clinical applicability, ensuring that healthcare professionals can better understand the system's decision-making process.

The model's performance was evaluated through 5-fold cross-validation and testing on a held-out dataset. The results are summarized below TABLE I.

TABLE I. PERFORMANCE METRICS

Metric	Training Set	Test Set
Accuracy	0.78	0.78
Precision	0.76	0.76
Recall	0.78	0.79
AUC	0.85	0.84

B. *Enhance Pronunciation Skills*

The proposed system successfully achieved its research objectives by integrating advanced computer vision, real-time tracking, emotion recognition, and interactive learning tools into pronunciation practice games for children with DS. The system effectively analysed facial expressions, tracked lip movements, and provided feedback to improve pronunciation. Additionally, a pronunciation quiz was implemented to assess children's progress, with scores stored in a database and analysed to measure improvements over time. The key results highlight significant enhancements in phonetic accuracy, vocabulary retention, and engagement levels among children.

The below TABLE II shows the summary of the key performace metrics.

TABLE II. SUMMARY OF KEY PERFORMANCE METRICS

Objective	Method
Emotion Recognition	CNNs & OpenCV
Phonetic Accuracy Improvement	Google Speech-to-Text & DeepSpeech
Instant Feedback Effectiveness	Web Speech API
Engagement Duration	Emotion-based adjustments
Vocabulary Retention	Interactive exercises
Quiz-Based Learning Enhancement	Score tracking and analysis

The Fig. 5 shows that emotion-based learning strategies enhance engagement and motivation, particularly for children with cognitive challenges. The integration of facial emotion recognition allowed the system to adjust its difficulty level dynamically, creating a personalised experience.

Fig. 5. Gamified Pronunciation Platform

Feedback significantly improved speech patterns, aligning with previous research that emphasizes multimodal learning benefits. The addition of a pronunciation quiz enabled systematic tracking of children's progress, helping to assess individual learning curves and overall effectiveness.

Data analysis from stored quiz scores revealed that consistent practice led to gradual and measurable improvements in pronunciation accuracy. Children who engaged in the quiz and received corrections demonstrated more stable pronunciation patterns over time. Additionally, the study identified some limitations, such as difficulties in recognizing less common words and environmental factors affecting facial recognition performance. Future enhancements, such as improved NLP models, expanded phoneme databases, and augmented reality-based exercises, could mitigate these limitations and further increase the system's usability and effectiveness.

C. *Enhance Mathematical Skills*

The results of this study demonstrate the effectiveness of adaptive learning in improving mathematical performance among children with DS. Data analysis revealed that Logistic Regression achieved the highest classification accuracy, correctly predicting student progression with over 85% accuracy. The TABLE III shows the classification accuracy based on different models and it confirms the model's reliability in determining appropriate difficulty levels for learners.

TABLE III. CLASSIFICATION ACCURACY BASED ON THE LEARNING MODELS

Supervised Learning Model	Accuracy
Logistic Regression	88.21%
Decision Tree	76.89%
XGBoost	74.43%

The TABLE IV shows the performance of the logistic regression model using both training and testing datasets. The model demonstrated strong and consistent predictive capabilities, with a training accuracy of 88.64% and a testing accuracy of 88.21%. This close alignment indicates that the model generalizes well to unseen data and is not overfitting. A detailed classification report further supports the model's effectiveness. For the class labeled ‘Not Ready’ (0), the model achieved a precision of 0.90, recall of 0.86, and an F1-score of 0.88. Similarly, for the ‘Ready’ (1) class, the model recorded a precision of 0.87, recall of 0.90, and an F1-score of 0.88. These metrics suggest that the model is capable of accurately identifying both readiness states with minimal bias. The overall accuracy on the test set was 88.21%, with both the macro average and weighted average F1-scores reported at 0.88, confirming balanced performance across both classes. These results indicate that the model is robust and sui for reliably predicting student readiness based on quiz data in the context of an adaptive learning environment for children with DS.

TABLE IV. MODEL EVALUATION METRICS

Metric	Class 0	Class 1	Overall
Precision	0.90	0.87	0.88
Recall	0.86	0.90	0.88
F1-Score	0.88	0.88	0.88
Training Accuracy	—	—	88.64%
Testing Accuracy	—	—	88.21%

Performance tracking showed that students who engaged with adaptive content exhibited faster response times and improved accuracy rates over time. Children who initially struggled with arithmetic operations demonstrated an average improvement of 23% in accuracy after continued exposure to personalised learning pathways. Additionally, educational animations significantly enhanced learning engagement, with 75% of students showing higher retention rates when animations were integrated into explanations.

Parental feedback analysis indicated that 90% of parents found generated reports useful in monitoring their child's progress. The interactive performance graphs allowed parents to visualize trends and identify areas requiring additional support. Moreover, personalised recommendations generated by NLP models helped parents implement effective learning strategies at home, leading to increased student motivation and engagement. These findings highlight the effectiveness of AI-driven adaptive learning systems in supporting children with DS. By dynamically adjusting learning content, providing real-time feedback, and integrating interactive animations, *EnlightenDS* enhances both learning outcomes and parental involvement in the educational journey of children with DS.

D. *Identify the Interests and Talents*

The implementation of this system allows kids to explore further into their interest and talent domains. Moreover, the feedback messages provided to parents will allow them to identify strengths in their kids so that they can better develop and support them. The test scores that follow are based on the data obtained from children who have DS, analysing measures such as interaction time, quiz marks, piano playing sequence, and drawing enhancement.

In the learning category, a skilled learning attempt is calculated as if the interaction time is between 5 to 20 minutes, and the quiz score exceeds 3. In the drawing category, a skilled drawing attempt is calculated from when the interaction time is between 5 to 20 minutes and the drawing similarity which is taken from visual comparison is more than 60%. In the piano category, a possible attempt calculated as when the interaction time is between 5 and 20 minutes, and the key count is acceptable. (1 to 6 min 100 < no_of_keys > 250, 6 to 10 min 200 < no_of_keys > 450).

These criteria will make the system recognize relevant and focused interactions, allowing them to track progress and areas of development.

Fig. 6 represents the results of the selected category and Fig. 7 represents sample database details.

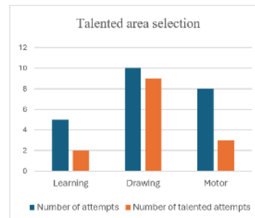

Fig. 6. Talent identification selection

Fig. 7. Database of Talent Identification

Fig. 8 represents the user interfaces of drawing platform and piano platform.

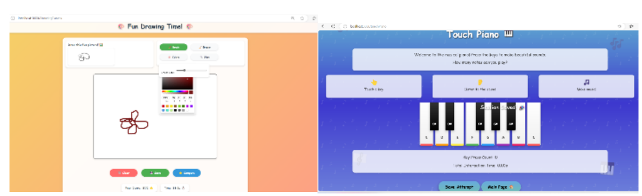

Fig. 8. Drawing platform and motor skill identification platform

V. CONCLUSION

This study shows how AI and machine learning can boost cognitive and creative growth in children with DS by using real-time feedback and interactive tools to support talents in music, learning, and drawing. The findings highlight significant improvements in pronunciation training, vocabulary retention and engagement levels, validating the system as a valuable tool in special education. Furthermore, the adaptive learning environment, supported by a mixed-method approach ensures personalised and data-driven educational experiences. The system also provides effective detection and assessment of DS, helping tailor interventions based on the unique needs of each child.

To ensure privacy and responsible data handling, the system does not store any images or video recordings. All collected data such as quiz results and speech inputs is encrypted using the AES encryption algorithm to prevent unauthorized access. Formal approval for data collection was obtained from the Zonal Education Authority and written consent was secured from parents and legal guardians. These procedures were followed to align with ethical standards and safeguard the rights of participating children. Future developments will focus on enhancing model accuracy, broadening the scope of talent evaluation, and integrating additional assistive technologies to improve accessibility. This research contributes to the field of special education by demonstrating how AI can be leveraged to create more inclusive, personalised, and effective learning environments for children with DS.

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