An Adaptive E-Learning Platform for Individuals with Down Syndrome

Sandaruwan U.V.S.
Department of Information Technology, Faculty of Computing, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
surensandaruwan222@gmail.com

Dias A.H.J.S.S.
Department of Computer Science and Software Engineering, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
ahjssdias@gmail.com

Shamindi H.M.H.
Department of Information Technology, Faculty of Computing, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
hansikashamindi1211@gmail.com

Priyawansha N.G.D.
Department of Information Technology, Faculty of Computing, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
ngdilshan2002@gmail.com

Chandrasiri L.H.S.S.
Department of Information Technology, Faculty of Computing, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
sanji.c@sliit.lk

Attanayaka B.
Department of Information Technology, Faculty of Computing, Sri Lanka Institute of Information Technology,
Malabe, Sri Lanka.
buddhima.a@sliit.lk

***Abstract*—Children with Down Syndrome (DS) encounter varying degrees of learning disabilities within the traditional education framework, requiring personalized interventions. This paper presents Blooming Minds, an adaptive, Machine Learning (ML) driven e-learning platform designed to support the development of cognitive, linguistic, and motor skills in children with DS. Built on the VARK (Visual, Auditory, Reading/Writing, Kinematic) theory, the platform provides personalized activities using real-time feedback mechanisms. The system includes nine interactive modules that cover the above VARK theory. It uses ML algorithms, including Support Vector Machine (SVM) and Random Forest (RF) for screening, Convolutional Neural Networks (CNN) for handwriting and speech analysis, Long Short-Term Memory (LSTM) for sequence prediction, and Reinforcement Learning (RL) for adaptive difficulties. Handwritten letters and voice samples from children with DS, both domestic and international, were specifically considered as inputs for this research. Progress tracking dashboards provide visual insights for educators, parents, and caregivers, improving support and adaptability. The system achieved 91.26% accuracy in letter recognition and 88% in speech classification. This e-learning platform has been recognized as an effective solution in Sri Lanka, allowing for further correlations and investigations to assess the knowledge capacity and ability to express that knowledge in children with DS.**

Keywords—Convolutional Neural Network, Down Syndrome, E-Learning, Learning Disabilities, Long Short-Term Memory, Machine Learning, VARK Theory

I. Introduction

Down Syndrome (DS), a genetic syndrome caused by an extra chromosome 21 [1], affects 1 in 1,000 live births and results in various cognitive impairments including language, visual perception and intellectual functioning. Children with DS have delays in physical and mental development and reach developmental milestones later than their peers. Each child with DS is unique with variations in physical, behavioral, functional, and cognitive abilities [2]. According to World Health Organization, Malta, Brunei and Ireland have the highest live birth rate of DS at 98.9, 97.2 and 93 per 100,000 respectively [3], while in Sri Lanka it is 1 in 700 live births [4], which is in line with global averages.

Children with DS are classified into different cognitive functioning levels based on Intelligence Quotient (IQ): mild (50-70), moderate (35-50), severe (20-35) [5], and mosaic DS (10-30) [6], with the majority of these children showing moderate levels. Early childhood development in DS is affected across various domains including visual-spatial skills, verbal and short-term memory, language, personality and social interaction. Physical characteristics such as low facial tone and small oral cavities contribute to articulation challenges, hearing issues and delays in speech development [7]. Typically, children with DS are not neurologically or physically prepared to speak until around 2-3 years but they start to understand spoken language as a communication tool by 10-12 months. Experimental research highlights that these children benefit significantly from visual aids for memory and learning [8].

In traditional educational settings children with DS struggle due to rigid and generalized teaching methods such as lectures, printed worksheets, oral instructions, and flashcards. These methods lack personalization and engagement for DS learners. Contributing factors are limited individual attention, outdated curricular, and inappropriate student-teacher ratios especially in developing countries like Sri Lanka where foundational education for these children is often insufficient. Therefore, tailored interventions that support their cognitive and developmental needs are crucial. We need to further study and understand their learning preferences and aversions [9] to develop effective educational strategies. Field visits show that children with DS are getting familiar with digital devices such as tablets, mobile phones and laptops which are obtained through local and international donations making digital educational interventions more feasible. Experts state that these children benefit most from personalized learning environments with continuous progress monitoring. Despite the growing interest in personalized education most of the current learning platforms lack the adaptability, multisensory engagement and real-time analytics to meet the needs of DS learners [10] To address this gap the 'Blooming Minds' platform was developed as an adaptive e-learning system based on the VARK (Visual, Auditory, Read/Write, Kinesthetic) learning theory. The system aims to create a new adaptive learning approach that identifies individual learning styles, tracks and visualizes progress and provides personalized engaging learning experiences. This combines real-time analysis and personalized feedback through Deep Learning (DL) and Machine Learning (ML)

979-8-3315-1323-8/25/$31.00 ©2025 IEEE

techniques. The main contributions of this research are as follows:

- Developed a multi-modal adaptive e-learning platform based on VARK theory for children with DS.
- Developed a Convolutional Neural Network (CNN) based evaluation for handwriting, enabling real-time accuracy calculation through pixel-wise comparison and time prediction using a logistic growth model.
- Designed a sequence memory and math learning game with adaptive difficulty levels powered by Reinforcement Learning (RL), Long Short-Term Memory (LSTM) and user interaction metrics.
- Applied ML classifiers Support Vector Machine (SVM) and Random Forest (RF) to model user performance patterns and deliver personalized feedback and adaptive interventions.
- Implemented auditory and kinesthetic games using image/audio processing and speech recognition (audio game, action-image association) for enhanced engagement.
- Developed progress tracking dashboards for real-time progress visualization, supporting parents and educators in tracking developmental.

The platform is based on the insights and experiences of educational experts, healthcare professionals, and educators who regularly work with children with DS. The primary objective of the proposed system is to improve cognitive and intellectual abilities of people with DS in a balanced manner and enabling students with DS to reach their full potential and better integrate alongside their peers in society.

II. Literature Rewiew

Assorted assistive platforms have been created for children with DS to develop cognitive and intellectual abilities and educational competencies. “Gimpanzees” [11] is a platform designed to support young people and children with disabilities between the ages of 11 and 25. Although it mentioned DS as a sub-section, the platform provides physical activities, motor skills development, resources, and tips that contribute to the individual’s development in general. Accordingly, the focus on physical development over cognitive development [12], the lack of personalized learning approaches, the limited integration of speech and language development, the lack of digital connectivity for distance learning, and the absence of continuous progress tracking are the major limitations that have been ascertained.

“DSE—See and Learn” [13] is a web-based approach for a screening that evaluates children with DS between the ages of 0 and 6. The program is an evidence-based platform designed to support the development of speech, language, reading [14], and concepts about the number system. A fundamental characteristic of children with DS is their aversion to monotony. This platform tends to be monotonous, and a minimum of variety in activities is observed. Furthermore, limited personalization [15], the requisite for parental involvement, and the absence of progress monitoring have been identified as limitations. “MAGRID” [16] is a language-free educational application designed to enhance early math, visual-spatial, and cognitive skills in children with DS, aged 3 to 9. This application is an evidence-based and scientifically validated platform. While it offers several qualitative approaches such as language-free design, friendly interface, development of visual-spatial skills, and independent learning, it also has limitations concerning intellectual development. Prominent among them is the focus on confined scope beyond mathematics, depending on digital access, the absence of personalized learning paths, and real-time progress monitoring.

A study was conducted for the assessment and automated analysis of speech in individuals [17] with DS. The main objective of the research is to explore the use of annotated speech corpus to assess phonological and fluency aspects in individuals with DS and to develop automated assessment systems to identify these speech quality dimensions. Aiming to provide an objective measure of pronunciation accuracy, the study uses the Goodness of Pronunciation (GoP) [17] metric to assess speech quality. However, the study found only a moderate correlation between GoP scores and human ratings, suggesting that GoP may not fully capture the phonetic nuances of DS speech. Furthermore, limitations such as solution recognition challenges and limited generalization ability can be identified. Kirsty-Lee Walker and Tevin Moodley investigated based on research [18] into the handwriting recognition of learners with DS. This research has several implications for improving the writing skills of children with DS. An objective assessment of handwriting, feedback mechanism, and improvements in assistive technologies are the implications identified from this research. A study [18] was conducted to classify handwritten samples using three architectures: VGG16, InceptionV2, and Xception. The results were based on 5 features. Three models were created using the collected data, and InceptionV2 was found to provide better results for classifying different subclasses with higher accuracy values compared to the other two models. However, the study acknowledges the paucity of handwriting samples available from individuals with DS and the potential for overfitting, resulting in a small dataset of 200 unique images. This limitation can affect the generalization ability and robustness of the DL models used.

In [19], research was conducted to investigate the specific challenges faced by the people with DS regarding verbal short-term memory. It was implemented using the phonological loop component of the working memory model. Although the study provides theoretical insights into memory deficits, it does not provide a concrete, interactive tool, or game for practical use. Furthermore, the identified flaws can be considered as a lack of engagement strategies, a lack of immediate feedback, and limited multi-sensor integration. The research [20] investigates the effectiveness of using tablets as a learning tool to teach mathematics to children with DS. Here, the research explores how electronic media can help in acquiring basic mathematical skills. The application supports the integration of electronic media, visual learning strategies, and real-world activities and digital tools. The identified shortcomings are considered as lack of engagement and interaction, specificity of targeted skills, adaptability and feedback, user experience design, and attractive features.

This [21] involved 30 children aged 6 to 10 years, who were divided into an Experimental Group (EG) and a Control Group (CG), where the EG participated in a 10-week sports-based training program, and the CG participated in traditional physical education activities. Both groups showed significant improvement in Fundamental Motor Skills (FMS), with the

EG showing superior progress. The study concludes that sports-based training is an effective method for improving FMS in children with DS. Compared to platforms such as [13], [16], and [11], Blooming Minds integrates multi-domain activities (encompassing VARK theory) and real-time ML-based adaptation. Table I summarizes key feature comparisons.

TABLE I. COMPARISON ON PREVIOUS RESEARCH VS PROPOSED SOLUTION

Feature	Blooming Minds	DSE [13]	MAGRID [16]	Gimpanzees [11]
Adaptive Learning	✓	✗	✓	✗
Real-time Feedback	✓	✗	✗	✗
Multi-sensory Input	✓	Limited	Visual only	Physical only
Progress Monitoring	✓	✗	✗	✗
Target Group	DS (broad 5–15y)	DS (0–6y)	DS (3–9y)	Mixed

To overcome these limitations and achieve more accurate and reliable outcomes, 'Blooming Minds' offers a unique responsive web-based solution for screening and intervention covering these learning disability conditions.

III. METHODOLOGY

The Blooming Minds web-based application leverages the VARK theory to support the screening and refinement of cognitive, visual, motor, and language skills in children with DS. Designed for students aged 5–15 across Sri Lanka, the system provides adaptive interventions based on individual learning styles. Data was collected through interviews and activities involving 10 teachers and 23 students with DS. The data used in this study included over 100,000 handwritten letter images and 1,000+ voice samples. Handwritten letter images were obtained by combining multiple sources, such as collaborations with local schools, local clinical centers, Kaggle datasets, and additional samples manually hand-traced by the researcher from internet-sourced (both local and international) images to ensure data diversity. Voice samples were collected through collaborations with local schools, local clinical centers, and publicly available speech datasets. Informed consent was obtained from the parents of all minor participants and ethical clearance from Sri Lanka Institute of Information Technology was obtained. Informed consent procedures were carefully followed to ensure compliance with ethical standards for research involving children with special needs. All data were anonymized to protect participant identities. Their selection included children from different provinces, drawn from across the spectrum of IQ and English-speaking backgrounds, to ensure representativeness. Through partnerships with regional schools and organizations, demographic bias in the participants was minimized as much as possible and participants included from diverse linguistic and cultural settings. The data obtained from them was also used to train models for skill assessment, using Flask and TensorFlow as middleware technologies. Python is used for the backend and MongoDB as the database. The research also uses ML concepts and algorithms, image processing, voice recognition techniques and other concepts in its implementation.

A. Visual Learning Enhancement System

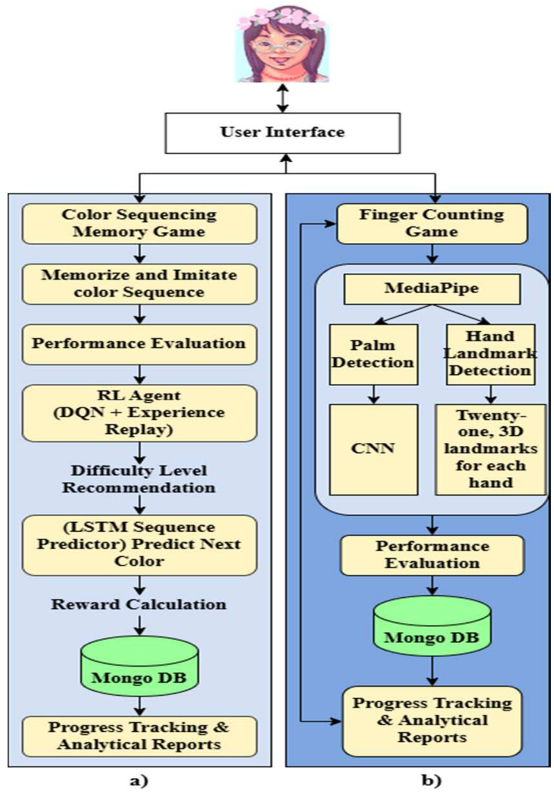

Fig. 1. Component architecture of the visual learning enhancement system

This component consists of two engaging game activities, all designed to enhance visual perception and short-term memory development. The first activity is the color sequence memory game shown in the flowchart section labeled (a) in Fig. 1. The child must memorize the order of colors displayed and the number of colored circles and accurately imitate them in the correct order. This aims to improve the child's cognitive skills and short-term memory. It consists of three levels. To determine and recommend the difficulty level, the RL agent (Deep Q-Network (DQN) with Experience Replay) uses accuracy measures (correct and incorrect takes), time efficiency, level completion data, and error patterns as primary performance measures, and uses LSTM network (sequential prediction model trains on these sequences) to predict the next possible color and generate personalized color sequences based on the child's attempted sequence and error frequency per color. Here, a reward calculation is also carried out as a motivation for the child. A user interaction tracking system monitors individual performance, which generates analytical progress reports.

As shown in the flowchart section labeled (b) in Fig. 1, the finger-counting game consists of two levels. In the first level, the user must represent the digits from 1 to 10 using their fingers, and the time taken for each digit, the number of incorrect representations, the number of attempts the user made of the given attempts, and the time taken to represent each digit are recorded and stored. In the second level, the same process occurs, but as a variation, the representation of digits from 1 to 10 is provided randomly. In this activity, the Computer Vision (CV) techniques and DL model were used. MediaPipe uses CNN for palm detection and hand landmark (get twenty-one 3D landmarks for each hand) detection, while simple geometric rules were used under CV to compare coordinates and to determine if fingers are up or down.

B. Auditory Learning Enhancement System

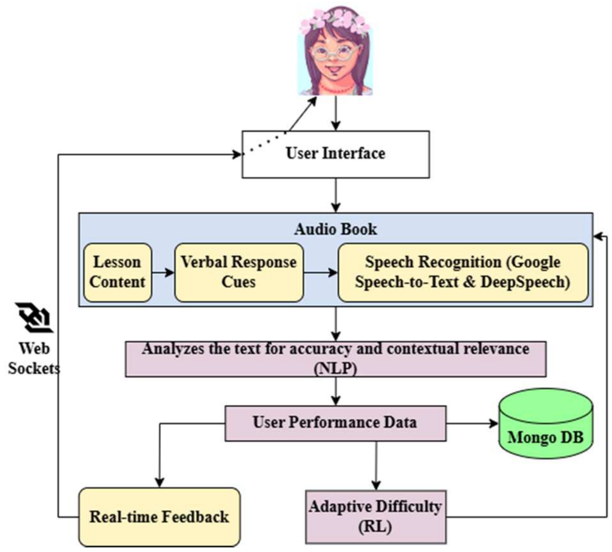

Fig. 2. Component architecture of the visual learning enhancement system

This component improves information processing, and memory retention for people with DS through adaptive difficulty and real-time feedback. In the Audio Book, as shown in Fig. 2, users can respond orally to questions in the audiobook module's planned lessons, which include verbal response cues. This improves memory and decision-making skills through real-time selection-based activities, allowing children to reinforce what they comprehend. The system customizes this activity by evaluating user-performance and modifying challenge level, while the ML-based suggestion engine tracks development and reinforce areas for improvement. The system uses Google Speech-to-Text Application Programming Interface (API) and DeepSpeech for speech recognition, analyzed with Natural Language Processing (NLP) for accuracy. A TensorFlow-based scoring mechanism tracks performance, while Web Sockets provide real-time feedback. A CNN-trained model using speech commands, common voice, and audio set enhances accuracy. RL adjusts lesson difficulty for personalized auditory learning.

C. Read Write Learning Enhancement System

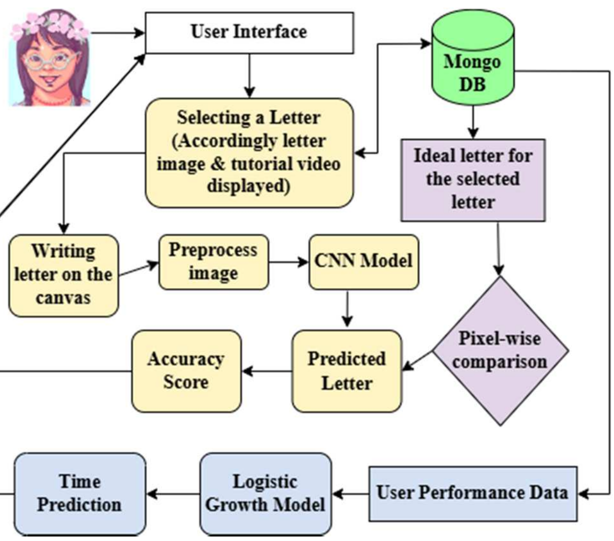

Fig. 3. Component architecture of read/write learning enhancement system

For the first gaming activity shown in Fig. 3, all 52 uppercase and lowercase letters of the English alphabet are used in the writing skill development exercise. This was chosen based on the guidance received from their teachers who frequently encounter children with DS. In this writing exercise, the user can select a letter and write the chosen letter in the given canvas, accompanied by the necessary tools to eliminate motion features. Based on an observation made while interacting with children with DS, the user interface provides a tutorial video and an image related to the letter to assist the user in writing the letter selected.

The custom CNN model was developed on letters gathered from children with DS aged 5 to 15 years. The model consists of 3 conv2D layers, 3 MaxPooling2D layers, a flat layer, and 3 dense layers. The kernel size of conv2D layers is generally 3x3 and the default step size and the filters use 32, 64, and 128, respectively. These convolutional layers are followed by MaxPooling2D layers, and respective ones have a 2x2 pool size and step size 2. The model also has a flat layer to transform the 2D feature maps into a 1D vector. This is followed by two dense layers of 64 and 128 units, respectively, and a final dense layer of 52 units, equal to the number of output classes for classification. In another utility process, a trained CNN model is used to read the accuracy of the character in terms of percentage. In CNN-based character recognition, the image is first converted to grayscale and binarized using a threshold to distinguish between the character and the background. The image is then resized to 28x28 pixels to standardize the dimensions and inverted so that the character appears white on a black background.

The pixel value is normalized to a range of 0 to 1 and the image is reshaped to fit the input shape of the model. The pre-processed image is fed as an input to the CNN model. The predicted character is compared to the ideal character obtained from the database using the formula that calculates the pixel accuracy. Using the Logistic Growth Model, the system predicts the estimated time (using days) and number of times to practice achieving 95% accuracy by the child with the use of time-stamped accuracy scores as the input. These scores, accompanying the date that the test was administered, are saved as a record in the database for future analysis by parents and teachers.

D. Kinesthetic Learning Enhancement System

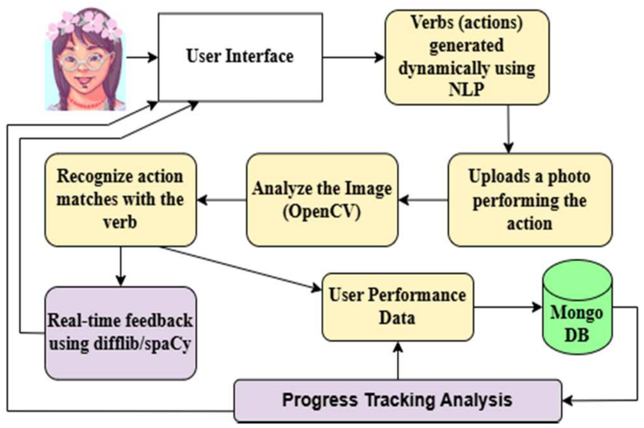

Fig. 4. Component architecture of kinesthetic learning enhancement system

The kinesthetic learning component, Action Quest, develops motor skills and language comprehension by linking verbs to movement-based activity. Verbs are generated dynamically using NLP (via Natural Language Toolkit (NLTK) and Flask). Users are asked to upload an image, usually a teacher or parent, rather than real-time video tracking as shown in Fig. 4. The system uses OpenCV and a pre-trained TensorFlow model to associate the action with the verb and deepen understanding. The React.js interface allows for interactive verb selection, and Axios for progress tracking. Real-time feedback is provided using Python libraries difflib and spaCy. Difficulty adapts dynamically based on user performance for a personalized and fun learning experience.

E. Common Features

A range of accessibility and adaptive features was integrated into the system design to ensure the system is inclusive and usable for children with DS.

- Simplified, Accessible UI: The interface features minimal screen clutter with large buttons, icons, limited text, and harmonious color combinations to ensure clarity, and clear visuals with audio prompts to support children with reading difficulties. The user interface, designed to be visually stimulating.
- Touch-Friendly Interaction: Designed with large tap areas and room for motor error to accommodate children with fine motor challenges.
- Engaging Feedback: Activities include immediate visual (animations, stickers) and auditory (claps, praise) rewards to motivate and reinforce learning.
- Adaptive Difficulty and Inclusive Learning Styles: A reinforcement learning engine personalizes task difficulty based on each child's performance, offering the right level of challenge. Content is designed around the VARK model to support visual, auditory, reading/writing, and kinesthetic learners.

Collectively, these features serve the purpose of the system in offering an adaptive, personalized, and accessible learning experience to children with DS at various developmental stages. During the pilot, feedback from teachers and parents corroborated the simplicity and flexibility of the interface as an advantage for students with lower functional abilities.

The RL agent impulsively changes the task difficulty using the historically aggregated user performance data and the concurrent feedback. The system includes gradual difficulty reduction with difficulty extending over a long period, hints, simple tasks, and positive reinforcement to avoid frustration and disengagement if the student fails repeatedly. Supportive actions such as breaks, or rewards are also activated by emotional cues captured through camera-based activity monitoring. The dual layering of the adaptation allows for the instantaneous responsiveness mixed in with the personalization to sustained motivation with a positive learning experience.

IV. Results and Discussion

The initial investigation involved 23 students diagnosed with Down syndrome but might not have been representative of the broader population due to limited diversity and differences in cognition, thus making the findings non-generalizable. Moreover, the 10-week duration was insufficient to determine long-term retention and transfer of learning. Issues related to ethics and logistics, such as informed consent, data protection, personalized support needs, and safety concerns, contributed to keeping the sample size limited. Future studies will entail expanding the number of learners to more varied learners and longitudinal investigations to assess learning retention and generalization over longer periods.

An observation made during the testing of the design Blooming Minds in the Sri Lankan educational setting was that the children with DS demonstrated a good understanding of English and could perform activities such as color recognition, number counting, and word reading via English-language images. This is in line with earlier research that, despite language and culture differences, such children are taught based on English at school, hence the reason why the system was initially developed for English. Future research will focus on deploying the system in other languages and cultures in order to make it more widely applicable. The system works well on low-cost laptops, Android phones, and plain camera and microphone-equipped tablets. Many of these devices were donated locally or internationally so it's accessible in urban and rural schools. Feedback from teachers and parents was high on usability and engagement with no major issues reported on camera, voice, or hand tracking even for children with DS.

To evaluate the significance of the observed improvements in students' performance, a 'Paired T-tests' were conducted on the results of the pre- and post-tests across activities. This test was chosen because of its suitability for comparing means from the same participants before and after the intervention. The analysis was performed using Statistical Package for the Social Sciences (SPSS), with a significance level of $p < 0.05$. Table II below demonstrates the results obtained.

TABLE II. PAIRED T-TESTS FOR GAMING ACTIVITIES

Activity	Pre-Test (%)	Post-Test (%)	Mean Differ.	t-value	p-value	Signific.
Color Matching	45.1	77.5	31.69	15.9	1.49E-13	Significant
Finger Counting	45.0	82.5	37.48	41.2	1.19E-15	Significant
Letter Writing	47.5	79.7	32.16	18.6	6.18E-15	Significant
Audio Book	48.1	79.6	31.44	20.4	9.14E-16	Significant
Action Quest	45.0	71.4	26.45	15.6	2.18E-13	Significant

A custom CNN was benchmarked against the VGG16 transfer learning model to evaluate handwriting recognition performance using the same dataset, training strategies, and augmentation methods. While VGG16 employed a two-phase fine-tuning process, the custom CNN was trained end-to-end for 40 epochs with a fixed learning rate. The custom model significantly outperformed VGG16 in terms of accuracy, inference speed, and model efficiency. VGG16 exhibited signs of overfitting, such as early plateauing and high validation variance, whereas the custom CNN showed better convergence and generalization. As confirmed by the benchmarking results in Table III, the custom CNN is better suited for real-time, resource-constrained adaptive e-learning applications, offering high accuracy and performance with significantly reduced latency and model size.

TABLE III. QUANTITATIVE BENCHMARKING

Metric	VGG16 Model	Custom CNN Model	Improvement
Test Accuracy	63.14%	91.26%	+28.12%
Inference Latency	42ms	5ms	8.4× faster
Model Size	58MB	4.8MB	12× smaller
Training Time	4h 22m	1h 48m	2.4× faster

In the letter writing activity, custom CNN was used for its high accuracy in classifying 2D image data, achieving 91.26% test accuracy. Figure 5 illustrates training and validation accuracy over 40 epochs.

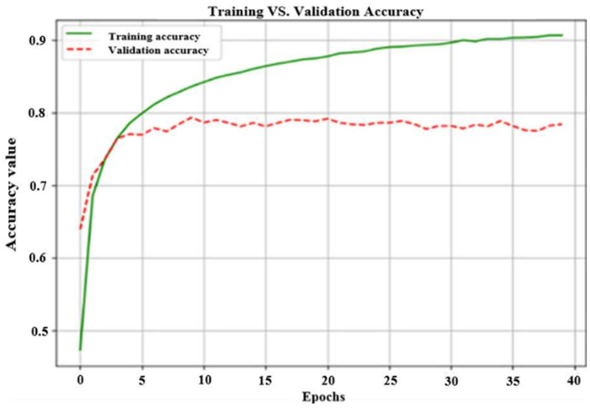

Fig. 5. CNN accuracy against 40 epochs for letter analysis

V. CONCLUSION

In this context, limited research has been conducted in the mentioned areas of learning disabilities. To meet the need, a responsive web-based solution, 'Blooming Minds', was implemented in English for screening and intervention processes, bypassing identified limitations for DS children. In the future, we plan to improve and expand this into a multilingual, lab-based platform involving neuroscience.

ACKNOWLEDGMENT

The researchers acknowledge that the supervision of Dr. Supun Premaratne, who services at the Anuradhapura Teaching Hospital, was invaluable in the medical field. We would like to express our gratitude to the Principal of Navodaya Special Children's Foundation, Moratuwa, Mrs. Lakshmi Karunajeewa, and the teaching staff for allowing us to collect data. We also extend our special thanks to the students and parents for their contributions.

REFERENCES

[1] S. Antonarakis, B. Skotko, M. Rafii, A. Strydom, S. Pape, D. Bianchi, S. Sherman and R. Reeves, "Down syndrome," *Nature Reviews Disease Primers,* vol. 6, no. 1, 2022.

[2] S. Buckley, L. H. Finestack, T. Keren-Portnoy, S. Loveall, B. Peter, V. Stojanovik and L. Thompson, "The case for early, time-sensitive speech, language, and communication interventions for young children with Down Syndrome or other intellectual and developmental disabilities," *International Review of Research in Developmental Disabilities,* vol. 67, pp. 71-109, 2024.

[3] "Down Syndrome Rates by Country 2025," World Population Review, [Online]. Available: https://worldpopulationreview.com/country-rankings/down-syndrome-rates-by-country. [Accessed 7 March 2025].

[4] D. Logan, "Resource Needs, Availability and Use Amongst Children with Down Syndrome and their Caregivers in Galle, Sri Lanka," Duke University, Durham, 2018.

[5] A. Kłosowska, A. Kuchta, A. Cwiklińska, K. Sałaga-Zaleska, M. Jankowski, P. Kłosowski, A. Mański, M. Furman-Zwiefka, P. Anikiej-Wiczenbach and J. Wierzba, "Relationship between growth and intelligence quotient in children," *Translational Pediatrics,* vol. 11, no. 4, pp. 505-513, 2022.

[6] L. M. Batshaw and P. H. Brookes, Children with Disabilities, Baltimore: Paul H. Brookes Publishers, 2002.

[7] R. D. Kent and H. K. Vorperian, "Speech impairment in Down syndrome: a review," *Journal of speech, language, and hearing research : JSLHR,* vol. 56, no. 1, p. 178–210, 2013.

[8] S. J. Bennett, J. Holmes and S. Buckley, "Computerized Memory Training Leads to Sustained Improvement in Visuospatial Short-Term Memory Skills in Children with Down Syndrome," *AMERICAN JOURNAL ON INTELLECTUAL AND DEVELOPMENTAL DISABILITIES,* vol. 118, no. 3, p. 179–192, 2013.

[9] S. Hargreaves, S. Holton, R. Baxter and K. Burgoyne, "Educational experiences of pupils with Down syndrome in the UK," *Research in Developmental Disabilities,* vol. 119, no. 1, pp. 104-115, 2021.

[10] S. T. Brynard, "Educating Learners with Down Syndrome Successfully: A Narrative Journey," *Mediterranean Journal of Social Sciences,* vol. 5, no. 20, pp. 1888-1901, 2014.

[11] S. Wheen, "Gympanzees," Gympanzees, [Online]. Available: https://www.gympanzees.org/. [Accessed 18 10 2024].

[12] F. Montalva-Valenzuela , A. Castillo-Paredes , C. Farias-Valenzuela, O. Andrades-Ramirez, Y. Concha-Cisternas and E. Guzmán-Muñoz, "Effects of exercise, physical activity, and sports on physical fitness in adults with Down syndrome: A systematic review," *Journal of Physical Education and Sport,* vol. 11, no. 4, pp. 577-600, 2024.

[13] "See and Learn," Down Syndrome Education Enterprises, [Online]. Available: https://www.seeandlearn.org/en-us/. [Accessed 22 December 2024].

[14] J. E. Roberts, J. Price and C. Malkin, "Language and Communication Development in Down Syndrome," *Mental Retardation and Developmental Disabilities Research Reviews,* vol. 13, no. 1, pp. 26-35, 2007.

[15] S. Er-rida, M. Oubibi, M. Mafhoum, M. H. Alami and A. M. Alaoui, "Challenges Faced by Parents of Children with Down Syndrome in Mainstream Schools: Exploring Inclusive Education," *The Open Psychology Journal,* vol. 18, pp. 1-8, 2025.

[16] T. Pazouki, V. Cornu, P. Sonnleitner, C. Schiltz, A. Fischbach and R. Martin, "MaGrid: A Language-Neutral Early Mathematical Training and Learning Application," *International Journal of Emerging Technologies in Learning (iJET),* vol. 13, no. 8, pp. 4-18, 2018.

[17] M. Corrales-Astorgano, C. Gonzalez-Ferreras, D. Escudero-Mancebo, L. Aguilar, V. Flores-Lucas, V. Cardenoso-Payo and C. Vivaracho-Pascual, "Pronunciation Assessment and Automated Analysis of Speech in Individuals with Down Syndrome: Phonetic and Fluency Dimensions," in *IberSPEECH*, Portugal, 2024.

[18] K. L. Walker and T. Moodley, "Handwriting Recognition in Down Syndrome Learners Using Deep Learning Methods," in *18th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, VISIGRAPP 2023*, Lisbon, 2023.

[19] C. Jarrold and A. Baddeley, "Short-term memory in down syndrome: Applying the working memory model," *Down Syndrome Research and Practice,* vol. 7, no. 1, pp. 17-23, 2001.

[20] V. Agheana and N. Duță, "Achievements of Numeracy Abilities to Children with Down Syndrome: Psycho-Pedagogical Implications," *5th World Conference on Learning, Teaching and Educational Leadership, (WCLTA),* vol. 186, pp. 38-45, 2015.

[21] G. Regaieg, G. Kermarrec and S. Sahli, "Designed Game Situations Enhance Fundamental Movement Skills in Children with Down Syndrome," *Journal of Intellectual Disability Research : JIDR,* vol. 64, no. 4, pp. 271-279, 2020.