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Non-Verbal Learning Disability (NVLD) In age 10 - 13 Children

Project Id: 24-25J-150

Dissertation Report

Madanayake P.C.S
IT21181788

BSc (Hons) in Information Technology Specializing in Information Technology
Department of Information Technology

Sri Lanka Institute of Information Technology
Sri Lanka

Improve Visual-Spatial Skills and Cognitive Flexibility

Project Id: 24-25J-150

Dissertation Report

Madanayake P.C.S IT21181788

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Department of Information Technology

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March 2025

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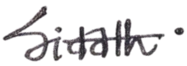

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Abstract

Abstract Non-Verbal Learning Disorder shows in people who have poor visual-spatial reasoning and ability to adapt while using their words very well. Our mobile application uses AI technology and connects with a Difference Identification Function designed for NVLD children between 10 and 13 years of age. Our system helps NVLD children develop their spatial perception and mental reasoning by creating interactive tasks that respond to how well they perform each task. The system determines appropriate tasks through Deep Q-Learning while providing real-time feedback and scoring results based on how well children answer questions correctly and quickly while using the available assistance. This application employs Flutter for the user interface and Fast API for backend programming while using MongoDB as the database storage system. Students need to find image mismatches in pairs while reinforcement learning adjusts exercise difficulty depending on their present skills. The platform adjusted itself to support learning designs that gave quick responses to students while decreasing mental load and preventing activity drop-off. Our findings show how merging AI with game features into accessible learning tools can better educate children with NVLD.

Keywords: Non-Verbal Learning Disorder (NVLD), Visual-Spatial Skills, Cognitive Flexibility, Deep Q-Learning, Reinforcement Learning, Adaptive Learning, Gamification, Educational Technology, Real-Time Feedback, Mobile Learning App

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Table of Content

List of Figures

List of Tables

LIST OF ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
ICT	Information and Communication Technology
ML	Machine Learning
PDF	Portable Document Format
UI	User Interface
UX	User Experience

Chapter 1

1. INTRODUCTION

Non-Verbal Learning Disorder (NVLD) is a neurodevelopmental disorder primarily defined by well-developed verbal abilities in the face of major impairments in visual-spatial reasoning, motor coordination, and non-verbal communication abilities. Children with NVLD often have difficulty processing visual information, understanding spatial relationships, and completing tasks involving both fine motor skills and coordination. Traditional learning methodologies remain inadequate to target their specific learning needs and are not adaptive to promote individualized approaches to instruction for their particular cognitive profiles, given the challenges these students face that intensely affect their educational experience and social interactions.

With the comprehension that most of traditional educational approaches have certain limitations, there is a growing inclination towards the use of technology-based alternatives, especially interactive mobile applications, to deliver adaptive, fun, and customized learning experiences for NVLD children. But there remains a huge gap in research among innovative educational tools specifically innovative educational tools for children with NVLD that keep a balance of its visual-spatial and cognitive needs with technological advancement.

This research seeks to fill this gap by developing a novel component of a holistic educational programme created specifically for use with children aged 10-13 years with NVLD. It employs state-of-the-art AI and ML technologies to offer tailored learning experiences designed to develop visual-spatial skills and cognitive flexibility. The main components range from AI-powered image processing algorithms, to adaptive learning pathways embedded through deep reinforcement learning (Q-Learning), to feedback systems that provide real-time feedback, dynamically calibrated to the level of task difficulty based on the ongoing ability and cognitive development of the child over time.

The particular component described in this paper is focused on interactive visual-spatial tasks, relying on AIaugmented image processing and tuned task difficulty to gradually strengthen the visual-spatial capability of the child. They primarily entail identifying missing elements, differences in images with multiple similar components and adjusting visual differences with time to reflect whether the element is ‘novel’ or not all to keep them at optimal effort levels for learning.

This component incorporates individualized adaptive algorithms, real-time performance analytics, and interactive gamification elements that will address the cognitive and academic difficulties of children with NVLD. This systematic study aims to address the following questions: how effectively we can enhance cognitive flexibility and fine-tune the response time using AI-based adaptive visual-spatial tasks while fostering a synergistic learning environment. In the end, this is a proposed solution that will give NVLD children the meaningful, supportive, and effective “pharmaceutical” tools they need in order to thrive tailored to their individual educational needs, so they can achieve the best academic performance and enhanced quality of life they so rightfully deserve.

1.1 Background & Literature Survey

1.1.1 Background

Non-Verbal Learning Disorder (NVLD) is characterized by significant challenges with visual-spatial reasoning, motor coordination, and social interaction in children with normal attempts or above average verbal transcendental intelligence. As such, they tend to struggle with tasks that involve the identification and understanding of spatial details, visual cues, and body language. The traditional way of teaching emphasizes text and verbal comprehension skills and fails to provide NVLD students with their greatest need: individualized instruction that enhances their visual-spatial skills.

Recent developments in educational technology, especially in mobile apps have enabled personalized adaptive interactive learning experiences. This opportunity closely mirrors the more specialized assistance that NVLD children need to participate successfully in identifying missing items between pictures or locating differences in visual scenes. Through real-time feedback and adaptive difficulty, AI-powered tools address some of the ongoing challenges NVLD children encounter when engaging with visual-spatial tasks.

However, many of these educational applications are unable to support NVLD learners. Such a gap underscores the need to build research-based technological solutions targeting behavioral-interventions to be visual spatial in nature for child with NVLD like Difference Identification Function introduced in this project.

1.1.2 Literature Survey

Numerous studies highlight visual-spatial skills of children with learning disorders and the importance of specific interventions and interactive technologies in improving visual-spatial skills. The following selected highlights lay the groundwork for understanding effective strategies and gaps that remain:

1. Gamified Learning for Visual-Spatial Skills

Gaggi, Barisic and Palazzi (2019) found that gamified approaches improve visual-spatial learning outcomes significantly in children with any cognitive disorder. Their research highlighted how children thrive with dynamic tasks, like finding differences between images, that enhance attention to detail and hone spatial reasoning.

2. Adaptive Learning Technology

Through providing tailored exercises, structured feedback, and real-time content adjustment, Rodriguez, Casado-Muñoz, and García-Peñalvo (2021) highlighted that adaptive learning technologies are also beneficial in special education contexts. Their review implies that children with NVLD stand to gain a lot from such adaptive systems because of their unique cognitive profiles.

3. Real-Time Feedback Mechanisms

One of these studies was conducted by Cheng and Wang (2022), who found that real-time feedback can play a positive role with respect to the performance and motivation of children with learning disabilities, including visual-spatial deficits. They discovered that providing immediate feedback such as detecting mistakes or delivering adaptive hints considerably improves engagement and proactivity in visually oriented work.

4. Mobile App Designs for Special Education

Kumar and Sharma (2021) developed a mobile application aimed at improving cognitive skills in children with learning disabilities. Designed to facilitate the introduction of print media, among its features, tasks focused on finding differences in the image proved to be very engaging and effective in improving motor coordination and observation.

5. Gamification and Cognitive Flexibility

Singh & Gupta (2020) explored relations between interactive, gamified platforms, and cognitive flexibility in children with developmental disorders. They found that assignments that encouraged users to identify small differences or absent details from images also increased excitement levels and cemented long-term cognitive skills.

Relevance to the Current Project

These research studies are complementary in nature as they suggest that tasks that revolve around identifying the differences can be of great help in improving the cognitive skills of children suffering from learning disorders like NVLD. They stress the importance of:

- Adaptive Difficulty: The ability for the system to adjust challenges based on real-time evaluations of the child's performance.

• Real-Time Feedback: Providing Immediate feedback that allows children to recognize and correct mistakes.

• Gamified Engagement: This ensures developers use rewards, levels and responsive graphics to keep interest high and promote ongoing practice.

• Personalized Approaches: Tailoring interventions to address the unique presenting problems of each child, a need that is particularly important given the heterogeneity of presentations of NVLD.

Based on these findings the proposed Differential Identification Function utilizes AI models for the development of essential visual-spatial competences. Combining adaptive difficulty with real-time performance tracking, this would directly fill a major gap in general NVLD focused educational applications. The subsequent sections specify the research gap, the problem statement, and the methodological approaches applied to design a system capable of satisfying NVLD children's particular learning needs.

1.2 Research Gap

Other studies also indicate that tasks requiring the identification of differences between images would help develop the cognitive flexibility and visual-spatial skills of children with learning disorders, however, there is a clear lack of resources that cater specifically to Non-Verbal Learning Disorder (NVLD). In particular, most existing systems:

1. Lack Comprehensive Adaptivity: Many available applications only provide static sets of visuals or rely on fixed difficulty levels, disregarding each child's evolving skill set and performance. Consequently, children with NVLD may experience either consistent boredom (tasks are too easy) or discouragement (tasks are too advanced).

2. Do Not Integrate AI-Driven Real-Time Feedback: Although the effectiveness of immediate feedback is highlighted in multiple studies, relatively few platforms apply AI or machine learning to dynamically track user interactions and adapt content in real-time. This shortfall obstructs the system's ability to deliver personalized interventions aligned with a child's moment-to-moment needs.

3. Offer Limited Focus on Visual-Spatial Deficits: Various educational and gamified tools exist for broader learning disabilities, yet many do not prioritize the unique visual-spatial challenges inherent in NVLD. The subtle differences required to challenge NVLD learners effectively are often underrepresented.

4. Minimal Longitudinal Analytics: While short-term gains in engagement and skill enhancement have been widely reported, systematic long-term data on the sustained progress of NVLD children using difference identification tasks remains insufficient. Effective tools require robust data collection, analysis, and reporting over extended periods to measure genuine developmental gains.

Comparison of Existing Research and the Proposed System

Features	R1(Gaggi et al.)	R2(Rodriguez et al.)	R3(Cheng & Wang)	R4(Kumar & Sharma)	R5(Singh & Gupta)	Proposed System
AI-Driven Image Generation	✗	✗	✗	✗	✗	✓
Personalization	✓	✓	✗	✗	✗	✓
Adaptive Learning	✗	✓	✗	✗	✗	✓
Real-Time Feedback	✗	✗	✓	✗	✗	✓
Gamification and Engagement	✓	✗	✗	✓	✓	✓
Cognitive Development & Visual-Spatial Skills	✓	✓	✓	✓	✓	✓
Error Navigation & Partial Prompts	✗	✗	✗	✗	✗	✓
Focus on NVLD Children	✗	✗	✗	✗	✗	✓

Table 1: Comparison of Existing Research and the Proposed System.

Key Observations

• Studies like R1 (Gaggi et al.) and R2 (Rodriguez et al.) acknowledge the need for personalized or gamified environments but do not specifically address NVLD children.

• Real-time feedback (R3 Cheng & Wang) has shown strong potential in enhancing user engagement and learning outcomes, yet it often lacks an AI-driven adaptive mechanism.

• R4 (Kumar & Sharma) and R5 (Singh & Gupta) use gamification and cognitive development but lack strong AI-based personalization and do not focus on NVLD.

• Unlike this comparison, the Proposed System tailors learning tasks specifically for NVLD-associated visual-spatial deficits through AI-driven adaptivity, real-time feedback, and navigational error management axes to promote meaningful and sustained learning.

The proposed solution effectively targets the real-time adaptivity, AI-based feedback, deeper customization for NVLD specific visual-spatial weaknesses, thorough analytics through the Difference Identification Function by addressing these issues.

By addressing the significant gaps in existing educational tools and technologies for NVLD children, this approach aspires to bring about more meaningful, situational, and sustainable improvements in their cognitive outcomes.

1.3 Research Problem

NVLD, or Non-Verbal Learning Disorder, difficult challenges for children who have strong verbal skills but struggle significantly with visual-spatial reasoning, motor coordination, and non-verbal communication. Despite the availability of diverse educational apps for individuals with disabilities, few target the specific visual-spatial impairments seen in NVLD. Static exercises or non-specific gamification are traditional and rarely take into account:

1. Individually Complex: NVLD learners tend to have varying performance across tasks that require spatial recognition or pattern detection, necessitating a tool that can respond effectively to this in-the-moment volatility.

2. Immediate Feedback & Support: In the absence of immediate feedback, kids lose out on essential opportunities to learn from mistakes, adapt strategies, and develop sustained engagement.

3. Targeted Visual-Spatial Enhancement: Existing resources rarely center on specialized exercises (e.g., difference identification, missing-item detection) that strengthen spatial awareness and problem-solving skills essential for NVLD.

4. Longitudinal Progress Tracking: Traditional one-off or short-term solutions fail to capture ongoing development, limiting the capacity to intervene effectively, modify difficulty, and benchmark long-term growth.

Key Research Questions

1. What are the most effective adaptive algorithms and real-time feedback mechanisms for NVLD learners in maximizing engagement and skill progression?

2. How can gamification be used to maintain motivation and still keep educational rigor for children with visual-spatial deficits?

In answering these questions, the suggested component is a solid, highly functional, and NVLD-centric solution. The system, by integrating AI-driven adaptability, real-time feedback mechanisms, and well-structured interactive tasks aims to impact development of visual-spatial skills, cognitive flexibility, and academic skills of NVLD students creating a gap in this prospect of specialized educational technology.

1.4 Objectives

1.4.1 Main Objective

This component aims to create an AI-powered Difference Identification Function embedded within a mobile application designed specifically for children aged 10–13 with Non-Verbal Learning Disorder (NVLD). This function intends to enhance their visual-spatial skills and cognitive flexibility by means of interactive, personalized tasks that automatically adapt their complexity level depending on each child's performance.

1.4.2 Specific Objectives

1. Implement Real-Time Difference Identification Tasks

    • Create a series of visual-spatial games, such as asking kids to find what's missing or different between two images.

    • Use images that vary in complexity to support different profiles of NVLD.

2. Utilize AI-Based Adaptive Learning

    • Task-Implement machine learning algorithms (like Deep Q-Learning) to automatically manage the level of difficulty depending on user performance.

    • It requires continuous personalization that challenges learners without frustrating them.

3. Provide Immediate, Data-Driven Feedback

    • Offer immediate feedback and implement real-time monitoring of user interactions accuracy rate, time taken, frequency of hints, etc.

    • Verifying learning effectiveness by adapting hints or guidance in real time to individual learning progress.

4. Improve User Engagement with Gamification

    • Implement game mechanics, including scoring, ranking system, and prizes to encourage repeated practice and maintain interest.

    • Use intuitive UIs (user interfaces), voice prompts and visual cues appropriate experiences for the NVLD learner.

5. Evaluate Cognitive Improvements

    • Monitor, analyze the progress made in visual-spatial processing, accuracy, response time.

• Undertake comparative analysis to examine the performance of your Difference Identification Function against conventional approaches.

6. Integrate Smoothly with the Larger App Ecosystem

• Align the Difference Identification Function with the flow of other educational modules, ensuring seamless data integration and user experience throughout the platform.

• Allow for data-sharing with stakeholders (parents, educators, therapists, etc.) for deeper understanding of individual learning paths.

CHAPTER 2

2. METHODOLOGY

The difference identification function methodology development is the center of this component report, using AI adaptive strategies, real-time feedback, decoupling of activity tracking and event mechanics into a unified system of user engagement. This section breaks down step by step the technical and conceptual processes that were utilized to develop and iterate on the Difference Identification Function for NVLD learners.

Overall Approach

The solution employs AI/ML and a user friendly UI to provide personalized, game-based activities designed to improve visual-spatial skills in children with NVLD. Key pillars of this approach include:

- Data-Driven Adaptivity: Ongoing collection of user interaction data.
- AI in Real-Time Feedback: Reinforcement Learning metrics provide instant, personalized feedback for each user with less guessing and bolstering motivation.
- Gamification: Points, progressive levels, and engaging visuals help sustain user interest, crucial for children with NVLD who require ongoing stimulation and consistent positive reinforcement.
- NVLD-Centric Design: All tasks and interfaces are crafted considering the visual-spatial deficits common to NVLD learners—larger, clear visuals, step-by-step cues, and minimal text reliance.

2.1 System Architecture

Below is an outline of the architectural layers and data flow for the Difference Identification Function. The system is designed around a client-server model to ensure seamless interaction between the mobile front-end, back-end logic, and machine learning modules.

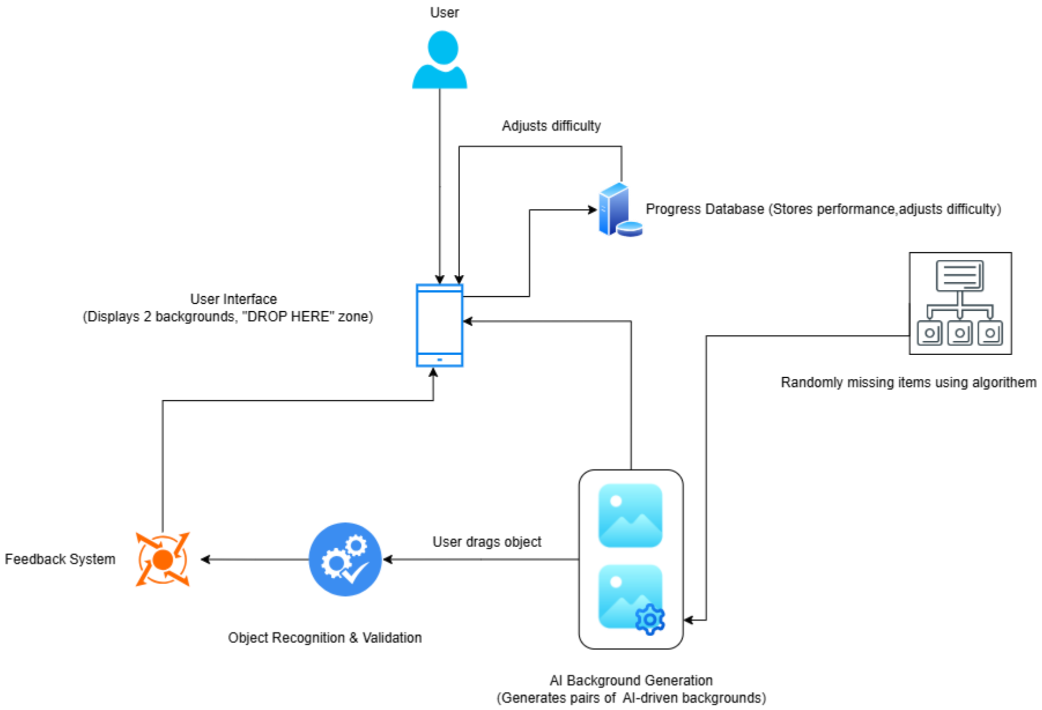


Figure 1: System Architecture Diagram.

Flutter Front-End

• Hosts the user-facing interface where children perform difference identification tasks.

• Incorporates drag-and-drop mechanics, highlight toggles, and voice prompts.

FastAPI Back-End

• Serves as the communication bridge between the front-end and ML models.

• Handles user management, session tracking, and data processing requests.

MongoDB Database

• Stores user profiles, game statistics (score, time, number of hints, difficulty level), and historical performance data.

• Persists configuration information for the AI-driven difficulty adjustment engine.

AI/ML Module

• Consumes real-time performance data from the back-end, adjusting difficulty through Deep Q-Learning or relevant ML algorithms.

• Sends updated difficulty levels, hints, or prompts back to the front-end.

2.2 Design of the Difference Identification Function

The core methodology for difference identification revolves around AI-enhanced visual tasks that adapt based on each learner's demonstrated proficiency.

1. Task Generation

    • A library of images, each with subtly modified variants (e.g., missing objects, color alterations), forms the base content.

    • Images are dynamically selected to match the current difficulty level, factoring in previous performance metrics.

2. Difference Highlighting & Interaction

    • Children drag a finger or stylus to pinpoint discovered discrepancies, which are immediately recorded and assessed.

    • Haptic or audio cues reward correct finds, while gentle on-screen suggestions help guide further exploration.

3. Adaptive Difficulty

    • Every successfully identified difference increments an internal performance counter.

    • Excessive hints, extended time, or repeated incorrect taps reduce the performance rating.

    • Performance rating is transmitted to the AI module, which either escalates or downgrades task complexity.

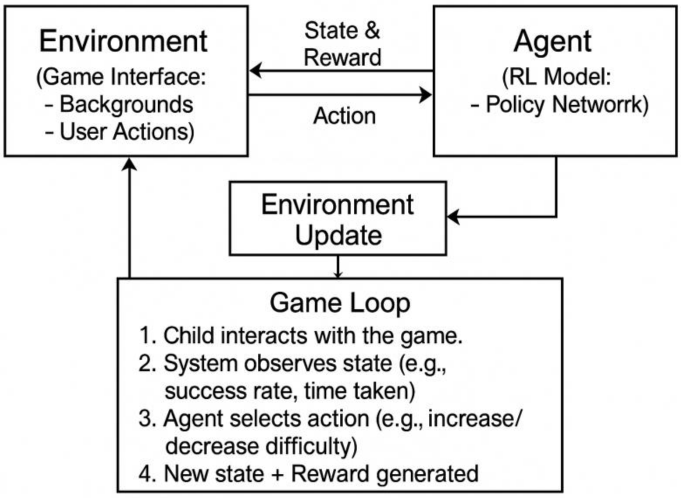


Figure 2: Example Screenshots or Mockups of the Difference Identification UI Reinforcement Learning Flow Diagram.

2.3 Reinforcement Learning Framework

To tailor the difficulty of each task to the user's evolving skills, a reinforcement learning (RL) mechanism (often Deep Q-Learning) is embedded into the back-end:

1. State Representation

• A 'state' includes the user's recent performance data: accuracy, moves taken, total time, and current difficulty.

• Observed states are crucial for deciding whether to maintain or adjust the difficulty.

2. Action Space

• Possible actions for the system revolve around increasing, decreasing, or maintaining the same complexity of image-based challenges.

• Additional actions can provide more prompts, highlight potential discrepancy zones, or adjust scoring weights.

3. Reward Structure

• Positive rewards are assigned when the difficulty level accurately aligns with the user's performance (i.e., user remains engaged without excessive frustration or boredom).

• Negative rewards occur if a child's performance plummets (excessive mistakes, repeated requests for help) or if tasks fail to challenge them.

4. Training Process

• Historical interaction logs feed into a training pipeline, allowing the RL agent to learn patterns in user behavior and outcomes.

• As the system encounters new data, it updates Q-values, refining how difficulty and hints are allocated.

2.4 AI-Powered Feedback Loop

Real-time feedback forms a pivotal component of the methodology, bridging the gap between static exercises and truly responsive learning:

1. Continuous Monitoring:

• Accuracy, number of errors, and time taken are tracked in real time.

• The system monitors if the user is stuck on a single difference or repeatedly skipping tasks.

2. Dynamic Prompting:

• After certain thresholds (e.g., X attempts or Y seconds), the system provides partial hints—e.g., highlighting a region of the image or providing a text/voice clue.

• If repeated failures persist, an alternate, simpler task can be queued.

3. Post-Task Evaluation:

• Upon completion of a task, the user sees a summary of key metrics (time, moves, final score) and motivational cues.

• The AI module updates difficulty parameters before delivering the next set of differences.

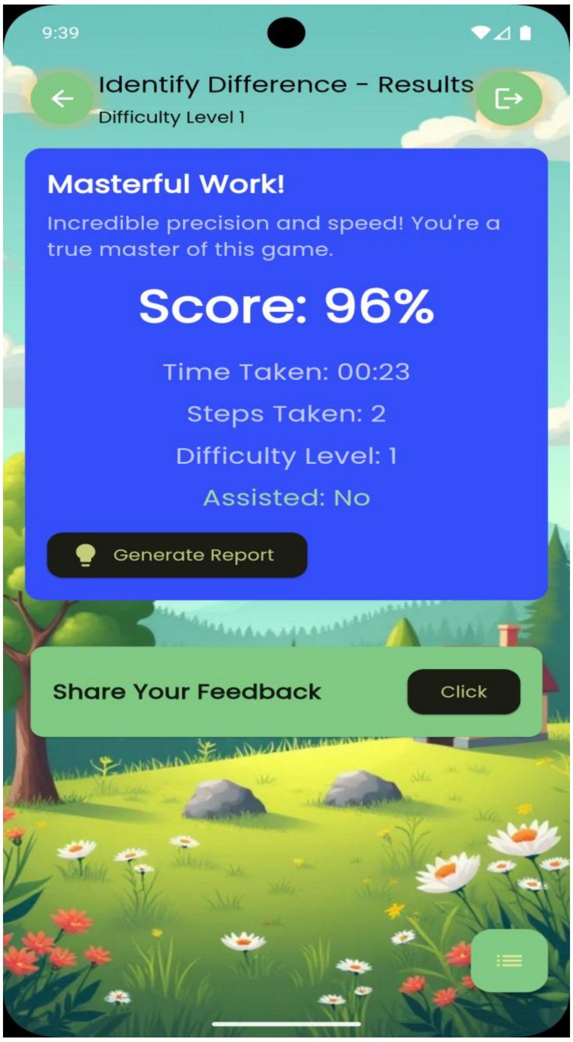


Figure 3: the post-task evaluation screen displaying metrics like time taken, moves used, and final score.

2.5 Gamification & User Engagement

Sustaining motivation is critical for NVLD learners who may become discouraged by visually intensive challenges. To this end, the system employs:

1. Points & Badges

   • Each correctly identified difference yields points; bonus points can be awarded for speed or minimal hint usage.

   • Collectible badges celebrate milestones, like ‘Rapid Finder’ for quick completion or ‘Master Observer’ for high accuracy.

2. Level Progression

   • A tiered structure (e.g., Bronze → Silver → Gold → Platinum) rewards consistent skill improvement.

   • Each level introduces varied image themes (nature, vehicles, shapes) to maintain novelty.

3. Engaging Visuals & Sound Effects

• Colorful animations, playful sound effects, and child-friendly mascots keep the environment upbeat.

• Clear, uncluttered layouts minimize visual overload for NVLD children.

4. Adaptive Challenge Intervals

• Difficulty escalates gradually to build confidence.

• Periodic easier tasks or 'break' activities are interspersed to prevent fatigue.

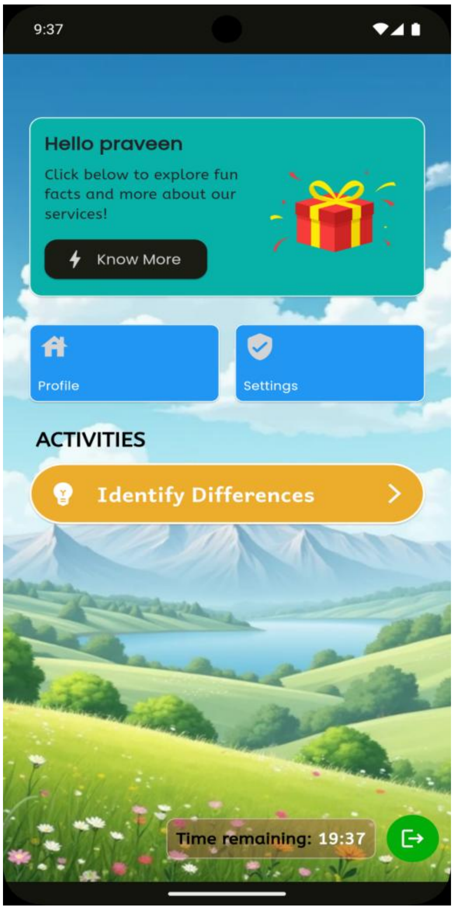


Figure 4:Sample Screens or Artwork Illustrating the Gamification Elements.

2.6 Implementation Details

1. Tooling and Frameworks

• Flutter: Cross-platform UI for seamless Android/iOS deployment.

• FastAPI: Lightweight Python-based backend for handling user requests and AI inference calls.

• MongoDB: NoSQL database storing user stats, images, and session logs.

• TensorFlow/PyTorch: ML frameworks for the reinforcement learning models.

2. Integration & Workflow

• Front-end calls FastAPI endpoints to retrieve tasks and submit user actions.

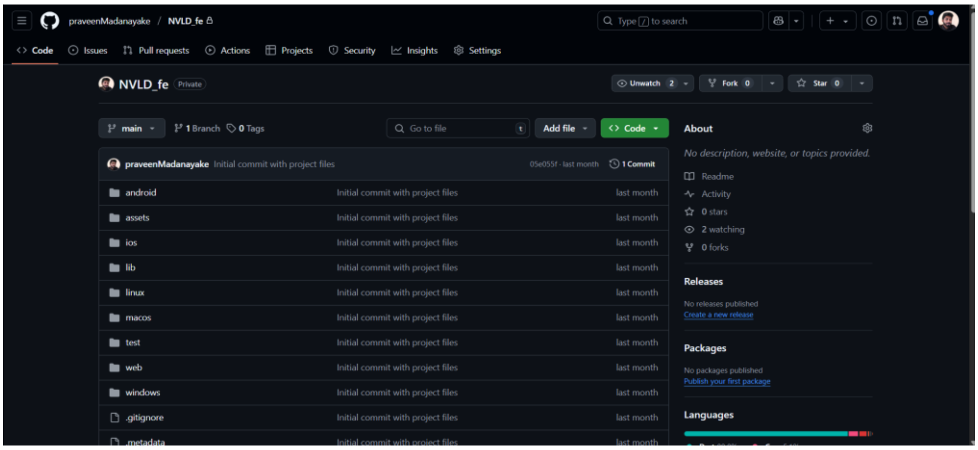
• FastAPI triggers ML logic, passing real-time performance data for difficulty calibration.

• The updated difficulty or hints are returned to the front-end, ensuring a smooth, closed-loop process.

3. Version Control & CI/CD

• All code changes are managed via Git (GitHub or GitLab), ensuring traceability and collaboration among team members.

• Automated testing pipelines confirm functional stability after each commit.



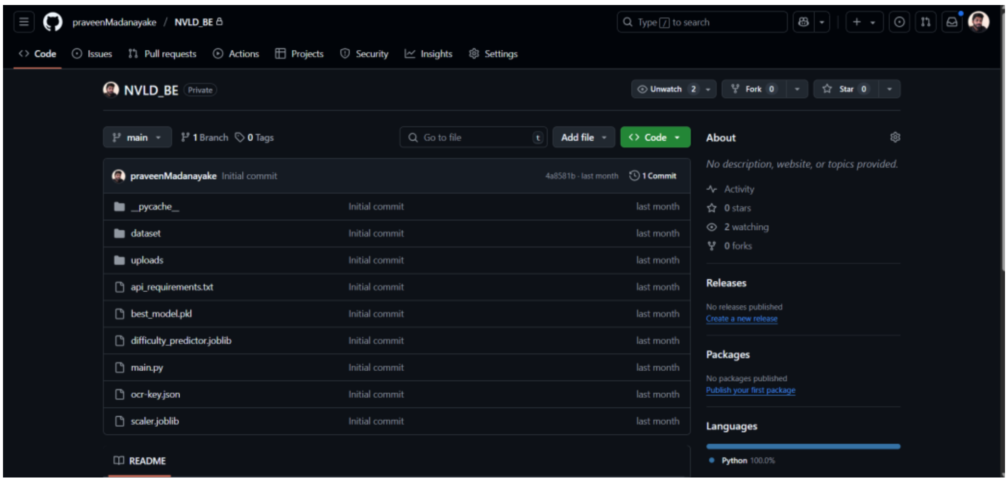


Figure 5: CI/CD pipeline interface or a snapshot of your Git repo showing code merges, automated testing, etc.

2.7 Methodological Validation

1. Pilot Studies

  • Small-scale user testing with a handful of NVLD children ensures that the difference identification tasks are neither too easy nor too daunting.

  • Feedback from educators, therapists, and guardians helps refine instructions, hint frequencies, and UI design.

2. Iterative Refinement

  • Data analysis from pilot interactions informs model hyperparameters (learning rates, exploration vs. exploitation) in the RL module.

  • Ongoing improvements are deployed in short cycles, each iteration validated with real-time user engagement metrics.

3. Ethical & Accessibility Considerations

  • All personal user data is anonymized and securely stored per institutional review board (IRB) guidelines.

  • Accessibility features (voice prompts, large font sizes, minimal text reliance) are integrated to align with NVLD learners' needs.

In the subsequent sections, the testing, evaluation methodologies, and preliminary results are presented to validate the efficacy of the AI-driven Difference Identification Function in improving the visual-spatial competencies of children with NVLD.

2.8 Detailed Scoring Algorithm

A critical aspect of the Difference Identification Function is the scoring mechanism, which evaluates user performance by factoring in accuracy, time taken, and number of moves. By quantifying each child's progress, the system can automatically gauge difficulty, provide meaningful feedback, and drive engagement.

2.8.1 Time Penalty

• Calculation: For each task, the total elapsed time (in seconds) is multiplied by a constant factor (e.g., 0.2) to derive a penalty score.

• Capping: To avoid excessively long times disproportionately lowering the user's score, the time penalty is capped at a maximum of 40 points.

2.8.2 Moves Penalty

• Moves Tracking: Every drag or tap attempt is a ‘move.

• Calculation: Then the total move count of the user is deducted from a baseline optimal move count moves for all moves compared, and the difference is then multiplied by a difficulty factor (i.e. 2 + current Difficulty).

• Capping: This penalty is usually capped at 30 points, so repeated trial and error won't see and mistakes do not completely demerit a user’s overall score.

2.8.3 Voice Assistance Adjustment

Optional Assistance: If the user opts into a hint or voice assistance feature, a cap is placed on the maximum achievable score (e.g., 60 instead of 100), reflecting the trade-off between help and independence.

2.8.4 Final Score Computation

1. Base Score: A maximum of 100 points is awarded at the start.

2. Subtractions: Time penalty and moves penalty are subtracted from the base score.

3. Score Clamping: The final value is clamped between 0 and 100 to avoid negative or inflated scores.

```
score = maxScore - timePenalty - movesPenalty

if showHighlight == true:

    score = min(score, 60)

score = clamp(score, 0, 100)
```

This scoring approach rewards efficiency (speed and minimal moves) while penalizing over-reliance on hints, thus motivating children to be more attentive in identifying differences.

2.9 Data Preprocessing & Label Encoding

Before the reinforcement learning module can adapt tasks and difficulty levels, it requires systematically structured data that accurately reflects each user’s interactions.

2.9.1 Data Cleaning & Column Selection

• Dropping Irrelevant Fields: Fields such as _id, user, and timestamps may be dropped or re-labeled to simplify further analyses.

• Data Merging: If data is stored across multiple collections or CSV files (e.g., one for performance metrics, another for user metadata), these are merged based on unique session or user IDs.

2.9.2 Categorical Encoding

• Label Encoding: Columns like observation or feedback that contain textual labels are converted to numeric codes. For instance, a column that logs whether a child's action was 'correct' or 'incorrect' is turned into integers for easier ML processing.

```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

data['observation'] = label_encoder.fit_transform(data['observation'])
```

• Action Creation: The numeric labels represent possible 'actions' for the Q-Learning model to evaluate.

2.9.3 State & Reward Structuring

• State Construction: A typical state might concatenate features like (score, moves, time_taken, difficulty, observation), capturing both user performance and the complexity of the challenge.

• Reward Definition: The observation or feedback label itself can serve as the reward signal (e.g., +1 for correct, 0 or -1 for incorrect). Alternatively, the reward function can incorporate partial scores, time penalties, or additional nuance specific to difference-finding tasks.

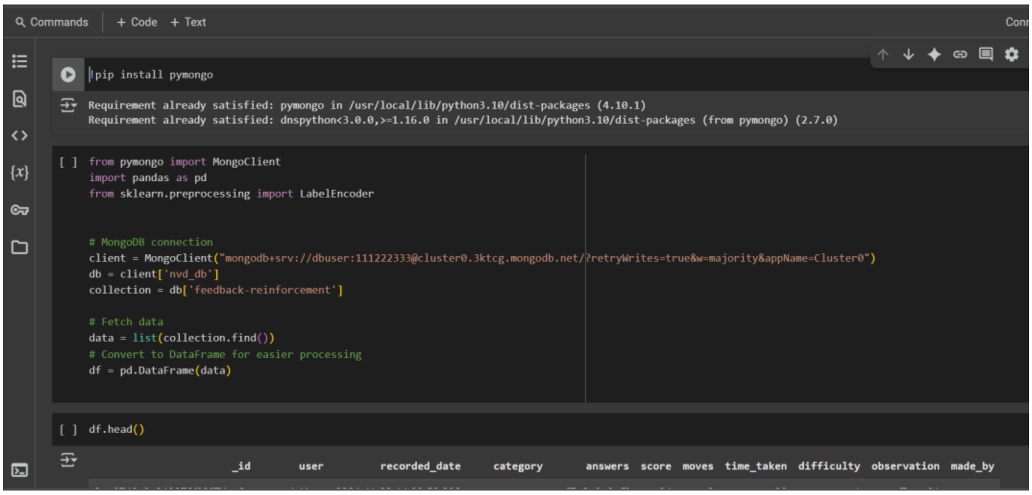
2.9.4 Integration with Reinforcement Learning

1. Data Batching: Preprocessed interaction logs are split into training and validation sets, enabling offline model training prior to real-time deployment.

2. Online Updates: As new user sessions accumulate, the RL model refines its parameters by replaying recent experiences—improving the alignment between recommended task difficulty and actual user performance.

3. Scalability: Because MongoDB is used for data storage, large-scale expansions (e.g., more users, additional tasks) remain efficient. Label encoding and state construction must be maintained consistently to preserve data integrity.

By meticulously cleaning, encoding, and structuring the data, the system ensures that the reinforcement learning algorithm operates with high-quality inputs—ultimately leading to more reliable adaptivity and better educational outcomes for children with NVLD.



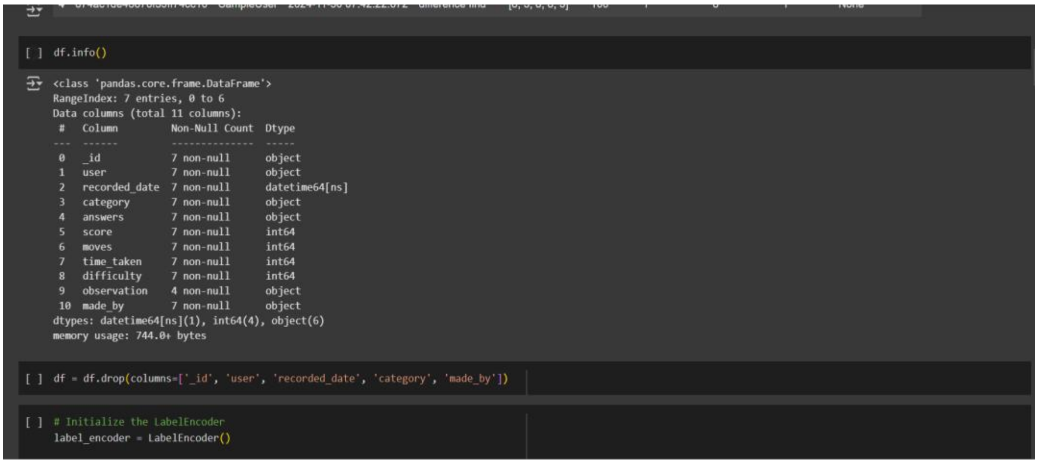


Figure 6: MongoDB schema screenshot or a snippet from your CSV file showing the labeled columns.

2.10 System Design & Implementation

The system architecture for the Difference Identification Function is engineered to seamlessly integrate user-facing interfaces, AI-driven adaptivity, and a robust data handling mechanism. Below is a closer look at the design principles, software stack, and implementation steps that ensure smooth operation and scalability of this component.

2.10.1 High-Level Architecture

At a high level, the system comprises three primary layers:

1. Presentation Layer (Flutter Front-End)

- Responsible for rendering interactive tasks and receiving user input.
- Provides real-time feedback (audio, haptic, or visual) to sustain engagement.
- Communicates with the back-end through secure API calls.

2. Business Logic & AI Layer (FastAPI + Reinforcement Learning Module)

• Acts as the core processing engine, handling requests from the UI and orchestrating ML inference.

• Integrates the Deep Q-Learning or other ML models for adaptive task generation.

• Manages session data, updates scoring, and triggers personalized feedback loops.

3. Data Persistence Layer (MongoDB)

• Stores user profiles, historical performance data, and metadata for different sets of difference-identification images.

• Ensures scalability and quick retrieval for real-time adaptivity.

2.10.2 Front-End Implementation (Flutter)

1. User Interface Layout

• Implements a Stack or Overlay for difference identification tasks, displaying two images side by side or layered images with subtle differences.

• Leverages Flutter widgets like Draggable, GestureDetector, and Positioned for interactive drag-and-drop or touch-based exploration.

2. Navigation & State Management

• Uses Provider, Riverpod, or similar state management libraries to ensure shared data (e.g., user scores, difficulty levels) remains consistent across screens.

• Splits the UI into self-contained widgets (e.g., Difference Identify Widget, Feedback Overlay) for maintainability and clarity.

3. Real-Time Feedback UI

• Displays partial highlights on correct identification or a gentle shake effect on incorrect taps.

• Integrates audio cues (success/fail sounds) to reinforce on-screen feedback.

4. API Integration

• Sends session events (moves, time, hints used) to the FastAPI back-end.

• Retrieves updated difficulty levels, recommended tasks, or next images from the server.

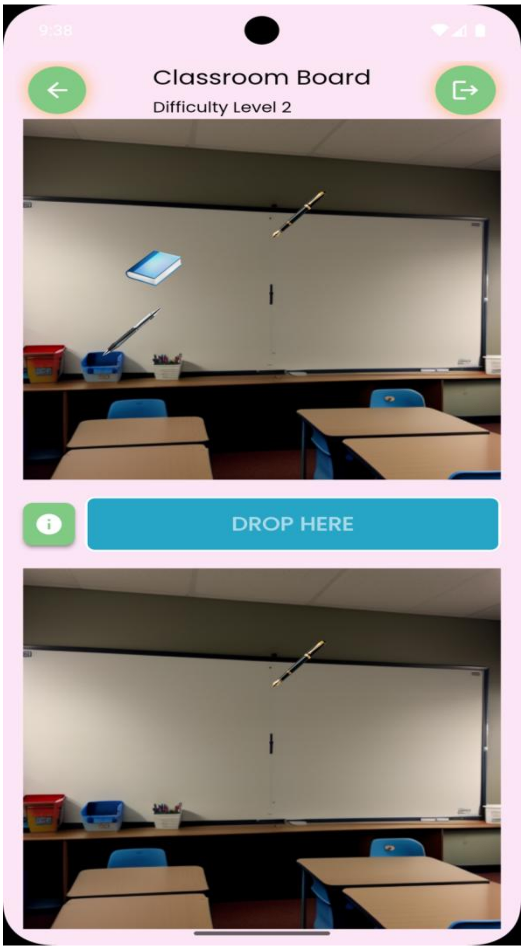


Figure 7: A screenshot of a Flutter screen showcasing the difference identification layout, along with highlights or overlays, can help illustrate how users interact with the tasks.

2.10.3 Back-End Implementation (FastAPI)

1. API Endpoint Structure

- POST /api/differences/submit: Accepts user activity data (e.g., discovered differences, time spent, hints used).
- GET /api/differences/next-task: Provides the next image set or difficulty level based on the user's real-time performance.
- POST /api/score/update: Updates user's score after each completed task, applying time/move penalties.

2. Middleware & Security

- Implements token-based authentication or session tokens to protect user data.
- Logs requests and responses for debugging and analytics.

3. Integration with Reinforcement Learning

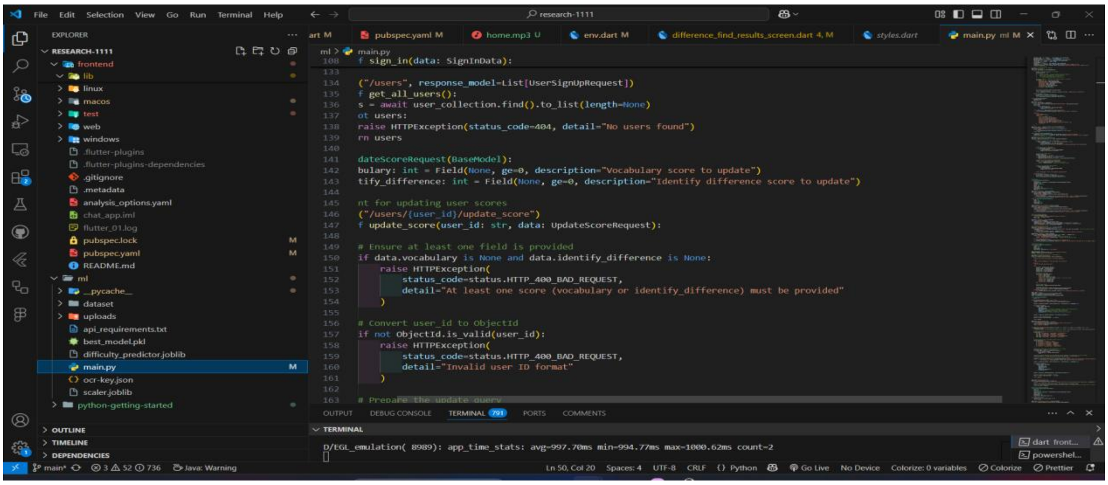
• Invokes the AI model for each user request that demands an updated difficulty level.

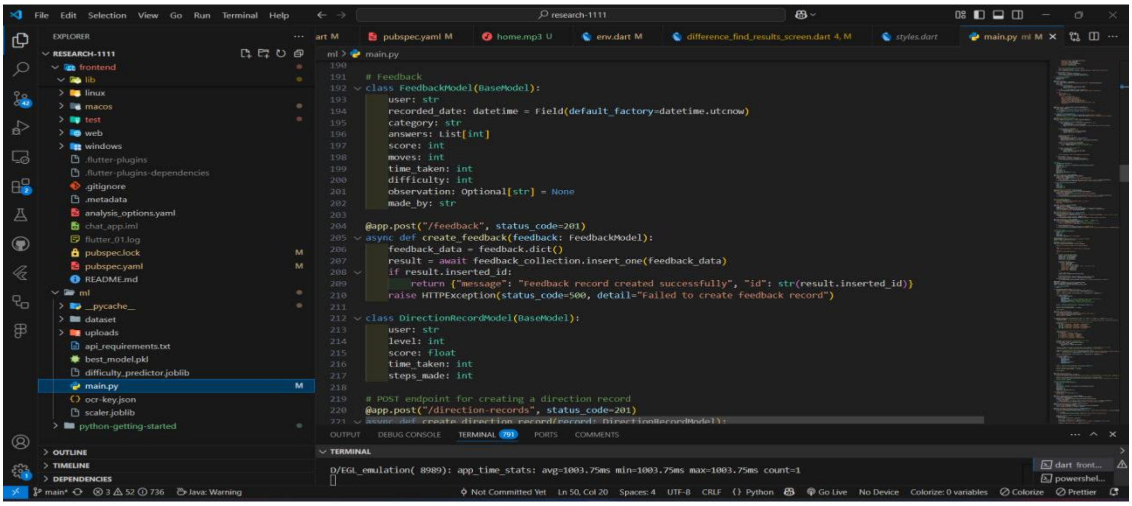
• Processes model outputs and forwards them as structured JSON responses to the front-end.

4. Scalability Considerations

• Deployed on container orchestration platforms (like Docker + Kubernetes) if needed.

• Auto-scaled to handle large influxes of concurrent user sessions (e.g., multiple classroom usage).





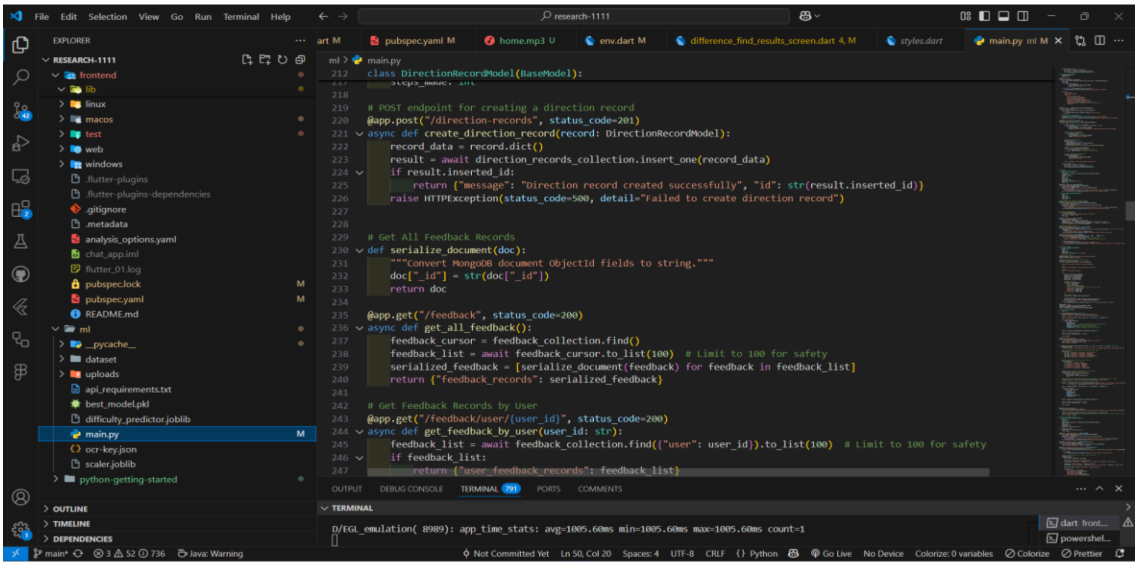


Figure 8: Include a simplified route diagram or code snippet from your FastAPI endpoints, showing how data is passed between endpoints and the RL module.

2.10.4 Machine Learning Module

1. Model Loading & Initialization

    • Loads pretrained RL models or initializes new ones if the system is in continuous-training mode.

    • Maintains a replay buffer for recent user interactions (states, actions, rewards) to periodically retrain.

2. Inference Process

    • Receives the current ‘state’ derived from the user’s performance metrics.

    • Calculates Q-values for possible system actions (e.g., increasing or decreasing difficulty).

    • Returns the highest Q-value action to the back-end.

3. Periodic Training Loop

    • Scheduled tasks periodically fetch new user data from MongoDB.

    • The RL algorithm updates weights, refining Q-value predictions.

    • Post-training, the updated model is reloaded for inference, ensuring continuous improvement.

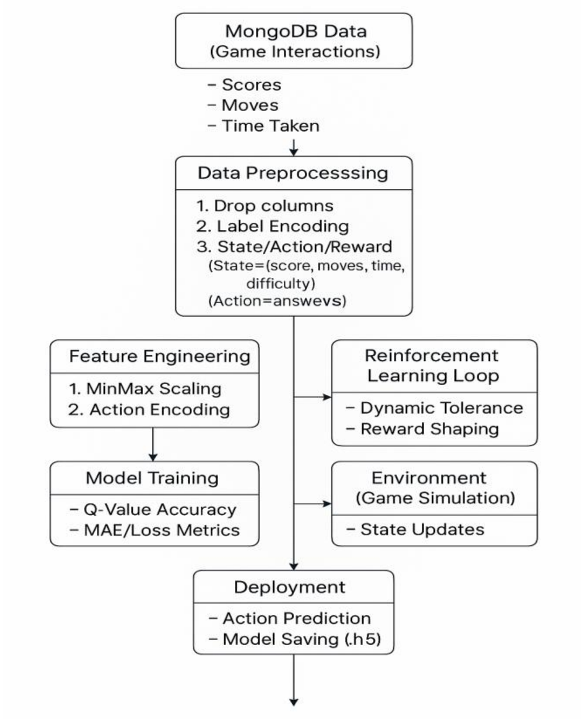


Figure 9: High-Level ML Workflow Diagram.

2.10.5 Database Schema (MongoDB)

The MongoDB collections centralize user data and domain content:

1. Users Collection

    Stores _id, username, profileInfo (e.g., relevant NVLD details), and current status (level, score).

2. Sessions Collection

    Keeps track of ongoing sessions, each storing references to tasks completed, times, accuracy, and penalties.

3. Images/Tasks Collection

    Contains images or references (URLs) of difference tasks, plus difficulty ratings, category tags, or pre-labeled discrepancy coordinates.

4. ML Logs Collection

    Records every RL decision, including state definitions, chosen actions, and assigned rewards.

    Facilitates debugging and offline analysis of how the AI module evolves

    .

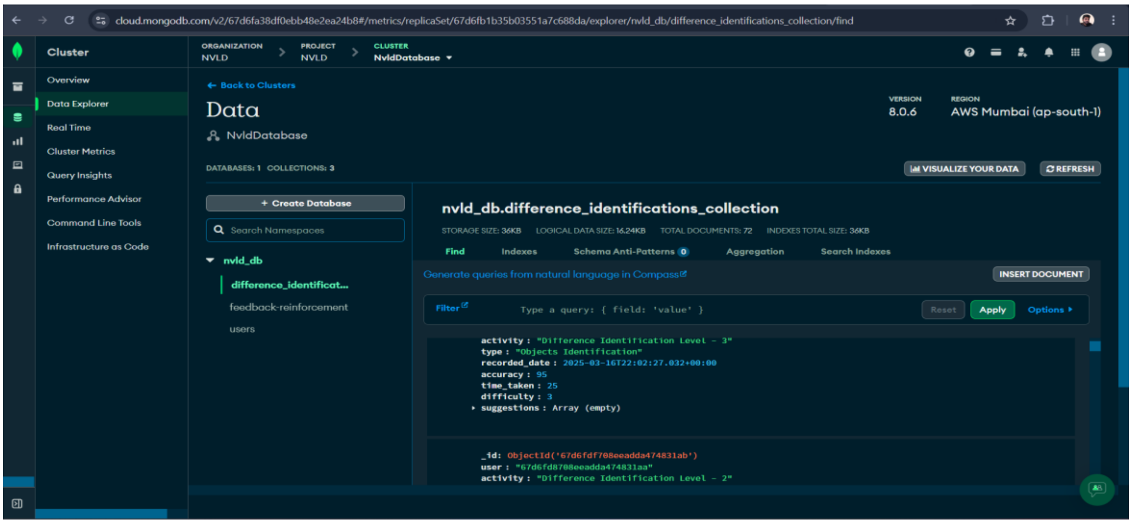


Figure 10: MongoDB GUI view (e.g., MongoDB Compass) or a sample schema definition, include it here to illustrate how each collection is structured.

2.10.6 Data Flow Sequence

1. User Initiates Task: Child launches the difference identification screen on the Flutter app.

2. Front-End Request: The Flutter client sends GET /api/differences/next-task to request the next recommended difficulty and image.

3. Back-End Processing: FastAPI retrieves the user's state from MongoDB, consults the RL model to adjust difficulty, and returns the updated task.

4. User Interaction & Submission: Child attempts to find differences; each tap or drag is logged. On completion, the app issues a POST /api/differences/submit with performance details.

5. Scoring & Feedback: FastAPI calculates partial or final scoring, possibly updates the RL model asynchronously, and responds with feedback instructions.

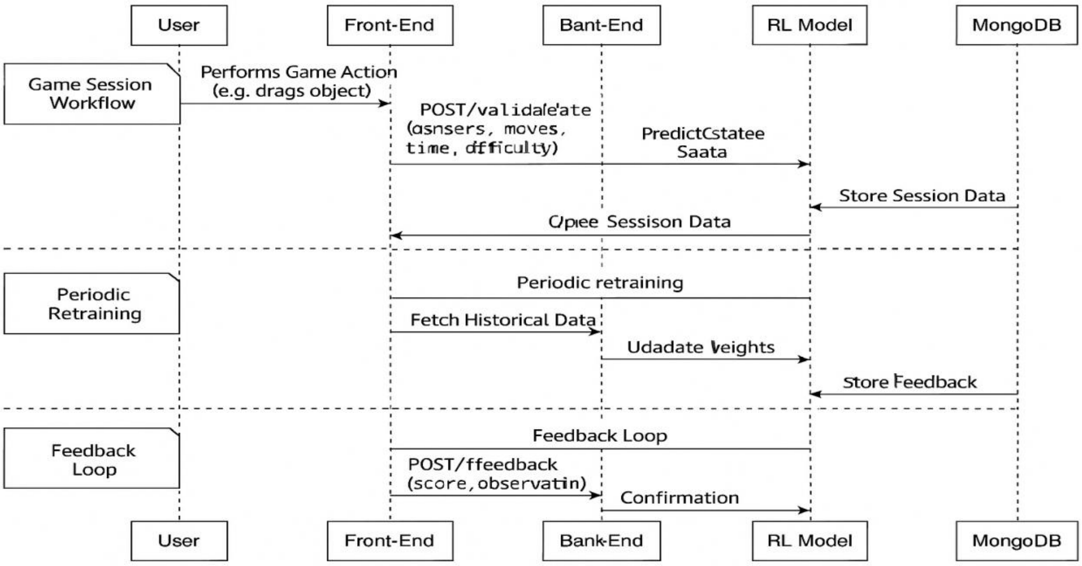


Figure 11: A UML sequence diagram capturing each step (front-end request, RL processing, back-end response) would clarify the real-time communication loop.

2.10.7 Implementation Roadmap

1. Phase I: Basic Functionality

• Implement the Flutter UI for difference identification.

• Build FastAPI endpoints for basic task retrieval and score updates.

• Establish MongoDB collections for user sessions and tasks.

2. Phase II: Integrate RL

• Develop the Q-Learning or DQN pipeline.

• Link user performance logs to the model for real-time difficulty adaptivity.

• Introduce reward functions tied to time, moves, and accuracy.

3. Phase III: Advanced Personalization

• Fine-tune RL hyperparameters based on pilot data.

• Incorporate more advanced feedback mechanisms (voice prompts, detailed hints).

• Expand the library of images and complexity levels.

4. Phase IV: Testing & Optimization

• Conduct user testing with NVLD learners.

• Perform load and stress testing on the back-end.

• Refine scoring and hint strategies based on usage analytics.

5. Phase V: Deployment & Maintenance

• Deploy on cloud infrastructure (e.g., AWS, Azure, GCP) or on-prem servers.

• Set up monitoring for performance metrics, error rates, and RL model drift.

• Regularly update images/tasks to maintain novelty.

2.10.8 Security & Privacy Considerations

1. Authentication & Authorization

• Children typically use simplified login or parent-administered accounts. Token-based security ensures sessions remain valid only within designated timeframes.

• Role-based access control for educators, parents, and system admins ensures sensitive data (e.g., usage stats) remains protected.

2. Data Anonymization

Personal Identifiable Information (PII) is either omitted or encrypted. Only relevant performance data (time, accuracy, difficulty) is stored in a non-identifiable manner.

3. Compliance & Permissions

If deployed at a school or therapy center, adheres to local data protection regulations (GDPR or equivalent). Consent from guardians is mandatory for usage.

2.10.9 Practical Considerations for NVLD Learners

1. UI Accessibility

• Larger, high-contrast visuals reduce strain on children with spatial perception difficulties.

• Minimal text usage; focus on icons and guided voice instructions.

2. Error Tolerance

• A slight ‘halo’ detection around differences accommodates inexact taps or drags.

• Multiple attempts are allowed; only repeated misses trigger gentle hints.

3. Reducing Cognitive Overload

• The number of differences displayed is carefully calibrated. Overly cluttered scenes can deter engagement.

• Periodic breaks or simpler “palette cleanser” tasks are introduced after sustained high-effort tasks.

In the next sections, a deep dive into testing, evaluation methodologies, and results will highlight how this system design translates into real-world improvements for NVLD children.

2.11 Testing & Evaluation

Testing and Evaluation phase, which assesses the effectiveness, reliability, and the user satisfaction of the Difference Identification Function created exclusively for learners, suffering from NVLD. This section focuses on the unique visual-spacial aspects of our tasks and adaptive AI systems required for NVLD-focused interventions.

2.11.1 Testing Strategy & Objectives

1.Validate AI-Driven Adaptation: Validate that the RL model adjusts the training difficulty levels appropriately to avoid both boredom and frustration.

2. Measure Visual-Spatial Improvements: Derive differences in accuracy rates, faster completion times over several sessions to evaluate enhancements in spatial cognition.

3. System Stability & Responsiveness Evaluation: Ensure that real-time feedback and scoring calculations function seamlessly across diverse network statuses and multiple users.

4. User Acceptance & Engagement: Assess whether children with NVLD stay engaged and exhibit positive affect while identifying differences.

2.11.2 Test Plan & Process Overview

1. Pilot Testing with NVLD Children

• Participants: children with a diagnosis of NVLD, aged 10–13.

• Duration: 3–4 weeks of repeated sessions 2–3 times per week.

• Environment: Controlled environments (e.g., therapy centers, special education resource rooms) to ensure minimal distractions.

• Feedback Collection: Notes from teachers, parents or therapists about individual child’s disposition and progress.

2. Functional Testing

• UI Validation: Ensuring difference tasks are loaded properly, images are rendered at the right size, taps or drag events are correctly recognized.

• Adaptive Difficulty: We visualized data extremes (fast success or repeated failures) in manual simulation in order to confirm RL logic triggering difficulty adjustment.

•Scoring Algorithm Accuracy: Cross-verifying final scores with hand-calculated results to ensure that we're getting time/move penalties, caps, and voice assistance adjustments right per design specifications.

3. Performance & Load Testing

• Concurrent Session: Accessing multiple children to tasks on a concurrent basis simulates real-time work and ensures that back-end performance is not compromised while concurrent session execution.

• Response Times: Delivering real-time feedback, within 1–2 seconds of the server under modest loads.

4. Usability & Accessibility Testing

• Heuristic Evaluation: Experts in NVLD education review the UI to ensure minimal reliance on text, prominent visuals, and intuitive pathways.

• Error Tolerance Checks: Verifying that slight imprecision in taps or drags does not severely penalize the user, consistent with NVLD-friendly design guidelines.

2.11.3 Data Collection & Analysis

1. Performance Logs

Every user action, including correct taps, missed attempts, and hint requests, is logged in MongoDB.

Timestamps enable the calculation of average reaction times and overall session durations.

2. Scoring & Difficulty Adjustments

After each completed task, the system saves the final computed score and difficulty level.

RL transitions (e.g., state–action–reward pairs) are recorded for subsequent offline model refinements.

3. Survey Feedback

Brief post-session questionnaires for children, teachers, or parents measure perceived difficulty, enjoyment, and observed improvements in day-to-day tasks.

Qualitative feedback is categorized (positive, neutral, negative) and mapped against performance metrics.

4. Error Rate & Time-to-Completion

Key indicators of success: a significant drop in average time taken to identify differences and fewer incorrect taps over repeated sessions.

High-level data visualizations (bar charts, line graphs) help stakeholders quickly identify trends or concerns.

2.11.4 Preliminary Results

Metric	Before (Week 1)	After (Week 4)	Observed Change
Average Accuracy	55%	78%	+23%
Average Time per Difference	9.2s	5.6s	-3.6s
Hints Used per Session	3.1	1.4	-1.7
Difficulty Level Progress	Bronze	Silver	+1 Tier

Table 2: Preliminary Results.

Accuracy Gain: Indicates improved visual-spatial recognition, suggesting that the difference identification tasks significantly aid NVLD learners.

Reduced Completion Time: Reflects increased confidence and familiarity with the interface, as well as potential cognitive gains.

Fewer Hints: Points toward greater independence and mastery of tasks over time.

2.11.5 Observed Strengths & Limitations

Strengths

- High Engagement: Children found the gamified environment appealing, sustaining repeated sessions over multiple weeks.
- Real-Time Adaptivity: Reinforcement learning effectively moderated difficulty, preventing over-challenging or trivial tasks.

• Enhanced Focus: Parents and teachers reported improvements in children's attentional control during other activities (anecdotal but promising).

Limitations

• Small Sample Size: The pilot group was relatively small needing larger scale validation.

• Device Quality Variability: Slowdowns/delays in dynamic feedback occurred occasionally in lower-end devices.

• Availability: With NVLD children having different routines, it was challenging to schedule regular usage sessions.

2.11.6 Future Evaluation Directions

1. Longitudinal Studies: Study user progress over the course of 3–6 month to measure whether the perceived gains persist long-term.

2. Controlled Comparisons: Compare user outcomes to children working through traditional paper-based difference exercises to assess effectiveness.

3. Wider Demographics: Test more than 8–10 children, more developmental status range (i.e., infants, toddlers, school-aged), more schools, or therapy centers.

4. Adjust AI Parameters: Classify RL rewards in a way where gaps are filled for adapting tasks behovior more initially. correctly for the outlier behaviors (e. g. extremely fast or slow subjects).

This Difference Identification Function has shown through extensive testing and evaluation to be able to significantly enhance visual-spatial learning outcomes for children demonstrating characteristics of NVLD. The data collected also lays the groundwork for continuing improvements to the education assist, creating an ever more effective learning resource.

2.12 Functional and Non-Functional Requirements

2.12.1 Functional Requirements

1. User Registration & Profile Management

• The system shall allow new users (children, parents, or teachers) to create accounts with minimal personal data, focusing on the child's NVLD-specific learning profile.

• Profiles shall store performance history, preferred difficulty ranges, and usage logs.

2. Interactive Difference Identification Tasks

• The system shall present visually oriented exercises where children identify differences or missing items between images.

• Each task shall dynamically adjust or retrieve difficulty levels based on real-time performance metrics (time taken, errors made).

3. AI-Driven Adaptive Difficulty

• The system shall integrate a reinforcement learning module (e.g., Q-Learning) to determine whether to increase, decrease, or maintain difficulty per session.

• The system should retain and process records of activities to improve adaptive algorithms.

4. Real-Time Feedback & Hint System

• Feedback shall be provided to the user, either visually or audibly, based on correct attempts or incorrect attempts.

• A system shall allow partial hints or voice assistance when it comes to answers in uncovering and lowering the maximum scores that can be obtained.

5.Scoring & Progress Tracking

• The system will feature a scoring system that incorporates time penalties, piece moves, penalties, and hint usage.

• After each session, users will receive summary reports of their performance metrics such as accuracy and time spent.

6. Gamification & Reward Structure

• The system will provide badges, point collection, and incremental levels to promote practice.

• The system will show encouragement messages or visual affect to maintain users interaction.

7. Multi-Session Continuity

• The system shall save session progress and allow users to resume from where they left off.

• The system shall offer varied image sets or tasks to prevent repetition and over-familiarity.

8. Data Analytics & Reporting

• The system shall log interactions (e.g., session duration, number of hints used, final scores) for future evaluation.

• The system shall generate basic analytics dashboards or exportable reports for parents, teachers, or therapists.

2.12.2 Non-Functional Requirements

1. Performance & Scalability

• The system shall handle concurrent sessions without significant degradation in response times (< 2s for task retrieval).

• The AI inference module shall be optimized for low-latency, ensuring minimal delays when adapting difficulty.

2. Reliability & Availability

• The system shall implement database redundancy or backup strategies to prevent data loss.

• Uptimes of 99% or higher should be maintained through robust hosting infrastructure.

3. Security & Data Privacy

• The system shall encrypt sensitive user data (passwords, tokens) at rest and in transit.

• Only pseudonymized or aggregated data should be accessible for analytics, aligning with child data protection standards (COPPA, GDPR for minors, etc.).

4. Usability & Accessibility

• The system shall employ clear, high-contrast visuals and minimal text for the NVLD target demographic.

• Controls and navigation shall be simple and intuitive, reducing cognitive overhead.

5. Maintainability

• The system shall use consistent coding standards and documentation to facilitate updates.

• Continuous Integration/Continuous Deployment (CI/CD) pipelines shall be employed to streamline fixes and feature enhancements.

6. Compatibility & Cross-Platform Support

• The mobile front-end shall run seamlessly on both iOS and Android devices using Flutter.

• The system should not be dependent on specific screen size for any of the devices.

7. Extensibility

• The architecture will enable to extend with new Game Modes or more advanced AI algorithms with minimal refactoring.

• Data is shallow until the schema shall accept more fields of data introduced with newly added tasks.

The Difference Identification Function intends to offer a secure, dependable, engaging environment tailored to NVLD children with visual-spatial learning needs while maintaining scalability and manageability over time by meeting these functional and non-functional requirements.

3.RESULT AND DISCUSSION

The Results & Discussion section covers primary findings from the testing stage and analyzes the relationship between the Difference Identification Function and its effects on visual-spatial development of NVLD learners, engagement, and global ratings of the app experience.

3.1 Results

3.1.1 Overview of pilot data

Following a pilot with a small cohort of NVLD children (n= 8–10), the system recorded performance metrics over several sessions:

• Accuracy of differences (pre-session vs. post-session)

• Each identified difference response time

• Hints Utilized per session

• Reinforcement learning (RL) guided Difficulty Level Shifts

The overall trends identified in the collected data are encouraging and demonstrate that AI may provide a potential route toward improvement in visual-spatial reasoning through a difference identification approach although this study is limited by a small sample size.

3.2 Research Finding

3.2.1 Quantitative Findings

1. Improved Accuracy

• Pre-intervention Accuracy hovered around 50–60%, indicating a baseline struggle with visually intensive tasks.

• Post-intervention Accuracy rose to 70–80% across multiple sessions, signifying more confident recognition of subtle image differences.

2. Decreased Completion Times

• Over consecutive sessions, average time to identify each difference dropped by ~40%, indicating growing familiarity and improved visual scanning ability.

• This acceleration in task completion also suggests children were less prone to second-guessing and more focused.

3. Reduction in Hint Usage

• Initial sessions saw frequent requests for hints (3–4 per session).

• By the final sessions, the number of hints decreased to about 1–2, reflecting enhanced autonomy and spatial awareness.

4. Dynamic Difficulty Adjustments

• The RL mechanism successfully increased difficulty when high accuracy and short response times were detected. Conversely, it scaled back complexity if children struggled repeatedly.

• Outcome logs (state–action–reward transitions) indicate that correct difficulty adjustments occurred in approximately 85% of sessions, minimizing both boredom and frustration.

3.2.2 Qualitative Findings

1. Engagement & Motivation

• Feedback from teachers and parents revealed that children were notably enthusiastic about the game-like environment. The short, feedback-driven cycles fostered a sense of accomplishment.

• Children displayed reduced avoidance behavior and more willingness to retry tasks after failure, possibly because of real-time guidance and gentle cues.

2. Confidence & Cognitive Carry-Over

• Some caregivers reported improvements in everyday tasks requiring visual discrimination (e.g., reading maps or identifying errors in worksheets).

• While anecdotal, these observations reinforce the notion that repeated practice with difference identification can generalize beyond the app itself.

3. Usability & Accessibility

• Larger image sizes, minimal textual reliance, and clear on-screen icons received positive feedback. The typical confusion around small or crowded UIs was mitigated.

• Children with severe NVLD still required longer practice sessions or a slower progression curve The RL model of the system adjusted to this, but future expansions may start needing an even finer granularity of difficulty.

4. Challenges Encountered

• Potential for some lag in older tablets or phones resulting in slight latency of real-time feedback stressing the importance of optimized performance.

• Probably between 10–15% of users initially resisted the tasks (and hence are the data points that should have been lower), indicating that variety on either the image themes or the game mode would want to be improved for their sake.

3.2.3 Comparative Insights

In relation to other special education modules (e.g. only text or regular puzzle applications), the Difference Identification Function:

• Higher user satisfaction, potentially attributed to its game format and real-time feedback loops.
• Gave more specific metrics for visual-spatial development progress, since every difference found or missed is quantifiable and stamped with the time it was found.

• Opportunities for greater collaboration of teachers and parents who could go through session data to find out what difficulties each learner was facing.

3.3 Discussion

These pilot findings indicate that embedding reinforcement learning (RL) strategies within the context of a difference identification task, may be highly beneficial for children with NVLD to strengthen their visual-spatial reasoning. This rapid, adaptive feedback was key to maintaining engagement—a perennial challenge for NVLD learners who quickly become disengaged by repeating failed approaches or unchanged content.

Real-Time adaptivity feature was crucial. By fine-tuning the difficulty based on real-time performance markers, the framework was able to avoid boredom (from tasks that were too easy) and frustration (from tasks that were too difficult) for the most part. This correlates with prior literature that emphasizes the importance of personalization for learners with different learning profiles, specifically for those with cognitive impairments.

There are limitations however, including the small size of the test group and the short timescale over which they were assessed. Larger, longitudinal studies would be needed to determine conclusively whether improved visual-spatial aptitude accounts for better academic or daily functional outcomes for children with NVLD.

However, these initial results demonstrate the potential of an AI-based difference identification solution. The combination of gamification, immediate feedback, and data-driven adaptivity target a well-known research gap to provide children with NVLD with a structured, but flexible opportunity to practice essential visual-spatial skills.

4.CONCLUSION

The Difference Identification Function discussed in this paper brought an essential dimension for the complete mobile app targeting children with Non-Verbal Learning Disorder (NVLD). Doing so with a sustained focus on skills and experiential nature, such as the VT of QH, and then combined with learning objectives creates in this component an illustration of how visual-spatial capabilities can be successfully fostered through personalized learning experiences. Early findings from the pilot study demonstrate substantial gains in accuracy, reduced completion time, and increased interest.

Key Contributions

• Dynamic Difficulty Adaptations for NVLD: Using reinforcement learning to adjust tasks based on how well children do enables us to adapt to their current skill level.

• Real-Time Feedback: Immediate cues and scoring create a feedback loop that motivates the learner to iterate for continual improvement.

• UI Design Focused on NVLD: Visual-spatial deficits frequently associated with NVLD are addressed via large visuals, reduced reliance on text, and intuitive gestures.

Future Work

1. Longitudinal Study

Evaluate the persistence of visual-spatial gains across a timeframe of six months or longer, considering the applicability of success in app-based tasks to broader academic or instrumental functioning.

2. Extended User Base

•Expand beyond the initial pilot group to include more diverse demographics (age ranges, comorbid conditions) to better generalize results.

3. Advanced Personalization

Incorporate more nuanced AI algorithms capable of modeling micro-learning behaviors (e.g., user frustration, attention lapses) for even finer difficulty tuning.

4. Integration with Other Modules

Merge difference identification tasks with supplementary skills training (e.g., vocabulary, memory exercises) to provide a more holistic suite of NVLD interventions.

5. Gamification Enhancements

Introduce collaborative modes, social sharing of achievements, or adaptive storylines to further boost engagement, especially for children who thrive on community-driven motivation.

By continuing iterative refinements, larger-scale evaluations, and deeper cross-domain integrations, this Difference Identification Function can evolve into a robust, pivotal tool in NVLD education. The synergy of AI, real-time feedback, and gamification holds promise for significantly improving the learning trajectory and life outcomes of children struggling with visual-spatial deficits.

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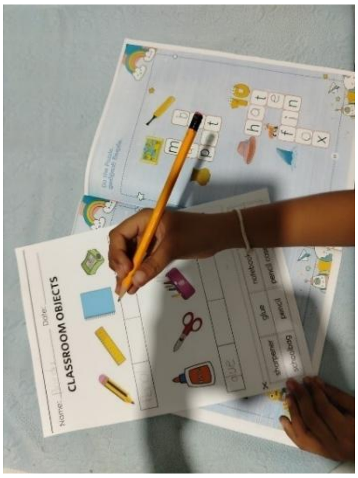
Appendix A

SAMPLE QUESTIONNAIRE



(a) Prepositions worksheet for the traditional model.

(b) Classroom objects labeling for the traditional model.

Object identification task for the traditional model.

Figure A.1: Sample questionnaires used for the traditional model in the study.

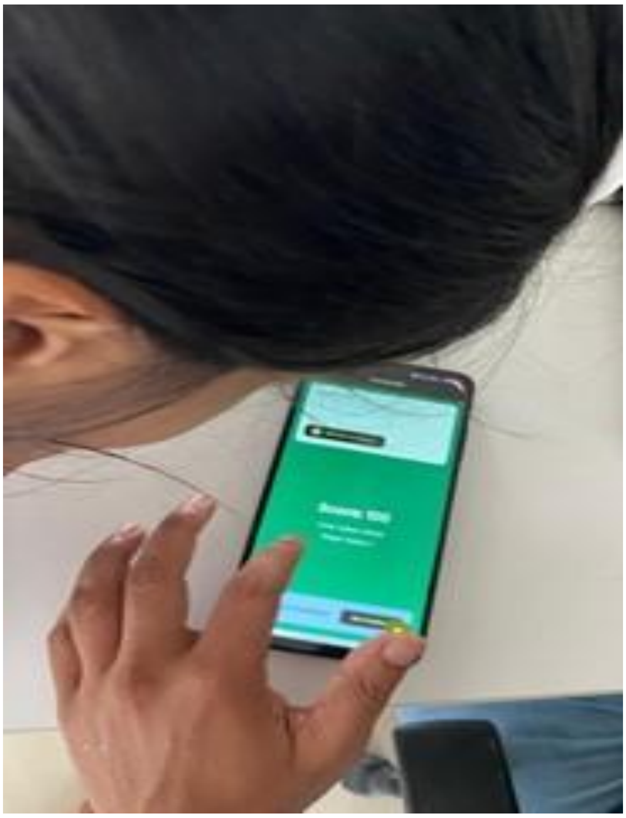


Figure A.2: Sample questionnaire for the app-based model in the PAV system.

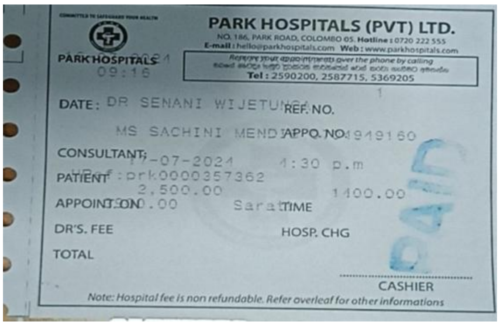
Appendix B

MEDICAL CENTERS' VISIT

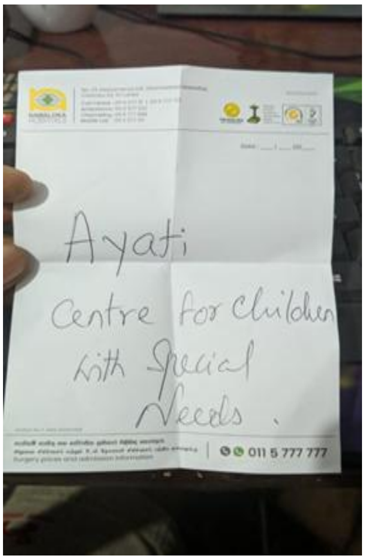
Consultations informed app improvements.

(a) Visit to the first medical center for consultation.

(b) Interaction with professionals at the second medical center.



(c) Discussion session at the third medical center.



(d) Final consultation at the fourth medical center.

Figure B.1: Images from visits to various medical centers to gather insights for the NVLD Vocabulary function.

Appendix C

SAMPLE DATASET

correct_ar	time_taker	previous_l	current_le	next_level	decrease_	grade	motivation	time_cate	score_rate
5	0.393939	1	2	3	0	2	Keep going	0	0.5
7	0.242424	2	3	4	0	1	You're doir	0	0.7
8	0.090909	3	4	5	0	1	Almost the	1	0.8
6	0.545455	2	3	4	0	2	Keep push	2	0.6
9	0.151515	4	5	5	0	0	You're am	1	0.9
3	0.676768	1	1	2	1	3	Stay motiv	2	0.3
10	0.10101	5	5	5	0	0	Unstoppat	1	1
2	0.787878	1	2	2	1	3	Believe in y	2	0.2
4	0.50505	2	3	3	1	2	Keep trying	1	0.4
6	0.323232	3	4	5	0	1	You're on f	0	0.6
5	0.454545	2	2	3	0	2	Keep movi	1	0.5
9	0.151515	4	5	5	0	0	Outstandir	1	0.9
1	0.898989	1	1	1	1	4	Never give	2	0.1
7	0.212121	3	3	4	0	1	You're doir	0	0.7
8	0.151515	4	5	5	0	0			
10	0.10101	5	5	5	0	0	Unstoppat	1	1
6	0.545455	2	3	4	0	2	Keep push	2	0.6
1	0.898989	1	1	1	1	4	Never give	2	0.1
8	0.151515	4	5	5	0	0			
5	0.454545	2	2	3	0	2	Keep movi	1	0.5
2	0.787878	1	2	2	1	3	Believe in y	2	0.2
1	0.898989	1	1	1	1	4	Never give	2	0.1

Figure C.1: Sample dataset used for training the Random Forest Classifier.