Comprehensive Interactive Learning Assistant for Indian Geography and Culture

Rajveer Yaduvanshi[1], Amisha Balwani[2], Hardik Sardana[3], Yatharth Jain[4]
[1,2,3,4]*Department of Electronics and Communication Engineering Netaji Subhas University of Technology, New Delhi, India*

***Abstract*—The teaching of geography, particularly the political geography of India, is often limited to passive learning methods such as textbooks and rote memorization, which result in low engagement and poor long-term retention. This paper presents the design and implementation of an interactive, multisensory educational system that integrates embedded hardware with evidence-based learning strategies to enhance student engage- ment and retention. The proposed system utilizes an ESP32-based architecture combined with a keypad interface, LED-based geo- graphic map, LCD display, and audio output module. It operates in two primary modes: a learning mode, which provides real-time visual, textual, and auditory information about states and union territories, and a quiz mode, which employs retrieval-based learning techniques to reinforce knowledge through active recall and immediate feedback. The system incorporates principles of multisensory learning and retrieval practice, both of which have been shown to significantly improve long-term memory retention and cognitive performance. Research indicates that retrieval- based learning strategies outperform traditional study methods in enhancing recall and understanding, while multisensory engagement strengthens neural encoding through simultaneous activation of multiple cognitive pathways. Experimental usage of the system demonstrates improved user engagement, faster recall, and better retention of geographic information. The integration of data collection and performance tracking further enables analysis of user learning patterns, supporting adaptive and personalized learning experiences. The proposed system represents a cost- effective and scalable solution that bridges the gap between traditional educational tools and modern interactive learning technologies, thereby contributing to advancements in embedded educational systems.**

***Index Terms*—Interactive Learning; Multisensory Learning; ESP32; Embedded Systems; Assistive Educational Technology; Retrieval Practice; Quiz-Based Learning; Human-Computer In- teraction; Educational Technology; Adaptive Learning Systems.**

I. INTRODUCTION

Geography education plays a critical role in developing an understanding of spatial relationships, cultural diversity, and socio-political structures. However, conventional methods of teaching geography often rely on static representations such as textbooks and maps, which do not actively engage learners. As a result, students frequently struggle with memorization and long-term retention of geographic information. Recent advancements in educational psychology and cognitive sci- ence emphasize the importance of interactive and multisen- sory learning environments. These approaches engage learners through multiple sensory channels and active participation, leading to improved comprehension and retention. The in- creasing integration of embedded systems in education has enabled the development of interactive learning devices that combine hardware and software to create engaging learning experiences.

Problem Statement: Despite technological progress, a significant portion of educational tools still rely on passive learning paradigms, characterized by one-way information delivery. Such approaches present several limitations:

- Low learner engagement
- Limited accessibility for diverse learning styles
- Poor retention of information over time
- Lack of immediate feedback mechanisms

Proposed Solution: To address these challenges, this work proposes an interactive embedded educational system designed to enhance geography learning through multisensory engage- ment and active participation. The system integrates:

- A physical map of India with LED indicators
- A keypad-based input interface
- A 16×2 LCD display for textual information
- An audio output system for spoken content
- Two operating modes, learning and quiz for feedback

II. LITERATURE REVIEW

The design and implementation of the proposed educational system is grounded in established pedagogical frameworks and cognitive science principles. In particular, three domains of research are highly relevant: multisensory learning, ac- tive learning and retrieval practice, and assistive educational technologies. Existing literature in these domains provides strong empirical support for the effectiveness of interactive, multimodal learning systems in improving comprehension, engagement, and long-term retention.

III. SYSTEM ARCHITECTURE

A. Overall System Design

The system consists of input, processing, and output mod- ules. User inputs are processed by the ESP32, which triggers audio playback and visual feedback.

Input Layer → Processing Layer → Output Layer

- Input Layer: Handles user interaction through a keypad matrix
- Processing Layer: Executes system logic using the ESP32 microcontroller
- Output Layer: Delivers feedback via LEDs, LCD display, and audio output

The ESP32 microcontroller serves as the central processing unit due to its dual-core architecture, high processing capa- bility, and extensive GPIO support, making it suitable for real-time interactive applications. Research on ESP32-based educational systems highlights its effectiveness in enabling interactive learning environments and enhancing student en- gagement through embedded platforms

In learning mode, the user selects a state/UT via the keypad. The system activates the corresponding LED. Relevant Infor- mation is displayed on the LCD. Audio narration is played. This sequence ensures: Visual reinforcement (LED), Textual support (LCD) and Auditory explanation (speaker).

In quiz mode, the user selects a quiz category. A question is displayed on the LCD.The user inputs an answer via keypad The system evaluates the response and feedback is provided instantly.

1) Correct answer → Positive confirmation
2) Incorrect answer → Correct answer displayed

Immediate feedback is critical for reinforcement learning, as it helps correct misconceptions and strengthens knowledge retention.

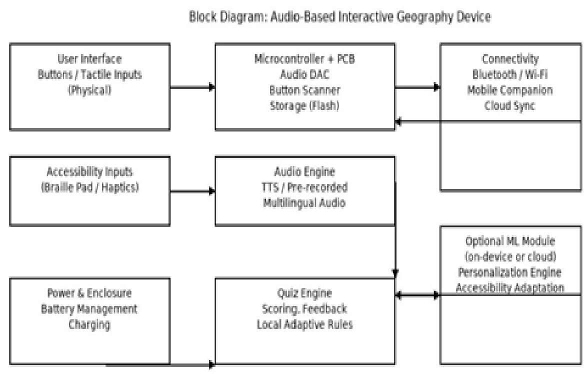

Fig. 1. System Block Diagram

B. Hardware Design

Key components include:

- ESP32 Microcontroller
- DFPlayer Mini Audio Module
- 16x2 LCD Display
- Matrix Keypad
- Shift Register (74HC595)

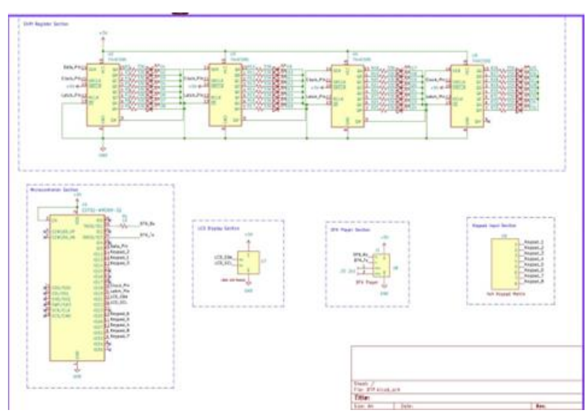

Fig. 2. Schematic diagram

C. Software Architecture

The software architecture is designed using a modular and state-driven approach, ensuring efficient execution and maintainability. The control logic module Implements system behavior using a finite state machine (FSM). The primary states include Idle state, Learning mode, Quiz mode and a feedback state. FSM-based design is widely adopted in embedded systems for managing deterministic and real-time operations.

IV. METHODOLOGY

The system operates as follows:
1) Power ON initialization
2) Mode selection (Learning / Quiz)
3) Audio playback or question display
4) User input and evaluation
5) Score calculation and display
6) Data Collection and Analysis using Machine Learning

V. DATA COLLECTION AND MACHINE LEARNING ANALYSIS

To evaluate the effectiveness of the proposed interactive learning system, a structured dataset was generated based on user interactions with the device. A total of 100 geography- related questions were initially prepared and organized with unique identifiers. From this pool, a subset of 10 representative questions was selected and repeatedly administered across 10 independent sessions to simulate consistent user engagement. During each interaction, the system automatically recorded key parameters including the selected response, correctness of the answer, and the response time for each question. These inputs were logged in a structured format (CSV/Excel), enabling systematic analysis of user behavior and performance patterns.

The collected dataset provided insights into how users interact with the system, particularly in terms of accuracy and cognitive response time. This data was further processed using basic machine learning techniques to extract meaningful patterns.

Three primary analytical approaches were applied:
- Accuracy Analysis: Accuracy per state Accuracy by state pertains to assessing how accurately users answer questions related to each specific state. For each state, the count of correct responses is divided by the total attempts made for that state, yielding a percent- age of accuracy by state. This metric assists in determining which states' ques- tions are more easily understood by users and which states repeatedly generate confusion
- Confusion Matrix: This confusion matrix visualizes how users answered state-based questions by mapping

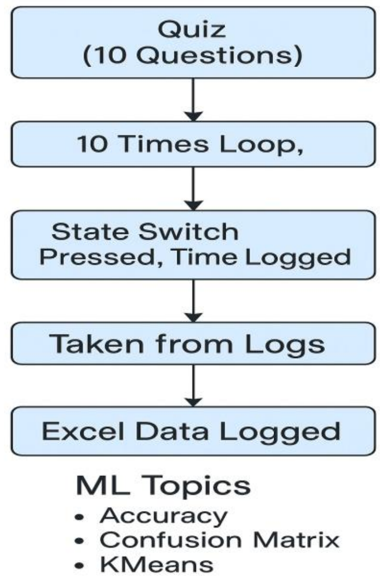

Fig. 3. Quiz and Data analysis flow chart

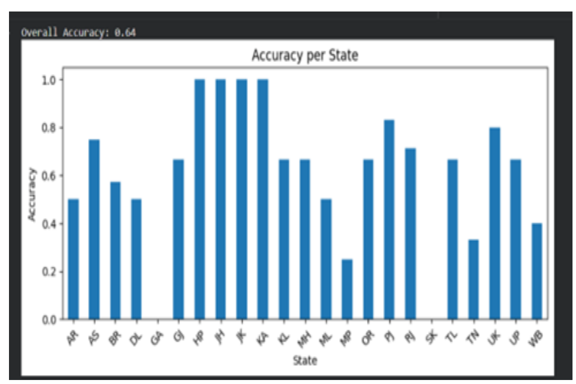

Fig. 4. Accuracy per state analysis

the actual (correct) state against the 28-state selected by the user. The darker diagonal cells indicate correct responses, showing that many states were identified ac- curately multiple times. The lighter off-diagonal cells represent misclassifications, highlighting specific cases where one state was confused with another (for example, geographically or linguistically similar states).

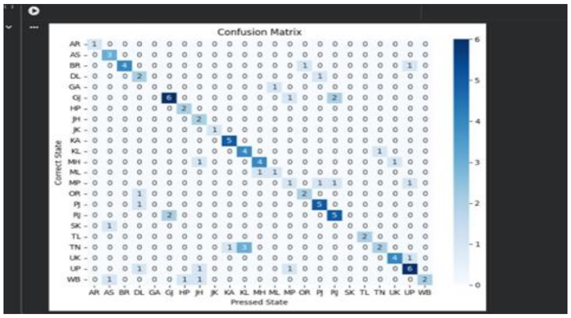

Fig. 5. Confusion Matrix

- K-Means Clustering: Response time for each state and the difficulty clusters were examined collectively to evaluate the comparative difficulty of questions based on state. The average response time for each state was determined using logged timestamps, with longer times signifying increased cognitive effort. Using machine learning methods, states were categorized into two dif- ficulty clusters Difficulty cluster 1 for states that had quicker response times (easier to address) and Difficulty Cluster 2 for states that had slower response times (more chal- lenging). This clustering effectively differentiated between simple and difficult states and facilitated analysis of content based on performance

	question_id	correct_state	pressed_state	is_correct	response_time	difficulty_cluster
0	1	OR	DL	0	3.92	1
1	2	AS	AN	0	4.60	1
2	3	UK	UK	1	4.78	2
3	4	RJ	RJ	1	5.93	2
4	5	UP	MP	0	6.87	2

Fig. 6. Difficulty analysis and k-means clustering

This data-driven approach goes beyond simple right- or- wrong evaluation by providing deeper insights into user learn- ing behavior. It enables the identification of learning gaps, frequently confused concepts, and relative difficulty levels, thereby supporting the development of adaptive and personal- ized learning systems in future iterations.

VI. RESULTS AND DISCUSSION

The performance of the proposed system was evaluated using the collected interaction dataset. The analysis focuses on understanding user learning patterns through accuracy, response time, and confusion trends.

A. Discussion

The results demonstrate that the proposed system not only facilitates interactive learning but also provides valuable ana- lytical insights into user behavior. By combining performance metrics with machine learning techniques, the system enables a deeper understanding of how users learn, where they struggle, and how the learning process can be improved.

Such insights can be highly beneficial for educators and parents, as they allow for more personalized and adaptive teaching strategies tailored to individual learning needs.

VII. FUTURE WORK

At the higher level of development, the device can be expanded into a full interactive quiz system, with scoring and progressive leveling to en- gage learners in a gamified experience to promote active participation and knowledge retention. Additionally, the integration of machine-learning based analysis that utilizes performance logs will allow for personaliza- tion within the system to support individualized learners by evaluating their strengths and weaknesses, adjust- ing question to recommendations, and ad- justing for difficulty.

Lastly, accessibility features would support an even greater ability for inclusive experience: speech recognition for voice- based input for individuals with limited mobility; large tactile buttons for im- proved usability; support for multiple lan- guages to represent a broader range of language backgrounds; and customization audio output for dif- ferent environments and users. These modifications can convert the device into a learning platform that is robust, adaptable, accessible, and inclusive.

VIII. CHALLENGES AND LIMITATIONS

LEDs and switches we wanted, leading to a challenging and error-prone wiring process. Since the system needed to support several operating modes, we also wanted to assign different switches to operate each mode; this increased the hard- ware requirements. To address the limitation on available pins, we integrated shift registers into the design, which introduced additional complexity in both the circuit design and programming. If some kind of issue came up while debugging, it could lead to huge time waste trying to figure out where the wiring or pin map- ping was wrong, or the timing of the code wasn't matching the hardware. Power considerations became important as well; powering several LEDs at a time places a load on the supply. In addition to the technical challenges, we also faced chal- lenges with scalability and learning - as we expanded the project, it sometimes involved re-evaluating our strategies and making changes to parts of the design, and, along the way, we were learning new concepts, such as multiplexing and synchronization between hardware and software.

IX. CONCLUSION

This paper presents an interactive and inclusive learning system that enhances geography education using embedded systems and machine learning. The system demonstrates im- proved engagement and provides valuable insights into user learning patterns.

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