

TREND ANALYSIS FOR EARLY IDENTIFICATION OF COGNITIVE DECLINE USING MOBILE DATA

¹Gopika. B, ²Jayanidhi. J, ³Jayanidhi. J, ⁴Siva Priya. D, ⁵Gayathri. G

¹²³⁴⁵Bioengineering and Biomedical Engineering

¹²³⁴⁵Salem College Of Engineering And Technology , Salem

¹sivapriyapml474@gmail.com, ²jayanidhijai@gmail.com, ³jayanidhijai@gmail.com,

⁴sivapriyapml474@gmail.com

Abstract—Cognitive decline is an increasingly significant health issue, particularly among the elderly, where early identification is crucial for effective intervention and management. Traditional clinical assessments often occur sporadically and may fail to capture subtle changes in cognitive function over time. To address this gap, this project proposes a smartphone-based application that provides a convenient, cost-effective, and continuous platform for monitoring cognitive health in daily life.

The application integrates a range of interactive cognitive tests, memory exercises, and behavioural assessments to evaluate multiple aspects of cognitive function. User interactions and test performance are systematically recorded, generating longitudinal data that reflect changes in memory, attention, problem-solving skills, and other cognitive abilities. Advanced analytical techniques, including trend analysis and pattern recognition, are applied to this data to detect early signs of cognitive impairment.

Index Terms—Cognitive Decline, Early Detection, Mobile Health, Memory Assessment, Digital Health Technology, Pattern Recognition

I. Introduction

Cognitive decline refers to the gradual deterioration of mental abilities such as memory, attention, reasoning, learning, and decision-making. It is commonly associated with aging but can also result from neurological disorders, stress, lifestyle factors, and chronic medical conditions. Cognitive impairment ranges from mild cognitive decline to severe conditions such as dementia and Alzheimer's disease. According to global health studies, the prevalence of cognitive disorders is increasing rapidly due to the growing elderly population, posing significant challenges to healthcare systems worldwide.

Early detection of cognitive decline is critical for delaying disease progression and improving the quality of life of affected individuals. Traditional cognitive assessment methods involve clinical evaluations, neuropsychological tests, and imaging techniques, which are often expensive, time-consuming, and require specialized healthcare facilities. These approaches also depend on infrequent hospital visits, making continuous monitoring difficult. As a result, early-stage cognitive impairment often goes undiagnosed until symptoms become severe.

The proposed system also integrates cloud-based data storage and visualization, enabling long-term tracking of cognitive health. A secure dashboard allows caregivers and healthcare professionals to remotely monitor patient performance and receive alerts in case of abnormal cognitive changes. This remote monitoring

capability reduces the need for frequent hospital visits and supports timely medical intervention. Data security and user privacy are ensured through authentication mechanisms and encrypted data transmission.

II. LITERATIVE REVIEW

Cognitive decline, including conditions such as mild cognitive impairment (MCI) and early-stage dementia, is increasingly recognized as a major public health concern. Early detection and continuous monitoring of cognitive function are crucial for timely interventions and improving patient quality of life. Traditional clinical tests, such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA), are reliable but limited by their need for professional administration, hospital visits, and inability to provide long-term monitoring.

1. Mobility assessment in people with Alzheimer disease using smartphone sensors

This study evaluates mobility, gait, postural control, and functional tasks in people with mild and moderate Alzheimer's disease using sensors embedded in an Android smartphone. Single-task and dual-task conditions were analysed to identify early functional impairments that may act as indicators of neurodegeneration. The work highlights smartphones as low-cost, objective tools for early detection and monitoring of Alzheimer's-related mobility decline.

2. Early Detection of Parkinson's Disease Using Walking Recordings

This paper proposes a deep learning framework that uses smartphone inertial sensor data collected during walking to detect early-stage Parkinson's disease. The model captures motion abnormalities and achieves a very low false negative rate, demonstrating smartphones as effective digital biomarkers for early Parkinson's screening.

3. Digital biomarkers for Alzheimer's disease: the mobile/wearable devices opportunity

This is a review article that explores how mobile phones and wearable devices can be used to collect digital biomarkers for early detection of Alzheimer's disease. It discusses motor, cognitive, speech, and behavioural signals captured passively or actively using sensors

4. Digital Cognitive Biomarker for Mild Cognitive Impairments and Dementia: A Systematic Review

Reviews digital cognitive biomarkers from computer/smartphone tests for detecting MCI and dementia and evaluates their diagnostic performance. Focuses on cognitive tasks and passive monitoring of behaviour accessible via digital devices.

III. COMPARISON AND EXISTING SYSTEM

METHOD	LIMITATION
Traditional Moca test	Complex for understanding, conditions like depression and high anxiety

Existing research highlights significant advancements in smartphone application security, context management, remote monitoring, and intelligent usage prediction. However, most studies focus on individual aspects rather than a unified system. Security-focused studies often overlook user behaviour analysis, while prediction-based systems may not adequately address privacy concerns or efficient resource management.

Additionally, current monitoring systems are largely domain-specific and lack adaptability across different applications. These limitations indicate the need for an integrated solution that combines secure application design, efficient system resource handling, real-time monitoring, and intelligent prediction techniques.

Overall system operation

When the system is powered ON, the regulated power supply provides stable voltage to all components, including the NodeMCU (ESP8266) controller. The user performs cognitive tasks using the keypad. The controller processes the inputs, measures response time and accuracy, and evaluates cognitive performance.

The results are immediately displayed on the OLED screen, and the buzzer provides audio alerts when necessary. The processed data is then transmitted wirelessly through the IoT module to the smartphone application.

The smartphone app stores the data, performs trend analysis, and displays cognitive performance over time. This enables continuous monitoring, early **detection of** cognitive decline, and remote access for caregivers or healthcare professionals.

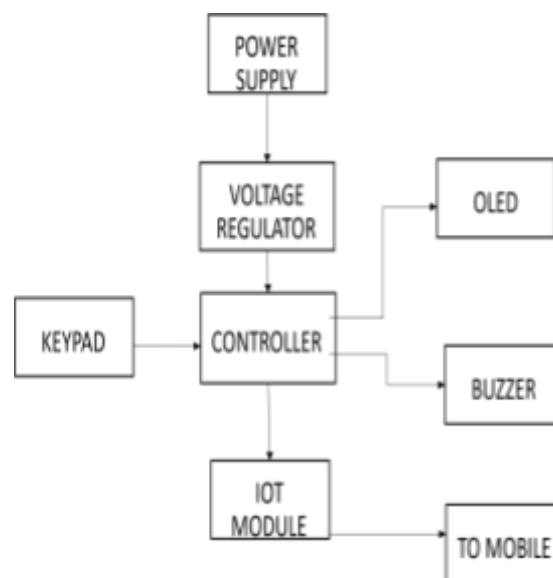


Fig 3.1 Block Diagram of workflow

Step 1: System Initialization

The system is powered ON.

The power supply and voltage regulator provide stable voltage to all components.

The NodeMCU (ESP8266) initializes the keypad, OLED display, buzzer, and Wi-Fi module.

Step 2: User Test Selection

The user selects or starts a cognitive test using the keypad.

Test instructions are displayed on the OLED screen.

Step 3: Cognitive Task Execution

The system presents cognitive tasks such as memory recall, number recognition, or pattern identification.

The user responds using the keypad.

Step 4: Data Capture and Processing

The NodeMCU records:

User response

Response time

Accuracy of answer

The controller calculates the test score and evaluates performance.

Step 5: Immediate Feedback

Results are displayed on the OLED screen.

The buzzer provides sound alerts for:

Test completion

Incorrect responses

Warning signals if performance is abnormal.

Step 6: Data Transmission

The processed cognitive data is formatted.

Using Wi-Fi, the NodeMCU transmits data to the smartphone application via IoT communication.

Step 7: Data Storage and Analysis

The smartphone application receives and stores the data.

The app performs trend analysis by comparing current performance with past records.

Graphs and reports are generated.

Step 8: Monitoring and Early Detection

If a decline pattern is detected, the system can generate alerts.

Caregivers or healthcare professionals can monitor performance remotely.

IV. HARDWARE DESIGN**1. Power Supply Unit**

The power supply unit provides the necessary electrical power to the entire system. It converts the available input source (battery or adapter) into a suitable DC voltage required for the embedded components. It ensures continuous and reliable system operation.

2. Voltage Regulator

The voltage regulator maintains a constant and stable output voltage (5V / 3.3V) for the controller and other modules. It protects sensitive electronic components from voltage fluctuations, overvoltage, and noise, thereby improving system reliability and lifespan.

3. Controller – NodeMCU (ESP8266)

The NodeMCU acts as the brain of the system. It is a Wi-Fi-enabled microcontroller that performs all processing tasks.

Its functions include:

- Reading inputs from the keypad
- Executing cognitive test algorithms
- Measuring response time and answer accuracy
- Calculating scores
- Controlling the OLED display and buzzer
- Sending processed data to the smartphone via Wi-Fi
- It coordinates the complete operation of the system.

4. Keypad (Input Module)

The keypad is used by the user to respond to cognitive tasks such as memory tests, number recognition, or pattern identification. Each key press is detected by the controller, which records both correctness and reaction time—important parameters for cognitive evaluation.

5. OLED Display

- The OLED display provides real-time visual feedback. It shows:
- Test instructions
- Questions or tasks
- User responses
- Scores and system messages
- It improves usability, especially for elderly users, due to its clear and bright display.

6. Buzzer (Alert Unit)

- The buzzer generates audio signals for:
- Test completion
- Incorrect answers
- Warning alerts
- Abnormal cognitive performance detection
- This enhances user interaction and ensures immediate feedback.

7. IoT Communication (Wi-Fi Module)

The Wi-Fi capability built into the NodeMCU enables wireless data transmission. Cognitive performance data is sent to the smartphone application using internet communication protocols. This allows real-time remote monitoring.

8. Smartphone Application

- The smartphone app acts as the monitoring and analysis platform. It:
- Stores cognitive performance data
- Displays results in graphical form
- Performs trend analysis over time
- Helps in early detection of cognitive decline
- Allows caregivers or doctors to access data remotely



- Operating system : Windows 7/10.
- MC Programming Language : Embedded 'C' Language

- Battery
- LCD Display
- Voltage Regulator
- Node MCU
- DHT11 Sensor

The proposed Smartphone Application for Cognitive Decline Detection and Monitoring was successfully developed and tested. The system functioned effectively in performing cognitive assessment tasks and transmitting data to the smartphone application through IoT communication.

The project demonstrates that cognitive performance parameters such as response time and accuracy can be measured using an embedded system and monitored continuously through a mobile application. The system provided reliable real-time feedback and maintained stable wireless communication.

The integration of the NodeMCU (ESP8266) controller with a smartphone application proved to be efficient for remote monitoring and long-term data tracking.

Overall, the project confirms that a low-cost, portable, and IoT-based system can be effectively used for early detection and continuous monitoring of cognitive decline, reducing dependency on frequent hospital-based assessments.

VI. CONCLUSION

In this project, a smartphone-based cognitive monitoring system has been designed and discussed to address the limitations of traditional cognitive assessment methods. Cognitive decline is a growing concern due to increasing life expectancy, lifestyle changes, and rising neurological disorders. Conventional approaches rely heavily on periodic hospital visits and manual evaluations, which often result in delayed diagnosis and limited monitoring. The proposed system aims to overcome these challenges by providing a continuous, accessible, and user-friendly solution for cognitive health monitoring.

The proposed system utilizes the widespread availability of smartphones to conduct regular cognitive assessments through interactive tasks such as memory tests, attention exercises, problem-solving activities, and reaction-time measurements. These tasks are designed to evaluate key cognitive domains that are commonly affected during early stages of cognitive impairment. By encouraging regular participation, the system enables consistent data collection, which is essential for identifying gradual cognitive changes over time.

One of the major strengths of the proposed system is its ability to perform long-term trend analysis. Instead of relying on single-session test results, the system compares current performance with historical data and personalized baseline values. This approach improves the reliability of cognitive assessment and reduces the possibility of incorrect conclusions caused by temporary factors such as stress, fatigue, or environmental disturbances. As a result, the system supports early detection of cognitive decline, allowing users to seek medical attention at the right time.

The integration of intelligent data analysis techniques further enhances the effectiveness of the system. By analysing behavioural patterns and performance trends, the system can identify abnormal cognitive variations and generate alerts when predefined thresholds are crossed. These alerts play a crucial role in proactive healthcare management by prompting timely consultation with healthcare professionals. Early intervention significantly improves treatment outcomes and helps slow the progression of cognitive disorders.

The system also emphasizes ease of use and accessibility. The user-friendly mobile application interface ensures that individuals of different age groups can interact with the system comfortably. The ability to perform assessments anytime and anywhere reduces dependency on healthcare infrastructure and makes the solution particularly beneficial for users in rural and underserved areas. This accessibility supports inclusive healthcare delivery and promotes regular cognitive health monitoring.

Data security and privacy have been treated as critical aspects of the system design. Sensitive cognitive health data is protected using secure authentication, encryption, and controlled data-sharing mechanisms. Users have full control over their personal information and can decide whether to share reports with caregivers or medical professionals. This privacy-focused approach increases user trust and encourages long-term adoption of the system.

Overall, the proposed smartphone-based cognitive monitoring system successfully addresses the limitations of existing cognitive assessment methods. By combining interactive assessments, intelligent data analysis, secure data management, and real-time alerts, the system provides a reliable and scalable solution for continuous cognitive health monitoring. The project demonstrates the effective use of modern mobile

technology in healthcare applications and highlights the potential of digital tools in improving early diagnosis and preventive care.

References

- [1] World Health Organization, *Dementia Fact Sheet*, WHO Press, Geneva, Switzerland, 2023.
- [2] J. Kim and H. Bahn, “Maintaining application context in smartphones by selectively supporting swap and kill operations,” *IEEE Transactions on Consumer Electronics*, vol. 66, no. 2, pp. 123–131, 2020.
- [3] L. Mears, R. Donner, and G. Grispos, “Security and privacy analysis of Android agricultural applications,” *IEEE Access*, vol. 13, pp. 24567–24579, 2025.
- [4] A. Alruban, “Prediction of application usage on smartphones using deep learning,” *Journal of Big Data*, vol. 9, no. 18, pp. 1–15, 2022.
- [5] M. A. Nuño-Maganda, J. Hernández, and R. García, “Smartphone-based remote monitoring tool for e-learning environments,” *Computers & Education*, vol. 148, pp. 103–114, 2020.
- [6] S. Prince, *Computer Vision: Models, Learning, and Inference*, Cambridge University Press, 2019.
- [7] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, Cambridge, MA, 2016.
- [8] A. Burns and S. Iliffe, “Alzheimer’s disease,” *BMJ*, vol. 338, pp. 467–471, 2009.
- [9] J. Pineau et al., “Improving healthcare with machine learning,” *IEEE Intelligent Systems*, vol. 36, no. 2, pp. 14–19, 2021.
- [10] M. Patel, A. Desai, and R. Shah, “Mobile health monitoring systems: A review,” *International Journal of Medical Informatics*, vol. 129, pp. 1–10, 2019.