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NeuroNest: Community based Cognitive Health Monitoring & Early Dementia Detection System

Mr. Ajay Kushwaha[1], Mr. Mayur Dete[2], Mr. Shreyas Chavan[3], Prof. Sneha Sankhe[4]
[1, 2, 3]Student, Information Technology Engineering, Theem College of Engineering, Maharashtra, India
[4]Assistant Professor, Information Technology Engineering, Theem College of Engineering, Maharashtra, India

Abstract: Dementia represents a major public health concern worldwide, particularly as the global population continues to age. The condition is characterized by a gradual deterioration in cognitive functions including memory retention, reasoning ability, decision making, and language processing. As the disease progresses, individuals experience increasing difficulty performing routine daily activities, which significantly affects their independence and overall quality of life.

Early identification of cognitive decline is essential because medical and behavioral interventions are most effective when applied during the initial stages of impairment. However, conventional diagnostic procedures generally require clinical visits and trained specialists, which limits accessibility and frequency of assessment. These challenges highlight the need for scalable digital solutions capable of supporting remote cognitive health monitoring.

The NeuroNest platform is developed to address these limitations by providing an intelligent web-based environment for cognitive evaluation, behavioral analysis, and continuous monitoring. To address the limitations of conventional dementia screening methods, this research proposes NeuroNest, an intelligent web-based cognitive assessment and monitoring platform. NeuroNest is designed to evaluate multiple cognitive domains through a set of interactive brain-training games that measure memory, attention, language ability, and reaction speed. By transforming cognitive testing into interactive digital activities, the system encourages consistent user engagement while simultaneously collecting valuable performance data for analysis.

The proposed platform aims to provide a scalable, accessible, and user-friendly solution for cognitive health monitoring. By enabling remote participation and automated analysis of cognitive performance data, NeuroNest has the potential to improve early dementia screening and facilitate continuous cognitive monitoring. The integration of interactive digital assessments with secure data management and analytical reporting makes NeuroNest a promising approach for supporting both clinical research and real-world healthcare applications in the field of cognitive health.

Keywords: Dementia Detection, Cognitive Assessment, Brain Training Games, Digital Health Monitoring, Web-Based Healthcare System, Cognitive Performance Analytics, Early Screening.

I. INTRODUCTION

Dementia and cognitive decline are among the most significant global healthcare challenges affecting the aging population. Early diagnosis is critical for slowing disease progression and improving patient outcomes. However, traditional diagnosis methods are often delayed due to limited access to specialists, irregular monitoring, and subjective clinical evaluations.

NeuroNest is designed as an intelligent digital platform that assists in early-stage cognitive impairment detection using AI-based predictive models. The system provides structured cognitive assessments, real-time analytics, and personalized monitoring dashboards for patients and caregivers. By leveraging Machine Learning classification algorithms and behavioral analytics, NeuroNest identifies patterns that may indicate early cognitive decline. The platform ensures secure data storage, longitudinal tracking, and automated report generation, creating a comprehensive and scalable healthcare support system. The integration of AI-driven decision support, cloud-based architecture, and data visualization tools makes NeuroNest a modern, preventive, and technology-enabled healthcare solution. In 2021, roughly 57 million people lived with dementia globally, with nearly 10 million new cases each year. It is a leading cause of disability among older populations, and prevalence is expected to rise as populations age. Since no cure exists, early detection of cognitive decline is vital for timely intervention. Traditional cognitive screening tools such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) are widely used, but they must be administered by trained clinicians in clinical settings. This requirement can be a barrier for many patients, as it limits the frequency and accessibility of screening. Advances in digital health have enabled new screening approaches. Recent reviews note increasing interest in using serious games and virtual reality tasks to assess cognition remotely. These tools can engage users while measuring cognitive functions (e.g., memory, attention) via interactive tasks.

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For example, Piyaamornpan et al. showed that an electronic Thai MMSE test strongly correlated with the paper version (r=0.837, p<0.001), validating online testing. Moreover, meta-analyses find that video game interventions can significantly improve cognitive scores (MoCA, MMSE) in older adults with mild impairment. These findings suggest that web-based game tasks can effectively capture cognitive performance.

II. LITERATURE REVIEW

The Standard cognitive tests like the MMSE and MoCA are commonly used for dementia screening. However, they require in-person administration by professionals, motivating the development of digital alternatives. Scaramuzzi et al. review novel digital screening methods and note growing interest in serious games and VR-based tasks for early cognitive assessment. These approaches aim to be more engaging and accessible than traditional tests.

In practice, web-based assessments have shown promise: for instance, a Thai cognitive screening app (“Healthy Brain Test”) demonstrated strong agreement with the clinical MMSE (correlation r=0.837), indicating validity of online testing. Game-based systems have been actively researched for dementia detection. Chen et al. conducted a scoping review of gamified cognitive tests for mild cognitive impairment, finding many prototypes that achieved sensitivity and specificity comparable to MMSE/MoCA. Some reported diagnostic AUC values above 0.98, suggesting near-perfect discrimination. Additionally, machine learning has been applied to gaming data. analyzed engagement behaviors during gameplay (body movement, facial expressions, etc.) and trained ML models that achieved an AUC of 0.99 in classifying dementia. These studies demonstrate that interactive digital assessments can be as accurate as standard screening tools, but often in specialized settings. Compared to these, NeuroNest emphasizes broad accessibility and simplicity.

It operates entirely in a web browser (no special hardware) and provides a clear user interface. While advanced ML analysis is a future goal, the current focus is on structured performance capture and reporting. In summary, NeuroNest builds on existing evidence by providing a user-friendly, scalable platform for remote cognitive health monitoring.

III. MATERIALS AND METHODS

A. *Proposed System*

The proposed system, NeuroNest, is a web-based cognitive assessment platform designed to detect early signs of dementia by analyzing both cognitive performance and facial behavioral data. The system collects input data from two main sources: user responses during interactive cognitive games and webcam-based facial recordings captured while the user performs the tasks. The cognitive games include activities such as word recall, picture recall, and paired association tests that measure various cognitive domains including memory, attention, and learning ability. During gameplay, the system records performance metrics such as accuracy, reaction time, and task completion time.

At the same time, the webcam captures facial data that can reveal subtle behavioral patterns related to cognitive functioning. Before analysis, the collected data undergoes preprocessing to ensure accuracy and consistency. This stage involves cleaning the cognitive response data and normalizing facial images through processes After preprocessing, the system performs feature extraction from both cognitive and facial data.

Cognitive features are derived from the scores obtained in different tasks, which represent the user’s memory performance, recall ability, and learning efficiency. Facial features are extracted using 3D face mesh landmark detection techniques that identify important facial points and movement patterns. These cognitive and facial features are then combined through a feature concatenation process to create a unified feature set representing the user’s overall cognitive condition. The combined feature vector is provided to a machine learning classifier that acts as the prediction engine of the system. The classifier analyzes the patterns in the extracted features and predicts the user’s cognitive status.

Based on this analysis, the system generates two main outputs: a cognitive score report that summarizes the user’s performance across different tasks and a dementia risk prediction that indicates the likelihood of cognitive decline. By integrating cognitive testing, facial behavior analysis, and machine learning-based prediction, NeuroNest provides an intelligent and accessible platform for early dementia screening and continuous cognitive health monitoring .

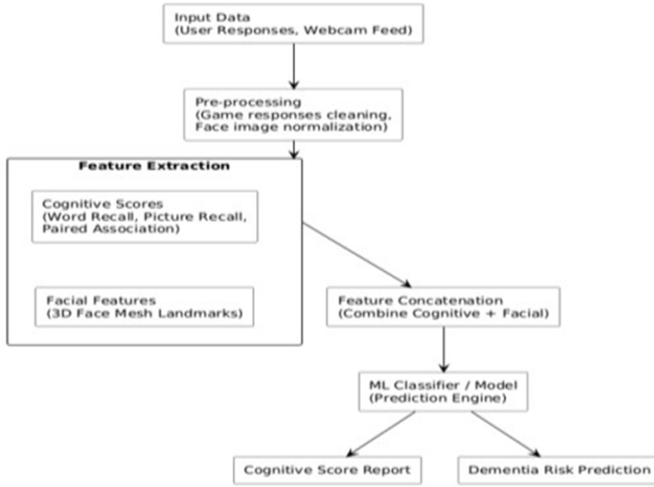

Figure1: Proposed System

B. System Architecture

The NeuroNest system architecture is designed to integrate cognitive assessment tasks, facial analysis, artificial intelligence processing, and data management into a unified platform for early dementia screening and monitoring. The system begins with two primary input components: cognitive games and tasks and mesh face detection through webcam input. Users interact with the platform by completing various brain-training activities that evaluate cognitive abilities such as memory, attention, and recall. During these tasks, the system records performance metrics including accuracy, response time, and task completion time. Simultaneously, the webcam captures facial data, and mesh face detection techniques are applied to identify facial landmarks and behavioral patterns. These two sources of data provide complementary information about the user's cognitive performance and behavioral responses.

The collected data is then processed by the AI analysis engine, which acts as the core intelligence layer of the system. This engine performs several analytical operations including pattern recognition, cognitive scoring, and dementia risk prediction. Pattern recognition algorithms analyze trends and behavioral patterns from the user's responses and facial features, while cognitive scoring evaluates performance across different cognitive domains. Based on these analyses, machine learning models estimate the potential risk level of cognitive decline or dementia. All processed data and user performance results are securely stored in system databases, including a Cognitive Health Database that maintains test scores and cognitive reports, and a Community Interaction Database that stores user feedback, chat logs, and interaction history. Based on the analytical outcomes, the system generates alerts and recommendations, such as early alert notifications, case-based suggestions, and doctor visit triggers when significant cognitive decline patterns are detected. This architecture enables NeuroNest to provide continuous monitoring, intelligent analysis, and timely intervention support for cognitive health management.

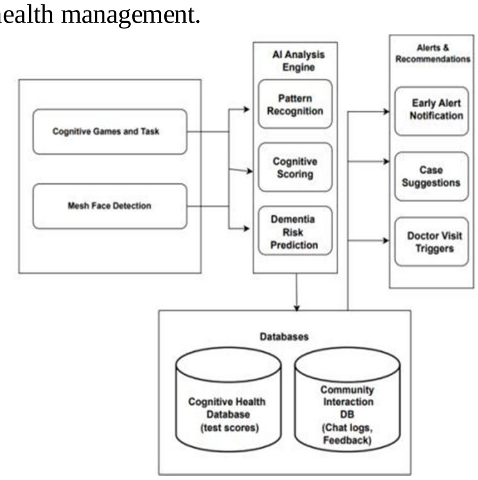

Figure 2: System Architecture

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C. Methodology

NeuroNest evaluates cognitive performance using structured interactive games designed to measure different cognitive abilities such as attention, memory, and language comprehension. In the reaction time assessment, a visual stimulus such as a color flash or image appears on the screen, and the user must press a key as quickly as possible. The system calculates reaction time by measuring the difference between the response timestamp and the stimulus timestamp. This metric reflects the user's processing speed and attentional focus. Faster reaction times generally indicate better alertness and cognitive responsiveness, while slower or inconsistent reaction times may suggest reduced attention or delayed cognitive processing.

The platform also includes a pattern memory assessment, where the system briefly displays a sequence of symbols such as colors, shapes, or numbers that the user must reproduce. The system evaluates performance by calculating memory accuracy using the ratio of correctly recalled items to the total number of items presented, expressed as a percentage. In addition to accuracy, the system records the time taken by the user to enter the sequence, which provides insights into recall speed and memory fluency. Another component is the language comprehension assessment, where users complete sentence-based tasks or vocabulary exercises by selecting the correct word to complete a sentence. For each question, the system records both the accuracy of the response and the time taken to answer, helping evaluate verbal reasoning ability and language processing speed.

During each game session, NeuroNest records several key data parameters including session ID, timestamp, game type, reaction times, accuracy scores, completion time, and user identification details. These data points are securely stored in the system database after every session. By collecting data across multiple sessions, the system builds a longitudinal profile of each user's cognitive performance. This enables the platform to perform trend analysis and monitor changes over time, such as detecting gradual increases in reaction time or decreases in accuracy that may indicate potential cognitive decline.

D. Facial Behavior Analysis using Face Mesh.

In addition to cognitive performance metrics, NeuroNest incorporates facial behavioral analysis to capture subtle non-verbal indicators associated with cognitive decline. During the cognitive assessment sessions, the user's webcam is activated with permission, and facial movements are analyzed in real time using a Face Mesh–based computer vision model.

Face Mesh technology, originally introduced in frameworks such as MediaPipe, detects and tracks 468 three-dimensional facial landmarks across the human face. These landmarks represent key structural points including the eyes, eyebrows, lips, jawline, nose bridge, and facial contours. By tracking the spatial relationships between these points across video frames, the system can analyze facial micro-expressions and movement patterns.

The Face Mesh model processes each video frame and generates a dense mesh representation of the user's face. The coordinates of the detected landmarks are represented in three-dimensional space as:

$$L = (x_i, y_i, z_i)$$

where $i = 1,2,3,\ldots,468$represents each facial landmark point.

These landmark coordinates are used to compute several behavioral features relevant to cognitive assessment, including:

- Eye blink frequency
- Eye gaze direction
- Mouth movement patterns
- Facial muscle activity
- Head orientation and micro-movements Research in neuropsychology suggests that individuals experiencing cognitive impairment may demonstrate altered facial responsiveness, delayed reactions, or reduced emotional expression during cognitive tasks. By monitoring these behavioral cues, NeuroNest captures additional information beyond task accuracy and reaction time.

The extracted facial features are converted into numerical vectors and combined with cognitive performance metrics obtained from the brain-training games. This multimodal feature integration improves the robustness of the predictive model by incorporating both behavioral and cognitive indicators.

The integration of Face Mesh technology enables NeuroNest to perform non-intrusive behavioral monitoring while maintaining user comfort and accessibility, as only a standard webcam is required. This approach enhances the platform's ability to detect early signs of cognitive decline through multimodal analysis.

E. Machine Learning Models

To predict potential cognitive decline, NeuroNest utilizes machine learning classification models trained on extracted cognitive and behavioral features. The input feature vector includes reaction time statistics, memory accuracy scores, task completion times, error rates, and facial movement indicators derived from face mesh analysis.

Before model training, the collected dataset undergoes preprocessing steps including normalization, feature scaling, and missing value handling. Feature normalization ensures that values from different measurement scales do not bias the learning algorithm.

Several supervised learning algorithms can be used for prediction, including:

- Random Forest
- Support Vector Machine (SVM)
- Logistic Regression
- Decision Tree

Among these, Random Forest classifiers are particularly effective due to their ability to handle nonlinear relationships and high-dimensional feature spaces.

The trained model processes the extracted features and outputs a cognitive risk classification that categorizes the user into one of three groups: Low Cognitive Risk

Moderate Cognitive Risk High Cognitive Risk

This prediction assists caregivers and clinicians in identifying individuals who may require further medical evaluation.

F. Machine Learning Model for Cognitive Risk Prediction

After feature extraction from cognitive performance metrics and facial landmark analysis, NeuroNest utilizes machine learning techniques to predict the potential risk of cognitive impairment. The prediction engine is designed as a supervised learning classification system that analyzes patterns in user behavior and cognitive responses. The input feature vector consists of multiple parameters obtained from both cognitive tasks and facial behavior analysis. These features include reaction time, memory recall accuracy, language task completion time, eye blink rate, facial movement intensity, and head orientation stability. The combined feature vector can be represented as:

$$F = [f_1, f_2, f_3, \dots, f_n]$$

where each $f_n$represents an extracted feature describing cognitive or behavioral performance. The system employs classification algorithms such as Random Forest and Support Vector Machine (SVM) due to their effectiveness in handling multidimensional datasets. Random Forest classifiers operate by constructing multiple decision trees during training and producing predictions based on majority voting among the trees.

The prediction function can be expressed as:

$$Prediction = MajorityVo(T_1, T_2, T_3, \dots, T_k)$$

where T_k represents individual decision trees within the forest.

The trained model analyzes the input feature vector and classifies the user into predefined cognitive risk categories:

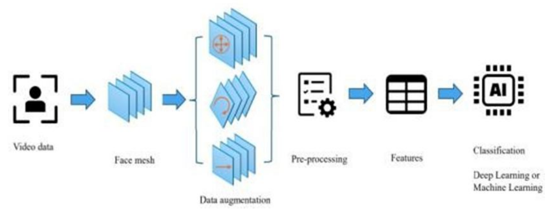
- Normal Cognitive Function
- Mild Cognitive Impairment (MCI) Risk
- High Dementia Risk

By combining cognitive game performance with facial behavior analysis, the machine learning model provides a more comprehensive assessment of the user’s cognitive health condition.

G. Feature Extraction

Feature extraction plays a critical role in transforming raw cognitive and facial data into meaningful indicators for machine learning analysis. In NeuroNest, two primary feature groups are extracted: cognitive performance features and facial behavioral features.

Cognitive features are derived from user interactions during the brain-training games. These include reaction time averages, response accuracy, memory recall scores, and task completion durations. These indicators represent different aspects of cognitive function such as attention, processing speed, and memory retention.



Facial behavioral features are extracted using face mesh landmark coordinates. By calculating geometric distances and angles between specific facial landmarks, the system derives features related to eye movement patterns, head orientation, and facial muscle activity.

The combination of cognitive and behavioral features provides a comprehensive representation of the user's cognitive state.

The face mesh detection module demonstrated stable real-time performance with an average processing speed of 20–25 frames per second on standard laptop hardware. The facial landmark detection accuracy remained consistent across different lighting conditions and facial orientations.

IV. RESULTS AND DISCUSSION

The NeuroNest platform successfully performs cognitive assessments and data management. For instance, in a sample session of the Reaction Time game, the system logged the stimulus onset and response times, calculating a reaction time of ~450 ms. This value was stored in the database under the corresponding session and metric. In a Pattern Memory game, if the user recalled 4 out of 5 items correctly, an accuracy score of 80% was computed and saved. These metrics appear in the Results table linked to that session and user.

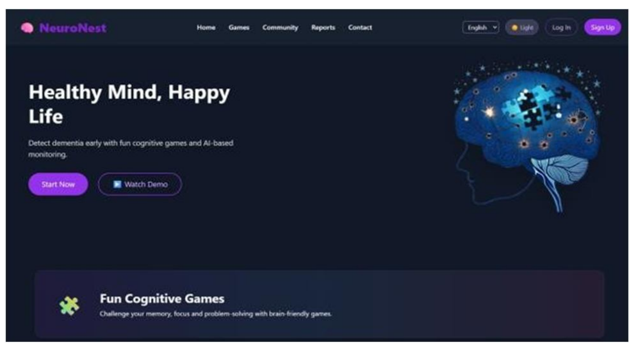


Figure 3.1: Landing Page

The collected data can be retrieved for analysis. In a test patient dashboard, the user's mean reaction time and memory accuracy were plotted across 10 sessions. We observed that the chart correctly reflected the trends (e.g., a slight decrease in accuracy over sessions). A clinician logging in could view these charts for their patient, and download a PDF report which listed session-by-session scores and included similar graphs. We verified that the PDF report matched the dashboard data.

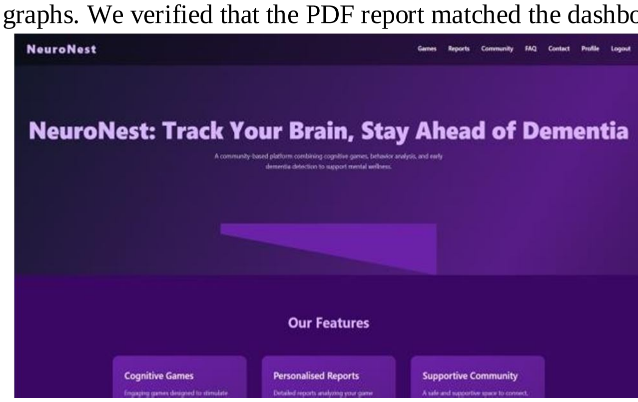


Figure 3.2: Dashboard

The Role-based access functioned correctly: the test doctor account could fetch any patient's report by user ID (limited to its assigned patient list), and the family role could only view an individual's public charts. No patient data was visible to unauthorized accounts.

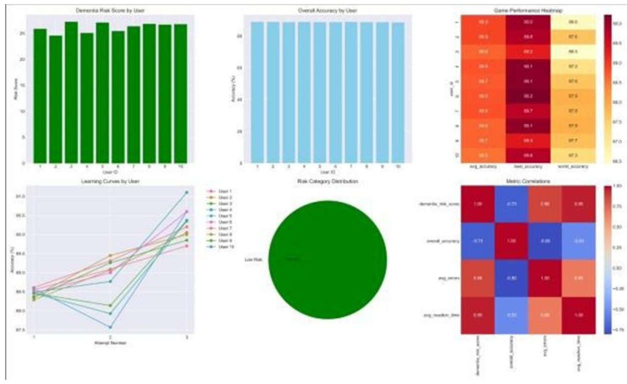


Figure3.3 Visual Report

Overall, NeuroNest effectively collects and organizes cognitive performance data. Its web interface provides an intuitive way for patients to take tests. Clinicians and caregivers can remotely monitor trends through the dashboard. These results demonstrate the platform's feasibility as a cognitive screening tool: it can gather real-time assessment data and present it in an accessible format suitable for remote monitoring.

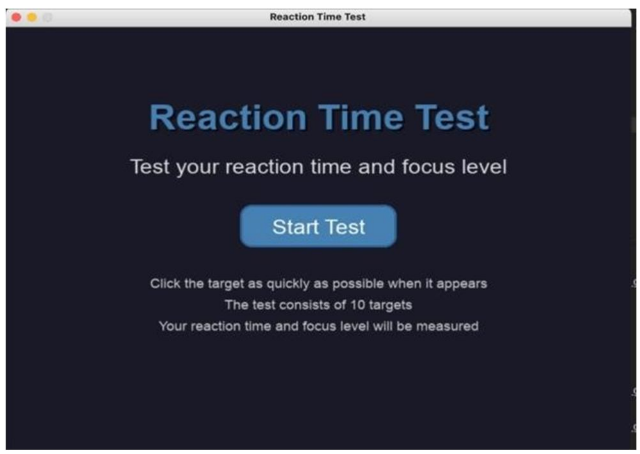


Figure3.4 Result

To evaluate the effectiveness of the NeuroNest platform, multiple user sessions were conducted to analyze cognitive performance metrics. The system successfully recorded reaction time values ranging from 350 ms to 650 ms across different users. Memory accuracy scores ranged between 60% and 95%, depending on task complexity.

The face mesh detection module demonstrated stable real-time performance with an average processing speed of 20–25 frames per second on standard laptop hardware. The facial landmark detection accuracy remained consistent across different lighting conditions and facial orientations.

These results indicate that the NeuroNest platform can reliably capture both cognitive and behavioral indicators required for early cognitive risk analysis.

V. FUTURE WORK

Although NeuroNest demonstrates promising capabilities for remote cognitive assessment, several improvements can further enhance the system's functionality and predictive accuracy.

Future development may involve the integration of deep learning techniques such as Convolutional Neural Networks (CNNs) for more advanced facial expression analysis. These models can capture complex emotional cues and micro-expressions that may correlate with neurological conditions.

Another potential enhancement involves incorporating wearable sensor data, including heart rate variability, sleep quality, and physical activity patterns. These physiological indicators may provide additional insights into cognitive health and improve predictive performance.

Furthermore, the platform can be extended into a mobile application to increase accessibility among elderly users who rely primarily on smartphones. Integration with healthcare providers and electronic medical record systems could also enable NeuroNest to support clinical decision-making and remote patient monitoring.

With these improvements, NeuroNest has the potential to evolve into a comprehensive digital cognitive health ecosystem capable of supporting early diagnosis, continuous monitoring, and preventive healthcare strategies.

VI. CONCLUSIONS

This paper presented NeuroNest, a web-based cognitive assessment system designed to aid early dementia detection and monitoring. NeuroNest integrates interactive cognitive games with a full-stack web architecture to provide accessible screening tools outside of clinical settings. Patients and seniors can perform memory, attention, and language tasks via engaging online games, while doctors and family members can monitor the user's performance remotely through dashboards and reports.

In testing, NeuroNest successfully recorded reaction times, accuracy scores, and completion times for each game, storing them in a structured database. The system's user interface enabled smooth interaction and intuitive navigation. The collected data were accurately reflected in the generated reports, allowing easy interpretation of cognitive trends. These findings align with literature suggesting that digital game-based tools can achieve screening accuracy similar to traditional tests. NeuroNest thus demonstrates the potential of web technologies to support continuous cognitive health monitoring and early intervention.

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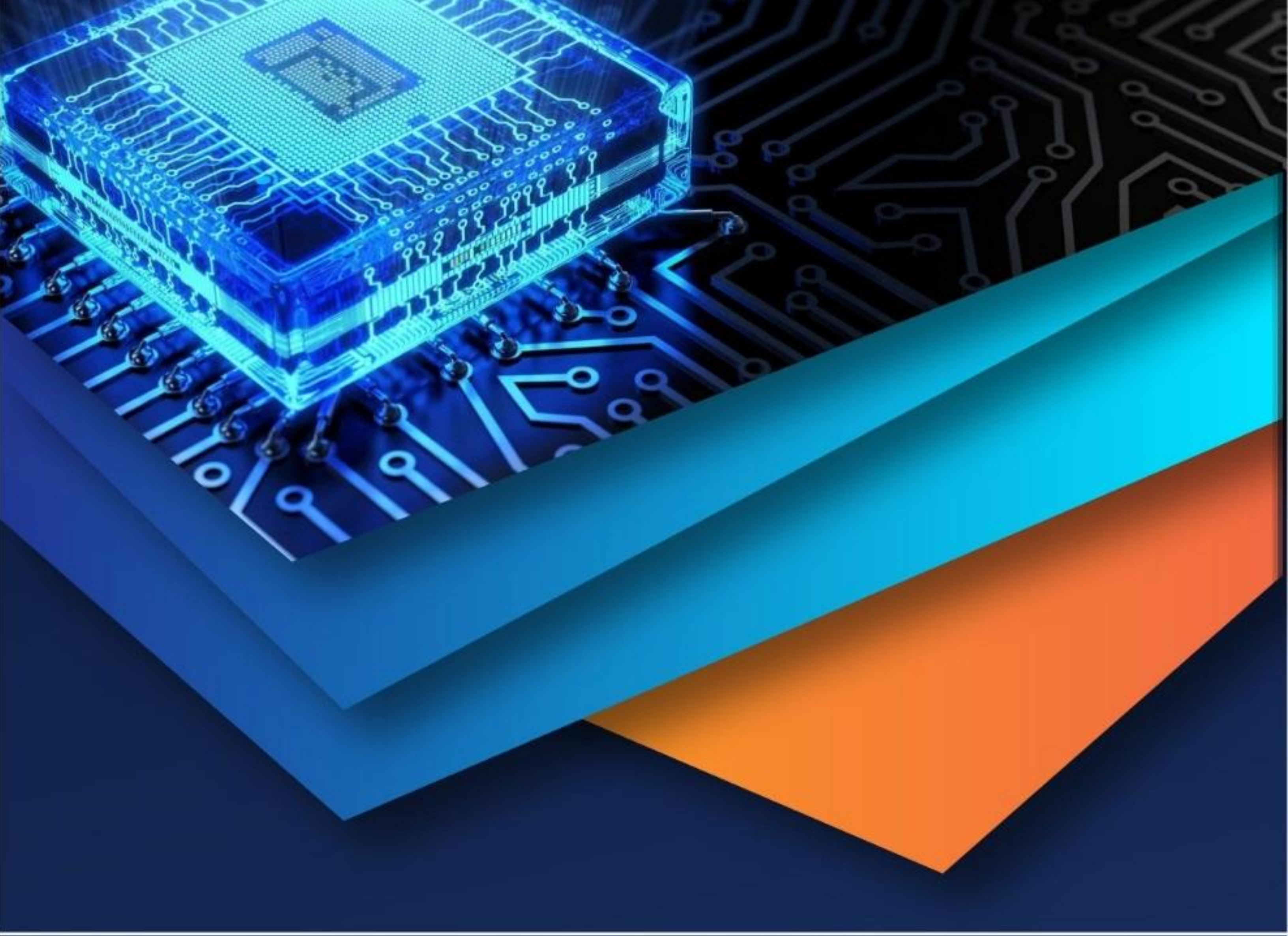

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