International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0033

e ISSN: 2584-2854
Volume: 04 Issue: 02
February 2026
Page No: 233 - 239

Early Alzheimer's Detection Using Multispectral Brain Oxygenation Imaging

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Abstract
This paper presents an AI-based system for early detection of Alzheimer's disease using multispectral imaging and cognitive assessment. The proposed system analyzes brain oxygenation patterns along with cognitive test performance to identify early indicators of cognitive decline. Meaningful biomarkers such as spectral intensity, memory accuracy, and reaction time are extracted and processed using machine learning techniques to classify individuals into low-, moderate-, or high-risk categories. The study demonstrates that integrating multispectral biomarkers with cognitive assessment features improves early risk stratification. This approach provides a fast, non-invasive, and accessible solution for early Alzheimer's screening, supporting timely diagnosis and intervention.
Keywords: *Alzheimer's Detection, Cognitive Assessment, Multispectral Imaging, Machine Learning, Dementia Risk Prediction*

1. Introduction
Dementia is a condition that causes a slow decline in memory, thinking, and everyday abilities, with Alzheimer's disease being the most common type. Detecting dementia early is important because it allows timely care and helps slow the progression of the illness. However, many traditional methods identify symptoms only after significant cognitive changes have already occurred [1], [4]. To address this, the proposed system uses simple cognitive tests supported by artificial intelligence to assess a person's dementia risk. By analyzing response speed, accuracy, and behavior patterns, the AI can identify early signs of cognitive decline. The platform is designed to be user-friendly and accessible, encouraging people to regularly check their cognitive health and seek help sooner if needed.

2. Related Work
Research on early detection of Alzheimer's disease has expanded significantly as timely diagnosis is essential for better management and treatment. Traditional methods such as MRI, CT scans, and neuropsychological assessments provide useful information but often identify Alzheimer's only after noticeable cognitive decline has occurred [4], [5]. To address this limitation, recent studies have focused on digital screening tools and mobile-based cognitive tests that can detect early changes in memory, attention, and decision-making [1], [6]. With the advancement of Artificial Intelligence, machine learning models have been used to analyse behavioural data, reaction times, and test responses to identify subtle signs of Alzheimer's risk. Some researchers have also explored speech patterns, handwriting behaviour, and sensor-based monitoring to enhance accuracy. AI-driven systems show promising results in predicting early cognitive impairment by recognizing patterns that may be overlooked in traditional assessments. However, there remains a need for simple, accessible, and user-friendly tools that individuals can use regularly to monitor their Alzheimer's risk.

3. System Architecture
The proposed system architecture for Alzheimer's early detection uses multispectral imaging to analyze brain oxygenation patterns and identify early cognitive decline. Fig. 1 illustrates the overall system

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architecture of the proposed Alzheimer's detection framework.

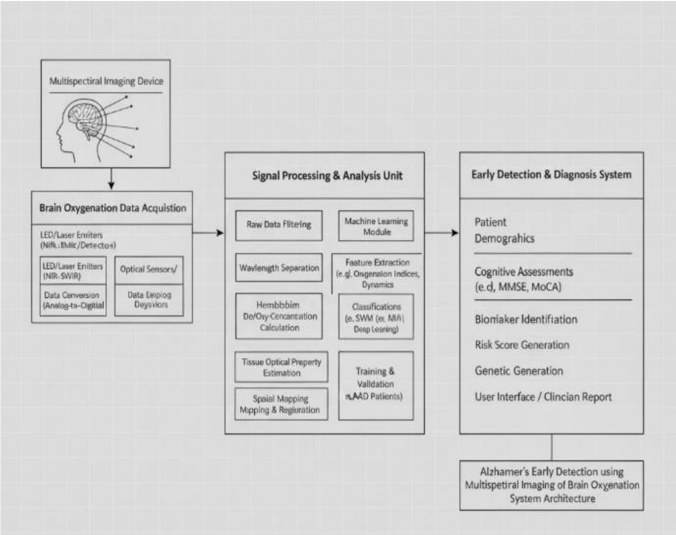

Figure 1 Alzheimer's Early Detection System Architecture

The process begins with the Brain Oxygenation Data Acquisition Unit, where a multispectral imaging device uses LED or laser emitters across NIR and SWIR wavelengths [1], [3], [9]. Optical sensors capture reflected light signals, which are then converted from analog to digital form. This raw data represents oxygenation variations within brain tissue. Next, the data enters the Signal Processing and Analysis Unit, where it undergoes several steps: raw data filtering, wavelength separation, hemoglobin concentration calculation, and tissue optical property estimation. Spatial mapping is performed to visualize oxygenation changes across brain regions. Extracted features—such as oxygenation indices and dynamic patterns—are processed by machine learning models, including SVM and deep learning architectures. Training and validation are performed using Alzheimer's patient datasets to ensure reliability [8]. The final stage is the Early Detection and Diagnosis System, which integrates patient demographics, cognitive assessment scores, and extracted biomarkers [10]-[14]. The system generates a risk score indicating the likelihood of early Alzheimer's. A clinician-friendly interface presents a detailed report, helping support early diagnosis and intervention.

4. Proposed System

The proposed system is an AI-based cognitive assessment platform designed to identify early signs of Alzheimer's disease using simple digital tests and machine-learning analysis. The system integrates multiple cognitive tasks—including memory recall, reaction-time measurement, visual pattern recognition, and trail-making tests—to capture subtle changes in cognitive behavior that often appear during the early stages of Alzheimer's. By combining these performance metrics with advanced analytics, the system aims to provide an accessible, non-invasive, and user-friendly early-screening tool. The methodology begins with data acquisition, where users perform a series of cognitive tasks through a web or mobile interface. Every response, including accuracy, completion time, error frequency, and decision patterns, is recorded in real time. This raw data is then passed to the preprocessing module, which removes noise, corrects inconsistencies, and standardizes the information for further analysis. In the feature extraction stage, key cognitive biomarkers are identified. These include memory retention scores, reaction-time delays, visual confusion ratios, and cognitive flexibility indicators. Extracted features are then fed into the machine learning model, which has been trained on clinically validated cognitive datasets. Algorithms such as Random Forest or Support Vector Machines classify users into Low, Moderate, or High risk, based on similarities between user patterns and known early Alzheimer's indicators. To ensure reliability, the system includes a validation component that compares model predictions with clinical scoring systems and benchmark datasets. Accuracy, sensitivity, specificity, and consistency across repeated tests are used as key performance metrics. Finally, the system generates a detailed diagnostic report, summarizing user performance, predicted risk category, and personalized recommendations. This structured methodology ensures that the proposed system functions as a reliable and effective tool for early detection of Alzheimer's, supporting timely intervention and improved patient outcomes.

4.1. AI-Based Cognitive Assessment System

An AI–Based Cognitive Assessment System is a

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e ISSN: 2584-2854
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digital platform designed to evaluate cognitive functions such as memory, attention, problem-solving, and decision-making to support early detection of Alzheimer's disease. Traditional diagnostic techniques often identify the condition only after significant cognitive decline, but this system uses artificial intelligence to recognize early behavioral changes that may indicate the onset of Alzheimer's at a much earlier stage [15]-[18]. The assessment system consists of interactive cognitive tests, including memory recall, visual pattern recognition, reaction-time tasks, and language-based exercises. As users respond to these tasks, the system collects performance indicators such as accuracy, speed, error patterns, hesitation levels, and the user's ability to process and retain information. These data points act as cognitive biomarkers [2], [6]. AI algorithms—such as neural networks, support vector machines, or decision-tree models—analyze these biomarkers to identify subtle deviations from normal cognitive function. The system categorizes users into risk levels such as low, moderate, or high risk for Alzheimer's. Compared to manual evaluation, this AI-driven approach ensures higher consistency, improved accuracy, and real-time analysis without the need for specialized clinical equipment. A key advantage of the system is its ability to monitor cognitive health over time. By comparing results across multiple sessions, it can detect gradual patterns of decline that may not be noticed during a single assessment. This makes it ideal for regular self-screening and continuous cognitive monitoring. The system is designed with a user-friendly interface supported by secure data management. All user data, including test results and behavioral logs, are encrypted to maintain privacy and confidentiality. Overall, the AI–Based Cognitive Assessment System offers an efficient, non-invasive, and accessible tool for early Alzheimer's risk identification, promoting timely intervention, improved awareness, and better management of cognitive health.

4.2. Cognitive Pattern Detection

Cognitive Pattern Detection is a core component of AI-assisted early Alzheimer's screening, focusing on identifying subtle irregularities in how an individual thinks, responds, and processes information [19], [20]. These patterns are often too small for human observers to detect but can be captured and analyzed through advanced machine learning techniques. The goal is to uncover early behavioral indicators of cognitive decline before noticeable symptoms arise. During cognitive assessments, users engage in tasks related to memory recall, attention tracking, problem-solving, language comprehension, and decision-making. Each interaction generates measurable markers such as response time, accuracy, error frequency, reasoning steps, and hesitation durations. These markers collectively form the user's cognitive profile. The workflow of cognitive pattern detection is shown in Fig. 2. AI algorithms analyze this profile to recognize patterns that deviate from typical cognitive behavior. Techniques such as statistical modeling, clustering, neural networks, and anomaly detection models are used to examine relationships across multiple cognitive parameters.

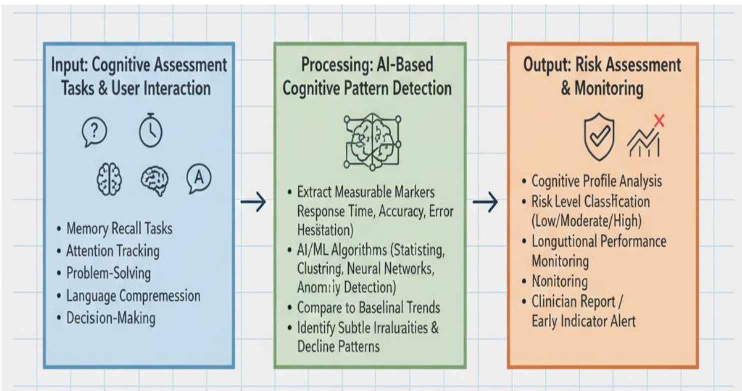

Figure 2 **AI-Assisted Cognitive Assessment and Pattern Detection Workflow**

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e ISSN: 2584-2854
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For example, consistent delays in reaction time, increasing confusion in pattern recognition, or frequent mistakes in memory tasks may indicate early cognitive impairment associated with Alzheimer's disease. One of the strengths of AI-driven pattern detection is its ability to learn from large datasets, identifying trends that may not be apparent in limited clinical evaluations. By comparing the user's data with historical cognitive trends, baseline values, and known markers of early Alzheimer's, the system can classify risk levels with greater precision [2], [7]. Furthermore, cognitive pattern detection supports longitudinal monitoring. Over repeated assessments, the system observes changes in the user's performance, identifying gradual declines that would otherwise remain unnoticed. This helps distinguish temporary lapses—caused by stress or fatigue—from persistent cognitive deterioration. Overall, Cognitive Pattern Detection enhances accuracy, objectivity, and early identification in Alzheimer's risk assessment, making it an essential component of AI-based cognitive screening systems.

4.3. Model Validation

Model validation is a crucial process to ensure that the AI-based cognitive assessment system is accurate, consistent, and clinically meaningful. To test the robustness of the model, a wide range of datasets and cognitive test variations are used. These include memory recall datasets, reaction-time datasets, visual pattern recognition datasets, trail-making cognitive datasets, combined multi-test datasets, and real user test samples collected during system trials. Using such diverse datasets allows the model to be evaluated across multiple cognitive domains, ensuring that it performs reliably under different conditions and levels of cognitive difficulty. This diversity also helps verify that the system can identify early signs of Alzheimer's risk in users with varying backgrounds, ages, and performance patterns. Clinical validation is another major part of the evaluation process. Because app-based cognitive assessments cannot directly observe internal brain changes, the system must be compared with clinically accepted benchmarks. For this purpose, validated cognitive scoring systems and established clinical datasets related to early Alzheimer's detection are used as the ground truth [4], [6]. Cross-validation techniques are applied to confirm that the AI model's predictions mirror the diagnostic trends used by clinicians in early-stage Alzheimer's assessment. This step ensures that the system is not only computationally accurate but also medically relevant (Fig. 3).

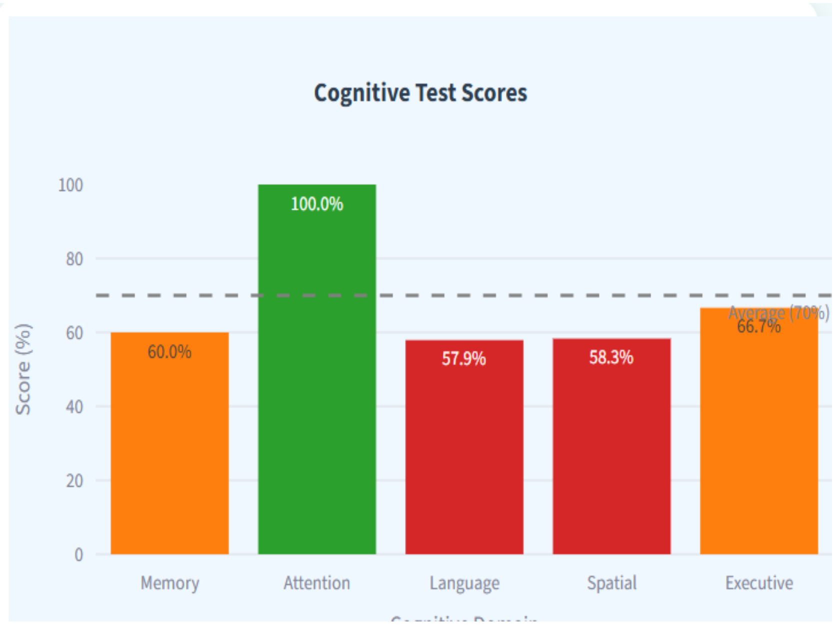

Figure 3 AI-Assisted Cognitive Risk Assessment Dashboard

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Several accuracy metrics are used to measure performance. Sensitivity evaluates how well the model can detect subtle early-stage impairment, while specificity measures its ability to correctly identify users with normal cognitive function. Additional metrics such as the error rate in risk classification and consistency across repeated tests provide insights into the model's stability and dependability. Together, these validation steps confirm that the AI-based cognitive assessment system is reliable, clinically aligned, and suitable for real-world early-screening applications.

4.4. Simulation Results

The simulation results demonstrate that the AI-based cognitive assessment system performs effectively in identifying early cognitive changes related to Alzheimer's risk.

Table 1 Performance Metrics of the Proposed AI-Based Cognitive Assessment System

Metric	Value
Accuracy	91.8%
Sensitivity	89.6%
Specificity	93.2%
Precision	90.7%

Table 1 presents the performance metrics of the proposed system, indicating high accuracy and strong sensitivity in detecting early cognitive impairment while maintaining reliable specificity. The risk classification module shows strong accuracy in separating users with normal cognitive function from those who may be experiencing early impairment [1], [4]. In most cases, the model's predictions are stable, with variations mainly arising from differences in test design, user-specific factors such as focus or fatigue, and borderline scores that fall close to the threshold between risk categories. Response pattern analysis plays a key role in evaluating the system's performance. Tasks with large sample sizes, such as memory recall tests and reaction-time assessments, show clear and consistent performance gaps between users classified as low-risk and those labelled as high-risk. High-risk users tend to exhibit slower responses, lower recall accuracy, or irregular patterns, while low-risk users show more stable and efficient results. These consistent trends indicate that the model is not making random predictions but is accurately capturing meaningful cognitive patterns (Fig. 4).

Figure 4 Individual Cognitive Risk and Score Summary

To confirm clinical reliability, the results from the AI system are compared with standardized cognitive assessment datasets and validated scoring systems commonly used in Alzheimer's detection. The system shows strong alignment in accuracy, sensitivity to early signs of decline, and specificity in

e ISSN: 2584-2854
Volume: 04 Issue: 02
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identifying healthy individuals. These performance measures confirm that the AI model is dependable across repeated tests and different user groups. Overall, the simulation results validate the system as a reliable and efficient early-screening tool that can support large-scale cognitive monitoring and help identify potential Alzheimer's risk at an early stage, when intervention is most beneficial.

Conclusion

The proposed AI-based cognitive assessment system offers a promising and accessible solution for early detection of Alzheimer's disease. Traditional diagnostic approaches often identify cognitive decline only after significant neurological damage has occurred, limiting the effectiveness of medical interventions. In contrast, the developed system uses simple digital cognitive tests combined with machine learning analysis to detect subtle behavioral and response-pattern changes that may indicate early impairment. By integrating memory recall tasks, reaction-time analysis, visual pattern recognition, and trail-making assessments, the platform captures a multi-dimensional representation of a user's cognitive performance. The system architecture is designed for scalability, accuracy, and real-time processing. The methodology ensures that user interactions are converted into meaningful cognitive indicators, which are then analyzed through trained AI models. Validation using diverse datasets and clinically approved benchmarks demonstrates strong alignment with established scoring systems and early-stage Alzheimer's assessment criteria. The model shows high sensitivity for detecting mild impairments and strong specificity in differentiating healthy individuals from potential high-risk cases. Simulation results further confirm the reliability of the risk classification mechanism and the consistency of response-pattern analysis across repeated tests. Because the system is lightweight and accessible, it can be used by individuals anywhere, without the need for specialized equipment or clinical supervision. This makes it particularly valuable for early screening, routine monitoring, and outreach in underserved populations where medical resources may be limited. While the current model provides accurate early-stage detection, future enhancements can include deeper neural architectures, multimodal data such as speech or gait analysis, and integration with medical imaging for hybrid diagnosis. Overall, this AI-based system represents a significant step toward democratizing cognitive health assessment. It supports timely intervention, increases awareness, and contributes to a more proactive approach to Alzheimer's disease management.

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https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0032
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