

Predictamind: A Multimodal System for Alzheimer's Alzheimer's Detection

Saran K S*, Adith Shaji#, Midhun Rajendran\$, Nikhil Mathew@, Abhijith Krishnan+, Shandry K K&

Department of CSE, College of Engineering Kidangoor, Kottayam, Kerala, India

*saranks2k21@gmail.com, #adithshaji07@gmail.com,

\$midhunrajendran94@gmail.com, @nikhilmathew876@gmail.com,

+abhijithkrishnanak123@gmail.com, &shandryl@ce-kgr.org

Abstract—PredictaMind is an AI-powered system designed for the early detection of Alzheimer's disease using a multimodal approach. Alzheimer's disease is a progressive neurological disorder that affects memory, thinking ability, and daily activities. Early detection is essential to slow disease progression and improve patient care. The proposed system integrates MRI brain image analysis with behavioral indicators such as eye blink patterns and typing dynamics. Eye blink and typing patterns help identify cognitive and motor decline, while MRI provides structural brain insights. Machine learning techniques are used to combine these features and generate accurate predictions. The system provides a non-invasive, cost-effective, and scalable solution for early Alzheimer's detection.

Index Terms—Alzheimer's Disease, Machine Learning, MRI, Eye Blink Detection, Typing Dynamics, Multimodal System.

I. INTRODUCTION

Alzheimer's disease is a progressive neurological disorder that affects memory, thinking, and daily functioning. Early detection is important for slowing disease progression and improving patient outcomes. Traditional diagnostic methods rely on clinical tests, MRI scans, PET scans, and cognitive assessments. These methods are often expensive, time-consuming, and require expert interpretation.

To overcome these limitations, PredictaMind proposes a multimodal approach that combines MRI brain images with behavioral data such as eye blink patterns and typing dynamics. Behavioral indicators can capture subtle cognitive and motor changes that occur in early stages of Alzheimer's disease. By integrating multiple data sources, the system improves detection accuracy and reduces dependency on invasive medical procedures.

The system provides a user-friendly platform where users can perform behavioral tests and upload MRI scans. The results are analyzed using machine learning models to generate an early diagnosis. This approach makes the system suitable for both clinical and non-clinical environments.

II. LITERATURE SURVEY

Recent advancements in artificial intelligence have significantly improved the detection of Alzheimer's disease. Many research works have focused on using deep learning techniques, especially Convolutional Neural Networks (CNNs), for analyzing MRI brain images [1]–[3]. These models automatically extract important features from MRI scans and classify

different stages of Alzheimer's disease with high accuracy. Studies using datasets such as ADNI and OASIS have shown that CNN-based models can effectively identify structural changes in the brain associated with cognitive decline.

AbdulAzeem et al. proposed a CNN-based framework for automated Alzheimer's disease classification using MRI scans [1]. Their model achieved strong performance in both binary and multiclass classification tasks by directly extracting features from raw MRI images.

Ajagbe et al. explored multiclass Alzheimer's disease classification using transfer learning approaches such as VGG16 and VGG19 [2]. Their work demonstrated that pretrained deep learning models can significantly improve disease stage classification accuracy.

Dardouri introduced a deep CNN architecture for early Alzheimer's disease detection using MRI images [3]. The study used extensive data augmentation techniques to improve classification performance and reduce dataset imbalance issues.

Several researchers have also explored transfer learning and optimized deep learning architectures to improve classification performance [4], [5]. Pre-trained models such as VGG16, VGG19, MobileNet, and ResNet have been widely used to enhance accuracy while reducing computational complexity.

Dar et al. developed a framework for classifying multiple stages of Alzheimer's disease using CNN-based transfer learning models [5]. Their study highlighted the effectiveness of lightweight deep learning models for practical healthcare applications.

Kaya and Çetin-Kaya proposed a Particle Swarm Optimization (PSO)-based framework to optimize CNN architectures for Alzheimer's disease classification [4]. Their optimized model achieved high accuracy while reducing overfitting and computational cost.

In addition to MRI-based detection, recent studies have investigated non-invasive behavioral biomarkers for early diagnosis [6], [7]. Eye-tracking techniques analyze gaze patterns, fixation points, saccadic movements, and pupil responses to detect early cognitive decline.

Tokushige et al. studied eye movement behavior for detecting cognitive decline in Alzheimer's patients [6]. Their findings showed that gaze fixation and pupil response patterns can effectively differentiate patients from healthy individuals.

Li et al. proposed an AI-driven eye-tracking framework using mobile devices for Alzheimer's disease prediction [7].

Their approach demonstrated that low-cost mobile-based systems can support accessible early-stage screening.

Altinkaya et al. presented a comprehensive review of deep learning techniques for Alzheimer's disease detection using MRI images [8]. The study discussed CNN-based methods, computer-aided diagnosis systems, and challenges related to interpretability and dataset quality.

However, most existing systems rely on a single type of data, either MRI or behavioral analysis. MRI-based methods provide high accuracy but are expensive and require medical infrastructure. On the other hand, behavioral methods are non-invasive and affordable but may not always provide sufficient reliability when used alone.

Therefore, recent research trends are moving towards multimodal systems, which combine imaging data with behavioral data to improve overall accuracy and robustness [8]. By integrating multiple sources of information, these systems can provide better early detection and reduce dependency on any single method.

The proposed PredictaMind system follows this multimodal approach by combining MRI analysis with eye blink patterns and typing dynamics, aiming to provide a more accurate, efficient, and scalable solution for early Alzheimer's detection.

III. METHODOLOGY

The proposed PredictaMind system is designed using a multimodal architecture that integrates behavioral analysis with medical imaging for early detection of Alzheimer's disease. The system follows a structured workflow in which user data is first analyzed using behavioral indicators such as eye blink patterns and typing dynamics. If abnormal behavior is detected, MRI analysis is performed to obtain deeper insights. Finally, the results from both behavioral and MRI analysis are combined to generate an accurate prediction. The architecture of the proposed system is illustrated in Fig 1.

1. User Module:

- Acts as the entry point of the system.
- Collects user details such as name, age, and email.
- Allows users to interact with the system.
- Ensures secure storage of user information.
- Provides access to system features like tests and results.

2. Data Extraction Module:

- Extracts behavioral features such as:
 - Blink rate
 - Blink duration
 - Typing speed
 - Keystroke latency
- Captures eye blink patterns using a webcam.
- Records typing dynamics through keyboard input.

- Converts raw data into structured format.
- Sends processed data to the prediction module.

3. Early Prediction Module:

- Analyzes behavioral data using machine learning techniques.
- Identifies abnormal cognitive and motor patterns.
- Compares user behavior with normal patterns.
- Determines whether the user shows early signs of Alzheimer's.
- Decides if MRI analysis is required for further evaluation.

4. MRI Processing Module:

- Allows users to upload MRI brain images.
- Processes MRI images using deep learning models such as CNN.
- Extracts structural features from brain scans.
- Detects patterns associated with Alzheimer's disease.
- Provides detailed analysis results.

5. Final Result Module:

- Combines results from behavioral analysis and MRI processing.
- Generates a final prediction.
- Displays results in a clear and user-friendly format
- Helps users understand their condition easily

6. Database Module

- Stores user data securely.
- Maintains behavioral and MRI analysis data.
- Keeps history of predictions.
- Ensures data consistency and easy retrieval.
- Supports future analysis and monitoring.

IV. RESULTS AND DISCUSSION

The PredictaMind system was successfully implemented as a web-based platform that integrates behavioral analysis and MRI-based detection for Alzheimer's disease. The system was tested using different user inputs to evaluate its performance across all modules.

The eye blink detection module demonstrated effective performance in capturing blink count and blink duration using a webcam. The system was able to detect variations in blink patterns, which are useful indicators of neurological and cognitive changes. The detection process was fast and worked in real-time under normal lighting conditions.

The typing dynamics module analyzed keystroke patterns such as typing speed, accuracy, and latency. The system identified differences in typing behavior, which can reflect motor coordination and cognitive function. This module provided consistent results across multiple test cases and contributed significantly to early-stage prediction.

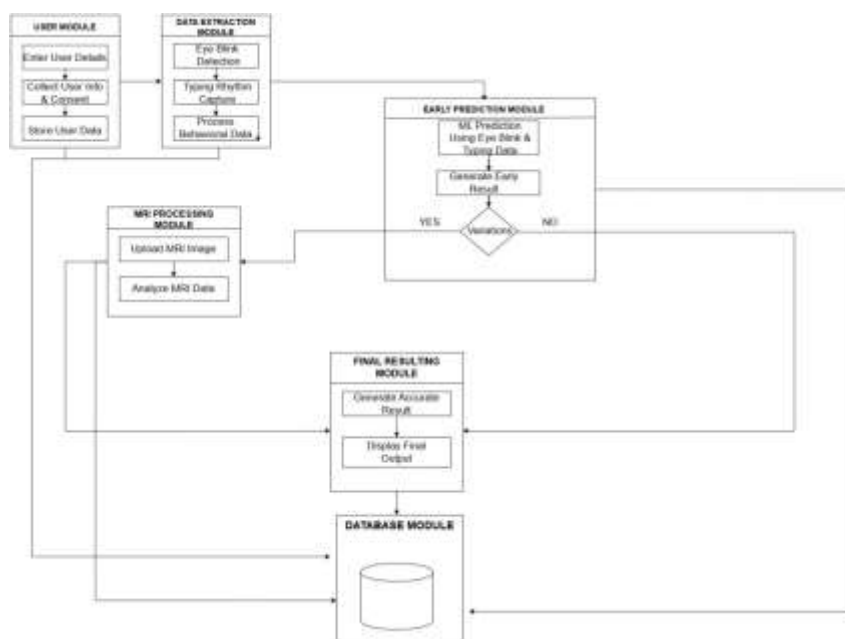


Fig. 1. System Architecture

The early prediction module combined blink and typing features to classify user behavior as normal or abnormal. This step helps in identifying potential risk at an early stage without requiring immediate medical imaging. The decision-based approach improves system efficiency by reducing unnecessary MRI analysis.

The MRI processing module provided detailed analysis of brain images using deep learning techniques. It was able to identify structural changes associated with Alzheimer's disease and classify the condition more accurately. This module enhances the reliability of the system when behavioral analysis alone is not sufficient.

The final result module successfully combined outputs from both behavioral analysis and MRI processing to generate a comprehensive prediction. The results were displayed clearly through the user interface, making it easy for users to understand their condition.

V. CONCLUSIONS

PredictaMind is a multimodal AI-based system for early detection of Alzheimer's disease. By combining MRI analysis with behavioral indicators such as eye blink patterns and typing dynamics, the system provides a more accurate and efficient diagnostic approach.

The system reduces dependency on expensive medical procedures and enables early-stage detection through non-invasive methods. Its modular design makes it scalable and suitable for real-world applications.

Future improvements can include enhancing model accuracy, adding more behavioral features, and integrating the system with healthcare platforms for continuous monitoring.

REFERENCES

- [1] Y. AbdulAzeem, W. M. Bahgat, and M. Badawy, "A cnn based framework for classification of alzheimer's disease," *Springer*, vol. 33, no. 16, pp. 10 415–10 428, 2021.
- [2] S. A. Ajagbe, K. A. Amuda, M. A. Oladipupo, O. F. Afe, and K. I. Okesola, "Multi-classification of alzheimer disease on magnetic resonance images (mri) using deep convolutional neural network approaches," *International Journal of Advanced Computer Research*, vol. 11, no. 53, pp. 51–60, 2021.
- [3] S. Dardouri, "An efficient method for early alzheimer's disease detection based on mri images using deep convolutional neural networks," *Frontiers*, vol. 8, p. 1563016, 2025.
- [4] M. Kaya and Y. Cetin-Kaya, "A novel deep learning architecture optimization for multiclass classification of alzheimer's disease level," *IEEE Access*, vol. 12, pp. 46 562–46 584, 2024.
- [5] G. M. u. d. Dar, A. Bhagat, S. I. Ansarullah, M. T. B. Othman, Y. Hamid, H. K. Alkahtani, I. Ullah, and H. Hamam, "A novel framework for classification of different alzheimer's disease stages using cnn model," *MDPI*, vol. 12, no. 2, p. 469, 2023.
- [6] S. Tokushige, H. Matsumoto, S. Matsuda, S. Inomata-Terada, N. Kotsuki, M. Hamada, S. Tsuji, Y. Ugawa, and Y. Terao, "Early detection of cognitive decline in alzheimer's disease using eye tracking," *Frontiers*, vol. 15, p. 1123456, 2023.
- [7] Q. Li, J. Yan, J. Ye, H. Lv, X. Zhang, Z. Tu, Y. Li, and Q. Guo, "Construction of a prediction model for alzheimer's disease using an ai-driven eye-tracking task on mobile devices," *Springer*, vol. 37, p. 9, 2025.
- [8] E. Altinkaya, K. Polat, and B. Barakli, "Detection of alzheimer's disease and dementia states based on deep learning from mri images: A comprehensive review," *Journal of the Institute of Electronics and Computer*, vol. 1, pp. 39–53, 2020.