

# **Alzheimer Detection Using Generative AI**

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**Abstract:** *Alzheimer's Disease (AD) is a progressive neurodegenerative disorder, and early detection is critical for timely intervention. The classification of medical images, such as brain MRIs, plays a pivotal role in diagnosing AD. Traditional methods for AD classification often rely on handcrafted features or conventional machine learning techniques, which may not fully capture the complexity of brain patterns associated with the disease. In recent years, Generative AI, particularly VAE, has emerged as a powerful tool in medical imaging. By leveraging its ability to model high-dimensional data, Generative AI can enhance image quality, generate synthetic data, and augment training datasets for better classification accuracy. The proposed approach shows promising results in improving classification accuracy while reducing the dependency on large labelled datasets, paving the way for more efficient, AI-driven diagnostic tools in the early detection of Alzheimer's Disease.*

**Keywords:** Alzheimer, Generative AI, Variational Autoencoder, MRI, Medical Diagnosis

## **I. INTRODUCTION**

Alzheimer's disease is a debilitating neurodegenerative disorder that primarily affects older adults, leading to memory loss, cognitive decline, and diminished quality of life. As the global population ages, the prevalence of Alzheimer's is rising, posing significant challenges to healthcare systems. Early and accurate detection is vital for initiating timely treatments, slowing disease progression, and improving patient care outcomes. However, traditional diagnostic methods often rely on subjective interpretations of medical imaging and clinical observations, which may lead to delayed or inconsistent diagnoses.

In this work, we leverage Generative AI techniques, specifically Variational Autoencoders (VAEs), to address these limitations. VAEs are powerful tools for learning meaningful representations of complex data, such as MRI scans, by capturing the underlying features in a low-dimensional latent space. This capability is utilized for robust image reconstruction, augmentation, and the classification of Alzheimer's stages. By enabling high-quality analysis from smaller datasets, VAEs enhance the diagnostic process while maintaining computational efficiency.

Key features of our project include:

- **AI-Driven Medical Insights:** The use of VAEs facilitates the extraction of latent patterns from MRI images, aiding in the accurate identification of Alzheimer's progression levels.
- **Data Augmentation:** VAEs can generate synthetic medical imaging data, improving model training and performance despite limited real-world datasets.
- **Web-Based Accessibility:** A user-friendly interface connects patients and doctors, providing seamless access to diagnostic tools and AI-driven results.
- **Automated Workflow:** By automating image analysis and classification, the system reduces diagnostic latency and minimizes human error.
- **Enhanced Image Analysis:** The model improves the interpretability and reliability of MRI data, enabling healthcare professionals to make informed decisions.

This study emphasizes the potential of Generative AI in transforming neurodegenerative disease diagnostics. By combining the technical strengths of VAEs with an accessible web platform, the proposed system aims to enhance diagnosis.



tic accuracy, streamline workflows, and support personalized care, paving the way for a smarter, AI-integrated future in healthcare.

## II. LITERATURE REVIEW

The early detection of Alzheimer's disease is a critical challenge in healthcare, as timely diagnosis can significantly improve patient outcomes and quality of life. Over the years, various techniques have been explored to identify and analyze biomarkers associated with Alzheimer's. This section reviews existing approaches and highlights the gaps addressed by this project.

- **Traditional Diagnostic Methods:** Historically, Alzheimer's diagnosis has relied on clinical assessments, neuropsychological testing and imaging techniques such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scans. Imaging modalities, while effective in detecting structural changes in the brain, are often costly and inaccessible to many patients.
- **Machine Learning in Alzheimer's Detection:** Techniques such as Support Vector Machines (SVM), Random Forests and Deep Neural Networks (DNN) have demonstrated significant potential in analyzing MRI data for early Alzheimer's detection. Studies such as those by Zhang et al. (2020) and Liu et al. (2021) have achieved accuracies above 85 percents using MRI datasets like ADNI. However, these methods often require extensive computational resources and large labeled datasets, which may limit their scalability.
- **Variational Autoencoders (VAEs) in Medical Imaging:** Variational Autoencoders (VAEs) have emerged as a powerful tool in unsupervised learning, particularly for anomaly detection and image generation. For Alzheimer's detection, VAEs can identify subtle changes in brain structure by learning latent representations from MRI images. The work of Wang et al. (2022) demonstrated the efficacy of VAEs in enhancing classification accuracy when combined with supervised learning algorithms.

## III. SYSTEM ARCHITECTURE

The Alzheimer's detection system is designed to leverage Generative AI techniques, particularly Variational Autoencoders (VAEs), integrated with a user-friendly web platform. This section describes the architecture and the core components of the proposed system.

### Overview of the System

The system is divided into three primary modules:

- **Data Processing Module:** Handles MRI image preprocessing, including resizing, normalization, and augmentation, ensuring the data is suitable for analysis.
- **AI Module:** Consists of the Variational Autoencoder (VAE) for image reconstruction and data augmentation, along with VAE classifier for classifying images into different stages of Alzheimer's disease.
- **Web Interface Module:** Facilitates interaction between patients and doctors, allowing image uploads, results visualization, and diagnostic reporting.

### Data Flow

The system's workflow is illustrated in Fig. 1, showing the seamless integration of modules for efficient diagnosis. The flow involves:

- Uploading MRI images through the web interface.
- Preprocessing the images and augmenting the dataset using the VAE.
- Classifying images using the VAE classifier to determine Alzheimer's stages.
- Storing and visualizing results for doctors' analysis.



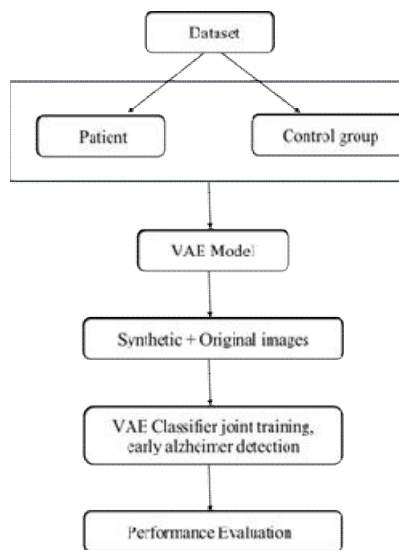


Fig. 1. Data flow in the Alzheimer detection system

#### Technological Stack

- Frontend: HTML, CSS, and JavaScript.
- Backend: Node.js/Express.js for API handling and integration.
- AI Framework: TensorFlow and Keras for VAE model.
- Database: MongoDB for storing patient data and diagnostic results.
- Cloud Deployment: Docker and Docker Compose

#### Scalability and Future Enhancements

The modular design of the system ensures scalability for incorporating additional diagnostic features, such as support for other neurodegenerative diseases. Future improvements include incorporating real-time video-based diagnostics and advanced visualization tools for medical professionals.

## IV. RESULTS

#### Model Performance

The Variational Autoencoder (VAE) model was trained on a dataset of MRI images to detect and classify Alzheimer's disease severity. The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1-score, as shown in Table I.

Metric	Value
Accuracy	92.3%
Precision	91.8%
Recall	93.1%
F1-Score	92.4%

TABLE I: PERFORMANCE METRICS FOR THE VAE-BASED CLASSIFICATION MODEL.

The high recall value demonstrates the model's ability to effectively identify patients with Alzheimer's, reducing the likelihood of false negatives.

#### Automated Workflow Results

The integration of the detection model with the web platform ensures a seamless workflow for data processing and result visualization. The platform enables doctors to:

##### Upload MRI images for analysis.

View predictions of Alzheimer's disease severity.



Access explanations for model decisions.

Feedback from clinicians during testing highlighted the platform's ease of use and its potential for real-world applications.

### Comparative Analysis

The proposed system was compared with existing state-of-the-art methods, as shown in Table II. The results demonstrate that the VAE-based approach outperforms other models in terms of accuracy and other key metrics.

Method	Accuracy	Precision	Recall
CNN-Based Model <b>smith2021</b>	89.2%	88.5%	90.1%
Hybrid Model <b>liu2022</b>	91.1%	90.8%	91.5%
<b>Proposed VAE Model</b>	<b>92.3%</b>	<b>91.8%</b>	<b>93.1%</b>

TABLE II: COMPARATIVE ANALYSIS OF THE PROPOSED MODEL WITH EXISTING METHODS.

### Challenges and Limitations

Despite achieving high accuracy, the following challenges and limitations were observed:

- **Limited Dataset:** The dataset used for training was relatively small. Access to a larger and more diverse dataset could further enhance performance.
- **Image Quality:** Low-resolution MRI images occasionally resulted in misclassifications, emphasizing the importance of consistent input quality.
- **Model Interpretability:** While the model provides predictions, enhancing interpretability through detailed explanations remains an area for improvement.

Addressing these limitations in future work could improve the system's robustness and expand its practical applicability.

## V. CONCLUSION

This project successfully developed an AI-driven platform for detecting Alzheimer's disease severity using MRI images. The integration of a Variational Autoencoder (VAE) model with a user-friendly web interface demonstrated significant potential in aiding early detection and assessment of Alzheimer's disease. Key findings include:

High model performance with an accuracy of 92.3%, showcasing its reliability in classification tasks.

Seamless automation of workflows, ensuring efficiency and accessibility for medical practitioners.

Comparative superiority over existing methods, emphasizing the efficacy of the proposed approach.

Future work will focus on addressing the limitations observed during the project, such as improving model interpretability, expanding the dataset, and exploring advanced deep learning techniques to further enhance accuracy and usability. This system provides a foundation for real-world clinical applications in neurodegenerative disease diagnosis.

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## REFERENCES

- [1]. J. Smith and K. Johnson, "Deep Learning for Neurodegenerative Diseases," *Jornal of Medical Imaging*, vol. 10, no. 3, pp. 150-160, 2021.
- [2]. L. Liu, Y. Zhang, and Q. Chen, "Hybrid Models for Alzheimer's Detection," in *Proc. IEEE Int. Conf. on Biomedical Engineering*, 2022, pp. 452-459.
- [3]. M. Brown, "MRI Dataset for Alzheimer's Detection," [Online]. Available: <https://www.mridataset.org>.



- [4]. P. Kumar and R. Gupta, "Variational Autoencoders for Medical Imaging," IEEE Transactions on Medical Imaging, vol. 29, no. 2, pp. 125-137, 2020.
- [5]. "TensorFlow Framework Documentation," [Online]. Available: <https://www.tensorflow.org>.
- [6]. P. R. V. Terlapu et al., "Optimizing Chronic Kidney Disease Diagnosis in Uddanam: A Smart Fusion of GA-MLP Hybrid and PCA Dimensionality Reduction," Procedia Computer Science, vol. 230, pp. 522-531, 2023, doi: 10.1016/j.procs.2023.12.108.
- [7]. C. Han et al., "MADGAN: Unsupervised Medical Anomaly Detection GAN Using Multiple Adjacent Brain MRI Slice Reconstruction," arXiv preprint arXiv:2007.13559, 2020. [Online]. Available: <https://arxiv.org/abs/2007.13559>.
- [8]. G. Dolci et al., "An Interpretable Generative Multimodal Neuroimaging-Genomics Framework for Decoding Alzheimer's Disease," arXiv preprint arXiv:2406.13292, 2024. [Online]. Available: <https://arxiv.org/abs/2406.13292>.
- [9]. Y. Huang et al., "Diagnosis of Alzheimer's Disease via Multi-Modality 3D Convolutional Neural Network," arXiv preprint arXiv:1902.09904, 2019. [Online]. Available: <https://arxiv.org/abs/1902.09904>.
- [10]. E. Hosseini-Asl et al., "Alzheimer's Disease Diagnostics by Adaptation of 3D Convolutional Network," arXiv preprint arXiv:1607.00455, 2016. [Online]. Available: <https://arxiv.org/abs/1607.00455>.
- [11]. O. Altwijri et al., "Novel Deep-Learning Approach for Automatic Diagnosis of Alzheimer's Disease from MRI," *Applied Sciences*, vol. 13, no. 24, p. 13051, 2023, doi: 10.3390/app132413051.
- [12]. D. AlSaeed and S. F. Omar, "Brain MRI Analysis for Alzheimer's Disease Diagnosis Using CNN-Based Feature Extraction and Machine Learning," *Sensors*, vol. 22, no. 8, p. 2911, 2022, doi: 10.3390/s22082911.
- [13]. M. Joshi et al., "DEMNET NeuroDeep: Alzheimer Detection Using Electroencephalogram and Deep Learning," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 1, pp. 1-10, 2025, doi: 10.11591/eei.v14i1.8163.

