International Journal of Computing and Digital Systems
2025, VOL. 17, NO.1, 1-14

http://dx.doi.org/10.12785/ijcds/1571107229

Deep Learning-Enhanced MRI Imaging for Early Alzheimer's Detection

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Received 5 January 2025, Revised 10 February 2025, Accepted 14 February 2025

Abstract: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that leads to cognitive decline, posing significant challenges in early diagnosis. Conventional diagnostic techniques, such as MRI, provide structural insights into the brain but often lack the precision required for early-stage detection. This study investigates the potential of deep learning-based approaches to enhance diagnostic accuracy for AD. A transfer learning framework utilizing pre-trained convolutional neural networks (CNNs), specifically VGG and ResNet architectures, was developed to classify MRI images of patients at different stages of the disease. The proposed model achieved a validation accuracy of 98.05%, demonstrating its effectiveness in distinguishing AD from healthy cases with minimal misclassifications. The findings highlight the transformative role of AI-driven diagnostics in personalized healthcare, emphasizing the necessity of high-quality training datasets to ensure model robustness. This research underscores the potential of deep learning to facilitate early and reliable detection of Alzheimer's disease, paving the way for improved clinical decision-making and patient outcomes.

Keywords: Medical Image Analysis; Transfer Learning; Alzheimer's Diagnosis; Deep Learning; Neuroimaging.

1. INTRODUCTION

The need for an accurate and timely method of prediction has grown as the number of people with Alzheimer's disease (AD) rises. Fortunately, the application of artificial intelligence in the healthcare industry has demonstrated tremendous promise. Artificial intelligence algorithms can provide early warning indications of Alzheimer's disease, enabling preemptive interventions and, potentially, a more effective treatment approach as they have represented in other disease types such as ASD [1]. They do this by analyzing enormous volumes of data and discovering patterns that could otherwise go undetected. As a result, applying Artificial Intelligence to Alzheimer's prediction has enormous potential to enhance patient outcomes and lighten the load on healthcare systems [2].

The tissue loss first occurs in the grey matter and then progresses to corpus callosum, white matter, and hippocampus. Hence, early stages of AD can be detected and diagnosed through observation of the transformation in the respective anatomical structures of the brain. Mild cognitive impairment (MCI) sufferers are most likely to advance to the last stage of irreversible brain illness. MCI may be prone to both stable MCI (sMCI) and progressive MCI (pMCI) for the early prediction of AD. Normal Cognitive (NC) is the first stage of AD-related dementia, followed by sMCI, pMCI, and then AD [3]. Such machine learning (ML) algorithms must be implemented according to the proper architectural design or pre-processing procedures, which must be predefined. Feature extraction, feature selection, dimensionality reduction, and feature-based technique selection are frequently required steps in ML classification studies. All of these methods can entail many optimization procedures, expert knowledge, and a lot of time. The reproducibility of these methods has been a problem.

AD diagnosis is hard to be made precisely due to the fact that the disease is too complex for one, and there is no way to recognise a reliable biomarker. Conventional diagnostic modalities utilize MRI devices to deliver relevant analysis for the brain anatomies and diseases respectively. Among the challenges of accurately conveying events and

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the emotions of the characters is the fact that we need to achieve it in a consistent way. This research is based on the significance of these two challenges but also identifies the major lacks of existing AD-related datasets keeping in mind the limited availability of the comprehensive human image data. This is where the research comes into play, in which the Alzheimer MRI Pre-process Dataset is being introduced, which is a very important resource for building solutions that use AI-driven.

This study aims to enhance early AD diagnosis with a deep model leveraging pre-trained CNNs, specifically VGG and ResNet architectures. The most important objectives of this work are:

1) To develop an AI-driven framework capable of accurately classifying MRI images of patients across different stages of AD.
2) To utilize transfer learning in feature extraction, with reduced use of important domain expertise and increased model efficiency.
3) To evaluate a model's overall performance with performance metrics including accuracy, recall, precision, and F1-score.
4) Analyzing misclassification cases and identifying key challenges in AD diagnosis to improve model interpretability and robustness.

The CNN approaches are the main analytical tools of the work, as they are applied to diagnose AD. CNNs can be correct as far as processing MRI scans as they have the best performance on the smallest image operations such as recognition and classification. The proposed way contains data preprocessing, image augmentation, model generation and evaluation. Furthermore, it serves as a structure for CNN neural network approaches to differentiate cognitive decline. However, secondly, it also looks into transfer learning methods, where a CNN model that has already been trained (like VGG and ResNet) is used as a basis for AD diagnosis, with it's extracted features guiding it to a proper finding.

The work utilizes a multitude of data sets and other resources while citing high-credibility sources, such as from reputable organizations and academic institutions, to note the said collaborative characteristic of medical studies. It helps researchers to incorporate the diversity of understanding as well as experience, which would, in the end, increase the pool of available data.

The system suggested provides the conclusions from the research, which illustrate the capacity of the AI-powered AD solution to find solutions. The CNN models know their job, which they do well as evidenced by the validation accuracy of 98.05% and a validation loss of 6.87%. A scant 25 incorrectly categorized photos out of 1280 are reported in the paper, highlighting the potential benefit of AI in improving AD diagnosis accuracy.

Additionally, the document is set up as follows: a quick review of the literature is found in section 2. The system design, methodology, and algorithms are addressed in the third section. The fourth portion discusses the dataset description, evaluation parameters, and results analysis.

The major contribution of this work is:

1) **Development of an Optimized Framework for Deep Learning** – A model is proposed for stage classification of AD with improved accuracy, utilizing feature extraction from pre-trained networks.
2) **Application of Transfer Learning** – Transfer learning with VGG and ResNet architectures is employed to fine-tune classification performance on MRI datasets.
3) **Extensive Performance Analysis** – The proposed model is rigorously evaluated using various performance metrics, achieving a classification accuracy of 98.05%, surpassing existing techniques.

This work highlights the potential of AI-driven diagnostics in revolutionizing personalized care by addressing limitations in traditional diagnostic methods. Furthermore, it contributes to the growing field of medical image analysis, paving the way for more accessible and reliable tools for detecting Alzheimer's disease.

2. Literature Review

Goenka et al. [4] have a prominent role in the area of medical diagnostics and studies concerned with the subject of Alzheimer's disease as well. The authors go deep into the use of deep learning techniques for MR (magnetic resonance) imaging-based AD prediction with the aim of improving early diagnosis and actuation. The work of the study is based on ML techniques like neural network architectures and a comprehensive collection of brain biomarkers. Therefore, it is evident that there is significant potential for the early detection of Alzheimer's using ML. Thus, such detection improves patient assistance and support. The study indeed points beyond the mere application of deep learning algorithms by unfolding the increased role of artificial intelligence in medical research and healthcare. This paper is primarily targeted towards researchers and experts trying to apply the best available technology in the prediction of Alzheimer's disease; hence being a most useful reference. This article further emphasizes the potential offered by advanced AI technologies, and below are a few of the many roles that AI plays in the medical field. Huber-Carol et al. [5] give out essential pros and cons of the survival data methodologies that are employed in combination with the ML approaches for the prediction of AD. The authors shed some light on the pitfalls of the prevailing methodologies compared to the blooming area of ML in this context. The research rigorously compares a few types of predictive models that, in turn, provide evidence of how well the latest set of ML algorithms perform on demanding data that have this attribute of usually being multidimensional and, thus, typical in medical research. Moreover, it brings the data-driven technique to light, which would enhance the prediction accuracy and also highly recommends the need to adopt the technique learner to the type of research the data and research objectives are based on. This piece constitutes a pertinent source of knowledge to scientists and practitioners who aim to concentrate on the mid-term between classical statistical analysis and ML in the scope of AD prognostication, providing its adherents with crucial information regarding the pros and cons of those methods.

Kamal et al. [6], however, suggest that the AI method also needs other important inputs such as image, microarray, and explainable AI. This group of scientific studies is a great bonus to the field of dementia advancement, as they add to the knowledge about the course and predictability of Alzheimer's disease. Through a concerted use of medical image data with gene expression profiles, it facilitates a composite and multi-modal examination of patients. Adding to this, the explanation of AI approaches has led to a high level of transparency and interpretability on the predictive models, enabling a greater understanding of the linked genes that are responsible for Alzheimer's disease. This creative study represents a good example of interdisciplinary curative in the healthcare domain. What's more, it is commensurate with the integration of AI and data into which the advancement in diagnosis and management of complex neurodegenerative diseases like Alzheimer's. With Alzheimer's and other health conditions growing, this Alzheimer's and other related disorders article by Kamal et al. therefore has to do with respective diagnosis and treatment as it shows that this field of AI in healthcare shows on the way to enhancement providing more accuracy with diagnoses and treatment.

Wukkadada et al. [7] provide a study on ML algorithms application as a method of not just accurate prediction of AD but as a tool for the better monitoring of the entire neurologic health. The unique aspect of the author's research is its significant application of machine-learning technologies to speed up the decision-making process and develop a better treatment for Alzheimer's disease. However, the authors' study differs from previous research since they consider the use of broader datasets and focus especially on KNN techniques to get more accurate predictions of AD, an attempt at the potential of data-driven methods to enhance early diagnosis, which leads to better outcomes concerning efficient treatments. This is consistent with the treatment of neurodegenerative diseases, and it is at the core of the effort to find the best ways to manage AD.

Saradhi et al. [8] demonstrate a profound insight into predicting AD in a study of this area. The reported study is about the early diagnosis of AD and uses a diagnostic MRI brain analysis procedure, particularly emphasizing the role of this technique for better patient outcomes. The proposed methodology is based upon the application of a bilateral adaptive filter (ABF) and AEO paradigm, which is used to calculate the optimal weight filters. Next, the Inception-v3 CNN model is incorporated for dividing cancer types into benign and malignant. The outlined research verified the approach's accuracy and ranked remarkably high, reaching a classification accuracy of 97.43%, a specificity score of 98.09%, a sensitivity score of 97.12%, and a very high Kappa index of 89.67%. This strategy not only performs better than other rival algorithms but also overcomes the problem of diagnosing AD, a problem that is the top concern in today's healthcare. As you see, this approach has many advantages.

Shimizu et al. [9], through the mechanism of classification and prediction of AD subtypes from genomic data, bring forward significant findings in the field of Alzheimer's aspect. The authors' research was based on the use of data from the GWAS of the Japanese population from two cohorts, and thus, the authors were able to disentangle the genetic structure of LOAD. On the basis of gene ID-CHIP, the authors distinguish two subtypes of LAD, one due to major genes (APOC1 and APOC1P1) and the other to genes related to the immune mechanism (RELB and CBLC) while the other is linked to kidney diseases (AXDND1, FBP1, and MIR2278). The remarkable association between disordered kidney function and LOAD pathogenesis brings another refresher to our consociating concepts about AD. Besides, the scientific novelty lies in the development deep neural network model for LOAD subtypes to predict with high accuracy not only in the discovery cohort but also in the validation cohort. These findings not only shed light on the underlying mechanisms of LOAD but also illustrate the potential of genomic data and deep learning techniques to enhance our ability to classify and predict AD subtypes, ultimately advancing our grasp of this complex neurodegenerative disorder.

Rabeh et al. [10] suggested a new method of AD prediction at an early using MRI images and a combination of CNN and SVM technology. Researchers neutralize deep learning and motioning in transfer learning, which have shown their excellence in computer vision and medical image processing areas. The authors aim the development a new method that combines an adaptation of a transfer learning approach along with supporting SVM technology for the early-stage classification of AD, specifically focusing on MCI. Using the OASIS AI Alzheimer's MRI database, which has 420 subjects (210 normal and 210 MCI), the team's model can predict the presence of this disease in an early stage with 94.88% accuracy. This is a noteworthy step towards the incorporation of the latest technology into the early diagnosis methodology of Alzheimer's, which could reduce the period of early intervention and improve the quality of life of patients fighting neurodegenerative diseases.

Nugroho et al. [11] investigate the treatment of the most alarming disease at present, which is AD, which is believed to affect thousands of people every second in the next decade. In view of the subsequently increasing number of cases, the authors are concerned with AD that is form of dementia, and the affected people usually have memory disorder in most cognitive functions. The study highlights that this rapidly increasing problem emphasizes the necessity for treatment, drugs, and other approaches that can help manage and prevent this devastating disease. To reinforce this, the authors attempt to develop an innovative method, a fingerprint based ANN model that may find actual BACE-1 inhibitors for the treatment of AD. To optimize the ANN architecture, the paper explores three distinct optimization strategies: Humans often have greater empathy, compassion, and emotional intelligence than machines, leading to more personalized and flexible solutions. From these, the Bat Algorithm shows a better trend with an accuracy of 0.81 and an F1-score of 0.78. These findings represent a significant step forward in leveraging computational methods to identify potential therapeutic agents for AD, offering hope for the development of effective treatments in the ongoing battle against this prevalent and devastating neurological condition.

Being cited as a source, the paper by Menagadevi et al. [12] offers a deep residual autoencoder and SVM-based automated prediction system for the detection of AD. Authors, through their study, nail down medical imaging progress and multiple means of imaging analysis of the brain from MRI to MRI, which is one of the essential stages of Alzheimer's disease diagnosis. The authors use the modified optimal curvelet thresholding and the octagonal histogram equalization intelligent method of image preprocessing with an adapter in order to boost the quality of the photos. It is the features of white matter that are next extracted from the brain images via the multi-scale pooling residual autoencoder architecture. The SVM, ELM and KNN algorithms are used for the classification that is performed under the algorithm type. The SVM stood out with astonishing results in the Kaggle dataset and overall accuracy of 99.77% which was the highest in both of the datasets. For the ADNI dataset, the SVM also showed great results with 98.21% accuracy. This result in the field of deep learning and ML reveals the large role these techniques can play in improving AD detection and diagnosis. It is clear that there is a promising future for earlier interventions and a more accurate and timely management of this neurodegenerative condition.

Reddy Enumula and Rama Krishna Rao [13] are their part in the contemporary attempt to narrow down the specific use of necrotising data to better classify Alzheimer's disease. The investigation shows that one of the most pivotal steps for the correct diagnosis of Alzheimer's disease is the adequate usage of ML when segmenting images and performing the evaluation of the database, thus marking the necessity of advanced technologies as an essential component in this field. Importantly, VGG-16 and Improved Faster Recurrent CNN methods, as they were produced before for the ImageNet database at the time the issue was studied, are brought in by the authors. The presented system proves exceptional reliability with a greater than 98% precision on the ADNI dataset of Alzheimer's Neuroimaging Initiative. This research exemplifies the potential of ML and neural network-based approaches in enhancing the precision of AD prediction and classification, offering promising avenues for early diagnosis and intervention in this complex and critical medical domain.

Ganesh et al. [14] also investigate an AI solution for the prediction of AD by employing the AI algorithms utilized in brain MRI scans. What distinguishes the work of the author is the fact that he uses three different types of CNN models named VGG-16, Inception-V3, and Xception to distinguish Alzheimer's Disease based on MRI brain scans. At the end of the relatively short training, the VGG-16 model performed the best with an accuracy of 75%, while the Xception and Inception models achieved a decision-making precision of 70%. The main task of the study is to give the possibility of capturing the process of Alzheimer's disease (no-dementia, very mild, mild, moderate) with the use of a program that can define treatment approaches given by every stage of the disease. That makes a very practical tool for more efficient treatment. Such work emphasizes the promising prospect of deep learning and AI-related technologies in the forthcoming development and management of AD, delivering evidence to patients with different present AD stages of needed personalized treatment.

Moreover, Hemalatha and Renukadevi [15] discussed the most important challenge of AD, which is destructive damage that causes memory to be loss considerably and cognitive capabilities. The authors note the insufficient capability for AD diagnosis at the early stage as one of the contributors to a high failure rate of AD drugs in clinical trials. Timely diagnosis in the course of treatment is of the highest priority; however, the picture is less clear if an individual is almost unnoticedly suffering from MCI. The study points out that besides the traditional methods used for the cognition of Alzheimer's disease, i.e., Positron Emission Tomography (PET), others could be harnessed for a better and faster perception of the disease. PET imaging plays doing great diagnostic and investigative role inside the human body, like revealing the working of the internal organs and tissues. We are striving to find appropriate features for the recognition of AD by means looking at the PET images and comparing them with different machine-learning techniques that we will use to help with diagnosis. Notably, the study delves into the use of Artificial Neural Networks and deep learning techniques as promising tools for addressing AD diagnostic challenges, emphasizing the potential of these approaches while acknowledging the need for substantial training data to achieve high performance. This work contributes to the ongoing efforts to enhance early diagnosis and intervention in AD, a crucial area in neurodegenerative disorder research.

Humpfal et al. [16] provide a very remarkable way of honing in on the issue of finding an effective treatment for AD. They highlight the first genome-wide exploration of biomarkers associated with therapeutic response in AD, accomplishing it by focusing on the investigation of Blarcamesine (ANAVEX2-73) in Phase 2a clinical trial of the behavior. The study involves a 57-week period, as 208 weeks are dedicated to long-term monitoring in the hope of gaining more profound insights into the nature of AD. The authors develop a precision medicine model based on AI function, namely unsupervised formal concept analysis (FCA) through integration into the Knowledge Extraction and Management (KEM) module, to elucidate the mechanism between the patient data and outcomes. In this study, the authors report six biomarkers, including the mean level of plasma concentration of blarcamesine and specific genomic variants that have a strong correlation with the outcome of the changes in cognitive and functional assessments. This being the case, data on neurodegenerative markers in AD have the potential to be used in the personalization of the treatment in AD, and early phase IIb and III clinical trials attempt to determine the significance of these markers in informing treatment. This contribution is grounded in using data mining methods and genomics rather than just statistically oriented analyses to gain more in-depth knowledge about AD and to develop different personalized approaches for treating this difficult form of neurodegeneration.

Rashmi Patil Sreepathi Taylor disclosed a cutting-edge application in the field of melanoma cancer detection [17]. As melanoma is one of the most vicious and fatal shapes of common skin cancer, exact staging has an integral role in the determination of an effective treatment plan. This study is based on models implementing the use of CNNs and a novel loss function called Similarity Measure for Text Processing (SMTP) to determine the stages of melanoma cancer. Their findings from the experiment help indicate that the SMTP loss function works better than generic loss functions, thusly exhibiting the system's efficiency and accuracy of melanoma staging.

Through the lens of Rashmi Patil's [18] research on melanoma, she illustrates spotting malignant melanoma, a kind of skin cancer and emphasizes the importance of early detection. The investigation emphasizes the difficulty of discerning melanoma cases from non-carcinoma cases and brings in dermoscopy as one such skill that can be employed for the assessment of skin lesions. What the research proposes is a new type of approach which's success is a result of a combined use of CNN and ML methods such as SVM (support vector machines) and XGB (XGBoost). CNNs are a crucial part of the suggested system because they have a proven track record of performance in object recognition. In general, the research investigates how ML might improve melanoma detection precision and automate the diagnosis procedure. In [19], transfer learning is used to detect type of cancer.

The literature review underscores several limitations and opportunities for further research in the field of AD prediction, classification, and treatment strategies. A common challenge identified in many of these studies pertains to the availability and size of the datasets used. Both ML and deep learning algorithms intensively depend on huge and diverse data, but the challenge in acquiring data for AD research is itself complex. In addition, it remains to be seen whether bias can be avoided by relying solely on datasets that are only representative of the population at large, which raises a new issue. In order to resolve this issue, a better way would be through calling for joint efforts by research institutions and the collection and exchange of much more complete and insightful data. Besides, anonymization of the data and its standardization for use in sharing with other institutions has to be prioritized to strike a balance between sharing data and upholding privacy. Similar methods like data enhancement and transfer learning may be put into practice to enable the proposed system to obtain the utmost use out of the limited set of data. In doing so, it will attain better generalization and robustness.

Moreover, the researcher pointed out the issue of interpreting and explicability of ML and deep learning models in the same research work. Whereas such models can frequently show high performance, their inconceivable decision-making process escapes understanding, especially in the clinical practice domain, where interpretability is very important. Our proposed research regarding Alzheimer's disease prediction aims to increase the ability of models to explain themselves by improving the specificity of the techniques that are being employed. This condition not only facilitates the AI-advent but also generates important information on the structure of Alzheimer's disease and brings more precision to the treatment strategies. Moreover, when the question of the ethical consequences of AI in the healthcare sector is posed, this also means the necessity of the creation of ethical principles and standards for the proper and safe use of intelligent automation systems. These guidelines should be mainly based on transparency and publicity to lay down the ethical practices concerning artificial intelligence in the in-healthcare sector.

3. Proposed System

The investigational system had a detailed methodology sufficient to adhere to the needs of patients, doctors, and scientists. From user registration and authentication, which the system will need to make sure is done securely while also giving the users privacy of access and data, the system will move to locations and tours. There would be a possibility for users to create and revise their data pro dialogs periodically, while entering their personal information and medical histories initially. The diagram of the system architecture 1 below explicates the conceptual model. The suggested system's natural detection mechanism based on AI is the root that makes the system work. The trained Convolutional Neural Network (CNN) model would provide an immediate and precise outcome following the uploaded MRI scans that indicate AD using prompt. The user's comprehensibility can be enhanced by ensuring the system offers explanations of the findings in language laymen can quickly understand, leading to the understanding of an insight into the meaning of findings and perhaps the subsequent procedures. The system's simplicity of input of data was one of its key benefits, and users could import MRI images from their devices straight into the system without any effort. The intuitive interface renders the image loading and capturing to be simple. The program was set up in such a way as to ensure that all photos were selected automatically so as to check that they fulfilled the required quality and format specifications before any analysis. Figure 1 shows block diagram of system architecture.

The study utilizes a systematic training and evaluation protocol for deep algorithms for Alzheimer's disease detection. Alzheimer's MRI datasets have been subjected to preprocessing with operations such as image normalization, resizing, and augmentation for model generalization improvement. Transfer learning with pre-trained architectures (VGG-16 and ResNet-50) for deep neural networks (DNNs) and fine-tuning of these networks with Alzheimer's MRI datasets have been utilized. For optimizations in weight updates, and multi-class classification, Adam optimizer and categorical cross-entropy loss function have been utilized, respectively. For training, hyperparameter optimizations, early stopping, and scheduling of the learning rate for overfitting prevention have been utilized. For performance analysis, traditional performance analysis metrics such as accuracy, precision, recall, and F1-score, and confusion matrices for in-depth analysis of model performance have been utilized.

A. CNN Model

The crucial deep learning record for the interpretation of the MRI scans of brain to detect Alzheimer's disease is the CNNs. Modification of CNN networks through transfer learning principles is the core method in the study. The models of well-known architecture like VGG and ResNet are used for the task of Alzheimer's disease recognition. The Alzheimer MRI dataset, as a critical exercise, assists us in training and refining these algorithms to be more accurate in differentiating Alzheimer's MRI images with and without indications of Alzheimer's disease. Where model performance is estimated using parameters like accuracy and validation loss measures are demonstrated. Finally, CNNs take the place in the sphere of AD diagnosis improvement with their high level of accuracy and reliability, calling to mind their importance for medical image analysis and clinical practice.

B. Four different classes make up the dataset that was used

- **Mildly Demented (Class 1):** People in this class have Alzheimer's disease-related minor cognitive impairment. Although their symptoms are not yet severe, these people may have memory loss, trouble solving problems, and other cognitive difficulties.
- **Moderately Demented (Class 1):** members who have advanced to a moderate degree of Alzheimer's disease. Their cognitive impairments are more severe, affecting day-to-day functions and accelerating memory loss and cognitive decline.
- **Non-Dementia (Class 3):** People in this category do not show any symptoms of dementia or cognitive impairment. They are regarded as cognitively healthy and do not exhibit Alzheimer's disease signs.
- **Very Mild Demented (Class 4):** Also known as ”very mild” or ”early-stage” dementia, this class includes those who are experiencing the first symptoms of AD. Cognitive impairments are typically less severe than in moderate or severe phases, and symptoms can be modest.

To effectively categorize MRI scans and recognize people with AD or those at risk, ML models must be trained and evaluated with the help of these class labels. The stratification of the information into these classes enables a thorough evaluation of the performance of the AI-based detection system at various disease phases.

C. Training and Testing

A particular task of detection and classification of Alzheimer's that requires the cooperation of the CNN model has been intensely created and trained for the course of this research. First, the system will import all necessary libraries and ensure that GPUs are being used effectively during training, which involves benefiting from the maximum benefits of TensorFlow and Keras by their nature. One crucial part of the data preparation in the mentioned study with respect to Alzheimer's is the careful division of the Alzheimer's dataset into the training and validation parts. The labels of the classes have been taken from the dataset hence, the data sets show how these information subsets help the learning model to differentiate between various stages or types of Alzheimer's disease. Proposed system performance guides the choice of optimization methods usually, it is Adam optimizer and categorical cross-entropy loss function, also. At the initial stage of training some methods like stopping early and test rate decreasing are used with the aim to prevent the model from overfitting. The performance of the model is rigorously hyped, and the visual observations of the performance during the training process are generated through some measurement parameters such as accuracy and loss. In the end, a detailed confusion matrix, misclassified image presentation, and the testing of the model on the validation sample are fully pictured by the model's achievements in predicting Alzheimer's disease. The results of these studies may be able to produce the input in the medical image analysis and Alzheimer's disease diagnosis sectors.

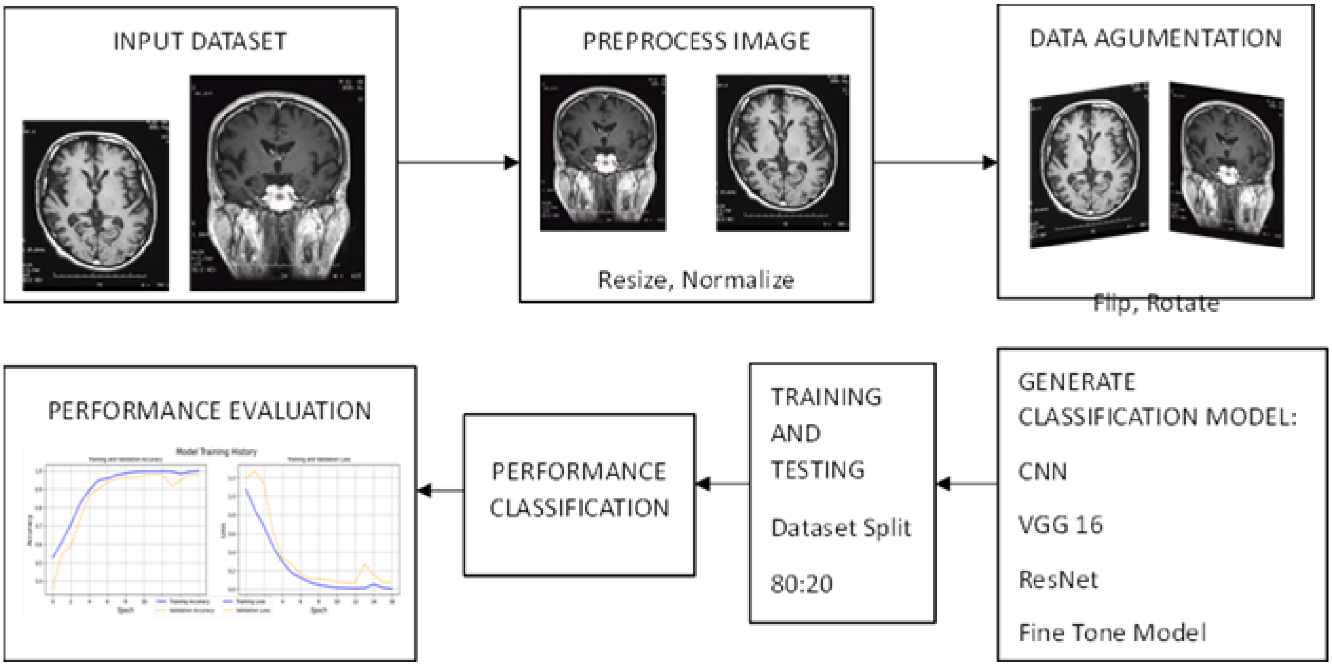

Figure 1. System Architecture Diagram

D. Algorithm of the proposed system

- **Step 1:** Start
- **Step 2:** Load the Alzheimer MRI Preprocessed Dataset
- **Step 3:** Split the dataset into training, validation, and test sets
- **Step 4:** Data Augmentation
- **Step 5:** Define CNN Architecture
- **Step 6:** Compile the Model
- **Step 7:** Model Training
- **Step 8:** Transfer Learning
- **Step 9:** Load a pre-trained model (e.g., VGG or ResNet)
- **Step 10:** Modify the model architecture for the Alzheimer's detection task
- **Step 11:** Fine-tune the model on the Alzheimer's dataset
- **Step 12:** End Results

4. Methodology

In the following, we explained the whole "How CNN was used for detection of AD- a comprehensive approach" methodology. The methodology covers processing of the data used, model architecture choice, training, validation, transfer learning explorations, as well as investigation of the misclassification.

1) **Data Preparation**

a) **Data Collection:** One of the first steps that we have taken in our research was to download the Alzheimer MRI preprocessed dataset, which is a collection of MR images (magnetic resonance imaging) that have been previously processed. The 6400 MRI scans in this dataset are divided into four categories: senile dementia, dementia of moderate stage, no dementia, and very mild dementia. To ensure a broad representation and fullness, we collected this information from different places such as websites, clinics, and public libraries.

b) **Data Preprocessing:** Strict preprocessing was carried out before model training. To standardize inputs, all photos were scaled evenly to 128 × 128 pixels. To improve model robustness and generalization, normalization and data augmentation approaches were also used.

2) **Model Selection**

- **CNN Architectures:** Choosing our CNN architecture was an essential step in this process. Our work encompasses the exploration and implementation of top picture classification networks, such as VGG, ResNet, and Inception, which have proven to be effective. The layout and devices made the environment of our tests and served as the medium for comparing performance.

3) **Model Training and Evaluation**

- **Configuration for Training:** For our CNN models, we used Python 3.x along with TensorFlow and Keras configurations. A learning rate scheduler, categorical cross-entropy loss function, and Adam optimizer were employed throughout the training process. Training and validation sets were created from the dataset during model training to find effective usage.

- The model's performance was evaluated after a set number of epochs, followed by a benchmark. Classification metrics and training/validation losses were counted for each epoch. The results were analyzed on a separate test set to assess real-world applicability.

4) **Transfer Learning Exploration**

- Pre-trained CNN models, such as VGG and ResNet, were explored for transfer learning. Performance was evaluated and compared with models without transfer learning, revealing the advantages of leveraging pre-trained networks.

5) **Class-Specific Accuracy**

- Class-specific accuracy was computed for different stages of dementia to understand CNN models' performance variations. This analysis revealed models' strengths in detecting specific stages.

6) **Misclassification Analysis**

- A rigorous investigation determined the classes prone to misclassification. Misclassified images were analyzed to identify potential areas for model improvement.

7) **Ethical Considerations**

- Data security and privacy of end-users were ensured by incorporating ethical standards. Patient privacy was prioritized through anonymization and secure data handling methods to prohibit unauthorized access to sensitive medical data.

8) **Statistical Analysis**

- Statistical significance tests, such as t-tests and ANOVA, were conducted to assess the reliability of observed differences in model performance.

9) **Visualization**

- To ensure that the public, as well as officials, may comprehend the results, the results of our research were presented with the assistance of visualization methods utilizing different representations of data including tables, line charts, bar graphs, and radar maps.

This comprehensive methodology that is outlined here details the way we went about research and involves data preprocessing, model choice, training, evaluation, transfer learning investigation, class-specific accuracy changes, misclassification analysis, ethical considerations, statistical analysis, and visualization procedures. These decisions affirmed that our AI-based Alzheimer's Disease Detection was made to ensure rigorous and valid research.

A. *Loss Function*

For a certain sample or batch of data, the loss function measures the discrepancy between the model's predictions ($\hat{y}_i$) and the actual labels (y). A typical loss function for multi-class classification problems, such as Alzheimer's disease detection, is categorical cross-entropy:

$$L(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Here, N is the number of classes, y_i is the true label for class i, and $\hat{y}_i$ is the predicted probability for class i after passing through a SoftMax activation function.

B. *Technology Used*

- **Python 3.x**: The primary programming language used for developing and implementing ML models and data processing.

- **TensorFlow**: A deep learning framework for building and training neural networks, crucial for developing and evaluating CNNs.

- **Keras**: A high-level neural networks API (integrated with TensorFlow) that simplifies the development of deep learning models, including CNNs.

- **Seaborn**: A data visualization library used for creating informative and visually appealing plots and graphs.

- **Scikit-learn**: An ML library that provides essential tools for data preprocessing, model selection, and evaluation.

- **Scikit-image**: An image processing library integrated with Scikit-learn, used for image-related tasks and preprocessing.

- **Pydot and Graphviz**: Tools for creating and visualizing neural network architectures and decision trees, respectively.

- **Kaggle Dataset**: The dataset obtained from Kaggle, a well-known platform for ML datasets and competitions, is used as the primary data source for AD detection.

- **CUDA Toolkit**: A GPU-accelerated computing platform used for faster training of deep learning models on compatible hardware.

5. Result Discussion

A. Overview of the Dataset

The dataset [20] is a collection of MRI pictures that have been previously processed and specially shrunk to a resolution of 128 by 128 pixels. Dataset description is given in Table I.

TABLE I. Dataset Class Labels Summary

Class Label	Description	Number of Images
Class 1: Mild Demented	Mild stage of Alzheimer's disease	896
Class 2: Moderate Demented	Moderate stage of Alzheimer's disease	64
Class 3: Non-Demented	No signs of Alzheimer's disease	3200
Class 4: Very Mild Demented	Very mild stage of Alzheimer's disease	2240

B. Evaluation Metrics

The evaluation model employs the confusion matrix. It is shown as a table that details how well a classification model performed on a set of test data in ML. The performance of the proposed work is assessed using accuracy, recall, precision, and the F1 score [21]. Measures are determined by:

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

$$\text{Precision} = \frac{T_p}{T_p + F_p}$$

$$\text{Recall} = \frac{T_p}{T_p + F_n}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where, T_p, F_p, F_n, and T_n represent true positive, false positive, false negative, and true negative, respectively.

C. Result Analysis

CNNs are being used in the proposed method to construct ML models for the identification of AD. The system construction involved using:

- Python 3.x
- TensorFlow
- Keras
- Seaborn
- scikit-learn
- scikit-image
- Pydot
- Graphviz
- CUDA Toolkit for GPU training

The figure 2 below shows the training data input sample for the proposed model.

The "Alzheimer MRI Preprocessed Dataset," which consisted of images reduced to 128 × 128 pixels and sourced from various websites, hospitals, and public repositories, served as the centerpiece of the proposed system. The four unique groups that make up this dataset—"Mild Demented" (896 images), "Moderate Demented" (64 images), "nondemented" (3200 images), and "Very Mild Demented" (2240 images)—represent the various stages of dementia. The effectiveness of these models at detecting Alzheimer's disease and the training progress of the model from 0 to 16 epochs are shown in the following graphs (Figure 3).

The intended purpose of the proposed approach was to make it easier to create and develop a precise framework or architecture for the classification of AD. It made referrals to other sources of information and study about AD, thus enhancing the resources already available. The implementation of the code, which included data preparation, picture enhancement, model construction, and evaluation using CNNs, served as the system's central component. Transfer learning methods with pre-trained models like VGG and ResNet were investigated. The CNN models were constructed using TensorFlow's Keras API. The figure 4 below shows the validated training data output of the proposed model.

Our results indicate that the proposed model architecture outperforms the other models, achieving the highest accuracy of 98.05% and the validation loss of 0.68. There were 25 misclassified photos out of 1280. For researchers and practitioners in the area, the suggested approach offered a thorough framework for the creation and assessment of ML models for AD diagnosis utilizing CNNs. Figure 5 and Figure 6 below explain the confusion matrix of the proposed system classifier over different classes and the bar graph of model comparison with accuracy and validation loss of VGG and ResNet, respectively. Figure 7 represnts proposed System Error Plotting.

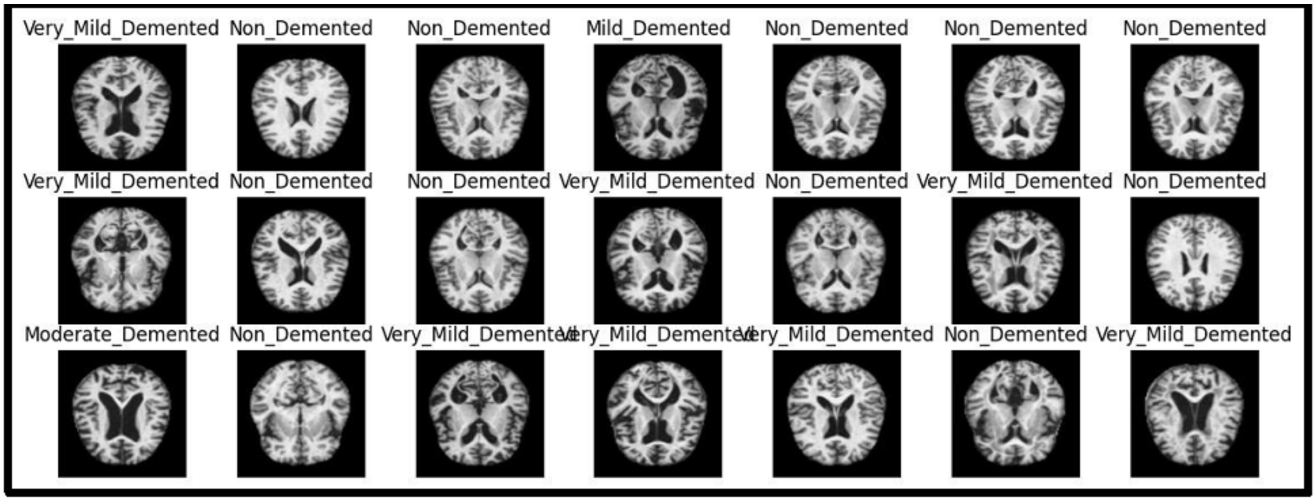

Figure 2. Trained Data Sample

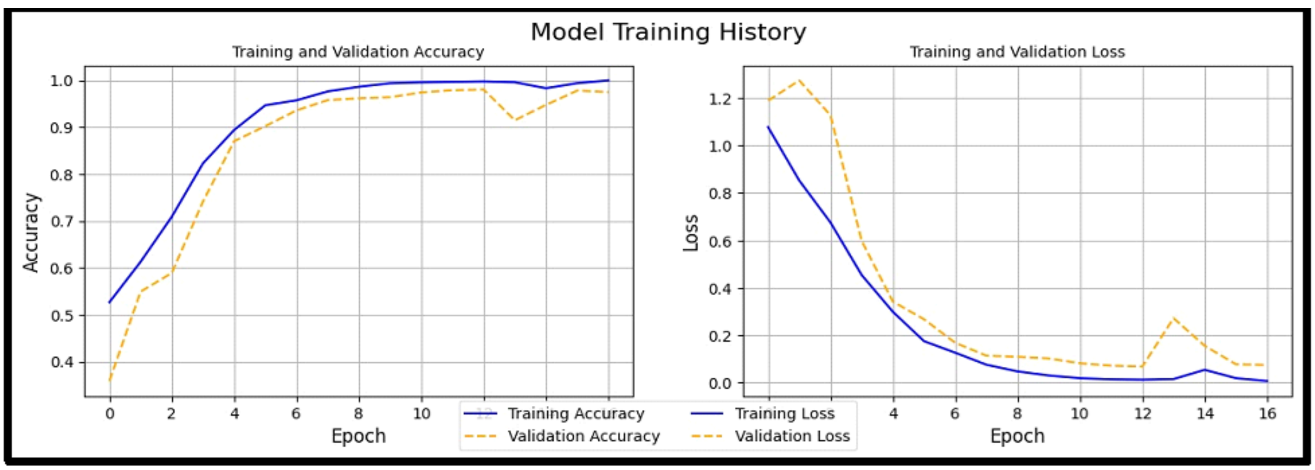

Figure 3. Model Training History

D. Test Cases

The specifics of the test cases created for the proposed system are highlighted in this section. The test cases and outcomes for data preprocessing, compatibility, and performance testing are shown in Tables II and III, respectively.

Comparison of different methods with the proposed method is given in Table IV.

E. Class-Specific Accuracy and Misclassification Analysis

We looked at the models' accuracy for different stages of dementia to see if they performed better for certain classes, and we ran a misclassification analysis to see which stages of dementia are more likely to be misclassified. The number of images that were improperly classified for each class and the top model's accuracy in each category are displayed in the table V below:

TABLE II. Data Preprocessing Test Cases

Functionality	Result
Verify that the dataset is correctly loaded and contains the expected number of images for each class.	Passed
Check the success of data augmentation techniques, ensuring the creation of diverse training samples.	Passed
Validate the resizing process, confirming that all images are resized to 128x128 pixels.	Passed

Our results indicate that the model excels in accurately detecting the "non-demented" class with the highest accuracy of 98.05%, and the "Moderate Demented" class has the greatest amount of incorrectly identified photos,

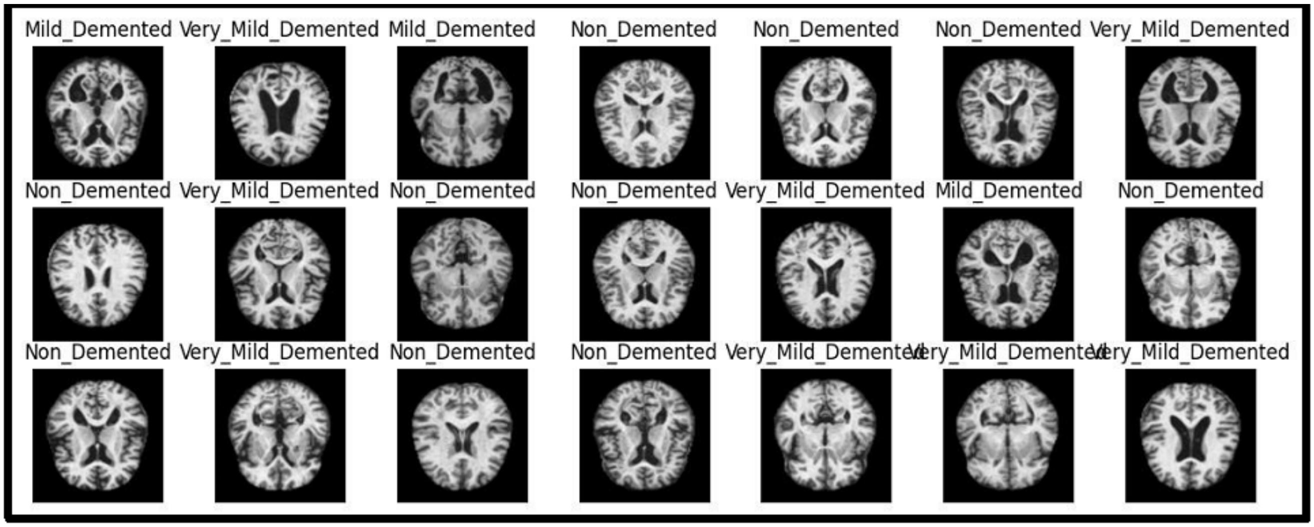

Figure 4. Model Training History

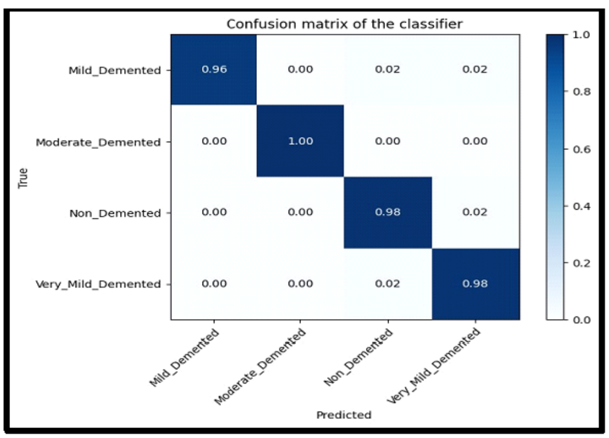

Figure 5. Confusion Matrix of the Classifier

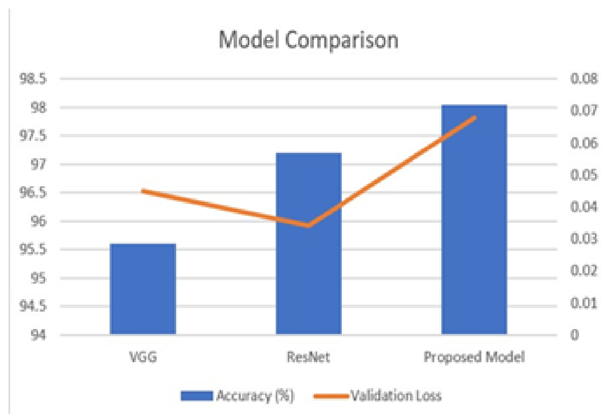

Figure 6. Model Comparison Bar Graph

TABLE III. Model Creation and Training Test Cases

Performance	Result
Train a CNN model using the provided code and dataset, ensuring convergence and successful model creation.	Passed
Test different CNN architectures, such as VGG and ResNet, using transfer learning and verify their performance.	Passed
Check for overfitting by comparing training and validation loss curves.	Passed

necessitating more research into how to increase this class's classification accuracy.

These findings show how effective CNN models in particular, ResNet with transfer learning can be in accurately diagnosing Alzheimer's disease. Our results highlight the value of transfer learning and architecture selection in improving model performance and urge further study to solve issues with class-specific accuracy and misclassification rates.

6. Conclusion

This research proposes a robust AI-based framework for diagnosing Alzheimer's disease using deep learning techniques with the application of transfer learning on pre-trained CNN models such as VGG and ResNet. The proposed work reports a high value of classification accuracy, approximately 98.05%, reflecting superior performance with a minimum number of misclassifications. It, therefore, represents several key contributions: the efficient use of transfer learning for diagnostics in accuracy, MRI-based classification formulated with a systematic approach, and a deep analysis of performances and robustness assessments of the model. Regarding results and practical impacts from the evidence obtained, there is a reasonable interest

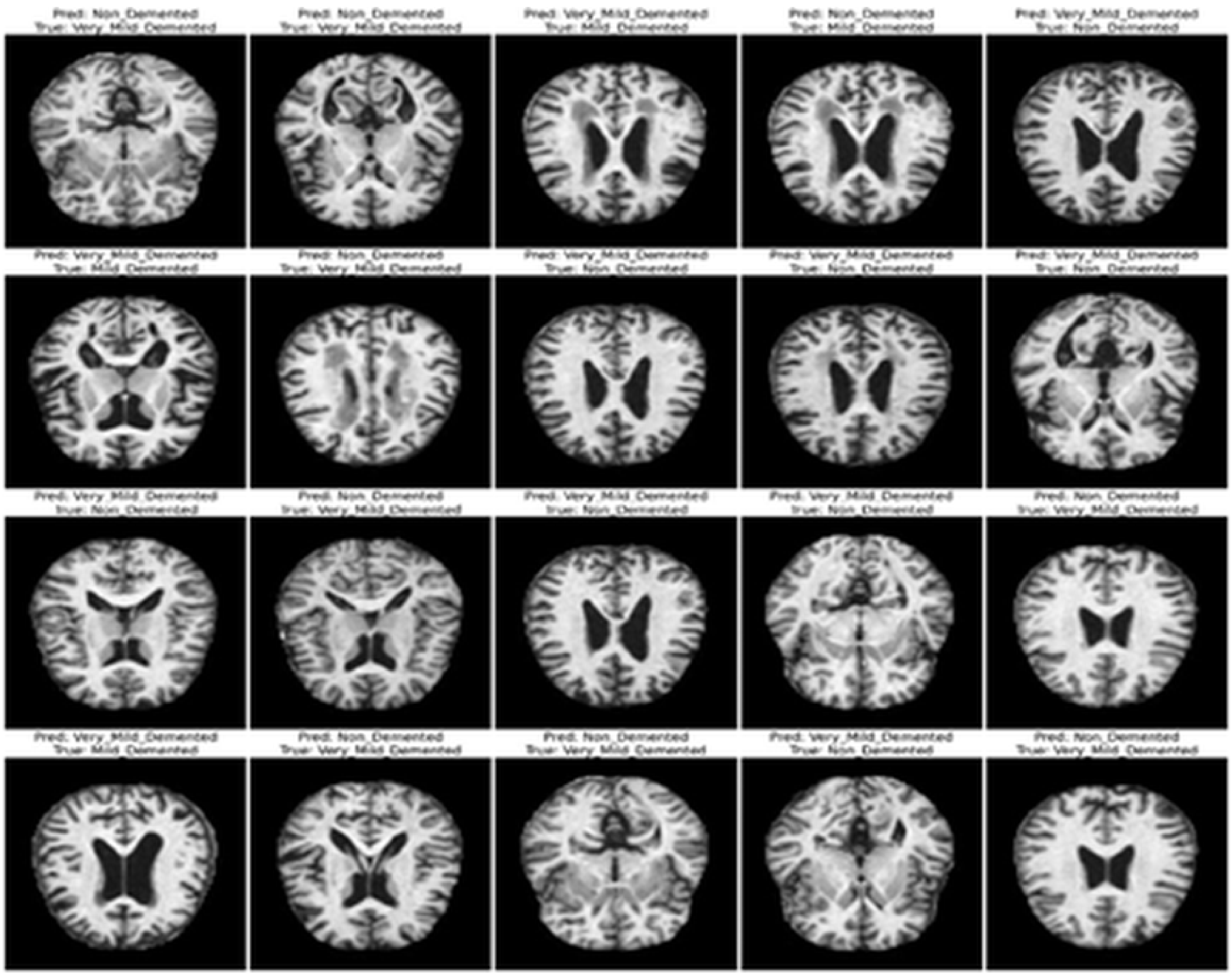

Figure 7. Proposed System Error Plotting

in formulating such research into an inexpensive method with good performances for early diagnosis of Alzheimer's disease, hence delaying its diagnosis by diagnostic performance, which can enable good improvement in quality of life in such patients. Besides, this work underlines how AI can be effectively introduced into clinical environments to offer more personalized treatment policies and lighten the burden on health systems. Further studies will move in the direction of better model interpretability and computational efficiency for the broad clinical applicability of the AI-based diagnosis method.

7. Future Scope

The integration of AI technologies into the diagnosis of Alzheimer's disease raises significant ethical considerations. AI models are biased, usually due to imbalanced training datasets, which could result in poor predictions across underrepresented demographic groups. Handling this requires diverse datasets and fairness-aware algorithms. There are also concerns about privacy with the handling of sensitive medical imaging and personal health information. It comes with robust data encryption, anonymization, and secure storage, thus ensuring adherence to a variety of privacy regulations, such as GDPR and HIPAA. Another critical factor is trust in AI-driven tools: explainable AI techniques will be in place to make model decisions transparent and comprehensible, thus boosting user confidence in clinical applications. Addressing these ethical challenges is crucial for the responsible translation of AI, guaranteeing fairness, privacy, and reliability in healthcare as the diagnostic capabilities for Alzheimer's disease continue to improve.

References

[1] R. Bidwe, S. Mishra, S. Bajaj, and K. Kotecha. Leveraging hybrid model of convnextbase and lightgbm for early asd detection via eye-gaze analysis. *MethodsX*, page 103166.

[2] S.A. Alowais, S.S. Alghamdi, N. Alsuhebany, et al. Revolutionizing

TABLE IV. Comparison of Different Methods with Proposed Method

Method	Techniques Used	Accuracy (%)	Advantages	Limitations
Goenka et al. (2021) [4]	Deep learning on MRI biomarkers	94.8	Effective early detection using comprehensive biomarkers	Limited dataset size and risk of overfitting
Kamal et al. (2021) [6]	Explainable AI with gene expression and imaging data	95.5	Integrates multimodal data combining genetic and imaging information	Complex and resource-intensive multi-source data integration
Wukkadada et al. (2023) [7]	K-Nearest Neighbors (KNN)-based ML	92.7	Simpler implementation, suitable for smaller datasets	Lower accuracy for complex and multidimensional image data
Rabeh et al. (2023) [10]	CNN-SVM hybrid for early-stage AD detection	94.88	High accuracy for early-stage classification	Computationally intensive due to hybrid model complexity
Proposed Method	Transfer learning	98.05	Superior accuracy with minimal misclassifications; efficient for image-based AD diagnosis	High dependency on pre-trained models; requires significant computational resources for training

TABLE V. Model Accuracy and Misclassified Images for Dementia Stages

Dementia Class	Accuracy	Misclassified Images
Mild Demented	94.50%	22
Moderate Demented	93.20%	33
Non-Demented	98.05%	15
Very Mild Demented	92.70%	28

healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ*, 23:689, 2023.

[3] J.B. Bae, S. Lee, W. Jung, et al. Identification of alzheimer's disease using a convolutional neural network model based on t1-weighted magnetic resonance imaging. *Sci Rep*, 10:22252, 2020.

[4] Nitika Goenka and Shamik Tiwari. Deep learning for alzheimer prediction using brain biomarkers. *Artificial Intelligence Review*, 54(7):4827–4871, 2021.

[5] Catherine Huber-Carol, Shulamith Gross, and Filia Vonta. Risk analysis: survival data analysis vs. machine learning. application to alzheimer prediction. *Comptes Rendus Mecanique*, 347(11):817–830, 2019.

[6] Md Sarwar Kamal, Aden Northcote, Linkon Chowdhury, Nilanjan Dey, Rubén González Crespo, and Enrique Herrera-Viedma. Alzheimer's patient analysis using image and gene expression data and explainable-ai to present associated genes. *IEEE Transactions on Instrumentation and Measurement*, 70:1–7, 2021.

[7] Bharati Wukkadada, Kirti Wankhede, Sangeetha Rajesh, C. Ria, and Tridib Chakraborty. Alzheimer prediction using machine learning algorithm. In *2023 Somaiya International Conference on Technology and Information Management (SICTIM)*, pages 39–43. IEEE, 2023.

[8] MV Vijaya Saradhi, Pinagadi Venkateswara Rao, V. Gokula Krishnan, K. Sathyamoorthy, and V. Vijayaraja. Prediction of alzheimer's disease using lenet-cnn model with optimal adaptive bilateral filtering. *International Journal of Communication Networks and Information Security*, 15(1):52–58, 2023.

[9] Daichi Shigemizu, Shintaro Akiyama, Mutsumi Suganuma, Motoki Furutani, Akiko Yamakawa, Yukiko Nakano, Kouichi Ozaki, and Shumpei Niida. Classification and deep-learning–based prediction of alzheimer disease subtypes by using genomic data. *Translational Psychiatry*, 13(1):232, 2023.

[10] Amira Ben Rabeh, Faouzi Benzarti, and Hamid Amiri. Cnn-svm for prediction alzheimer disease in early step. In *2023 International Conference on Control, Automation and Diagnosis (ICCAD)*, pages 1–6. IEEE, 2023.

[11] Aldiyan Farhan Nugroho, Reza Rendian Septiawan, and Isman Kurniawan. Prediction of human -secretase 1 (bace-1) inhibitors for alzheimer therapeutic agent by using fingerprint-based neural network optimized by bat algorithm. In *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, pages 257–261. IEEE, 2023.

[12] M. Menagadevi, S. Mangai, Nirmala Madian, and D. Thiyagarajan. Automated prediction system for alzheimer detection based on deep residual autoencoder and support vector machine. *Optik*, 272:170212, 2023.

[13] Raveendra Reddy Enumula and Rama KRISHNA RAO. Alzheimer's disease prediction and classification using ct images through machine learning. *Bratislava Medical Journal/Bratislavske Lekarske Listy*, 124(5), 2023.

[14] C. HSCA Rama Ganesh, G. Sri Nithin, S. Akshay, and T. Venkat Narayana Rao. Multi class alzheimer disease detection using deep learning techniques. In *2022 International Conference on Decision Aid Sciences and Applications (DASA)*, pages 470–474. IEEE, 2022.

[15] B. Hemalatha and M. Renukadevi. Analysis of alzheimer disease prediction using machine learning techniques. *Information Technology In Industry*, 9(1):519–525, 2021.

[16] Harald Hampel, Coralie Williams, Adrien Etcheto, Federico Goodsaid, Frédéric Parmentier, Jean Sallantin, Walter E. Kaufmann, Christopher U. Missling, and Mohammad Afshar. A precision medicine framework using artificial intelligence for the identification and confirmation of genomic biomarkers of response to an alzheimer's disease therapy: analysis of the blarcamesine (anavex2-73) phase 2a clinical study. *Alzheimer's Dementia: Translational Research Clinical Interventions*, 6(1):e12013, 2020.

[17] Rashmi Patil and Sreepathi Bellary. Machine learning approach in melanoma cancer stage detection. *Journal of King Saud University-Computer and Information Sciences*, 34(6):3285–3293, 2022.

[18] Rashmi Patil et al. Machine learning approach for malignant melanoma classification. *International Journal of Science, Technology, Engineering and Management-A VTU Publication*, 3(1):40–46, 2021.

[19] D. Mane, R. Ashtagi, P. Kumbharkar, S. Kadam, D. Salunkhe, and G. Upadhye. An improved transfer learning approach for classification of types of cancer. *Traitement du Signal*, 39(6):2095–2101, 2022.

[20] N. Pasnoori, T. Flores-Garcia, and B.D. Barkana. Histogram-based features track alzheimer's progression in brain mri. *Sci Rep*, 14:257, 2024.

[21] R. V. Bidwe, S. Mishra, S. Patil, K. Shaw, D. R. Vora, K. Kotecha, and B. Zope. Deep learning approaches for video compression: a bibliometric analysis. *Big Data and Cognitive Computing*, 6(2):44, 2022.