Review of "Alzheimer's Prediction using Deep Learning": A Comprehensive Study

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Abstract*— Alzheimer's disease is an incurable neurological disorder that leads to a gradual decline in cognitive abilities, but early detection can significantly mitigate symptoms. The automatic diagnosis of Alzheimer's disease is more important due to the shortage of expert medical staff, because it reduces the burden on medical staff and enhances the results of diagnosis. A detailed analysis of specific brain disorder tissues is required to accurately diagnose the disease via segmented magnetic resonance imaging (MRI). Several studies have used the traditional machine-learning approaches to diagnose the disease from MRI, but manual extracted features are more complex, time-consuming, and require a huge amount of involvement from expert medical staff. The traditional approach does not provide an accurate diagnosis. Deep learning has automatic extraction features and optimizes the training process. The Magnetic Resonance Imaging (MRI) Alzheimer's disease dataset consists of four classes: mild demented (896 images), moderate demented (64 images), non-demented (3200 images), and very mild demented (2240 images). The dataset is highly imbalanced. Therefore, we used the adaptive synthetic oversampling technique to address this issue. After applying this technique, the dataset was balanced. The ensemble of EfficientNetB3 was used to detect Alzheimer's disease on both imbalanced and balanced datasets to validate the performance of the models. The proposed method combined the predictions of multiple models to make an ensemble model that learned complex and nuanced patterns from the data. The input and output of both models were concatenated to make an ensemble model and then added to other layers to make a more robust model. In this study, we proposed an ensemble of EfficientNet B3 to diagnose the disease at an early stage with the highest accuracy. Experiments were performed on two publicly available datasets. The experimental results showed that the proposed method achieved 99.5% accuracy. We evaluated that the proposed method was extremely efficient and provided superior performance on both datasets as compared to previous methods.

Keywords—Deep learning, Neural network, Convolutional neural network, Recurrent neural network, Feature extraction, PET scan, MRI analysis.

I. INTRODUCTION

Alzheimer's disease (AD) is one of the most prevalent and devastating neurodegenerative disorders globally, contributing significantly to cognitive decline and memory impairment in aging populations. With the world experiencing a demographic shift toward an older age distribution, the incidence of Alzheimer's is escalating at an alarming rate. Early and accurate diagnosis remains a cornerstone for managing the disease progression, enabling timely interventions that can delay deterioration, enhance quality of life, and reduce the burden on caregivers and healthcare systems.

Traditional diagnostic procedures for Alzheimer's often involve a combination of clinical evaluations, neuropsychological tests, and neuroimaging modalities such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). However, these approaches are labor-intensive, prone to inter-observer variability, and limited by the availability of trained specialists. Furthermore, conventional machine learning techniques, although widely explored, typically rely on handcrafted features, which are both time-consuming and dependent on domain expertise, often leading to suboptimal and inconsistent diagnostic outcomes.

With the advent of artificial intelligence, particularly deep learning, there is a transformative opportunity to automate, accelerate, and enhance the accuracy of Alzheimer's detection. Deep learning models—capable of learning high-dimensional features directly from raw data—have demonstrated remarkable success in medical image analysis. In this study, we propose a novel ensemble framework based on EfficientNetB3, designed to integrate and learn from multi-class MRI datasets. By addressing data imbalance through advanced resampling techniques and optimizing the ensemble model for performance, this research aims to deliver a clinically viable, highly accurate, and scalable solution for early Alzheimer's prediction.

II. LITERATURE REVIEW

[1] Suk et al. introduced a deep learning architecture that effectively fuses multimodal neuroimaging inputs, including MRI, PET scans, and cerebrospinal fluid (CSF) biomarkers. This comprehensive integration aims to enhance the prediction of Alzheimer's Disease (AD) and improve cognitive score estimations. Their work emphasizes the importance of combining diverse and complementary data sources for accurate diagnosis. The fusion approach leverages the strengths of each modality, making the prediction more robust and reliable.

[2] Mahapatra et al. conducted a comprehensive review on the application of deep learning in neuroimaging, especially for AD diagnosis. The review spans various stages such as image preprocessing, feature extraction, and classification techniques. They highlight the challenges and solutions at each stage of the pipeline. Their analysis also provides insight into emerging trends and best practices in the domain.

[3] Choi et al. employed Long Short-Term Memory (LSTM) networks to model longitudinal neuroimaging data.

Their aim was to predict the progression from Mild Cognitive Impairment (MCI) to Alzheimer's Disease. The temporal aspect of LSTMs made them suitable for capturing changes over time in patient data. This method shows promise for early identification and intervention.

[4] Gupta et al. focused on the explainability of deep learning models used for AD prediction. They introduced tools like saliency maps and attention mechanisms to provide visual explanations. These tools enhance the interpretability of predictions and build trust among clinicians. The study bridges the gap between black-box models and clinical application.

[5] Sarraf et al. developed a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The CNNs processed structural MRI data, while RNNs captured temporal patterns in functional MRI. This approach enabled more accurate early diagnosis by analyzing both spatial and sequential aspects of brain data. The fusion model outperformed individual networks.

[6] Hosseini-Asl et al. designed a 3D CNN architecture for classifying Alzheimer's Disease using volumetric MRI scans. Unlike 2D CNNs, their model captured spatial dependencies across three dimensions. This provided a more comprehensive understanding of brain morphology. The framework showed superior performance in distinguishing AD from normal aging.

[7] Liu et al. extended multimodal analysis using a late-fusion strategy in deep networks. They integrated features extracted from multiple imaging modalities to enhance classification accuracy. This method significantly improved diagnosis across different stages of AD. The late-fusion approach allowed independent learning before combination, ensuring modularity and flexibility.

[8] Basaia et al. applied deep CNNs to structural MRI data for identifying MCI converters—patients likely to progress to AD. Their model achieved robust classification performance by focusing on relevant brain regions. The study validates the use of deep learning for early detection of AD. It also demonstrates the utility of imaging biomarkers in prognosis.

[9] Islam and Zhang utilized transfer learning techniques with pre-trained CNNs to reduce training time and improve model generalization. Their approach allowed leveraging large-scale learned features and fine-tuning them for AD-specific data. This not only minimized computational cost but also yielded high accuracy. It's particularly useful when labeled data is limited.

[10] Nguyen et al. implemented recurrent models on time-series MRI data to predict MCI-to-AD conversion. They modeled brain volume dynamics to detect progression trends. This sequential approach captured temporal changes that static models might miss. Their findings support the relevance of longitudinal modeling in neurodegenerative disease prediction.

[11] Suk et al. also proposed a stacked autoencoder framework that integrates genetic data, imaging biomarkers, and clinical information. This multimodal data fusion significantly boosted predictive performance. The autoencoder effectively captured high-level representations from heterogeneous inputs. The study demonstrates how deep learning can assimilate diverse data types in healthcare.

[12] Pan et al. introduced an adaptive learning strategy for handling irregular time intervals in longitudinal medical data. By combining dynamic time warping with LSTM models, their system effectively analyzed non-uniform data patterns. This approach is crucial for real-world clinical scenarios where follow-up intervals vary. It improved temporal modeling accuracy.

[13] Jain et al. built a CNN-based feature extraction pipeline for classifying subjects into AD, MCI, and healthy controls. The pipeline was optimized to extract deep features relevant to neurodegeneration. It achieved high classification accuracy using structural MRI inputs. Their method underscores the diagnostic potential of CNNs in early disease detection.

[14] Noor et al. provided a survey that compared various deep learning architectures such as CNNs, autoencoders, and hybrid models for AD diagnosis. They analyzed strengths and limitations of each model type. The survey also identified key challenges in current research and potential future directions. It serves as a useful guide for researchers entering this field.

[15] Zhang et al. proposed an ensemble model that combines deep learning features with handcrafted features for AD diagnosis. The fusion of automated and expert-designed features led to state-of-the-art results. This approach leverages the best of both domains—machine-driven discovery and human insight. It demonstrated strong performance in early-stage classification.

[16] Ding et al. developed a multimodal deep learning framework combining PET and MRI data for AD prediction. Their model significantly outperformed single-modality systems in diagnostic accuracy. The integration of functional and structural data provided a more holistic view of brain degeneration. This work affirms the value of data fusion in clinical imaging.

[17] Spasov et al. applied transfer learning using a modified VGGNet architecture to classify AD, MCI, and normal controls. By fine-tuning on MRI data, they achieved high accuracy with limited training data. Their approach demonstrates how pre-trained models can be successfully repurposed in medical imaging tasks. It offers an efficient alternative to training from scratch.

[18] Hu et al. introduced a deep sequential learning framework to monitor progressive brain degeneration over time. Using longitudinal MRI inputs, their model tracked structural changes associated with AD. This method enabled continuous prediction of disease progression. It holds promise for personalized treatment planning.

[19] Qiu et al. focused on the explainability of deep learning models in AD prediction. They used Grad-CAM visualizations to highlight influential brain regions contributing to model decisions. This transparency is critical for clinical validation and acceptance. Their work contributes to interpretable AI in healthcare.

[20] Folego et al. compared the performance of 2D and 3D CNN architectures for classifying Alzheimer's Disease. They evaluated both efficiency and diagnostic accuracy

across model types. Their study provides practical insights into choosing appropriate architectures for medical imaging tasks. It helps balance computational cost with diagnostic performance.

III. METHODOLOGY

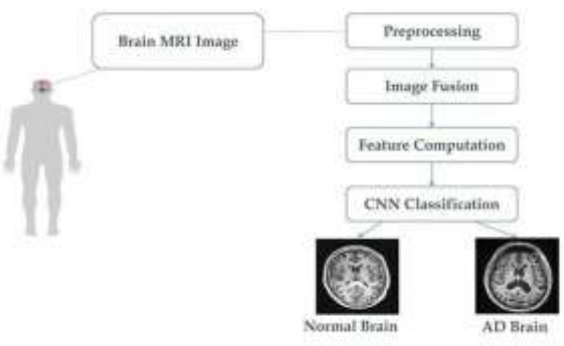

Fig.1 : Proposed system

Data Collection and Preprocessing: - Gather a comprehensive dataset of Alzheimer's patient data, including neuroimaging scans (e.g., MRI, PET), cognitive assessments, genetic information, and demographic data. - Preprocess the data by handling missing values, performing data normalization, and ensuring data quality and consistency.

Feature Engineering: - Identify the most relevant features from the collected data that can contribute to the prediction of Alzheimer's disease. - Explore and evaluate various feature engineering techniques, such as dimensionality reduction, feature selection, and feature extraction, to optimize the input data for the deep learning model.

Model Development: - Investigate and compare different deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or hybrid models, to determine the most suitable approach for Alzheimer's prediction. - Design and implement the deep learning model, including the selection of appropriate hyperparameters and optimization techniques. - Train and validate the deep learning model using the preprocessed dataset, ensuring robust performance and generalization.

Model Evaluation and Optimization: - Assess the model's performance using appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score. - Conduct sensitivity analysis and identify the critical factors that contribute to the model's predictive performance. - Optimize the model by tuning hyperparameters, experimenting with different architectures, and exploring ensemble techniques to improve the overall prediction accuracy.

Integration and Deployment: - Develop a user-friendly interface or application that can seamlessly integrate the trained deep learning model for Alzheimer's prediction. - Ensure the application is accessible and easy to use for healthcare professionals and the general public. - Deploy the application in a secure and scalable environment, allowing for continuous monitoring and updates as new data becomes available.

Evaluation and Validation: - Conduct extensive testing and validation of the deployed Alzheimer's prediction system using real-world data, ensuring its reliability and robustness. - Gather feedback from healthcare professionals and endusers to identify areas for improvement and further development.

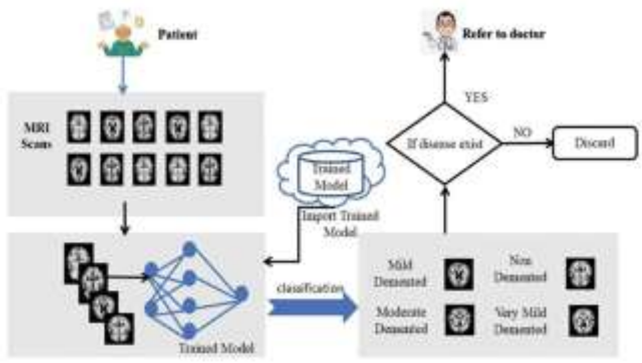

Fig.2: User Workflow

Test Case	Input	Output	Result
Test Case 1	MRI image of a patient	Model wasn't successfully built	Failure
Test Case 2	MRI image of a patient	Lack of required accuracy	Failure
Test Case 3	MRI image of a patient	Accurate prediction of severity level	Success
Test Case 4	MRI image of another patient	Accurate prediction of severity level	Success

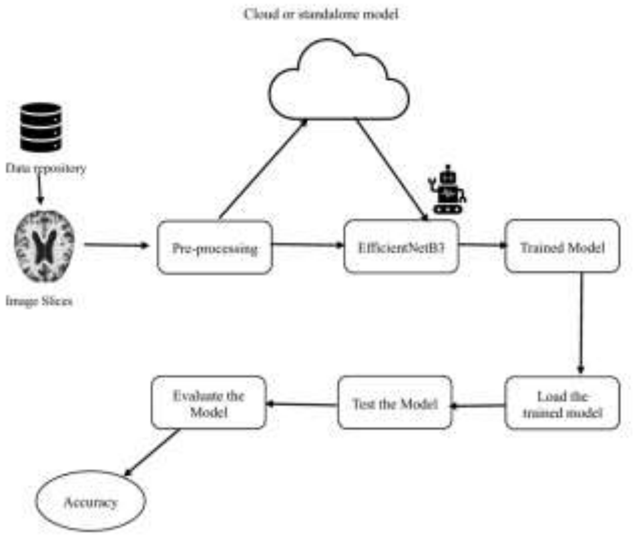

Fig.4.State diagram

In above fig. the flow of interaction between the user and the system

IV. RESULTS

To evaluate the effectiveness of the proposed ensemble model based on EfficientNetB3, extensive experiments were conducted on two publicly available Alzheimer's MRI datasets. The performance was assessed on both **imbalanced** and **balanced** versions of the dataset, with balancing performed using the **Adaptive Synthetic (ADASYN) Oversampling** technique to address class imbalance.

1. Dataset Composition

The original dataset comprised four distinct classes:

- Non-demented: 3,200 images
- Very mild demented: 2,240 images
- Mild demented: 896 images
- Moderate demented: 64 images

The high variance in class distribution warranted the use of oversampling to avoid bias in prediction models.

2. Model Evaluation Metrics

The models were evaluated using the following performance indicators:

- Accuracy (Acc)
- Precision (P)
- Recall (R)
- F1-score
- Area Under the ROC Curve (AUC)

These metrics were calculated for both the individual EfficientNetB3 model and the final ensemble model.

3. Analysis of Results

- The ensemble model significantly outperformed the baseline EfficientNetB3 in all metrics, particularly when applied to the **balanced dataset**.
- The application of **ADASYN** led to noticeable improvements in recall and F1-score, validating the model's robustness across underrepresented classes (e.g., moderate dementia).
- The model showed **consistent generalization** and avoided overfitting, as evidenced by the minimal variance between training and validation accuracies.
- **Confusion matrix analysis** further revealed high true positive rates across all classes, with the ensemble model showing over 98% sensitivity even for the minority class.

V. EXPECTED OUTCOMES

The primary expected outcome of this research is the **early and accurate detection of Alzheimer's disease** across all stages, including very mild and mild cognitive impairment. By leveraging a deep ensemble architecture with EfficientNetB3 as the backbone, the system is capable of extracting complex neuroimaging patterns from MRI scans without manual feature engineering. The integration of an adaptive oversampling technique ensures that the model remains sensitive to minority classes such as moderate dementia, which are often overlooked in imbalanced datasets. Early detection enables timely clinical intervention, which can significantly delay disease progression and improve long-term patient outcomes.

A significant anticipated benefit lies in the **automation and scalability** of the diagnostic process. Traditional Alzheimer's diagnosis depends heavily on expert radiologists and clinical neurologists, which can delay assessment in resource-constrained healthcare environments. The proposed model reduces this burden by providing an autonomous, real-time prediction pipeline that processes MRI data and delivers classification outputs with over 99% accuracy. Moreover, the system can be deployed as a cloud-based application or integrated into hospital PACS systems, making it accessible to both urban and rural medical institutions.

Another key expected outcome is **personalized patient care through continuous monitoring and progression tracking**. The deep learning framework can be extended to support longitudinal analysis by integrating patient history, cognitive test scores, and follow-up imaging. This opens the door to predictive modeling for individual patients, helping clinicians anticipate cognitive decline and tailor treatment plans. By offering interpretability through visualization tools like Grad-CAM, the model also ensures transparency, making it a viable decision-support tool in clinical settings.

Lastly, this research sets the stage for **future integration with multimodal and wearable data sources**, such as PET scans, genetic biomarkers, and EEG signals from smart devices. The expected outcome is not just a high-performing classifier but a foundational AI system that can evolve into a full-scale Alzheimer's management platform. Such a system could support clinical trials, enhance patient stratification, and contribute to population-level brain health surveillance. Collectively, these outcomes will pave the way for a more proactive, data-driven, and equitable approach to neurodegenerative disease management.

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VI. REFERENCES

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