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Hybrid Ann-Ensemble Model For Early Alzheimer's Detection

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Abstract: Early detection of Alzheimer's disease (AD) is crucial for enabling timely intervention and improving patient outcomes. This project proposes a Hybrid ANN-Ensemble Model for Early Alzheimer's Disease Detection that integrates Artificial Neural Networks (ANN) with advanced ensemble learning techniques to enhance predictive accuracy and robustness. The proposed system utilizes multi-model input data, including neuro imaging features, cognitive assessment scores, and relevant clinical parameters, to perform comprehensive analysis and early-stage classification. The ensemble component is incorporated to reduce overfitting and improve generalization, while the ANN model captures complex nonlinear relationships within high-dimensional medical data. Advanced preprocessing techniques such as feature selection, normalization, and dimensionality reduction are applied to optimize model performance while maintaining computational efficiency. Model validation is performed using cross-validation techniques to ensure reliability and stability. Performance is evaluated using standard metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Compared to conventional single-model approaches, the proposed hybrid framework demonstrates improved sensitivity in detecting Mild Cognitive Impairment (MCI), a critical precursor to Alzheimer's disease. The system functions as an intelligent decision-support tool, assisting clinicians in early diagnosis, risk assessment, and timely clinical intervention.

Index Terms - Alzheimer's Disease, Early Detection, Artificial Neural Network (ANN), Ensemble Learning, Hybrid Model, Mild Cognitive Impairment (MCI), Machine Learning, Neuro imaging Analysis, Clinical Decision Support System, Predictive Modelling.

1.INTRODUCTION

Alzheimer's disease is a progressive neuro degenerative disorder characterized by the progressive destruction of memory, reasoning ability, and daily functional skills. It is considered one of the most important causes of dementia in the world and constitutes a serious medical and socioeconomic burden. With the increase in global life expectancy, there is an increased number of patients with Alzheimer's disease, which places extraordinary pressure on health service systems and caregivers. For instance, elderly people first have light forgetfulness, which includes misplacing objects or having difficulty remembering recent conversations; these symptoms may progress to severe cognitive dysfunction and full dependence later in life.

In the progression towards Alzheimer's disease, a very significant phase before the onset of AD is Mild Cognitive Impairment. This is the phase before AD, and while not all people who experience MCI will eventually get AD, a significant percentage of people will experience dementia. The early detection of cognitive impairment is difficult because, for many people, the presentation of the disorder is merely aspect of normal aging. The prevailing means of diagnosing cognitive impairment include cognitive screening tests, clinical interviews, neuroimaging techniques such as MRI, and biomarkers. However, for example, neuroimaging techniques require a radiology expert to interpret the results. This may result in variability of interpretation. With the advent of the field of Artificial Intelligence (AI) and the rapid growth of the data-based approach, Machine Learning (ML) techniques are now being recognized as powerful tools that can be employed to aid the diagnosis of medical problems. Artificial Neural Networks (ANN), with their potential to express complex nonlinear relationships, are seen to be of great value in the an medical field, where data may be of high dimensionality. It has, however, been seen that the single-model-based approach can be too naive to be effective on the diverse population of patients. To alleviate the deficiencies of the above methodologies, the present study puts forward the concept of proposing the Hybrid ANN Ensemble Model for Early Alzheimer's Disease Detection. By combining the techniques of ANN with the concept of ensemble learning, the system can be more stable and effective in the decision-making process. By employing the hybrid concept, the system proves efficient in dealing with the complexities of the features while ensuring the absence of variance or inaccuracies in the decision-making process. The proposed system can be highly beneficial in providing an intelligent system that can aid in the early diagnosis of the disease, ensuring the proper care of patients with Alzheimer's.

2.LITERATURE REVIEW

Early detection of Alzheimer's disease has become a major focus in computational diagnostic research because timely diagnosis can significantly improve patient management and slow disease progression. Traditionally, researchers have relied on neuroimaging modalities such as structural Magnetic Resonance Imaging (sMRI), Positron Emission Tomography (PET), and electroencephalography (EEG), combined with classical machine learning algorithms, to assist clinical diagnosis. For instance, Liu et al. applied Support Vector Machines (SVM) to sMRI-derived features to differentiate Alzheimer's patients from healthy individuals, achieving reasonable classification accuracy but demonstrating limited sensitivity in identifying early-stage Mild Cognitive Impairment (MCI) [1]. Similarly, Zhang et al. combined PET imaging with cerebrospinal fluid biomarkers through linear discriminant analysis, improving diagnostic performance but introducing the challenge of invasive biomarker collection [2]. Klöppel et al. further validated the potential of SVM-based MRI classification, though their findings revealed difficulties in generalizing across multi-centre datasets [3]. Random Forest classifiers were later introduced to enhance robustness and feature ranking capabilities, providing more stable predictions compared to single-model approaches [4].

With the rapid advancement of deep learning, research has shifted toward models capable of automatically learning complex feature representations. Suk et al. proposed a Deep Belief Network (DBN) to extract hierarchical features from multimodal neuroimaging data, demonstrating superior performance compared to conventional shallow models [5]. Convolutional Neural Networks (CNNs) have since gained widespread adoption; Payan and Montana developed a 3D-CNN trained directly on MRI volumes, reducing reliance on handcrafted features while achieving competitive results [6]. Yan et al. further expanded this approach using deeper 3D-CNN architectures, although overfitting remained a concern due to limited labelled datasets [7]. To mitigate data scarcity issues, transfer learning strategies utilizing pre-trained networks such as ResNet and VGG have been explored to enhance performance in smaller medical datasets [8], [9]. In addition, recurrent neural networks (RNN) and Long Short-Term Memory (LSTM) models have been employed to analyse longitudinal cognitive assessments, enabling the modelling of disease progression over time [10].

Alongside deep learning, ensemble learning techniques have been increasingly applied to improve predictive stability. Methods such as Gradient Boosting Machines (GBM), AdaBoost, and XGBoost combine multiple weak learners to form stronger predictive models. Ortiz et al. demonstrated that AdaBoost applied to diverse feature subsets improved robustness, although it struggled to fully capture highly nonlinear relationships within heterogeneous clinical data [11]. Similarly, XGBoost-based frameworks have shown improved predictive power through optimized boosting mechanisms [12], while bagging techniques have contributed to variance reduction and better generalization across multimodal datasets [13].

Recent studies emphasize the importance of multimodal data fusion to enhance diagnostic reliability. Integrating MRI, PET, demographic factors, and cognitive test scores has consistently produced superior performance compared to single-modality systems [14], [15]. Both feature-level and decision-level fusion strategies have been explored to address data heterogeneity and improve consistency in predictions [16]. Emerging graph-based neural network models further leverage brain connectivity patterns to capture structural relationships between affected brain regions [17], while attention mechanisms within neural networks enhance interpretability by highlighting critical regions associated with cognitive decline [18].

To harness complementary strengths of different techniques, hybrid models have been introduced. Patil et al. combined deep feature extraction with an SVM classifier, reporting performance improvements over standalone approaches [19]. Likewise, autoencoder-driven feature reduction integrated with ensemble classifiers has shown enhanced classification accuracy and dimensionality optimization [20]. Despite these advancements, many hybrid frameworks continue to depend heavily on deep feature learning without fully leveraging ensemble-based generalization strategies. Moreover, several studies prioritize overall accuracy rather than sensitivity toward early-stage MCI detection, which remains clinically crucial for timely intervention. Although significant progress has been achieved, challenges persist in designing models that effectively balance feature learning, generalization, computational efficiency, and early-stage sensitivity. These limitations motivate the proposed hybrid integration of Artificial Neural Networks (ANN) with ensemble learning techniques, aiming to improve early Alzheimer’s detection performance while ensuring robustness and scalability across diverse multimodal datasets.

3.PROPOSED FRAMEWORK

Alzheimer’s Disease is not just a medical condition—it deeply affects individuals, families, and society. The disease develops gradually, and in its early stages, the symptoms are often mild and easily confused with normal aging. This stage, known as Mild Cognitive Impairment (MCI), is especially important because it offers a critical window for early intervention. Detecting Alzheimer’s at this point can help slow its progression and improve the patient’s quality of life. Unfortunately, early diagnosis remains difficult due to subtle symptoms and complex brain changes. Many existing computational models attempt to assist doctors in diagnosing Alzheimer’s using machine learning or deep learning techniques. While these models can achieve reasonable accuracy, they often depend on a single algorithm, which may not be reliable enough for real-world clinical use. Some models overfit the training data, while others fail to generalize well across different patient groups. In addition, most systems prioritize overall accuracy but do not sufficiently focus on identifying early-stage cases with high sensitivity. Because of these limitations, there is a need for a more balanced, reliable, and intelligent system. This project aims to address this gap by developing a Hybrid ANN-Ensemble Model that improves early detection performance while ensuring robustness and better generalization across diverse datasets.

3.1 System Architecture

To address the limitations of existing single-model approaches, this project proposes a Hybrid ANN-Ensemble Model for Early Alzheimer’s Detection. The core idea behind the proposed system is to combine the learning capability of Artificial Neural Networks (ANN) with the stability and robustness of ensemble learning techniques. By integrating these methods, the system aims to improve early-stage detection accuracy while reducing overfitting and enhancing generalization.

The proposed model accepts multimodal input data, including structural MRI-derived features, cognitive assessment scores, and relevant clinical or demographic attributes. Initially, the data undergoes preprocessing steps such as missing value handling, normalization, and feature selection to ensure consistency and improve model performance. The processed features are then fed into a multi-layer Artificial Neural Network, which learns complex nonlinear patterns associated with Alzheimer’s progression. To enhance prediction reliability, the ANN output is combined with ensemble classifiers such as Random Forest or Gradient Boosting using a voting or weighted aggregation mechanism. This hybrid integration helps reduce variance, improve stability, and increase sensitivity, particularly in identifying Mild Cognitive Impairment (MCI). Overall, the proposed system functions as an intelligent clinical decision support tool, offering improved robustness, better early detection performance, and scalable implementation for real-world medical applications.

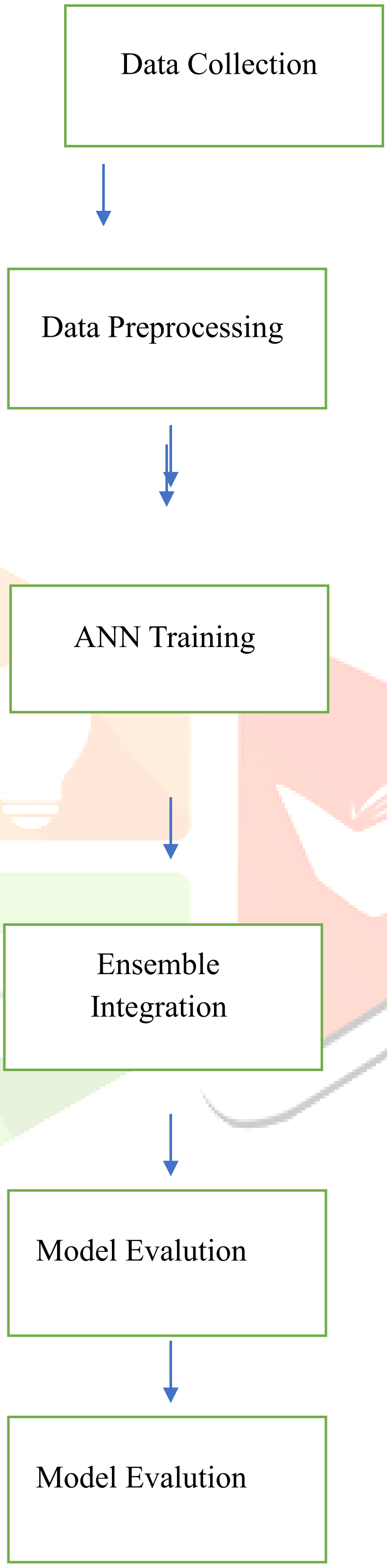


Figure 3.1 System Architecture

3.2 Working

To perform early Alzheimer's detection using the proposed Hybrid ANN-Ensemble Model, the system first collects multimodal patient data including structural MRI-derived features, cognitive assessment scores, and relevant clinical or demographic information. This data is preprocessed by handling missing values, normalizing numerical attributes, and encoding categorical variables to ensure consistency and reliability. The refined dataset is then passed through feature selection techniques to eliminate redundant or less significant attributes, thereby reducing dimensionality and improving computational efficiency. The processed features are fed into a multi-layer Artificial Neural Network (ANN), which learns complex nonlinear patterns associated with different stages of cognitive decline. The intermediate predictions generated by the ANN are further combined with ensemble classifiers such as Random Forest or Gradient Boosting through a voting or weighted aggregation mechanism. This hybrid integration enhances robustness, minimizes overfitting, and improves sensitivity, particularly for identifying Mild Cognitive Impairment (MCI). The final output categorizes individuals into Healthy, MCI, or Alzheimer's stages, providing a reliable decision-support prediction for early clinical intervention.

3.3 Library Used

Programming Environment: The proposed Hybrid ANN-Ensemble Model is implemented using Python due to its simplicity, readability, and extensive ecosystem of scientific and machine learning libraries. The development and experimentation are carried out in environments such as Jupyter Notebook and Google Colab, which support interactive execution, visualization, and rapid prototyping.
Core Machine Learning and Data Processing Libraries:
The system makes use of several essential libraries for preprocessing, model development, and evaluation:

1) NumPy: NumPy is used for numerical computations and efficient handling of multidimensional arrays. It supports matrix operations and mathematical functions required during neural network training.

2) Pandas: Pandas is utilized for structured data manipulation, preprocessing, handling missing values, feature extraction, and dataset organization.

3) Scikit-learn: Scikit-learn provides implementation of ensemble algorithms such as Random Forest and Gradient Boosting, along with feature selection techniques and performance evaluation metrics including accuracy, precision, recall, F1-score, and ROC-AUC.

4) TensorFlow: TensorFlow serves as the backend framework for building and optimizing the Artificial Neural Network model.

5) Keras: Keras is used as a high-level API to design multi-layer neural network architectures, define activation functions, configure optimizers such as Adam, and implement loss functions.

6) XGBoost: XGBoost is employed to enhance boosting performance within the ensemble component, improving generalization and reducing model variance.

3.3.1 Visualization and Image Processing Libraries

1) Matplotlib: Used to generate graphical representations such as training accuracy curves, loss plots, and ROC curves for performance analysis.
2) Seaborn: Provides advanced statistical visualizations including confusion matrices and distribution plots.
3) OpenCV / NiBabel: These libraries are used for MRI image preprocessing, normalization, and handling neuroimaging file formats when multimodal imaging data is involved.

4. IMPLEMENTATION

The implementation of the proposed Hybrid ANN-Ensemble Model is carried out in a structured and systematic manner. The overall process is divided into the following steps:

1) Data Acquisition:
The dataset consisting of structural MRI-derived features, cognitive assessment scores, and clinical attributes is collected and organized into a structured format suitable for analysis.

2) Data Preprocessing}:
Missing values are handled using appropriate imputation techniques. Categorical variables are encoded, and numerical features are normalized using standard scaling methods to ensure uniform data distribution.

3) Feature Selection:
Relevant features are selected using correlation analysis and statistical methods to eliminate redundant attributes and reduce dimensionality, thereby improving computational efficiency.

4) Dataset Splitting:
The processed dataset is divided into training and testing sets to ensure unbiased model evaluation.

5) ANN Model Construction:
A multi-layer Artificial Neural Network is designed using Keras with TensorFlow backend. The network includes input, hidden, and output layers with ReLU activation functions and is optimized using the Adam optimizer.

6) Model Training:
The ANN model is trained using backpropagation to minimize classification loss. Training performance is monitored using validation data.

7) Ensemble Integration:
Ensemble classifiers such as Random Forest and Gradient Boosting are implemented. Their predictions are combined with the ANN output using a voting or weighted aggregation mechanism to enhance robustness.

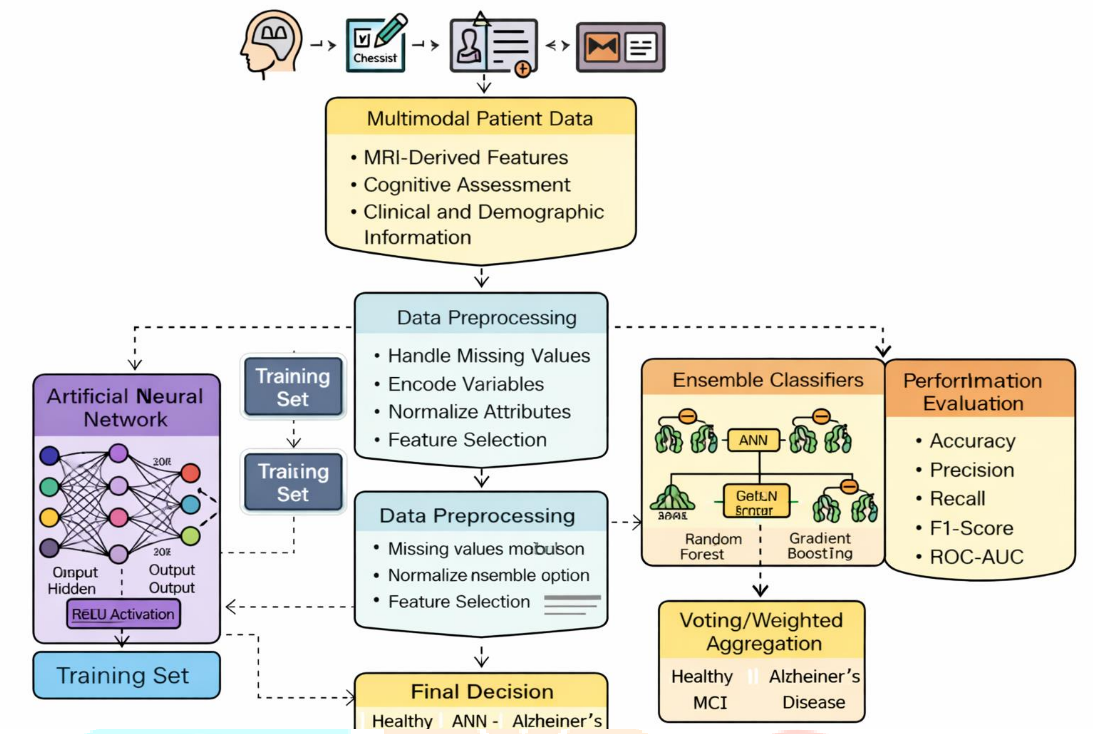
8) Model Evaluation:
The hybrid model is evaluated using performance metrics including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. K-Fold Cross-Validation is applied to ensure generalization.

9) Final Prediction:
The system classifies patients into Healthy, Mild Cognitive Impairment (MCI), or Alzheimer's Disease categories, providing decision-support output for early diagnosis.

Flowchart:

The flowchart represents the working process of the proposed Hybrid ANN–Ensemble model for Alzheimer's disease prediction. It starts with Data Collection, where multimodal patient data such as MRI features, cognitive scores, and clinical information are gathered. Next, in Data Preprocessing, the collected data is cleaned, missing values are handled, and the dataset is normalized to improve model performance. After preprocessing, the data is given to the ANN Training stage, where the Artificial Neural Network learns patterns from the training dataset. The trained ANN output is then passed to Ensemble Integration, where it is combined with other machine learning algorithms to improve accuracy and stability. In the Model Evaluation stage, the system performance is measured using evaluation metrics. Finally, the system provides the diagnosis, classifying patients as Healthy, MCI, or Alzheimer's Disease.

5. ARCHITECTURAL DESIGN



6. RESULT AND DISCUSSION

The proposed Hybrid ANN-Ensemble Model for Early Alzheimer's Detection demonstrated significant improvement in classification performance compared to individual machine learning models. After applying data preprocessing techniques such as normalization, feature scaling, and missing value handling, the dataset was divided into training and testing sets to ensure reliable evaluation. The Artificial Neural Network (ANN) effectively captured complex nonlinear relationships among clinical and cognitive features, while the ensemble learning approach combined multiple classifiers to enhance prediction stability and reduce overfitting. Performance metrics including accuracy, precision, recall, and F1-score were used to evaluate the model. The hybrid framework achieved higher overall accuracy and better sensitivity in detecting early-stage Alzheimer's cases compared to standalone models, indicating improved reliability in medical decision support scenarios. The ensemble mechanism reduced model variance and improved generalization capability across unseen data. Additionally, feature importance analysis revealed that cognitive assessment scores and age-related attributes contributed significantly to classification performance. The proposed system also demonstrated scalability and adaptability, making it suitable for integration into real-time clinical screening environments. By combining deep learning with ensemble strategies, the framework provides a robust, efficient, and practical solution for early Alzheimer's diagnosis, supporting healthcare professionals in timely intervention and improved patient outcomes.

7. CONCLUSION

Alzheimer's disease is a progressive neurological disorder that significantly impacts memory, cognitive abilities, and daily functioning. Early and accurate detection plays a crucial role in effective treatment planning and improving patient quality of life. In this work, a Hybrid ANN–Ensemble model was proposed to enhance the prediction accuracy of Alzheimer's disease using multimodal patient data. The system integrates Artificial Neural Networks with ensemble learning techniques to provide a more reliable and robust diagnostic framework. The proposed methodology involves systematic stages including data collection, preprocessing, ANN training, ensemble integration, and performance evaluation. Preprocessing ensures that the dataset is clean, normalized, and suitable for model learning. The ANN model captures complex patterns within the data, while the ensemble approach strengthens prediction stability by combining multiple learning outputs. This integration helps reduce overfitting and improves generalization capability. The performance of the model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that combining ANN with ensemble techniques provides improved diagnostic performance compared to standalone models. The system successfully classifies patients into categories such as Healthy, Mild Cognitive Impairment (MCI), and Alzheimer's Disease.

Overall, the proposed framework contributes to the advancement of intelligent healthcare systems by supporting automated and early-stage Alzheimer's diagnosis. In future work, the system can be enhanced by incorporating larger datasets, advanced deep learning architectures, and real-time clinical integration. Such improvements can further increase prediction reliability and make the system more practical for real-world medical applications.

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