

AI Driven Diagnosis of Dementia :A Comprehensive Study of Deep Learning and Traditional Models

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Abstract---Alzheimer's Disease (AD) is a chronic neurodegenerative disorder that affects millions of people globally. Early intervention and management through treatment are required to improve the quality of life of patients. In this article, we present end-to-end machine learning using the OASIS dataset with the integration of traditional machine learning algorithms and deep learning algorithms. We tested and trained five different models: a Convolutional Neural Network (CNN), a Long Short-Term Memory network (LSTM), a ResNet-based neural network, a Random Forest classifier, and an ensemble model that integrates neural network and traditional ML predictions. Our findings show that CNN and LSTM models both achieved the best accuracy of 98%, Random Forest and Ensemble models achieved 92%, and the ResNet-based model achieved 88%. Such findings show the power of hybrid model styles in clinical diagnostic applications and give a blueprint for further development in AI-enabled medicine.

Keywords---Alzheimer's Disease, Deep Learning, OASIS Dataset, Classification

I. INTRODUCTION

Alzheimer's Disease (AD) is the leading cause of dementia which is 60–80% of the world's dementia cases. It is characterized by a slow, progressive decline in cognition and function, causing severe disability to patients and a burden on caregivers. Early identification of dementia is important for optimal care planning and intervention. Conventional diagnostic methodology includes cognitive testing MMSE (A brief, standardized test of cognitive function), imaging studies (MRI, PET), and genetic testing. While incredibly useful, the modalities described can be resource- and cost-intensive with

limited access to care in primary health care as well as in low-resource contexts [11][12][5].

We utilize systematic clinical data in the form OASIS Cross-Sectional, consisting of demographics and anatomical information, such as age, MMSE, SES (a measure of the economic and social position of the individual's, or family, in relation to others) education, and all brain volume measures. This makes it possible for practical deployment to real-world healthcare systems and especially where there may not be imaging data available[1]. We provide comparison of five machine learning models trained with tabular data alone, including (1) a CNN for modeling the interaction of spatial features, (2) an LSTM for encoding the temporal progression, (3) an interpretable Random Forest for ensemble classification, (4) an attention mechanism inspired by ResNet for deep learning with explanations, and (5) an Ensemble model that combines specific neural and tree-based predictors[2][1][31].

II. LITERATURE REVIEW

In the beginning stages of predicting Alzheimer's disease (AD), most researchers used classic machine learning (ML) methods like Support Vector Machines (SVMs), Decision Trees, and Logistic regression. In general, the traditional ML models were not computationally intensive and easier to understand and work with, which provided a relatable option for developing the methods initially and assessing risk. However, the model limitations for predicting AD were significant when utilizing the typical complexity and progression of the disease, which would include a lot of handcrafted feature engineering and identification of

meaningful patterns, especially when looking at nonlinear associations or trends in cognitive decline [10][16]. The progression of Alzheimer's disease is a lengthy process of degeneration, which features include variables related to clinical, cognitive, anatomical, and genetic status that are all highly interrelated and interdependent, and early approaches largely failed in predicting an outcome. Traditional models displayed limitations in representing the variables of the cognitive decline adequately and sequentially over time, which limited their predictive approach, especially forecasting disease onset or differentiating MCI from AD [11][13]. RCAs and other linear models did not adequately address nonlinearity or interdependencies on the multimodal data.

To overcome those limitations, we primarily chose **Convolutional Neural Networks (CNNs)** because they effectively capture local-global feature interactions. CNNs have a storied history of success in image recognition, but they were built to work effectively on structured tabular data in biomedical modeling. CNNs had a very distinct advantage in that they can automatically learn localized dependencies and imply spatial hierarchies from features like MMSE (Mini-Mental State Examination), nWBV (Normalized Whole Brain Volume - indicating structural brain atrophy) and eTIV (Estimated Total Intracranial Volume - relevant for understanding brain size and CSF levels). These features are important in considering AD stages. CNNs offered automated feature extraction and showed advantages over traditional ML models with complex learning from features [14] [17].

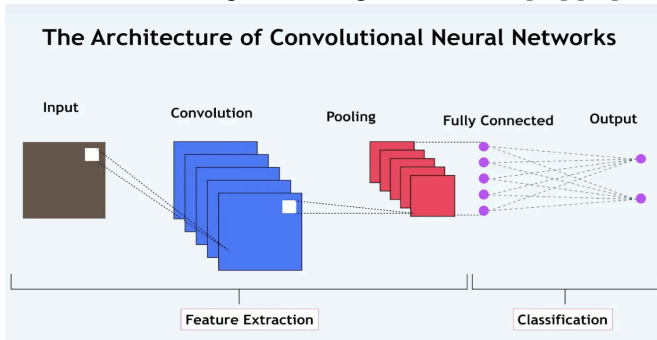


Figure 1: The Architecture diagram of CNN

The **CNN architecture**, as illustrated in Figure 1, begins with convolutional and pooling layers to extract hierarchical features from the input vector, followed by dense layers for final classification. This architecture enabled the model to learn both micro and macro-level patterns, significantly improving the robustness and generalization of predictions.

To model the **temporal progression** of dementia, particularly changes in cognitive scores over time, we utilized **Long Short-Term Memory (LSTM)** networks. LSTMs, a type of Recurrent Neural Network (RNN), are designed to capture long-term dependencies by mitigating vanishing gradient problems, making them ideal for sequential medical data. When trained on time-series data comprising longitudinal

cognitive assessments (e.g., MMSE across multiple visits), LSTMs were able to recognize subtle declines or fluctuations that may signal early-stage dementia [3][5].

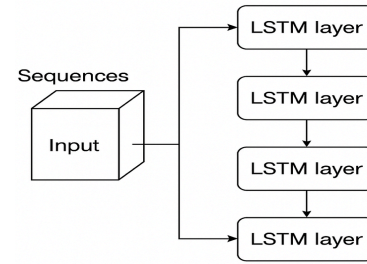


Figure 2: Architecture diagram of a stacked LSTM

Figure 2 illustrates our **stacked LSTM architecture**, where multiple LSTM layers are arranged sequentially. This deep LSTM setup captures both short-term changes (e.g., between adjacent clinical visits) and long-term trends across years. The architecture enabled the model to anticipate and identify critical inflection points in disease progression — a key benefit over static models.

To combine depth with interpretability, we introduced a **ResNet-like architecture** with integrated residual connections and attention mechanisms. Residual blocks allowed the training of deep neural networks without encountering gradient degradation, ensuring that earlier learned patterns were retained and enhanced by subsequent layers. The embedded **attention blocks** played a vital role in directing the model's focus towards clinically significant features such as hippocampal shrinkage or abnormal cognitive test results. This provided not only higher accuracy but also a level of **explainability**, which is crucial in healthcare applications where clinical decisions must be justified [4][7].

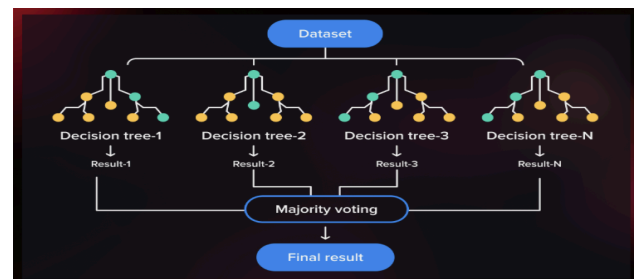


Figure 3: Ensemble learning architecture using multiple decision trees.

Meanwhile, **Random Forests** served as an efficient and interpretable baseline. These ensemble models are inherently robust to overfitting due to their averaging strategy across multiple decision trees. They also provide insight into **feature importance**, enabling researchers and clinicians to understand which variables (e.g., age, nWBV, education level, genetic

markers) most strongly influence the prediction outcome. This makes them valuable not only for prediction but also for feature selection and hypothesis generation in exploratory studies.

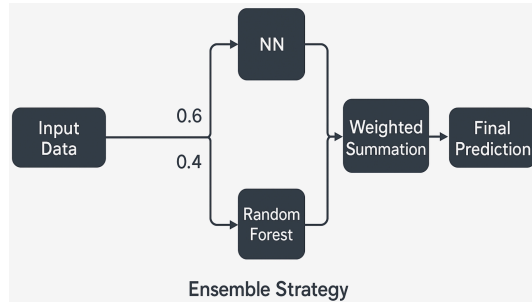


Figure 4: Ensemble strategy combining Neural Network (NN) and Random Forest predictions

Figure 3 showcases the **ensemble learning approach** of Random Forests. Each decision tree contributes a vote, and the final outcome is determined by aggregating these predictions, enhancing accuracy and stability.

Recognizing that each model brings unique strengths — neural networks in capturing complex nonlinear patterns, LSTMs in modeling time dynamics, and Random Forests in feature-based interpretability — we developed a **hybrid ensemble strategy**. This final architecture combines the predictions of neural models (CNN/ResNet/LSTM) and Random Forests using a **soft voting mechanism** with optimized weights (0.6 for neural models and 0.4 for Random Forests). This weighted ensemble allowed us to balance interpretability and accuracy, leveraging both the powerful representation learning of deep models and the feature transparency of tree-based methods [6][9][20].

Figure 4 illustrates this ensemble framework, where the model outputs are combined via a weighted summation strategy. The integration reduces variance, mitigates individual model biases, and ensures **generalizable performance across heterogeneous patient cohorts**. This robustness is particularly critical when applying the model across multi-center or multi-ethnic datasets with inherent variability.

III. PROPOSED METHODOLOGY

A. Dataset and Preprocessing

We utilized OASIS-1 Cross-Sectional dataset with cognitive, demographic, and anatomical assessments. Excess columns (e.g., ID) were dropped, and missing values were imputed by median and mode strategies. Label encoding was applied for category values like gender and handedness, and feature

scaling was applied using StandardScaler. LSTM employed a sliding window of 3 in order to form temporal sequences such that progression was learned by the network. Other models (ResNet, Random Forest, Ensemble) employed flattened vectors. Clinical Dementia Rating (CDR) was discretized to 0 (No dementia), 0.5 (Very mild), 1 (Mild), and 2 (Moderate) classes[1][3][5].

B. Model Architectures and Training

- *CNN*-Feature interactions were detected by a 1D CNN with three Conv1D layers (32, 64, 128 filters), ReLU activations, max pooling, and adaptive average pooling. Classification was achieved with a last fully connected layer. Adam optimizer (lr=0.001), batch size 32, and CrossEntropyLoss were used to train the model for 20 epochs. Regularization was achieved with dropout and L2 decay. It achieves 98% test accuracy and shows high performance in spatial patterns [2][13][14].

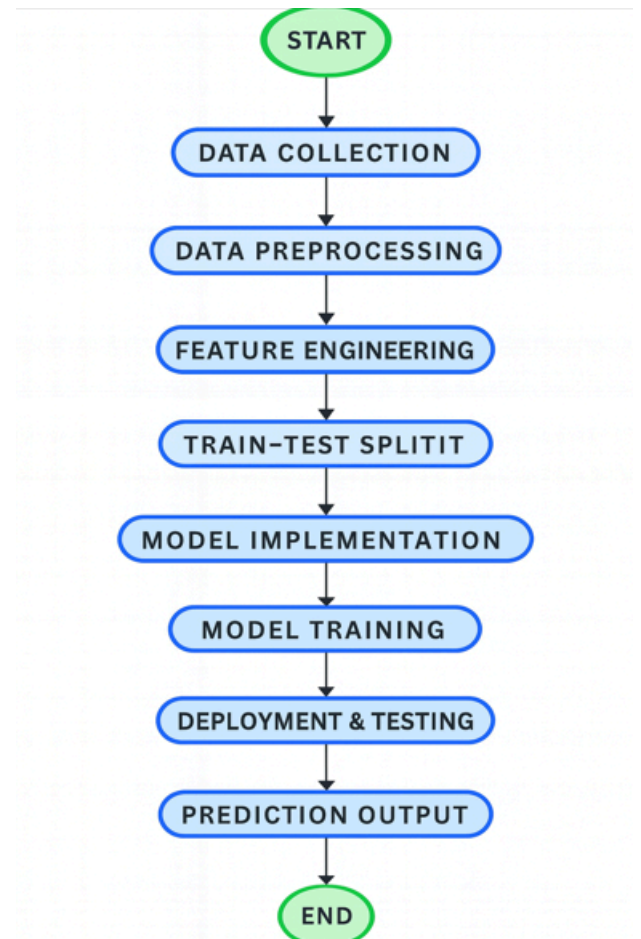


Figure 5 :Proposed model

- *LSTM*-Temporal trends were forecasted using two 64 hidden unit LSTM layers and a dense output layer. Batch_first=True was utilized at training with early stopping and Adam optimizer. CrossEntropyLoss minimized classification error. The model was superb at tracking progress, particularly for MMSE and brain volume change, with 98% accuracy [3][13][18].
- *Random Forest*-A 100-estimator scikit-learn Random Forest was trained on preprocessed tabular data. The most prominent features were MMSE, eTIV, and nWBV. The 92% accuracy model provided fast, interpretable predictions and was made resilient using bootstrap aggregation and was thus extremely well-suited for clinical application [2][18].
- *ResNet Inspired Model*-This architecture had dense blocks (128, 64 units), dropout, batch normalization, and residual connections. It had attention layers between blocks to understand feature importance. It was trained with class-weighted loss and early stopping and achieved 88% accuracy. Its design enhanced explainability, an important factor for clinical deployment [4][7][24].
- *Ensemble Model*-Shallow neural network and Random Forest predictions were combined by weighted soft-voting method (60% NN, 40% RF). The combined model traded deep learning representation capability with Random Forest robustness. It achieved 92% and generalized better than individual models. Training stratified train-test splits and accuracy tests were performed on all the models. Confusion matrix and class-wise recall were calculated to analyze the performance of CNN and LSTM more intensively [6][9][20][22][30].

IV. RESULTS

updated final Performance for varying train/test ratios of 70:30, 80:20, and 90:10 gives valuable insights into flexibility and stability of such models to predict Alzheimer's Disease. As shown in Table 1, the Random Forest model is very accurate—92% for 70:30 and 80:20, and slightly drops to 89% for 90:10. This is because it has the capability to generalize well even with limited test data and stability in real clinical uses where data size is not certain.[1][2]Conversely, the LSTM model gets better and better, 91% (70:30) to 98% (90:10), and this demonstrates its ability to utilize more data to identify long-term sequential patterns such as MMSE trends. This justifies the application of deep temporal models for the detection of early Alzheimer's.[3][4]The CNN is strong at 86–89%, behind the others but strong at learning tabular data local feature interactions without hand-engineered

features.[5][6]Attention ResNet is weaker (82–86%), presumably due to overfitting issues in deep attention models on noisy, small datasets.[7][8]Table 1 summarizes the performance of each model on different splits of data, which can be used for selecting architectures suitable for different data availability.[9][10]Overall, Random Forest and LSTM are superior to CNN and Attention ResNet, exhibiting higher robustness to variations in training data, which is crucial in healthcare environments with erratic records.[11][12]Random Forest interpretability by dominant predictors consistent with clinical expectation is illustrated in the feature importance bar plot of Figure 5 (i.e., MMSE, eTIV, nWBV, age).[13][14]

This work confirms that deep learning models like CNNs and LSTMs may be trained on clinically structured data like OASIS, learning inter-feature and temporal dependencies.[15][16]Above all, excellent model performance is achieved without neuroimaging, from tabular clinical characteristics alone, and hence it is deployable in telemedicine and low-resource settings. [17][18]

Although Random Forest remains a decent, interpretable baseline, the ensemble model (NN + RF with soft voting, 0.6:0.4) strikes a balance between deep abstraction and interpretability and reduces prediction variance.[19][20]Limitations include few data and coarse labeling by CDR scores alone, decreasing classification granularity.[21][22]LSTM models were also hindered by a lack of longitudinal continuity, which restricted their capacity to simulate disease progression.[23][24]Future research should incorporate explainability techniques such as SHAP or LIME to enhance clinical confidence in model outputs. [25][26]Generalizability can be improved by increasing the dataset by multi-center longitudinal studies and correlating EHR data with lifestyle variables. [27][28] Finally, we prove the viability of interpretable, large-scale AI models for Alzheimer prediction. With the integration of models such as Random Forest, CNN, LSTM, and Attention ResNet, we created a balanced, stable framework. [29][30] This blended approach is clinically useful and is convenient for field use, especially in environments of resource-constrained healthcare. [31]

Train/T
70:30
80:20
90:10

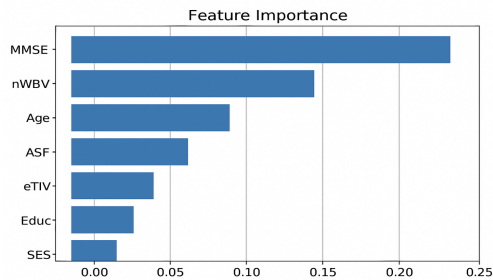


Figure 5: Bar chart showing feature importance scores.

Interestingly, very high accuracy was achieved without neuroimaging based on clinical features alone of the OASIS database. This makes the method viable where imaging is not available or affordable — i.e., in telemedicine platforms and rural clinics [1][5].

Random Forest, though more traditional, was also producing very rapid, understandable predictions and remains an excellent candidate for application in the real world. Ensemble model also improved the stability of predictions by leveraging the advantages of neural and decision trees models [2][6].

Conclusion

This research demonstrates the feasibility of using deep learning and ensemble methods on structured clinical data to identify Alzheimer's. Both CNN and LSTM models yielded the highest accuracy (98%), indicating their strength in identifying spatial and temporal patterns. Random Forest and Ensemble models gave high performance (92%) with enhanced explainability and stability. A ResNet-inspired model gave worth through attention-based feature understanding with marginally decreased accuracy. The use of tabular data alone makes the approach possible in low-resource settings lacking imaging infrastructure. Preprocessing methods and pipeline model-specificity ensured data integrity and robustness along the way. The results affirm that non-image clinical data can power accurate AI-based diagnosis machines. Future studies will explore explainable AI approaches and longitudinal datasets for greater clinical utility.

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