Developing A Neural Network Based On Deep Learning Approach In The Early Detection And Diagnosis Of Alzheimer's Disease

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ABSTRACT

In order to identify Alzheimer's disease (AD), this study introduces a novel hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model technique. The proposed model aims to improve the accuracy and robustness of AD diagnosis by using information from structural and functional neuroimaging. The model shows better performance than conventional techniques and standalone CNN or LSTM models by using CNNs to extract spatial features from structural MRI scans and LSTMs to capture temporal patterns from functional MRI (fMRI) time-series data. High accuracy, sensitivity, and specificity are demonstrated in the classification of AD patients and healthy controls in an extensive dataset evaluation. Additionally, interpretability analysis of the model's learnt features and attention mechanisms provides information about AD biomarkers, aiding in a deeper comprehension of the pathophysiology of the illness. All things considered, the CNN-LSTM hybrid model offers a viable way to identify AD early on, which could improve clinical diagnostic and treatment approaches. After training the model in conjunction with other models, the CNN-LSTM model had a noteworthy validation accuracy of 92.13%, indicating the model's efficacy.

INTRODUCTION

The resolution and specificity of MRI and PET scans, in particular, have improved dramatically in recent years, leading to a previously unheard-of level of understanding of Alzheimer's disease.

These imaging methods provide information about both structural abnormalities and dynamic changes in brain function, providing light on the finer points of Alzheimer's disease progression. Convolutional Neural Networks (CNNs) have opened the door to a new era of precise and automated diagnostic skills in the field of medical image processing. CNNs are ideally suited for the complex features found in neuroimaging data suggestive of Alzheimer's Disease because they are skilled at identifying minute differences and complex patterns within images. The flexibility and scalability of CNNs offer a strong answer to the problems brought on by the complexity and variety of AD pathophysiology, especially as the discipline of deep learning advances.

Furthermore, the use of hybrid models in AD detection has potential for improving accuracy as well as democratizing access to early diagnosis. Hybrid model-based automation and standardization of diagnostic procedures may lessen the workload for medical staff, optimize the diagnostic workflow, and offer effective and affordable options for mass screening. This paper's methodology part will go into great detail on how to train and fine-tune hybrid models to perform at their best in AD detection. It will look at things like data augmentation methods, transfer learning approaches, and choosing pertinent imaging features. We'll also take a close look at issues like interpretability, generalizability across different demographics, and ethical issues when using AI in healthcare settings.

It becomes increasingly important to comprehend the implications of hybrid models in the context of AD detection as we traverse the nexus between medical imaging and deep learning. This study project aims to contribute to the larger

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conversation on the ethical, social, and economic aspects of incorporating cutting-edge AI technology into healthcare systems, in addition to its primary objective of accurately diagnosing patients.

In the end, the combination of hybrid models with medical imaging for Alzheimer's disease diagnosis has the potential to revolutionize both clinical practice and the field of neurodegenerative disease research. In this research, we use LSTM to investigate the field of AD diagnosis and progression monitoring, drawing on the findings of study [1] to attempt to construct a hybrid model with improved classification accuracy. Additionally, We will evaluate the model's efficacy critically and provide a thorough analysis of its strengths and future development opportunities. Our investigation is not only a scholarly endeavor but also a journey into the core of automated healthcare, with the potential to have a significant influence on a wide range of applications. This work essentially acts as a lighthouse pointing the path towards more ethical, practical, and effective ways to treat Alzheimer's disease and other neurodegenerative illnesses.

METHODOLOGY

A. Description of the Dataset

The study employed a highly maintained dataset to diagnose Alzheimer's disease, guaranteeing a thorough depiction of the disease progression stages. As illustrated in Fig. 1, it is composed of three main classes: There are three stages of Alzheimer's disease: non-demented, stage 1, and stage 2, which range in severity. Each class had 666 photographs at first, which is a respectable balance. Nonetheless, significant efforts were undertaken to expand the dataset in recognition of the critical role that diverse data plays in improving model performance.

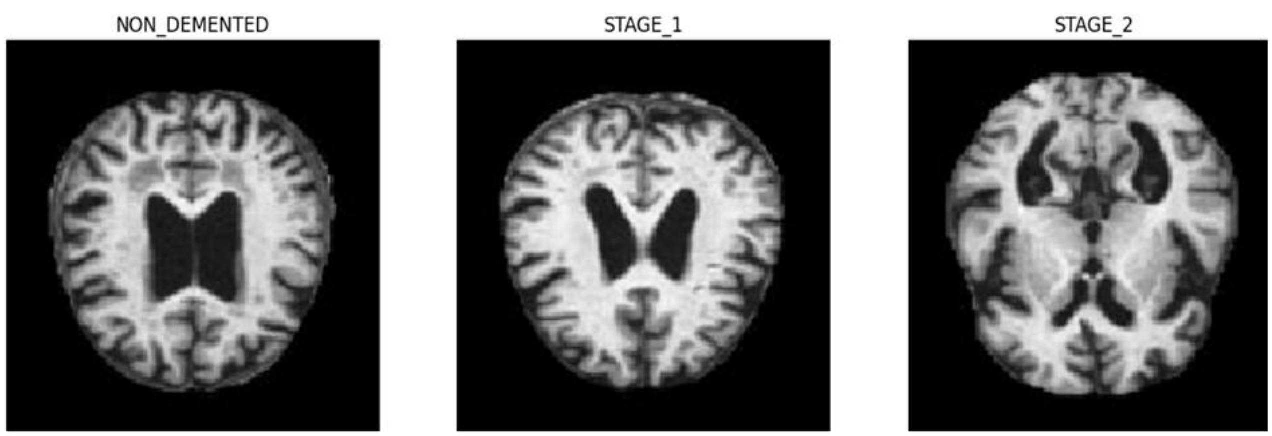

Fig 1: Selected photos from each class's dataset

The dataset was enhanced by the use of data augmentation techniques, which included image noise addition, rotation, scaling, and flipping. These methods increased the quantity of the dataset and added variability, which helped the models acquire strong features and improve their capacity to generalize to new data. Additionally, great care was taken to guarantee that the augmented photos retained the diseased features and underlying anatomical structures, preserving the dataset's therapeutic value.

By adding to the dataset, we hoped to reduce potential biases, improve the model's resilience to variations in imaging settings, and boost the classifiers' overall robustness and generalization abilities. This systematic approach to dataset augmentation demonstrates our commitment to developing reliable and effective models for the categorization of Alzheimer's disease, facilitating more accurate diagnosis and early intervention strategies.

B. Applied Algorithm

For regression and classification, supervised machine learning methods such as support vector machines (SVMs) are practical and adaptable. It is also frequently applied to classification-related challenges. In terms of application, SVM is distinct from other machine learning methods. Because of its ability to handle several continuous and categorical data, it is widely utilized. Although they can be used to solve regression and classification problems as well, decision trees work best for classification problems. Decision trees are usually easier to understand since they mimic how individuals actually think while they are making decisions.

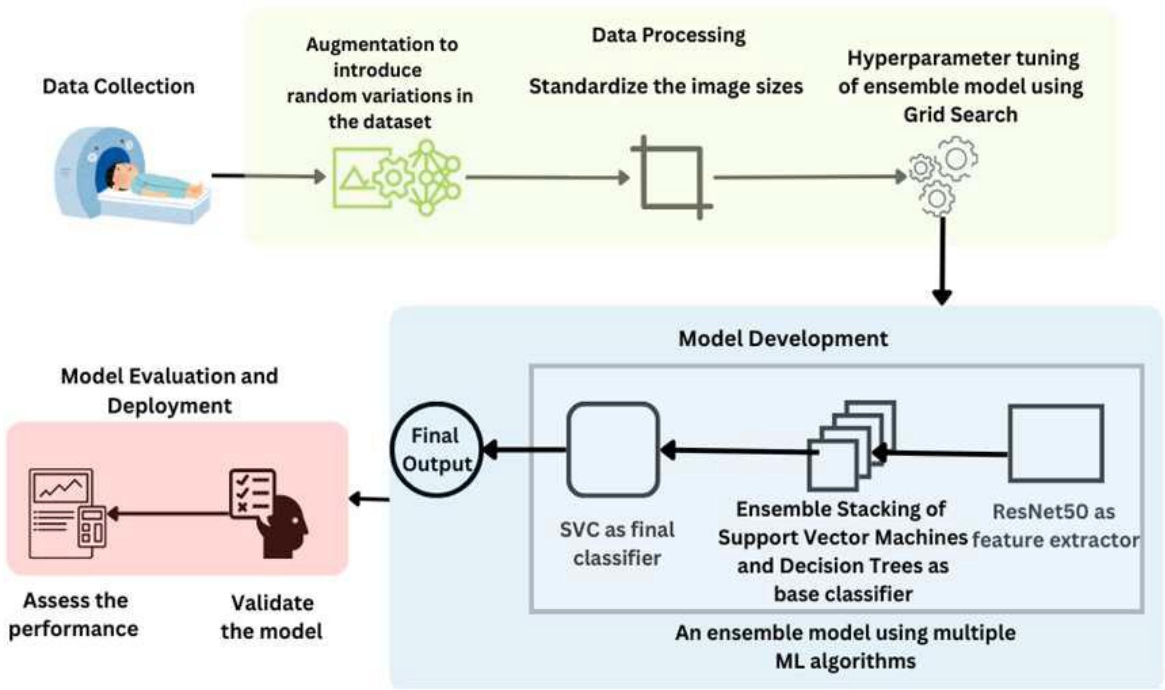

Fig 2: ResNet50 proposed approach diagram

An enhancer was strategically applied as a crucial preprocessing step to solve the problem of data sparsity that is frequently present in medical picture datasets, as illustrated in Fig. 2. The logic of decision trees is easy to understand because of their tree-like form. Convolutional neural networks, also referred to as CNNs or ConvNets, are used to identify photos using a pretrained deep learning model called ResNet-50. For image analysis, this is the most often used class of deep neural networks. trained using a million images across a thousand categories from the ImageNet database. There are 50 layers in ResNet-50. Additionally, this model demonstrates an architecture with 23 million trainable parameters that can improve picture identification. Custom models need you to collect data and train yourself, but pre-trained models are significantly more efficient.

The CNN-LSTM hybrid model's implementation will be the main focus going forward. The hybrid model proposed in the study paper, as illustrated in Fig. 3, combines LSTMs and CNNs to overcome the challenge of achieving reliable and accurate categorization. To standardize the input dimensions across the entire dataset, rescaling the photos to a desired form was a crucial preprocessing step. Furthermore, the strategic use of an augmentor efficiently solved the problem of data sparsity that is frequently present in medical picture collections.

By exposing the model to a wide variety of augmented images, this data augmentation strategy not only improves the general resilience of the model but also raises the volume of minority class samples.

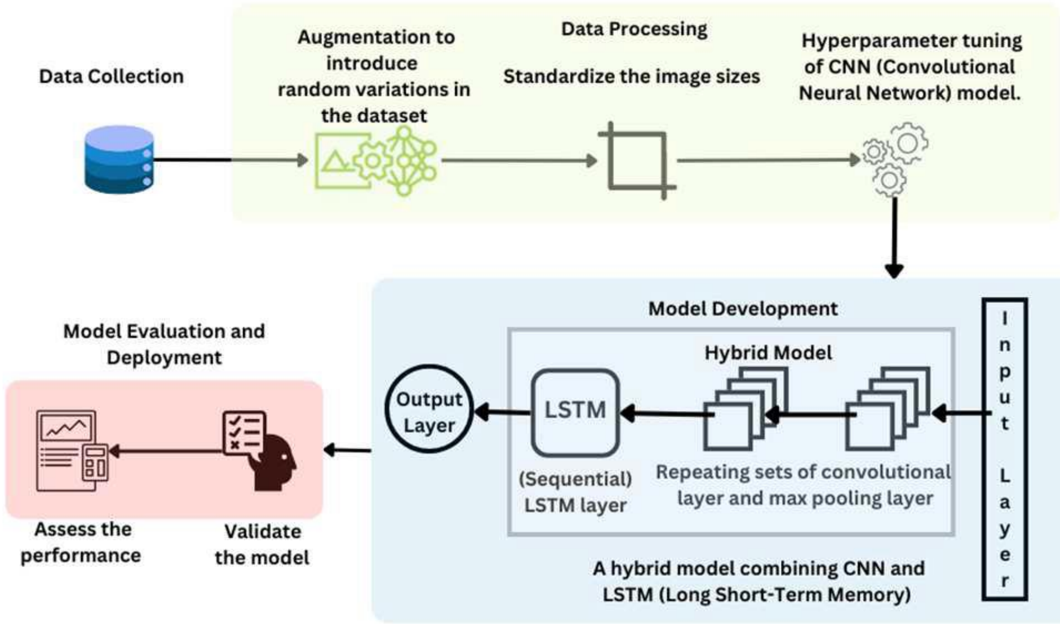

Fig. 3. CNN-LSTM model methodology diagram

The proposed CNN-LSTM model architecture, as shown in Fig. 4, combines convolutional neural networks (CNNs)—which are specifically created for the categorization of Alzheimer's disease—with long short-term memory (LSTM) networks. The advantages of CNNs and long-term dependency memory (LSTM), which are well-known for their effectiveness in extracting spatial properties from visual data, are utilized in this architectural design. It was demonstrated that LSTMs can improve CNN's feature extraction capabilities when used in a layered approach. When patterns are retained for longer periods of time by LSTMs, CNNs are better at identifying the important components.

An attention mechanism is another addition to the design. It comes after the LSTM layer and is used to selectively focus on pertinent areas or features in the input sequence. This attention mechanism dynamically weights the significance of various spatial temporal elements in the classification process, improving the interpretability and discriminative power of the model. Improved diagnostic accuracy may result from the attention mechanism, which focuses the model's attention on prominent areas in the input images for more efficient feature extraction and classification.

The model is assembled using the Adam optimizer and the categorical cross-entropy loss function during the training phase, making it appropriate for evaluating the results of a multi-class classification task. At this point, optimizing hyperparameters like learning rate and optimizer is essential to achieving a balance between generalization and model complexity. The Model Checkpoint callback's implementation makes it possible to save the top-performing model based on validation accuracy. In order to avoid overfitting, the Early Stopping callback is also used to stop training when the validation accuracy stops improving. Additionally, we have created saliency maps for every class to help determine which areas of the input photos are essential to the model's predictions.

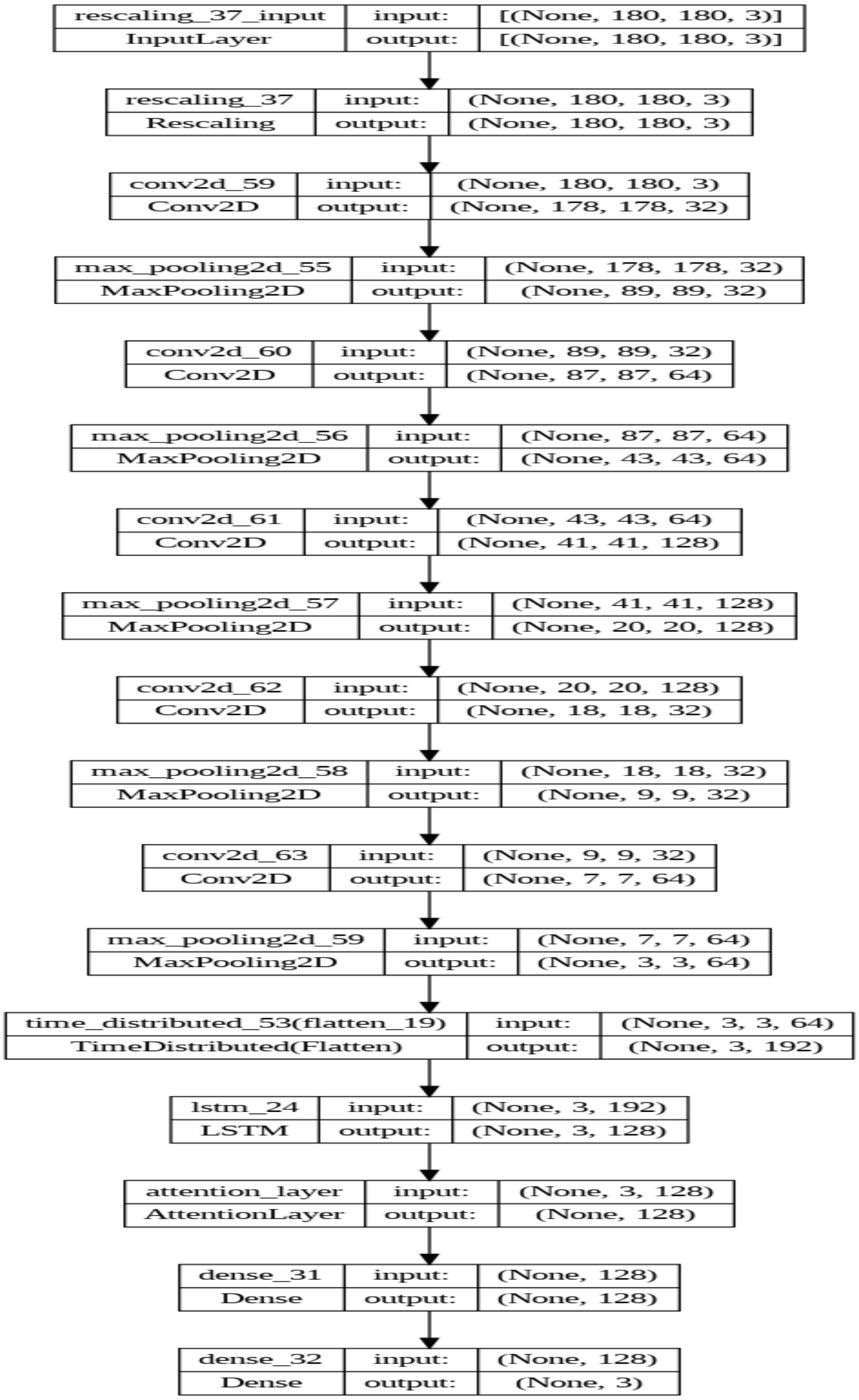

Fig 4: Model Architecture

C. Algorithm parameter setting

•A specialized Attention Layer further improves the model's ability to identify salient features within the input data, adding to its efficacy in extracting discriminative information necessary for accurate classification. The hybrid model architecture uses CNN and LSTM built for image classification tasks.

• Input Layer: An input layer defines the format of the input data and is where the model starts. Here,

Pictures with 180 by 180-pixel dimensions and RGB (three-color channels) are required.

• CNN Layers for Extracting Features: The input images are processed using a series of MaxPooling (MaxPooling2D) and Convolutional (Conv2D) layers to extract hierarchical spatial information.

This sequence of convolutional processes gradually isolates spatial characteristics and complicated patterns necessary to differentiate between various phases of the course of Alzheimer's disease.

• Time-Distributed Flatten Layer: This layer filters the CNN layers' output to ensure that it is consistent with the sequential design of the LSTM architecture, hence facilitating subsequent processing by the LSTM layer.

• LSTM Layer with Attention Mechanism: The CNN layers extract sequential data, while the LSTM layer, configured with return_sequences=True, extracts temporal dependencies within the data. By dynamically adjusting the weighting of various spatial-temporal components, the Attention Layer improves the discriminative power of the model by introducing a mechanism for focused selection of relevant features.

• Dense Layers: The LSTM is followed by a thick (completely connected) layer, which enables the model to discover intricate correlations and patterns in the retrieved information.This layer adds non-linearity to the model with 128 neurons and ReLU activation function, allowing it to recognize complex patterns hidden in the data.

• Output Layer (Classification): Using a softmax activation function, the final dense layer in the model is its output layer. The number of neurons is equal to the number of classes in the classification task, and the activation function converts raw output values into probabilities that show the likelihood of each class. In this instance, the model forecasts the probability distribution over three classes, which stand for various phases of the development of Alzheimer's disease.

With the help of an Attention Layer and the complementary strengths of CNNs and LSTMs, this comprehensive architecture successfully extracts and analyzes spatial-temporal features from neuroimaging data, enabling the accurate and trustworthy classification of Alzheimer's disease progression stages. The model is a promising tool to support early diagnosis and intervention techniques in clinical settings because of its robustness and versatility.

EXPERIMENTAL RESULTS

The results of the experiment show how accurately Alzheimer's patients are classified using the ensemble stacking method.

By applying a grid search method, we were able to determine the ideal hyperparameters for the ensemble model. yielding an impressive 84.25% accuracy. SVM (C=0.1, gamma=0.01) and DT (min_samples_split=2) are the optimal parameters found by grid search, and they greatly improve classification performance. This illustrates how well ensemble approaches work to maximize the complementing qualities of various classifiers.

The results of our investigation show how well the CNNLSTM model does in the difficult task of identifying Alzheimer disease. It performs better than the ensemble model in every way. As seen in Fig. 6, the model demonstrated remarkable performance during the training phase, with a training loss of 0.0375. The model's ability to minimize the difference between its projected values and the actual ground truth in the training dataset is demonstrated by this low loss number. In addition, the model showed a respectable training accuracy of 98.71%, demonstrating its proficiency in accurately classifying different kinds of Alzheimer's within the parameters of the training set.

Beyond just numerical numbers, the obtained training metrics are significant because they highlight the model's strong learning abilities and its ability to identify complex patterns in the Alzheimer's data. The model's overall efficacy is attributed to its ability to capture the underlying traits that differentiate distinct classes of Alzheimer's, as seen by the low training loss.

The validation set, which is an assessment of data that has never been seen before, gives the model's generalization skills more context. At 0.3020, the validation loss—a crucial indicator of prediction accuracy on fresh samples—is recorded. The validation accuracy of 92.13% in Fig. 5 emphasizes even more how well the model performs in recognizing Alzheimer's under a wide range of peculiar circumstances. In every metric, it performs better than the model derived from the study [1].

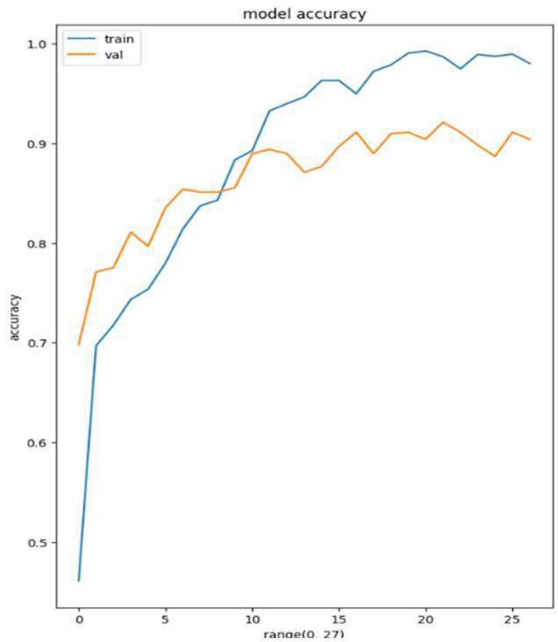

Fig 5: CNN-LSTM Model Accuracy

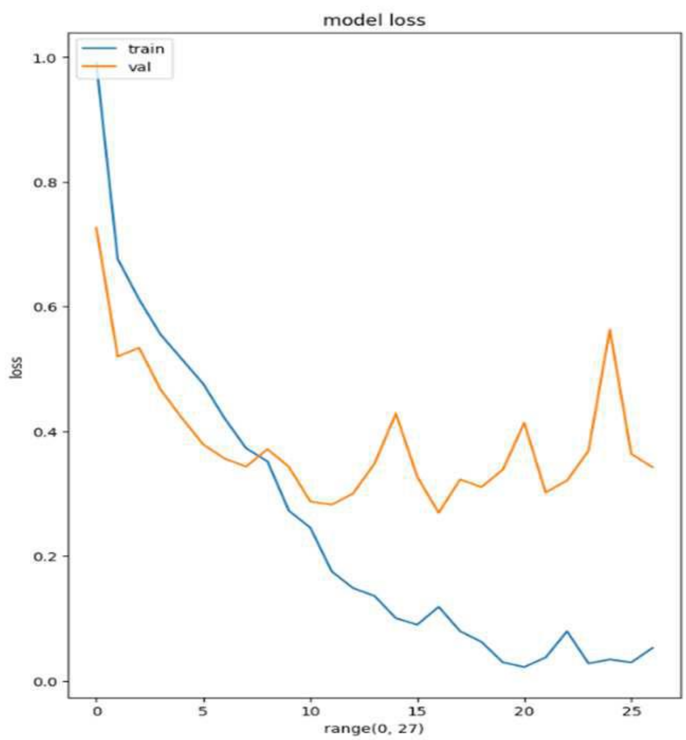

Fig. 6. CNN-LSTM Model Loss

To improve interpretability and comprehension of the model's decision-making process, we used a novel strategy. To be more precise, we created several saliency maps, as seen in Fig. 7, for each of the several forms of Alzheimer's that were found in our dataset. Saliency maps are useful tools for visualizing regions of interest that have a substantial influence on the categorization choice made by the model. Our goal was to identify the essential components and regions that are essential to the network's discriminative powers by using saliency mapping on a variety of classes.

This study contributes to a better understanding of the model's behavior and enhances the classification process's transparency and interpretability. A significant layer of understanding is added to our study by the incorporation of saliency maps, which provides researchers and clinicians with a clearer understanding of the model's decision-making process as well as possible insights into the unique visual cues influencing the classification of various types of

Fig. 7. Saliency Maps for each class

Alzheimer's. As you can see, the saliency map above highlights a particular type of Alzheimer's that is common in our dataset.

The orange portions of this visual depiction represent areas of relatively lower value in the classification process, whereas the reddish tones correspond to regions of higher importance that considerably influence the CNN's classification decision for Alzheimer's. Our study's incorporation of such comprehensive visual insights not only improves the interpretability of our model's decision-making process, but it also has potential applications for physicians who are looking for direction in detecting crucial markers inside MRI scans for diagnostic purposes.

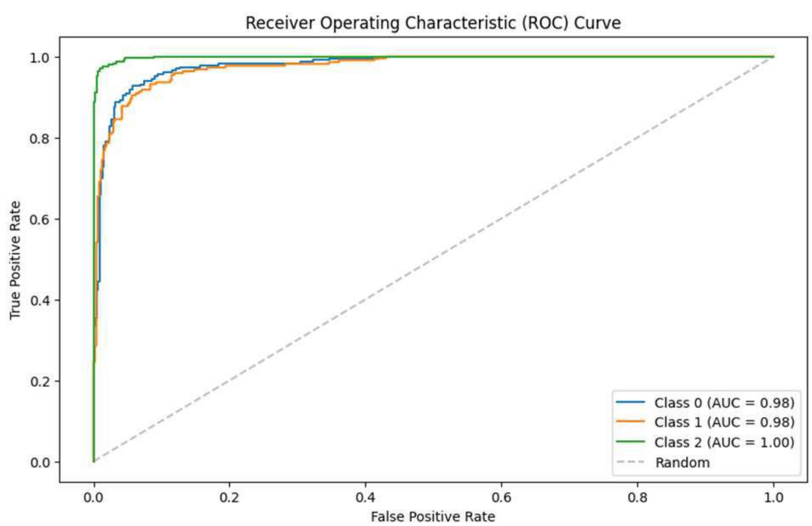

Fig 8: ROC Curve according to Class

The ROC curve in Figure 8 illustrates the performance of a model designed to identify three distinct classes, each represented by a different color curve. The percentage of negative cases that are incorrectly classified as positive, or the false positive rate (FPR), is displayed on the x-axis of the curve.

The true positive rate (TPR), or the proportion of positive instances that are accurately categorized as positive, is displayed on the y-axis. The area under each ROC curve (AUC) indicates how well the model performs in terms of discriminating between positive and negative examples; a higher AUC indicates superior performance. The model shows excellent classification performance in each of the three classes, according to the ROC analysis. The model is particularly good at correctly classifying instances of Class 2, as seen by the highest AUC value, which is followed by Class 0 and Class 1.

Table I displays the precision values for the CNN-LSTM model for both non-demented and dementia patients at different stages of the disease.

TABLE I. PRECISION VALUES OF CNN-LSTM

Class	Average Precision
Non Demented	0.27
Stage 1	0.29
Stage 2	0.31

Furthermore, 0.9211 is given for the weighted F1 Score, a complete metric that strikes a compromise between recall and precision.

This score provides an in-depth analysis of the model's general efficacy across all classes. The increased weighted F1 Score indicates a well-balanced combination of recall and precision, highlighting the model's resilience in obtaining a reliable and comprehensive Alzheimer's categorization. These class wise precision and recall numbers, when combined with the weighted F1 Score, contribute to a thorough evaluation of the model's performance.

CONCLUSION

Alzheimer's disease detection has advanced significantly with the addition of an attention layer and sophisticated deep learning models, namely CNN-LSTM and ResNet50. When these models are combined, it becomes easier to manage neuroimaging data effectively and accurately identify important biomarkers linked to the condition.

Notably, our results offer a thorough rundown of both models, which can be applied going forward to improve both models' performance. Additionally, it shows that the ensemble stacking method is not as effective as the CNN-LSTM model with the attention layer, underscoring the significance of utilizing deep learning architectures customized to the unique properties of medical imaging data.

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