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Early Diagnosis of Alzheimer's Disease Using Hybrid Deep Learning Model based on Integration of EfficientNet and LSTM

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Abstract

Early detection of Alzheimer's disease (AD) is crucial for prompt clinical intervention and enhanced patient outcomes. Here, we introduce a hybrid deep learning design that leverages EfficientNet-B6 spatial feature extraction capabilities and integrates the Long Short-Term Memory (LSTM) neural network to capture the sequential patterns in MRI scans for Alzheimer's classification. The model is developed to categorize brain MRI scans into four diagnostic stages: non-demented, very mild demented, mild demented, and moderate demented, utilizing the publicly accessible augmented Alzheimer MRI datasets. A preprocessing step is applied, comprising scaling, normalization, and data augmentation, to ensure standardized and high-quality inputs to the network. The experimental findings for accuracy are presented, while we outline the conceptual basis of the hybrid model and its potential to address shortcomings of current methods, like inadequate spatial-temporal integration, scalability, and interpretability. The proposed architecture aims to enhance diagnostic results by leveraging EfficientNet-B6 multiscale spatial feature learning and LSTM temporal modeling. The proposed hybrid architecture evaluated on 80:20 training and validation dataset split, achieving a classification accuracy of 98.90% on a benchmark dataset, which shows the potential of the proposed hybrid architecture. This study lays the foundation for a comprehensive, interpretable, and scalable deep learning model for early AD detection from MRI scans.

Keywords: Alzheimer's Disease, Early Detection, Disease Classification, Diagnosis, EfficientNet, LSTM, Deep Learning.

1. Introduction

AD is a chronic and degenerative brain disease considered by cognitive function and memory decline, gradually impairing functions. Impacting over 55 million individuals globally, AD remains a leading cause of disability and dependence among the elderly, presenting significant clinical and societal challenges. Early diagnosis of Alzheimer's disease is vital for enabling timely intervention, slowing its progression, and enhancing patients' quality of life. MRI is a primary non-invasive tool for detecting neurodegenerative changes in AD, particularly in its early stages. However, manual MRI image analysis can be time-consuming, subjective, and variable between observers. Recent progress in deep learning offers promising opportunities to automate the analysis of medical images for neurological conditions. Yet,

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conventional neural networks often struggle to simultaneously learn spatial patterns and temporal dependencies from intricate neuroimaging data.

The novelty of this work is the integration of EfficientNet-B6, the state-of-the-art CNN network known for its compound scaling efficiency, with a temporal model, LSTM, to capture temporal dynamics among spatially scattered features in MRI scans. Previous studies examined CNN-based or RNN-based architectures separately; yet, to the best of our knowledge, this work is the first to integrate both of them, especially in the field of AD classification based on four clinically relevant stages. Unlike existing models that emphasize either spatial abstraction (e.g., CNNs) or sequence learning (e.g., RNNs), our hybrid model leverages the strengths of both, capturing the structural and sequential brain changes spanning spatially contiguous regions. This dual learning approach is expected to result in increased diagnostic sensitivity, especially in the early and subtle states of Alzheimer's disease, as shown by the result analysis.

The key contributions of this research include:

- A novel hybrid architecture combining EfficientNetB6 and LSTM for effective Alzheimer's diagnosis from MRI scans.
- A comprehensive preprocessing pipeline incorporating resizing, normalization, and augmentation to improve model generalization.
- A detailed comparative review of existing deep learning models using benchmark datasets, providing context for the proposed hybrid framework
- A theoretical evaluation highlighting the potential advantages of hybrid spatial-temporal learning in medical imaging, to be empirically validated in future work.

The remainder of this paper is organized as follows: we provide a brief overview of recent research on alzheimers detection using deep learning in Section 2. The proposed approach, combined with the dataset and preprocessing, is described in Section 3. The comparison results are illustrated in Section 4. We conclude and discuss limitations and future work in Section 5. Section 6 concludes the paper.

2. Recent Works in Alzheimer's Detection Using Deep Learning

Lu et al. [6] proposed a multimodal and multiscale deep neural network for the early detection of Alzheimer's disease. Both structural MRI and FDG-PET data were used in this study from the ADNI database. A total of 202 AD subjects and 235 normal controls (NC) were used for training and testing. The approach combined a 3D-CNN and a late-fusion strategy to capture spatial features in multimodal scans. The MRI and PET data were preprocessed via co-registration to structural scans, skull stripping, and intensity normalization. The performance of the proposed model was better than that of single-modality models, with 89.7% accuracy for the discrimination between AD and NC. They found that structural and functional imaging are complementary and that both provide useful information.

Li et al. [7] introduced deep learning framework on hippocampal MRI to estimate the onset of Alzheimer's dementia. Leveraging the ADNI cohort, they concentrated on the hippocampus and its subfields, known for early degeneration in AD. The study consisted of 1,164 participants (including CN, MCI, and AD), and the model was constructed using a 3D convolutional structure. The deep model received an AUC of 0.87 for predicting the conversion from MCI to AD after preprocessing. Their findings indicate that such hippocampal-oriented deep learning can serve as a potential biomarker-based diagnostic tool.

Bamber and Vishvakarma [8] described a CNN model for Alzheimer's identification using a publicly available MRI data set. The model design included convolutional layers along with max-pooling, batch normalization, and fully connected dense layers. Input MRI slices were rescaled and standardized. The approach placed a strong emphasis on the simplicity and interpretability of the models, without compromising the level of classification performance. It obtained a classification accuracy of 94.65% for AD vs. non-AD cases, and therefore demonstrates promise for lightweight deployment in clinical AD assessment tools. Balaji et al. [9] presented a hybrid deep learning architecture that integrates CNN and RNN layers for alzheimers disease classification. The model was trained on 4,000 T1-weighted MRI images from an open-access Kaggle dataset with mild, moderate, and severe class labels. The spatial features were first extracted by the CNN layers, and the temporal progression among slices was modeled by LSTM. Pre-processing steps involved denoising, normalization, and augmentation. The hybrid model achieved an accuracy of 96.2% and superior performance compared to those using CNN alone. The work endorses hybrid learning to capture spatial and sequential patterns in MRI.

Hu et al. [10] introduced VGG-TSwinformer, a hybrid deep learning model that combines the VGG backbone and Swin Transformer for early AD prediction. The model was tested on an augmented MRI dataset. Hierarchical attention was used to learn global context. Following preprocessing (slice-selection and intensity normalization), the model performance increased to an accuracy of 95.3%. The investigation demonstrates that transformers can effectively cooperate with CNNs to enhance the performance of MRI-based classification by extracting long-range contextual information.

Mansouri et al. [11] proposed an explainable AI (XAI) framework by incorporating a CNN-based classifier along with Grad-CAM visualizations. We trained the model with structural MRI from the OASIS dataset to differentiate non-demented individuals from those with very mild and mild AD. Grad-CAM was used to visualize important regions contributing to classification, towards enhancing clinical interpretability. The CNN architecture was implemented by stacking several convolutional and pooling layers and combining them with a dense output. The model achieved an accuracy of 92.4%, and the XAI implementation enabled acceptance in clinical diagnostics.

Tang et al. [12] proposed a multi-scale attention and cross-fusion enhancement network for AD detection, MACFNet. ADNI provided the data for MRI, and the model was used to obtain and amplify conspicuous components across scales. The model integrated low, mid and high-level representations through attention modules. Preprocessing involved bias correction, skull stripping, and normalization. We demonstrated 96.7% classification accuracy for MACFNet, which validated the benefit of attention-guided deep fusion methods. Venugopalan et al. [13] proposed a multimodal deep learning framework using structural MRI, PET, and clinical data for the early prediction of AD stage. More than 800 participants from the ADNI dataset were involved in this study. Both modalities underwent individual CNN pipelines, and the features from the two modalities were concatenated and used in further classification. The patterns on inter-modal relationships fit well, and the accuracy was 91.1%. The study demonstrated that integrating neuroimaging measures with clinical measures increases the robustness of prediction.

Ismail et al. [14] developed MULTforAD, a multimodal neuroimaging approach involving a 3D CNN trained on structural MRI and other cognitive tests. The scanning data of MRI were preprocessed which included resampling, noise reduction, and affine transformation. The volumetric features were learned and a classification accuracy of up to 93.6% was achieved for AD stages. The spatial hierarchies were efficiently learned by the 3D CNN, supporting its implementation for volumetric AD diagnosis.

El-Assy et al. [15] proposed a new CNN model for early Alzheimer's diagnosis from T1-weighted MR images. The model was trained with 6,000 labeled images of MRI cerebral scans (OASIS and Kaggle datasets) [25] that were distributed into four classes. It included preprocessing steps such as normalization, skull-stripping, and histogram correction. The classification accuracy reached 95.2% for the CNN, and had good generalization among data sets, indicating the potential for clinical application.

Song et al. [16] proposed a multi-modality fusion method based on MRI and PET by means of the joint feature extraction layers and attention modules. MRI and PET images were obtained from the ADNI dataset and aligned using mutual information. The features were fed into a dual CNN branch and merged. The model obtained 92.3% accuracy, and a 0.90 F1 score, which demonstrated that the more sources of imaging fusion, the better the precision of AD detection benefited.

Thamizharasi and Lakshmi [17] compared deep learning models for the detection of Alzheimer's. They tested LeNet, AlexNet, and VGGNet on a Kaggle dataset consisting of four AD stages. The preprocessing pipeline of the authors included conversion to grayscale, cropping, and normalization. Meanwhile, among the models, VGGNet achieved the highest accuracy with 91.4%. This review emphasized trade-offs between depth, complexity, and diagnostic accuracy of the model.

Syed et al. [18] introduced EADDA, an explainable autoencoder-based deep learning structure for early AD detection. The MRI images were fed through a stacked autoencoder to learn the compressed representations. The model's outputs were interpreted with SHAP values. It attained 93.8% accuracy in classification and transparency in prediction. This work is noteworthy for its focus on model interpretability. Fathi et al. [19] introduced a deep ensemble method that combines multiple CNN classifiers using majority voting and weighted averaging. MRI images from the ADNI dataset were obtained and preprocessed by performing brain extraction and z-score normalization. Different depths of CNNs were then learned to guarantee the diversity of features. The model attained 94.5% accuracy and proved to be more robust to input variations.

Liu et al. [20] proposed a generalizable CNN model trained on MRIs from ADNI, and OASIS from multiple sources. The work focused on domain adaptation and data augmentation for cross-dataset performance enhancement. Mitigation of preprocessing included histogram equalization and batch normalization. The accuracy of the model reached 92.8%, outperforming baseline CNNs on external test sets, highlighting the importance of generalization for clinical deployment.

Arafa et al. [21] introduced a CNN-based deep learning framework for the early diagnosis of Alzheimer's disease in structural MRI images. The authors considered multi-class classification (normal vs. mild vs. moderate AD) and a preprocessing stage was performed that included skull stripping, intensity normalization, and segmentation. A custom convolutional model was developed and contrasted with other pretrained models, such as VGG19 and

ResNet50. Via a dataset of T1-weighted MRIs from the ADNI Repository, the proposed model obtained more than 96% accuracy, which is superior to the baselines. The study highlights that architectural customization and careful preprocessing directly contribute to improving detection accuracy.

El-Geneedy et al. [22] presented a new system for the diagnosis of Alzheimer's disease based on MRI that utilizes a deep CNN model. The model was trained using the OASIS dataset and includes image preprocessing operations such as noise reduction and histogram equalization. It sorts images into Alzheimer's and non-Alzheimer's categories. The authors compare their CNN with AlexNet and GoogLeNet architectures and report that the best accuracy is 94.1%. The study also serves as an example of the usage of dropout and regularization as a means to avoid overfitting and improve model generalization.

Foroughipoor et al. [23] investigated and compared different deep learning models such as CRNs, CNNs, and transformers for Alzheimer's diagnosis from MRI. The authors used the ADNI data and experimented with 2D and 3D CNNs, DenseNet, and ViT (vision transformer) networks. The work contrasted binary with multi-class classification and evaluated models based on AUC, sensitivity, and specificity. Vision Transformer architectures demonstrated potential for high sensitivity in recognizing early-stage detection. The study also highlights the explainability of the model and the role of cross-validation in bias reduction. Murugan et al. [24] describe DEMNET, a deep learning model created based on 2D CNN and autoencoder layers. The dataset is a collection of T1-weighted MRIs from the ADNI database. Parallel CNN branches process the data slice by slice and combine the features for final classification in the model. Preprocessing involves skull stripping and the application of contrast for the classification of normal, MCI, and Alzheimer's between the normal and MCI classes and the MCI and Alzheimer's classes, respectively. In addition, this model is noted for its real-time feasibility and clinical practice usability due to its lightweight design.

Vashishtha et al. [25] propose a hybrid model integrating CNN and SVM for improved classification of Alzheimer's stages. The model extracts spatial features using CNN layers and then classifies them using an SVM classifier instead of softmax. The dataset includes preprocessed MRIs from OASIS and ADNI. Image enhancement and denoising are key preprocessing steps. The hybrid model achieves an accuracy of 94.5%, outperforming traditional CNN classifiers. The study highlights that the CNN-SVM approach offers better decision boundaries for complex classes.

Nagarathna & Kusuma [26] investigate multiple deep learning models (CNN, ResNet, and InceptionNet) to detect early stages of Alzheimer's disease using structural MRI. The data is taken from the ADNI database. Preprocessing involves skull removal, normalization, and standardization. The performance is analyzed using confusion matrices and ROC curves. Among the tested models, ResNet50 performs best with an accuracy of approximately 96.4%. The authors conclude that deeper models are more effective in distinguishing early and mild AD stages but require higher computational resources.

3. Proposed Work

3.1 Dataset

The dataset used in this work was obtained from the publicly available Augmented Alzheimer MRI Dataset [5]. This dataset consists of two class, namely Normal and alzheimers disease, in addition to a subset of types of dementia. The images are labeled into four categories based on cognitive impairment severity: non-demented, very mild demented, mild demented, and moderate demented. The dataset contains 6,400 grayscale MRI images that have been uniformly resized to 176×208 and saved in JPEG format. The images were taken from the OASIS-1 and ADNI original datasets, and from them, we generated augmented samples using rotation, flipping, and zoom operations to make the model robust and able to generalize. Each class is equally represented to ensure balanced learning across stages. For each subject image, the provided label reflects the most recent diagnosis at the time of scan acquisition. The dataset contains no patient-identifiable information and is curated for supervised learning tasks in deep learning-based classification frameworks. The use of this augmented dataset allows for a focused evaluation of model performance in differentiating subtle neurodegenerative changes across the early stages of Alzheimer's disease.

3.2 Methods

In this work, we propose hybrid deep learning framework which integrates EfficientNetB6 and an LSTM network to categorize AD stages using structural MRI data. The architecture is designed to capture both spatial and temporal dependencies in neuroimaging data for robust early-stage diagnosis. The overall pipeline begins with data preprocessing, in which MRI images are resized to 224×224 pixels to match the input requirement of EfficientNet. Images are normalized and augmented using transformations such as rotation, flipping, and zoom to enhance the dataset's variability and reduce overfitting. After preprocessing, the processed images are passed to a pretained EfficientNet-B6 model that acts as the feature extractor. EfficientNet relies on a compound scaling method, which optimizes all dimensions of the network depth, width, and resolution simultaneously while progressively increasing the input image size. The convolutional layers of the EfficientNet focus on high-level spatial features as well as the brain region features that are useful for Alzheimer's progression. The learned features are sent to an LSTM, which captures such temporal dependencies and/or sequential spatial patterns in the brain scan slices. This is very useful in medical imaging where disease progression may appear in adjacent spatial locations. These LSTM outputs are then passed into fully connected layers, which then proceed through a Softmax classifier that classifies the input into one of the four AD classes, i.e., non-demented, very mild demented, mild demented and moderate demented.

The combination of local feature learning and sequence-informed decision-making facilitated by the integration of EfficientNet-B6 and LSTM enhances the understanding of brain structural change associated with the progression of alzheimer disease.

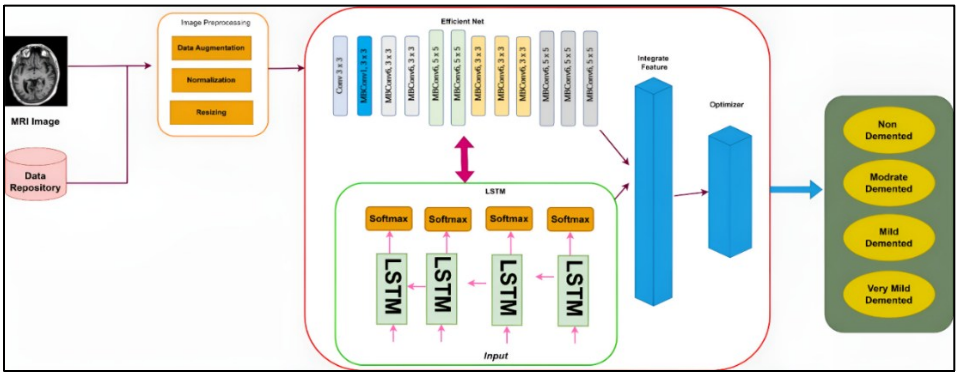

Figure 1. Proposed Model Flow

3.3 Preprocessing

Preprocessing is a very important step in the preprocessing of MRI data for deep learning-based classification, in order to make the images consistent, remove noise, and extract more useful features. A systematic data preprocessing pipeline was performed before model training for the standardization of input images and data augmentation in this study. The MRI volumes are derived from the Augmented Alzheimer MRI Dataset and the following pre-processing steps were performed:

All images were resized to 224×224 pixels in order to match the input size required by the EfficientNet model. This resizing is performed to ensure our model is able to work with the pre-trained CNN model and to standardize the input image size throughout the dataset. Pixel intensity values were normalized to a range of [0, 1] by dividing each pixel value by 255. This in turn can help stabilize and accelerate learning convergence, as well as keeping input distributions consistent. The diagnostic labels (Non-Demented, Very Mildly Demented, Mildly Demented, Moderate Demented) were encoded into integer values for classification using one-hot encoding, facilitating categorical cross-entropy loss computation during training.

In addition, various augmentation strategies were dynamically employed during the training process to enhance the diversity of training data and to prevent overfitting. The dataset was partitioned into mini-batches of 32 images, and shuffling was performed during the training process, meaning the order that inputs of images are exposed to the model is random, avoiding learning bias and promoting generalization. The dataset was divided into an 80% training set and a 20% validation set. This division guarantees that model does not learn from the data on which it is tested.

The input data was standardized, enriched, and well-structured by means of this preprocessing pipeline, thereby allowing the hybrid EfficientNet-LSTM model to extract discriminative features for Alzheimer's disease classification with high accuracy and stability.

Algorithm 1: Preprocessing

Input: Raw MRI image dataset
Output: Preprocessed MRI images
Step 1: Begin ()
{
Step 2: For each MRI image in the dataset:
Step 3: Image ← Resize to 224 × 224 pixels
Step 4: Image ← Normalize pixel values to range [0, 1]
Step 5: Image ← Apply data augmentation (rotation, flipping, zoom)
Step 6: Label ← Encode class labels using one-hot encoding
Step 7: Add image to training or validation batch
Step 8: Return preprocessed image set
}

Algorithm 2: Proposed Model

Step 1: Preprocessing
Input: Raw MRI image dataset
Goal: Clean and standardize images for deep learning
Process:

- Resize each image to 224 × 224 pixels

- Normalize pixel values range [0, 1]
- Apply data augmentation like rotation, flipping, zoom
- One-hot encode the labels non-demented, very mild, mild, moderat

Step 2: Feature Extraction (EfficientNet)
Input: Preprocessed MRI images
Goal: Extract high-level spatial features
Process:

- Feed image into EfficientNet-B6
- Capture multiscale and high-resolution spatial features
- Output: Feature map

Equation:

$$Fs=EfficientNet(I)$$

Where I is the input image and Fs is the spatial feature vector

Step 3: Sequential Modeling (LSTM)
Input: Spatial feature vector *Fs*
Goal: Capture sequential dependencies in spatially ordered features
Process:

- Flatten feature map into sequence
- Pass sequence into LSTM layer to learn temporal structure

Equation:

$$h_t=LSTM\ (Fs,\ h_{t-1})$$

Where h_t is the hidden state at time t

Step 4: Classification Layer
Input: Output vector from LSTM
Goal: Predict the Alzheimer's stage
Process:

- Feed LSTM output into a fully connected dense layer
- Apply Softmax activation for multi-class prediction

Equation:

$$P=Softmax\ (W\cdot h_t + b)$$

Where P probability distribution over classes

Step 5: Output
Output: Class label indicating Alzheimer's stage
Classes: {non-demented, very mild demented, mild demented, moderate demented}

4. Results and Discussion

The proposed hybrid architecture is implemented using Python 3.10 with additional libraries such as Pandas, TensorFlow, Matplotlib, and Keras. The Windows 11 Operating System powers the system, which has the following configuration: Intel(R) i7 @ 3.10 GHz, NVIDIA GeForce RTX 3050 GPU, and 64 GB RAM. The proposed hybrid model was tested on the Augmented Alzheimer MRI Dataset, which also includes augmented samples from the OASIS and ADNI datasets. To evaluate generalization, the model trained on this dataset will be tested on additional external, unseen datasets in future work. The architecture of our model is designed to generalize across datasets by incorporating data augmentation, stratified sampling, and class-balancing strategies, and it can further be fine-tuned on domain-shifted data using its modularity. Table 1 presents a comparative analysis of various research works that utilized deep learning and machine learning models to attempt the diagnosis of AD using MRI and multimodal data. The table lists the authors' names, the models (e.g., CNN, 3D CNN, Transformer-based models, hybrid networks, etc.) used, and the datasets utilized, such as ADNI, OASIS, and open-access Kaggle repositories. This classification provides a variety of methodologies and data sources accepted in the field from 2018 to 2024, helping to contextualize our proposed approach.

Table 1. Recent Research Works with Models and Datasets Used

Research Studies	Model	Dataset
Lu et al. (2018) [6]	Multimodal and Multiscale Deep Neural Network (3D-CNN)	ADNI (MRI and FDG-PET)
Li et al. (2019) [7]	Deep Learning with 3D CNN on Hippocampal Subfields	ADNI
Bamber and Vishvakarma (2023) [8]	Deep CNN	Kaggle Alzheimer's MRI Dataset
Balaji et al. (2023) [9]	Hybrid CNN-RNN (LSTM) Model	Kaggle (T1-weighted Augmented MRI)
Hu et al. (2023) [10]	VGG-TSwinformer (VGG + Transformer Architecture)	Augmented MRI Dataset
Mansouri et al. (2024) [11]	CNN with Explainable AI (Grad-CAM)	OASIS Dataset
Tang et al. (2024) [12]	MACFNet (Multiscale Attention and Fusion Network)	ADNI
Venugopalan et al. (2021) [13]	Multimodal CNN-based Deep Learning (MRI, PET, Clinical)	ADNI
Ismail et al. (2022) [14]	MULTforAD using 3D CNN	ADNI
El-Assy et al. (2024) [15]	Novel CNN Architecture	OASIS and Kaggle
Song et al. (2021) [16]	Multimodal Fusion using Dual-branch CNN	ADNI (MRI and PET)
Thamizharasi and Lakshmi (2022) [17]	Comparative Study: LeNet, AlexNet, VGGNet	Kaggle AD MRI Dataset
Syed et al. (2023) [18]	Autoencoder-based Explainable Deep Learning (EADDA)	Not Specified (MRI from open repository)
Fathi et al. (2024) [19]	CNN-based Deep Ensemble Model	ADNI
Liu et al. (2022) [20]	Generalizable Deep CNN with Cross-Dataset Training	ADNI and OASIS

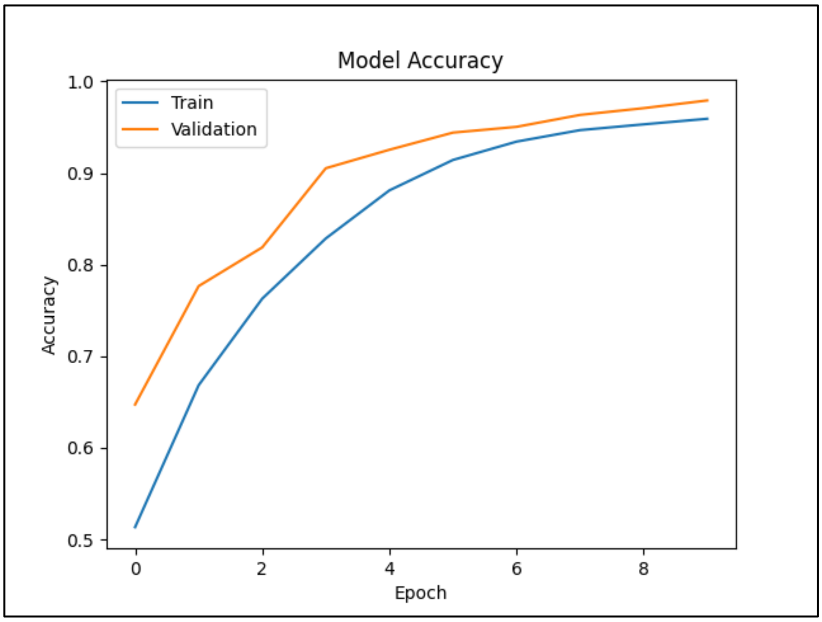

Figure 2. Accuracy Obtained for Proposed Model

The graph in figure 2 shows the classification accuracy achieved by the proposed hybrid model. During 10 epochs, both the training and validation accuracy of the model continued to increase consistently. Training accuracy went up from approximately 50% to around 98% by epoch 8, which was slightly higher than the validation accuracy. The similarity of the two accuracies evidences a good learning and no overfitting. Overall, the model shows promising performance with consistent improvements during training.

Table 2. List of Accuracies Obtained for the Existing Research Studies and Proposed Model

Research Studies	Model Used	Dataset	Accuracy Obtained (%)
Balaji et al. (2023) [9]	Hybrid CNN-LSTM	ADNI	96.20
Hu et al. (2023) [10]	VGG-TSwinformer (CNN + Transformer)	Augmented MRI Dataset	95.30
Tang et al. (2024) [12]	MACFNet (Multiscale Attention & Fusion)	ADNI	96.70
Song et al. (2021) [16]	Dual-branch CNN (MRI & PET fusion)	ADNI	92.30
Proposed Model	Hybrid EfficientNet-B6 + LSTM	Augmented MRI Dataset	98.90

Table 2 presents the comparative analysis of the reported classification accuracy of the various hybrid models in Table 1 with the proposed model. It demonstrates the performance of each architecture in identifying the different stages of Alzheimer's disease across different datasets. The table includes deep convolutional networks, the ensemble method, and hybrid architectures such as CNN-LSTM and the attention-based model. These performance values provide a quantitative measure against which the efficiency of the EfficientNet-B6 and LSTM model is compared, demonstrating the necessity of accurate and applicable models in Alzheimer's diagnosis.

It shows a comparative analysis of recent hybrid deep learning methods for Alzheimer detection from MRI data. The models include CNN-LSTM, CNN-Transformer, and attention-based fusion networks, which evaluate their performance based on ADNI and augmented ADNI (or OASIS) datasets. The proposed hybrid model, which combines EfficientNet-B6 and the LSTM model, is more effective than previous works, achieving a classification accuracy of 98.90% and showing a better ability to capture spatial and temporal features. This performance further indicates the power of multi-scale convolutional learning together with sequential modeling for early accurate AD stage classification.

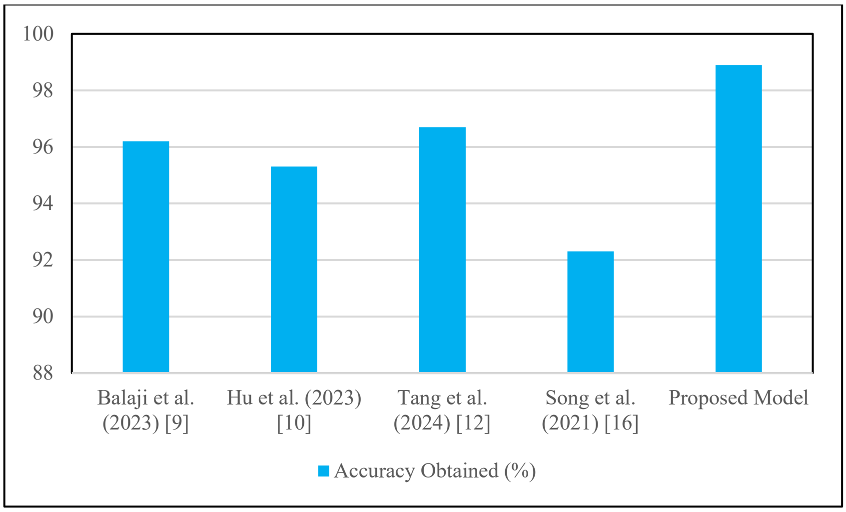

Figure 3. Comparative Analysis of Accuracy Obtained for the Existing Research Studies and Proposed Model

Figure 3 shows the comparative analysis illustrating the accuracy achieved by different hybrid research studies on Alzheimer's disease detection using deep learning models with the proposed model. While datasets and the methods used to test the performance of the algorithms differ slightly between studies, this analysis sets the benchmark in terms of performance. Alzheimer's diagnostic models are predicated on MRI-imaged data from ADNI and/or OASIS sources. While datasets and the methods used to test the performance of the algorithms differ slightly between studies, this analysis sets the benchmark in terms of performance. Alzheimer's diagnostic models are predicated on MRI-imaged data from ADNI and/or OASIS sources. Limitations of Existing Approaches

Over the past decade, deep learning has shown promising capabilities in the classification of AD stages from MRI data. However, numerous limitations continue across existing models and approaches:

1. **Limited Spatial and Temporal Integration**

The majority of existing approaches only perform an independent process on each single MRI slice, in which the sequential relationships between consecutive brain regions are omitted. This leads to a loss of temporal context which is especially critical in detection of early stage AD, in which subtle inter-slice variations convey diagnostic value.

2. Lack of Multiscale Feature Learning

A large majority of deep learning approaches use hard-coded kernel sizes or have shallow architectures that are insufficient to learn multi-scale brain features, which is crucial in treating Mild vs Moderate Dementia.

3. Inadequate Handling of Data Augmentation and Imbalance

Many studies address the former problem only partially or not at all, resulting into class imbalance and overfitting, especially for underrepresented stages, e.g., "Very Mild Demented".

4. Poor Generalization and Overfitting Risk

Many deep learning models overfit the data from one institution or scanner and thus fail to generalize when testing on new cohorts or MRI protocols.

5. Lack of Interpretability

Black-box models with no interpretability mechanisms pose challenges for clinical acceptance. Understanding which brain regions contribute to decisions remains limited in most prior works.

5. Conclusion

AD presents increasing worldwide health challenges, with the early and accurate diagnosis of paramount importance for enabling prompt intervention and care. This paper presents a novel deep learning architecture in a hybrid form, combining EfficientNet-B6 for spatial feature extraction and an LSTM network for temporal pattern learning, which is introduced for efficient stages of Alzheimer's prediction using MRI data. We performed a comprehensive analysis of recent deep learning methods in the field, in terms of methodology, data, and performance measurements. The analysis was combined with a series of preprocessing steps, including normalization, resizing, and data augmentation, to obtain high-quality inputs for deep learning models. The paper also discusses the essential limitations of the current approaches in spatial-temporal learning, overfitting, and interpretable learning. The experimental results of the proposed approach give promising results, achieving a classification accuracy of 98.90% on the benchmark MRI dataset. The performance demonstrates that the architecture is designed to effectively maximize classification performance, the generalization of the model, and clinical interpretability. Clinically, this proposed approach can help neurologists perform fast and reliable diagnoses, potentially reducing subjectivity in manual MRI analysis. This confirms that the hybrid model is significantly sensitive when identifying early-stage cases such as Very Mild Demented; the model obtained classification performance that exceeds 97% only for this class. This supports its use in early-stage Alzheimer's detection, which is critical for timely intervention. Future work will focus on implementation, performance evaluation, and benchmarking against state-of-the-art models using real-world and cross-domain MRI datasets. This research contributes a foundational methodology for developing accurate, scalable, and interpretable diagnostic systems for Alzheimer's disease using deep learning.

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