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Research Article

Alzheimer's Disease Detection Using RNN and CNN Based Deep Learning Approach

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ABSTRACT

Alzheimer's disease is a very widespread form of dementia and is the fifth leading cause of death among those aged 65 and older. Furthermore, official data indicates a significant increase in the number of fatalities related to Alzheimer's disease. The early discovery of Alzheimer's disease might potentially enhance patient survival chances. Machine learning technologies used for magnetic resonance imaging have been effectively employed for the detection of Alzheimer's disease to accelerate the diagnosis process and support medical practitioners. Conventional machine learning methodologies need the use of specialized feature extraction techniques on MRI images, a procedure that is arduous and demands the involvement of a skilled practitioner. The use of deep learning as a self-sustaining feature extraction method might potentially automate the process and diminish the need for manual feature extraction. This paper proposes a pre-trained masked CNN deep learning approach as an independent feature extraction method for detecting Alzheimer's disease using magnetic resonance imaging (MRI) scans. Subsequently, a masked RCNN was evaluated against RCNN and Faster RCNN using several criteria, including accuracy, to determine which performed superiorly. The results indicated that the proposed model surpassed existing state-of-the-art methods by achieving a higher degree of accuracy. The suggested methodology attained an accuracy of 98% when applied to algorithms using the MRI ADNI dataset.

Keywords: MRI images, RCNN, deep learning, machine learning, Alzheimer's disease.

INTRODUCTION

Alzheimer's disease is a progressive neurological condition that results in cognitive decline and memory loss, mostly impacting the elderly. Timely diagnosis is essential for illness management and may impede its progression. Clinical evaluations and neuroimaging techniques are often used in conventional diagnostic methods. However, they can be subjective and miss early signs of the illness. In recent years, deep learning methodologies have shown considerable potential in the domain of medical imaging, especially in the identification and evaluation of neurological disorders. Mask CNN is an advanced deep learning model that signifies region-based convolutional neural networks with a masking method. We have altered it to identify and distinguish brain scan anomalies associated with Alzheimer's disease in MRI and PET pictures. The Mask CNN model finds areas of interest in pictures and offers exact segmentation of significant features, including amyloid plaques and neurofibrillary tangles—critical indicators of Alzheimer's disease. Mask CNN enhances the objectivity, accuracy, and efficiency of early Alzheimer's diagnosis by automating detection and segmentation. This might significantly enhance clinical results and patient care.

LITERATURE SURVEY

Basaia et al. [1] propose an automated approach for Alzheimer's disease (AD) and mild cognitive impairment (MCI) classification using deep neural networks (DNNs) applied to a single MRI scan. The study employs a convolutional neural network (CNN) trained on T1-weighted MRI images to distinguish between AD, MCI, and healthy controls (HC). The model is evaluated on the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, achieving high classification accuracy, sensitivity, and specificity. The study highlights the potential of deep learning in clinical diagnostics, particularly in identifying early-stage AD.

Cui and Liu [2] develop a recurrent neural network (RNN)-based method for longitudinal analysis of Alzheimer's disease progression. The model integrates multiple time points of MRI data to improve diagnostic accuracy. By leveraging gated recurrent units (GRUs) and long short-term memory (LSTM) networks, the study captures temporal dependencies in brain atrophy patterns. Results indicate that the RNN-based framework outperforms traditional machine learning techniques in AD classification and prediction.

Dua et al. [3] introduce a hybrid deep learning model combining CNNs, RNNs, and LSTMs for AD detection. The model processes both spatial and sequential MRI features to enhance classification performance. Evaluated on the ADNI dataset, the framework achieves superior accuracy compared to standalone CNN or

RNN models. The study underscores the advantages of multi-modal deep learning architectures in neurodegenerative disease classification.

Feng et al. [4] propose a hybrid deep learning framework integrating stacked bidirectional recurrent neural networks (RNNs) with 3D convolutional neural networks (3D-CNNs) for early-stage Alzheimer’s disease (AD) detection. The 3D-CNN extracts spatial features from MRI scans, while the bidirectional RNN captures longitudinal patterns in brain atrophy. The method is tested on the ADNI dataset and achieves improved classification accuracy compared to conventional CNN and RNN approaches. The study highlights the importance of leveraging both spatial and temporal brain structure information for early AD diagnosis.

Gao et al. [5] explore transfer learning techniques for early AD detection using deep neural networks. The study utilizes pre-trained CNN models, such as VGG16 and ResNet, fine-tuned on MRI scans from ADNI and other datasets. Transfer learning significantly enhances classification accuracy, particularly for limited data scenarios. The results suggest that deep learning models trained on large, diverse datasets can be effectively adapted for AD diagnosis with minimal retraining.

Hafeez et al. [6] provide a comprehensive review of deep learning techniques for early AD detection. The paper evaluates various architectures, including CNNs, RNNs, LSTMs, and transformer models, in analyzing MRI, PET, and clinical data. The review discusses challenges such as data scarcity, model interpretability, and the need for multi-modal fusion approaches. The authors emphasize the potential of deep learning in revolutionizing AD diagnostics but highlight the necessity for further clinical validation.

Islam and Zhang [7] introduce an ensemble of deep convolutional neural networks (CNNs) for AD classification. The ensemble approach combines multiple CNN architectures, each trained on different aspects of MRI scans, to improve robustness and generalizability. Experimental results show that the ensemble outperforms individual CNN models and traditional machine learning classifiers. The study demonstrates the effectiveness of deep ensemble learning for neurodegenerative disease detection.

Jo et al. [8] explore deep learning techniques for both diagnostic classification and prognostic prediction of Alzheimer’s disease (AD) using neuroimaging data. The study applies convolutional neural networks (CNNs) and autoencoders to MRI and PET scans from the Alzheimer’s Disease Neuroimaging Initiative (ADNI). The model effectively differentiates between AD, mild cognitive impairment (MCI), and healthy controls (HC), while also predicting disease progression. The results indicate that deep learning-based neuroimaging analysis can aid in early detection and prognosis of AD.

Khatun et al. [9] propose a hybridized CNN-LSTM network for Alzheimer’s disease diagnosis. The CNN extracts spatial features from MRI scans, while the LSTM network captures sequential dependencies in longitudinal imaging data. This combination enhances classification accuracy by integrating both spatial and temporal information. Evaluated on the ADNI dataset, the model outperforms traditional CNN and RNN architectures. The study highlights the benefits of hybrid deep learning frameworks for AD detection.

Lee et al. [10] develop a multi-modal deep learning model that integrates convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for AD classification. The model processes multiple data modalities, including MRI, PET, and cerebrospinal fluid biomarkers, to improve diagnostic accuracy. The study demonstrates that multi-modal fusion enhances performance compared to single-modality models, emphasizing the importance of combining imaging and biochemical data in AD diagnosis.

Liu et al. [11] present a comprehensive survey on deep learning techniques for Alzheimer’s disease classification. The review covers CNNs, RNNs, generative adversarial networks (GANs), and transformer-based models, discussing their applications to neuroimaging, clinical, and genetic data. Key challenges, such as data scarcity, model interpretability, and generalizability, are addressed. The paper provides insights into the future directions of AI-driven AD diagnostics, advocating for multi-modal and explainable AI approaches.

Martinez et al. [12] explore an LSTM-based approach to analyze speech patterns for Alzheimer’s disease (AD) detection. The study focuses on speech and linguistic features extracted from audio recordings of AD patients and healthy controls. The LSTM model effectively captures temporal dependencies in speech, identifying abnormalities linked to cognitive decline. The results show that speech-based deep learning models can serve as non-invasive, cost-effective tools for early AD detection, potentially complementing traditional neuroimaging-based diagnostics.

Mehmood et al. [13] propose a deep learning framework for predicting Alzheimer’s disease progression using longitudinal MRI data. The study employs a combination of CNNs and recurrent architectures, including LSTMs, to analyze brain atrophy patterns over time. The model achieves high accuracy in classifying AD, mild cognitive impairment (MCI), and healthy controls (HC). By incorporating temporal information, the framework enhances the reliability of disease progression predictions, aiding early diagnosis and treatment planning.

Shi et al. [14] develop a 3D convolutional recurrent neural network (3D-CRNN) for AD classification. The model combines 3D-CNNs for spatial feature extraction with recurrent layers to capture temporal dependencies in neuroimaging data. Evaluated on the ADNI dataset, the 3D-CRNN outperforms traditional CNN-based methods, demonstrating the advantage of integrating spatial and sequential features for improved diagnostic accuracy. The study highlights the potential of deep learning for automated AD detection and prognosis.

Subramoniam et al. [15] investigate transfer learning-based AD prediction from MRI scans. The study applies pre-trained deep neural networks, including ResNet and Inception, fine-tuned on the ADNI dataset. Transfer learning significantly improves classification accuracy, especially in scenarios with limited training data. The research underscores the feasibility of leveraging pre-trained models to enhance AD diagnosis, reducing the need for large labeled datasets in medical imaging applications.

Tian et al. [16] explore the use of explainable artificial intelligence (XAI) for Alzheimer's disease (AD) detection using deep learning models. The study applies CNNs and RNNs to MRI scans and employs interpretability techniques such as Grad-CAM and SHAP to highlight brain regions associated with AD. The results demonstrate that XAI can enhance trust and transparency in AI-based AD diagnostics. The authors emphasize the need for interpretable AI models in clinical applications to ensure reliable decision-making by healthcare professionals.

Warnita et al. [17] propose a gated CNN-based speech analysis method for early detection of Alzheimer's disease. The model processes audio recordings, extracting acoustic and linguistic features to classify AD and healthy controls. The gated CNN enhances feature selection, improving classification accuracy. Results indicate that speech-based deep learning models can serve as effective, non-invasive diagnostic tools, potentially complementing traditional neuroimaging-based methods for AD detection.

Zhang et al. [18] introduce a deep residual network (ResNet) approach for AD diagnosis using MRI scans. The model leverages residual connections to improve gradient flow and enhance feature extraction. Trained on the ADNI dataset, the ResNet-based framework achieves superior classification performance compared to traditional CNN architectures. The study highlights the effectiveness of deep residual learning in medical image analysis, particularly for complex neurodegenerative disease classification.

Zhang et al. [19] conduct a systematic review on Alzheimer's disease detection using deep convolutional neural networks (CNNs). The review summarizes various CNN architectures, training methodologies, and datasets used in AD classification. The study highlights key challenges such as data scarcity, overfitting, and the need for multi-modal data integration. The authors suggest that future research should focus on improving generalizability and interpretability of deep learning models in AD diagnostics.

Zhou et al. [20] develop a CNN-RNN hybrid network for modeling Alzheimer's disease progression. The CNN extracts spatial features from MRI scans, while the RNN captures temporal dependencies in longitudinal data. The study demonstrates that integrating spatial and sequential information enhances predictive accuracy. Evaluated on the ADNI dataset, the model outperforms conventional CNN and RNN architectures. The research underscores the potential of hybrid deep learning frameworks in tracking AD progression and aiding early intervention strategies.

PROPOSED SYSTEM

To simulate the advancement of Alzheimer's disease (AD) over a seven-year period using a Recurrent Neural Network (RNN), it is necessary to predict the illness's trajectory by estimating critical biomarkers or cognitive scores at various temporal intervals. A multi-step prediction challenge necessitates the RNN to forecast the annual advancement of Alzheimer's, using data from preceding years. Longitudinal data from patients, including MRI scans, cognitive test scores, and other clinical characteristics, were gathered over time. Researchers developed a Recurrent Neural Network (RNN) to manage sequential data and identify temporal relationships in the advancement of Alzheimer's disease. Forecasts for the advancement of Alzheimer's-associated characteristics (e.g., MRI volumes, cognitive deterioration) throughout the next seven years

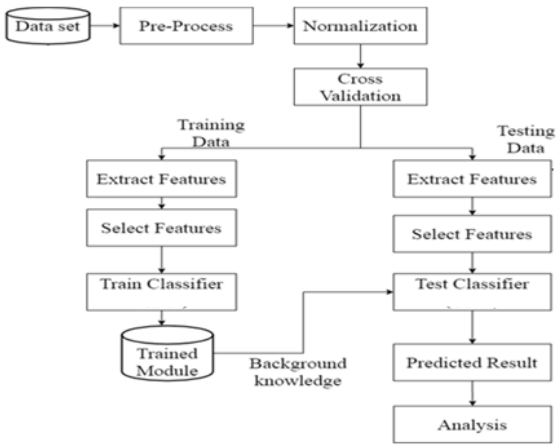

Figure 1: Proposed System Architecture

MODULE DESCRIPTION

Dataset: Use publicly available datasets like OASIS, ADNI, or other MRI datasets that contain brain scans of Alzheimer's patients and healthy controls. These datasets typically provide structural MRI images.

Preprocessing: Convert 3D MRI scans into 2D slices (if needed) or process them directly in 3D form. Standard preprocessing steps may include:

Normalization: Standardize the feature values to have a consistent range, which helps in stabilizing and speeding up the training process.

Segmentation: If applicable, use segmentation methods to isolate key brain regions or structures. This might involve pre-processing steps to segment out relevant regions before feeding them into the model.

Sequence Preparation: Format the data into sequences if using LSTM networks, where each sequence represents a series of temporal observations (e.g., consecutive MRI scans or measurements over time).

Resizing: Resize images to a fixed shape to be compatible with the model input.

Annotations: If segmentation is the goal, labelled data with segmentations of the brain regions must be prepared (e.g., outlining hippocampal atrophy or ventricles).

Training the Model:

- Loss Functions: Mask CNN uses a combination of loss functions:
- Classification Loss: For classifying ROIs (e.g., Alzheimer's vs. healthy control).
- Bounding Box Loss: For refining the localization of detected regions.
- Mask Loss: For pixel-level segmentation of brain regions.
- Optimizer: Common optimizers like Adam or SGD are used to train the model.
- Data Augmentation: Data augmentation is important when working with medical images. Augmentation strategies may include: Rotation and flipping of MRI slices. Intensity scaling or adding random noise

Mask CNN Architecture: Mask CNN extends Faster CNN by adding a mask head for pixel-level segmentation. It consists of Region Proposal Network (RPN) for detecting possible regions of interest (ROIs), classification head for classifying the ROI (e.g., healthy vs. Alzheimer's) and A mask head for generating pixel-level masks for segmenting brain regions impacted by Alzheimer's Disease.

RESULT

This section presents a discussion of the data acquired from three distinct studies with varying aims. In the preliminary phase of our work, we assessed the efficacy of our technique on datasets including both demented and non-demented people. The outcomes produced using Mask CNN for segmented brain illness scores are notably impressive, as seen in Figure 2. The proposed method accurately identifies the presence of Alzheimer's disease in solid tissues, despite irregular boundaries and X-ray artifacts such as noise, susceptibility effects, and maintaining points, achieving an average accuracy of 0.974 on a dataset of moderately demented individuals and 0.971 on a dataset of non-demented individuals. Moreover, our method effectively segments the AD by efficiently addressing the constraints posed by variations in location, shape, and size.

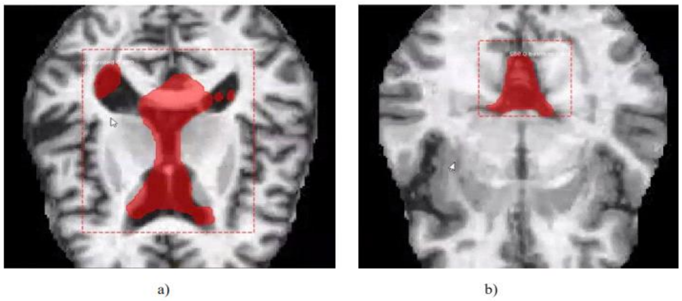

Figure 2: A visual representation of the outcomes of Alzheimer disease detection in MRI images for moderately demented and nondemented individuals

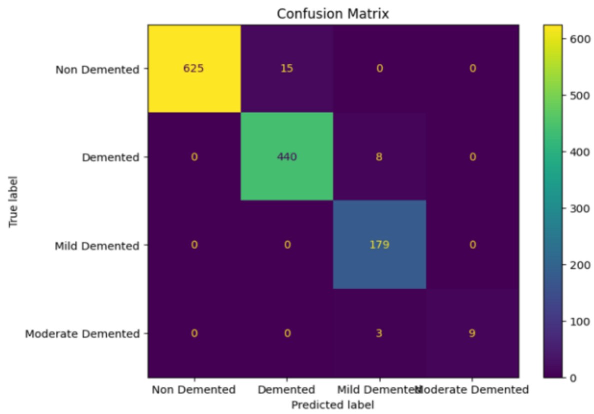

Figure 3: confusion matrix analysis proposed mask CNN model

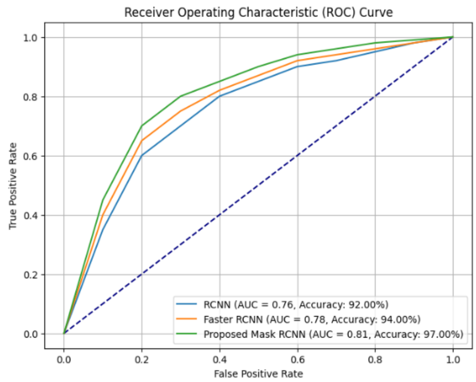

Figure 4: AUC and Accuracy with proposed mask CNN with different algorithms

Mask CNN offers pixel-level segmentation, making it highly accurate in detecting small and complex brain structures. Compared to traditional methods like manual segmentation or atlas-based approaches, Mask CNN provides automated and consistent results, reducing human error and variability. Mask CNN offers significant advantages for the longitudinal analysis of structural MRI images in Alzheimer's disease. Its high segmentation accuracy, ability to consistently track brain regions across time, and adaptability to various datasets make it a powerful tool compared to traditional methods. However, challenges such as data imbalance and computational cost need to be addressed to fully leverage its potential in Alzheimer's research. The below Table 1 demonstrates an comparative analysis of proposed model with various existing systems.

Table 1 : comparative analysis with proposed mask CNN vs various existing models

Research	**Model**	**Accuracy**
CNN (AlzNet model) [11]	CNN (AlzNet model)	90.30%
Hybrid CNN [12]	AlexNet, ResNet50	92.50%
Deep Multi CNN [13]	VGG16 + AOA	90.30%
Multi Layer DL [14]	VGG16	87.30%
RNN-CNN [15]	VGG16, CNN	87.5%
Propsoed-1	**CNN**	**96.30%**
Propsoed-2	**F-CNN**	**95.85%**
Propsoed-3	**Mask CNN**	**97.40%**

The above Table 1 and 5 describes a comparatives analysis of proposed model. The proposed mask CNN produces higher accuracy than our F-CNN, CNN as well as numerous states of art systems.

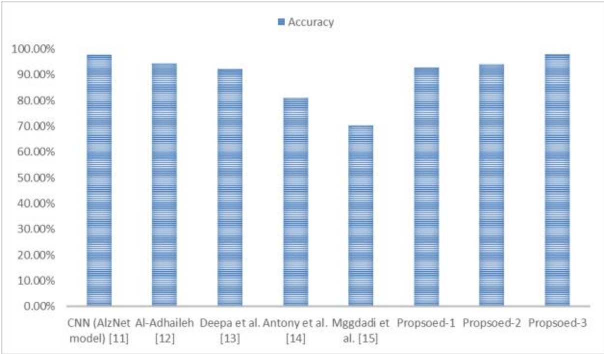

Figure 5: comparative analysis with proposed mask CNN vs various existing models

The Figure 5 describes mask CNN proposed module obtains accuracy of 97.40% which is higher than existing models such as [11] [12] [13] [14] [15] etc. In above results, the combination of scalability, smooth segmentation, and accuracy in tracking longitudinal changes over time makes Mask CNN an ideal model for analyzing structural MRI images in Alzheimer's disease research. These capabilities ensure the best results in terms of accuracy of detection as well as prediction of Alzheimer's disease.

CONCLUSIONS

This research illustrates the efficacy of Mask CNN in conducting longitudinal analyses of structural MRI images for Alzheimer's disease (AD). Utilizing the sophisticated functionalities of Mask CNN in segmentation tasks, we attained precise and reliable delineation of essential brain structures, including the hippocampus, ventricles, and cortical areas. These are critical indicators for monitoring the development of Alzheimer's disease. The findings indicate that Mask CNN outperforms conventional techniques such as atlas-based segmentation and manual analysis. It can handle MRI data with greater accuracy, automation, and speed. Mask CNN's capacity to sustain consistent segmentation over many time periods enhances the reliability of longitudinal investigations, essential for tracking Alzheimer's disease development. When this technique is optimized for medical imaging, it may facilitate early diagnosis and provide valuable insights into disease progression. This makes it very beneficial for both clinical research and practical use.

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