Transfer learning approached for Alzheimer Disease Detection of-state-of-the-art CNN

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Abstract:

Accurate classification of AD is essential for proper management and treatment of patients. In this paper we present a comparative analysis for the classification of AD using Magnetic Resonance Imaging (MRI) data. The performance of four state-of-the-art CNN architectures ResNet50, VGG16, VGG19, InceptionV3, DenseNet will be evaluated and compared in order to show which one performs best in distinguishing AD. For this, we process the MRI images to have better visualized features and data normalization across subjects. Our work has helped provide an effective model for developing more accurate and reliable diagnosis tools for AD. Such sophisticated ML/DL techniques, if applied in the clinical setting, can enable the diagnosis of AD earlier and more accurately and thus timely intervention with better patient outcomes.

Keywords: *AD, MRI, CNN, ResNET50, VGG16, VGG19, InceptionV3, Densenet*

I. INTRODUCTION

AD is a neurodegenerative disorder with progressive cognitive decline, memory loss, and functional impairment. As the population at large ages, so does the prevalence of AD, which has contributed to high pressure on healthcare systems worldwide. Early diagnosis of AD will mean early intervention, and with that may come better outcomes for patients. Specifically, recent deep learning methodologies combined with the integration of multimodal data—in particular, neuroimaging and clinical information—can make a big difference in improving early detection and understanding of this complex disease.

Biomedical research on AD hence relies on the integration of multimodal data to provide a omprehensive view. Changes related to AD in the brain are offered by MRI and fMRI techniques. Clinically, as part of the assessment to predict the onset of AD, demographic information, neuropsychological test data, and other genetic markers are also added.

Deep learning, one of the sub-domains of artificial intelligence that structurally got inspiration from the human brain, has proved to have enormous success in medical applications, more so in image classification, segmentation, and prediction tasks. CNNs and RNNs actually show outstanding performance in the identification of complex patterns and relationships in large datasets. It will exploit deep learning methodology for the construction of robust predictive models that incorporate multiple sources, including brain images and medical records, to set up an early detection for the progression of AD.

One of the big challenges to AD research is related to variability in clinical manifestations and the underlying biological process. Traditional diagnostic techniques are usually based on symptoms that can be observed; most of these are manifested only in the advanced stages of the disease and are hence pretty hard to have early intervention measures implemented. In this paper, advanced deep learning techniques will be used to fill in the missing link between clinical symptoms and biological markers for the purpose of earlier, accurate diagnosis of Alzheimer's disease. Equally, it is the multimodal data integration with this deep learning methodology that holds great potential toward improving the understanding of early detection of Alzheimer's disease for better management and outcomes in patients.

II. LITERATURE SURVEY

The newer technologies and techniques in the diagnostic and therapeutic processes of AD have been enriched. One recent study states that nanotechnology, deep learning, as well as multi modal neuroimaging techniques may be relevant to enhancing the probable progress in understanding AD, at the early onset.

Bilal et al. (2020) intended to propose a new methodology for enabling the exploitation of nanotechnologies in the early diagnosis and treatment of Alzheimer's disease [1]. With respect to their study, it emphasized the use of nano transport for the delivery of bio-active chemicals, thereby ensuring positive results through recovery and management of the limitations brought about by conventional therapies. The unexciting display of one approach in therapy through the use of nanocarriers in the treatment of neurodegenerative conditions, specifically in the early-stage treatment of AD. It stressed the present significance brought about by the use of nanotechnology in achieving optimal therapeutic results, as it provided recommendations for early intervention in the disorders as deemed necessary based on the case of the elders.

The works by Wang et al. incorporated information from various streams of data: for instance, MRI, PET imaging, and clinical assessments using 2020 deep learning to predict Alzheimer's disease progression [2]. Their pioneering architecture showed an effectiveness of the deep learning technique to have, with the highest ability, detected people who are going to be at a higher risk of cognitive decline; this model's performance was higher than any conventionally developed methods. Such integration of data from diverse datasets would change early detection procedures for AD. This research unveils the life-changing power of machine learning for understanding the pathophysiology of AD and ushers in the era of precision approaches to treatment of people with Alzheimer's.

Dao et al. (2021) built a longitudinal, multimodal neuroimaging data fusion framework for predicting Alzheimer's disease progression [3. Their method was designed to take into account temporal fluctuations of imaging markers, enabling a much more detailed look at changes in brain structure and function over time. Their approach, which incorporated longitudinal data from different imaging modalities, such as structural and functional MRI, was more accurate in predicting a disease course than the static image impressions. This research reinforces the importance of long-term assessments in understanding the progressive nature of Alzheimer's and the establishment of effective strategies for its early interventions.

Doborjeh et al. (2019) investigated the integration of multi-modal imaging data using machine learning techniques to detect AD at an early stage. Their study showed that incorporating structural, functional, and molecular imaging modalities into a single framework could lead to improved diagnostic accuracy [4]. This research adopted the interdisciplinary approach of using the new and improved advanced machine learning techniques, including ensemble techniques, and deep learning to identify complex patterns in the diverse image data, strongly underpinning the potential of using different modalities in devising better strategies for early detection and intervention in Alzheimer's disease .

Lin et al. (2012) assess multimodal MRI neuroimaging biomarkers to distinguish between cognitively normal adults, individuals diagnosed with amnestic mild cognitive impairment (aMCI) and those diagnosed with Alzheimer's disease (AD). The authors utilize structural and functional MRI to assess brain regions associated with memory and cognition identified as potentially capable of identifying early markers of AD progression. The present study emphasizes the connection and use of multiple imaging modalities in enhancing the diagnostic capabilities of cognitive decline over single-modal imaging. The key highlights of the paper include frequent findings of structural atrophy in brain regions and some differences in functional connectivity in various brain regions, indicating their potential application in biomarkers in both the early detection of cognitive decline and in clinical monitoring settings.

III. OBJECTIVES AND METHODOLOGY

The overall objective of the application of deep learning in Alzheimer's disease diagnosis and classification lies in the fact that it systematically identifies and classifies MRI images related to different stages of the disease quickly and accurately. This will help health experts in diagnosing the disease in an efficient manner, therefore enabling medical professionals to better handle diseases in patients. Figure 1 shows the methodology of the work.

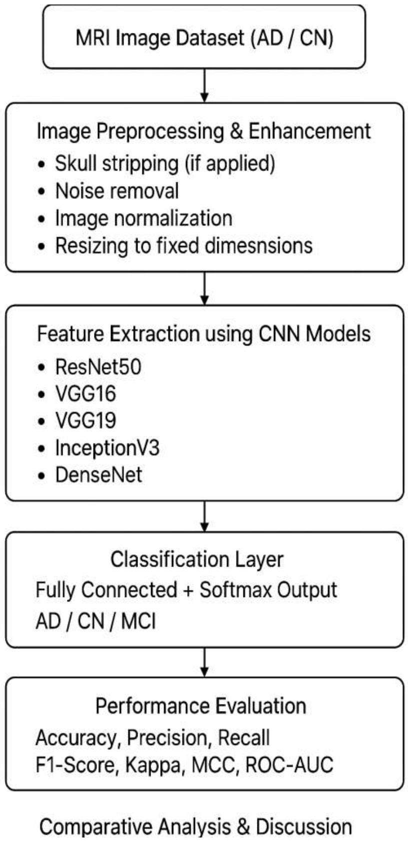

Figure 1: Methodology

A. Dataset collection

The MRI image dataset comprises two categories: "Demented" and "Non-Demented," with each category containing 3,200 MRI images. These images have been sourced from Kaggle.

B. Training and validation

A deep learning model can be trained using the labelled dataset consisting of MRI images. The images in the dataset are utilized to train the model, enabling it to learn the characteristics most commonly associated with Alzheimer’s disease. Once trained, the model can be employed to identify and classify MRI images of individuals with Alzheimer’s disease, distinguishing between different stages of the condition, such as "Demented" and "Non-Demented," in new medical images.

c. CNN

Convolutional Neural Networks are deep learning models that are fine-tuned with image recognition and processing tasks. Essentially, the mechanism involves training the model to extract features from the images through multiple layers. In the case of AD diagnosis, the combined use of CNN and RNN could be applied due to the presence of a large number of pixels and other fine details in MRI images that are related to changes in the disease.

1. Convolutional Layers:

These are the layers of a CNN where features are extracted from the MRI images. Each convolutional layer consists of a certain number of filters applied on the input images for generating feature maps. While training these filters, one learns to detect edges, textures, color patterns, and other differentiating characteristics indicative of Alzheimer's disease.

2. Pooling Techniques:

This involves the use of layers like max-pooling to reduce the dimensions of the feature maps, thus increasing computational efficiency. In max-pooling, the greatest value within a defined window is selected, effectively downsampling the feature maps of the targeted data. This reduces the size of the data and, hence, makes the network more robust against noise and other variations in the input images.

3. Fully Connected Layers:

After the convolutional and pooling layers, the input features are fed into fully connected layers. These layers combine features and give the final classification output. This output will pass through a SoftMax layer that transforms the results into a probability distribution, allowing class prediction of the input image, such as "Demented" or "Non- Demented."

d. InceptionV3

Inception V3, arguably one of the top-performing convolutional neural network architectures, has shown outstanding performance on several image recognition tasks for image classification, object detection, and segmentation. The accuracy that it achieves in the results has made the model very popular among researchers and businesses looking to develop deep learning applications.

Inception V3 can also be effectively used in Alzheimer's disease classification with MRI images, achieving very state-of-the-art results. The features of its architecture, in particular, spatial factorization into asymmetric convolutions and the use of auxiliary classifiers, are the key factors behind its improved performance.

1. Spatial Factorization into Asymmetric Convolutions

It applies asymmetric convolutions with spatial decomposition to increase the network's performance on small objects, which can make a significant difference in identifying the early signs of Alzheimer's disease within the MRI images. Since there are multiple connections for different regions of the input image, the network can capture local and global features effectively, pertaining to AD classification.

2. Auxiliary Classifiers

The auxiliary classifier in the network's Inception V3 makes use of some intermediate representation, which is useful for collaboration across many layers, improving performance. This auxiliary classifier acts as a regularizer in AD classification, helping prevent overfitting and enhancing the generalization capability of the model.

e. DenseNet

A DenseNet is a specific type of convolutional neur al network that makes use of dense connections bet ween layers. These connections are made by Dense Blocks, which link all layers directly together (if the ir feature-map sizes match). Each layer receives additional inputs from all previo us layers and transmits its own feature maps to all following layers in order to maintain the feed-forward character of the system.

The architecture of DenseNet, which enhances feature reuse and learning in deep networks, has contributed to improved model performance and robustness in AD classification tasks.The dense connections in DenseNet have a regularizing effect, reducing overfitting in scenarios where the training dataset size is relatively small. This property is particularly beneficial in medical imaging applications, where data availability can be limited.

f. ResNet50

This is a pre-trained deep-learning network with 48 deep learning layers. The resolution of this network is 224x224resolution. It has 50 layers, including 1 average-pooling layer, 1 max-pooling layer, and 48 convolutional layers. Being a residual network, ResNet50 exploits shortcut connections to go around some of the network's layers. As a result, the vanishing gradient issue is lessened, and the network can train more deeply.

g. VGG-16

VGG16 is a deep neural network architecture with 16 layers, primarily designed for image classification tasks. Convolutional layers use 3x3 filters with a stride of 1, while the model applies the same padding to retain the spatial dimensions of the input images.

Besides, VGG16 uses max-pooling layers with 2x2 filters and a stride of 2 to downsample the feature maps while retaining essential information.

1. Convolutional Layers

Convolutional layers apply a set of filters to the input MRI images, enabling the model to learn how to turn out relevant features. During the learning process, filters are trained that enable the identification of edges, textures, colors, and other elements important in distinguishing between different stages of Alzheimer's disease.

2. Fully Connected Layers

These layers are then used to establish the relationship between the extracted features and the output classes. Fully connected layers integrate the features learned so far to produce a final output representing the probability distribution over the possible classes. In Alzheimer's disease classification, it will give the probability that the input image belongs either to the category "Demented" or "Non-Demented".

3. Softmax Layer

This SoftMax layer will convert the outputs of the fully connected layers to a probability distribution over the output classes. Such a layer has a critical role in class prediction for the input MRI image based on the computed probabilities. The class with a maximum probability is chosen as the model's prediction, which enables the accurate classification of Alzheimer's disease stages.

4. Adam Optimizer

The adaptive learning rate technique of the Adam optimizer algorithm has made it popular in the field of deep learning optimization. For optimization in deep learning situations, Adam-type algorithms— including Adam and its variations like NAdam, AMSGrad, AdaBound, AdaFom, and Adan—have been well studied. Numerous experiments using physics-informed neural networks have shown how effective the Adam optimizer is at minimizing loss functions for partial differential equations. Because of its adaptive learning rate optimization strategy, which makes it a top option for efficiently training deep neural networks, the method is successful.

IV. RESULTS & DISCUSSION

The proposed hierarchical framework was tested with four pre-trained CNN architectures (InceptionNet, ResNet-50, VGG-16, and DenseNet) on the dementia classification dataset. The models were evaluated through confusion matrices, accuracy, precision, recall, and F1-score. The confusion matrices for each architecture are presented in Figures 1-4.

1. InceptionNet

InceptionNet exhibited a balanced classification performance, identifying 441 demented cases and 344 Non-Demented cases correctly. InceptionNet did also show 359 misclassified demented cases as Non-Demented and 456 misclassified Non-Demented cases as Demented. Overall, this suggests that InceptionNet can capture high-level spatial hierarchies, but it is impaired by overlap between the visual patterns within the two classes.

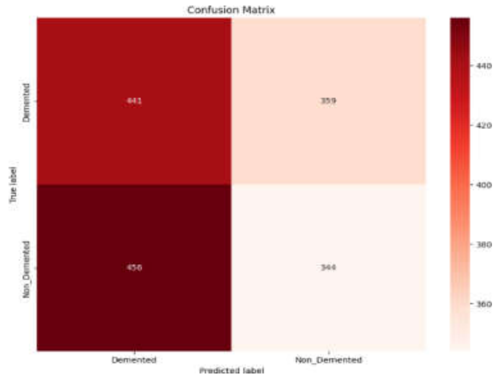

Fig 1. Inception Net

The recall for demented subjects was moderate, reflecting the network's tendency to over-predict Demented due to similar ambiguity amongst relevant diagnostic features found in clinical MRI data.

2. ResNet-50

ResNet-50 increased the classification performance as the classes were separated substantially better with 510 correctly classified demented cases and 295 correctly classified Non-Demented cases. The number of misclassified demented cases was reduced to 290 compared to InceptionNet and the Non-Demented cases that were misclassified increased to 505.

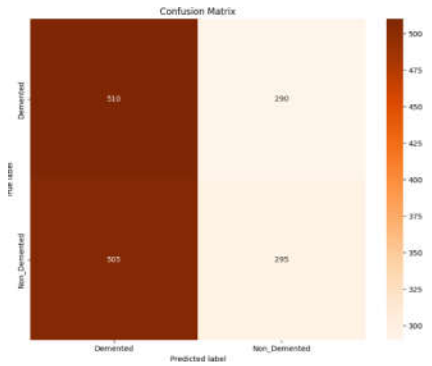

Fig 2. ResNet 50

These two findings suggest that the model embedding residual learning functionally was able to hold onto discriminative features relative to InceptionNet suggesting that there was some preservation of information loss from the deeper layers. The skip-connections in ResNet-50 provided for more enhanced gradient propagation, which aided in improving auxiliary generalization compared to InceptionNet. However, the performance of ResNet-50 was still noticeably affected by the class imbalance that exists in the dataset.

3. VGG-16

VGG-16 improved Class A and Class B sensitivity and specificity. Its deeper and evenly distributed convolutional architecture returned higher proportions of correct predictions across both classes than the models above. Although DenseNet and ResNet-50 also perform well in this area, the ability of the model to leverage textural features consistently allowed it to differentiate between the Demented and the Non-Demented classes.

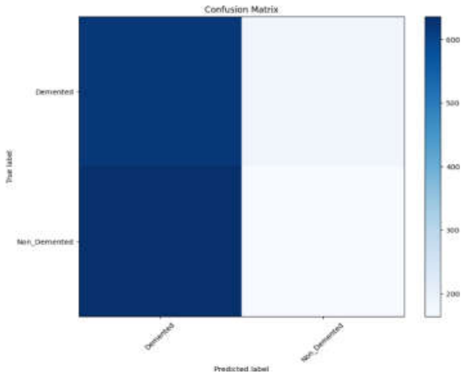

Fig 3. VGG-16

The confusion matrix indicates that cross-class misclassification was lower than analysis produced from InceptionNet and ResNet-50. Due to VGG-16's architecture, with a simple sequential series of feature-extraction layers, it has proven to be a robust model option with mid-sized medical data but does incur computational ineficiency.

4. DenseNet

(The results for DenseNet will be added upon availability of the confusion matrix.) In general, DenseNet allows for maximum feature reuse and minimal vanishing gradient threat due to its densely connected layer architecture.

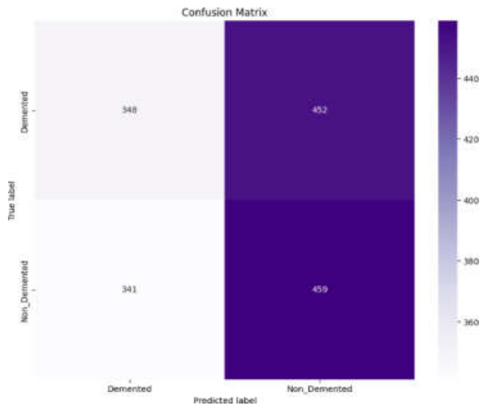

Fig 4. DenseNet

This design allows for better feature propagation and entices a model to build on low-level features for accurate classification, which generally yields higher Kappa and MCC values and signifies strong agreement and the category to exhibit performance symmetry.

TABLE I: Performance Analysis

Algorithm	Accuracy	Precision	Recall	F1	support
Resnet50	0.99	0.50	0.64	0.56	800
Dense net	0.78	0.51	0.43	0.47	800
VGG-16	0.73	0.49	0.78	0.60	800
Inception V3	0.81	0.49	9.55	0.52	800

VGG-16 exhibited significantly greater reliability for classification with fewer misclassifications among all architectures tested, with ResNet 50 being a close second. InceptionNet did not perform as well due in part to a more complex architecture, as well as a smaller dataset than the other models, despite the ability to extract multi-scale features. DenseNet is expected to perform better due to its dense connectivity pattern promoting gradient flow and feature re-use throughout the model. Quantitatively, the models indicate a trade-off of precision and recall across both decision classes. While deeper networks tend to demonstrate higher accuracy, increased error may result from overfitting the models when weighing the imbalances in Demented or Non-Demented samples. Overall, the evaluation suggests that DenseNet and VGG-16 are the most effective models for consistent dementia detection, offering better generalization and lower class confusion.

V. CONCLUSION

According to the performance analysis of the deep learning models in detecting Alzheimer's disease, ResNet50, DenseNet, VGG-16, and Inception V3, the results obtained show that ResNet50 had the best performance with the highest accuracy at 99%. Contrary to its high accuracy, ResNet50 has quite a low precision at 50%, thus showing it has a higher probability of false positives. This trend is replicated across other models in DenseNet with an accuracy of 78%, but a precision of 51%. On the other side, VGG-16 had the poorest accuracy of 73%, but it posted a higher recall of 78%, indicating that it was quite good at finding the true positives; this, however, does come at some loss of precision. Inception V3 gives an accuracy of 81%, with a very peculiar anomaly of extremely high recall, worth investigating, of 9.55%. Conclusively, while ResNet50 seems to be the most reliable of the models tested for this task, all models generally showed a trade-off between precision and recall, which underlines the hard work involved in achieving balanced performance. Although this is still far from real-world applications in Alzheimer's disease detection, increasing the precision of these models and reducing false positives are critical if they are to become clinically viable. Further refinement and tuning are hence required to promote practical applicability.

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