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Early Detection of Alzheimers Disease using Deep Learning

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***Abstract*—Alzheimer's disease (AD) poses a significant challenge to global healthcare systems due to its progressive nature and impact on patient's lives. Accurate and early detection of AD is crucial for timely intervention and management. In this paper, we propose the use of deep learning models, including Convolutional Neural Networks (CNNs), MobileNet, and VGG16 for the classification of Magnetic Resonance Imaging (MRI) scans into different AD stages.**

***Index Terms*—Alzheimer's disease , Deep Learning , Convolutional Neural Networks(CNN) , MobileNet , VGG16 , MRI scans**

I. Introduction

Medical advancements have become paramount in contemporary society, with researchers and medical experts striving to enhance diagnostic procedures, treatments, and examinations to improve human health and quality of life. Among the many health challenges, Alzheimer's disease (AD) stands out as a significant concern. AD is a neurodegenerative disease that causes irreversible brain damage and progresses after onset[1]. Symptoms of AD include memory loss, language difficulties, and disorientation. AD presents a significant and growing challenge to global healthcare systems, with an increasing prevalence, particularly among the elderly population[2]. The progressive nature of AD underscores the critical need for early and accurate detection to enable timely intervention and management strategies[3]. In this context, medical imaging techniques have emerged as indispensable tools for aiding in the diagnosis and classification of AD.

Traditionally, AD diagnosis involves clinical observation of symptom progression or invasive procedures like lumbar puncture to detect specific biomarkers in the cerebrospinal fluid[4]. However, medical imaging techniques such as Magnetic Resonance Imaging (MRI), Position Emission Tomography (PET), and Single-Photon Emission Computed Tomography (SPECT) offer less invasive alternatives[5-11]. Among these, MRI stands out as a non-invasive method, particularly revealing structural changes in the brain associated with AD, such as atrophy of the cerebral cortex and enlargement of ventricles and hippocampus atrophy [12].Figure 1 shows a comparison of a healthy brain and a brain affected by AD.

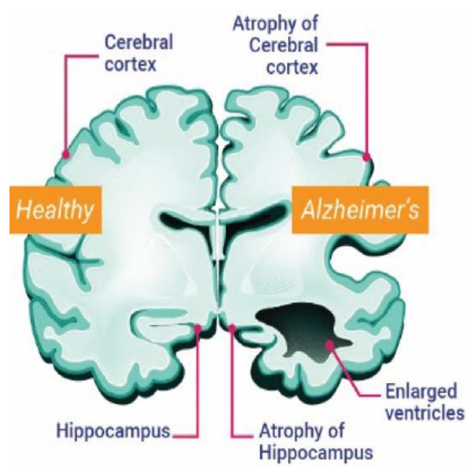

Fig. 1. Healthy versus Alzheimer's.

However, despite advancements in imaging technology, accurately interpreting MRI scans to diagnose AD remains a challenging task, particularly in its early stages. Traditional machine learning algorithms have been employed in medical image analysis for AD diagnosis, including preprocessing, segmentation, feature extraction, and classification. However, these conventional approaches often rely on handcrafted features and may struggle with complex image data such as MRI scans of the brain. Additionally, they may require extensive manual intervention and domain expertise, leading to limitations in scalability and generalization[13].

To address these challenges, deep learning techniques have emerged as powerful tools for medical image analysis, offering automated feature learning and end-to-end training capabilities. Convolutional Neural Networks (CNNs), in particular, have shown remarkable success in various image classification tasks, including medical imaging. By automatically extracting hierarchical features from raw data, CNNs eliminate the need for handcrafted features and achieve superior performance in complex tasks such as AD diagnosis [14,15].

In this study, we propose the utilization of deep learning models, including a proposed CNN model, MobileNet, and VGG16, for the classification of MRI scans into different stages of Alzheimer's disease, i.e., Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented. These models leverage the inherent capabilities of deep learning to learn discriminative features directly from the input data, enabling more accurate and efficient classification compared to traditional machine learning methods. By exploiting the power of deep learning, we aim to overcome the limitations of conventional approaches and contribute to the advancement of AD diagnosis and treatment.

II. Literature Review

Alzheimer's Disease (AD) is a progressive neurodegenerative condition that poses significant challenges in early diagnosis and effective management. In recent years, there has been a growing interest in utilizing advanced computational techniques, particularly deep learning (DL) algorithms, for the detection and classification of AD using medical imaging data such as MRI scans.

The paper by Suhad Al-Shoukry et al. presents a mini-review focusing on relevant research on AD, utilizing brain imaging techniques such as MRI scans, PET, and SPECT, along with Machine Learning (ML) and Deep Learning (DL) techniques applied to various AD datasets. ML has been utilized in the past decade to detect MRI biomarkers of AD, while DL, described as a new area of ML research, aims to bring ML closer to its original goal of Artificial Intelligence. The paper emphasizes the importance and effectiveness of DL methods, particularly in tasks such as Alzheimer's disease detection from MRI scans. DL techniques like convolutional neural networks (CNNs) are highlighted for their feature extraction capabilities and improved classification accuracy in bio-image analysis. While DL is prominently showcased, the effectiveness of ML methods is not discounted; support vector machines (SVM) are mentioned as a successful approach for categorizing mild cognitive impairment (MCI) cases. The paper also discusses the availability of different types of datasets for this classification task[16].

Similarly, Shiny Pershiya A et al. discusses the use of Convolutional Neural Networks (CNNs), specifically the LeNet-5 model, for classifying Alzheimer's Disease (AD) using MRI data. AD, a progressive neurodegenerative condition, necessitates early diagnosis for effective management. Data from a Kaggle dataset undergoes preprocessing, including skull-stripping and motion correction, before employing deep learning algorithms for classification. The LeNet-5 architecture, adapted for MRI data, achieves high accuracy (98.664% over five runs) in distinguishing between AD and healthy individuals. These results highlight the effectiveness of CNNs in early AD diagnosis, offering potential for predicting disease progression and stages across age groups. The study underscores the promising application of deep learning in medical image analysis, with implications for enhancing patient care and outcomes in neurodegenerative diseases[17].

III. METHODOLOGY

A. Convolutional Neural Networks (ConvNets)

Convolutional Neural Networks (CNNs) draw inspiration from the complex mechanisms of the human visual system to process and understand visual data effectively. They are tailored for tasks involving images due to their inherent assumptions about the two-dimensional nature of the input data. The architecture of CNNs is designed with unique features such as local connections, parameter sharing, and invariant representations, which not only reduce computational complexity but also simplify network design.

A CNN typically comprises several essential components: convolutional layers for extracting features from input images, pooling layers to reduce the dimensionality of feature maps, fully connected layers for generating class scores, and for making predictions. The convolutional layers play a crucial role in feature extraction, transforming raw pixel data into hierarchical representations of visual features. Subsequently, pooling layers are employed to downsample the feature maps, thereby reducing the computational burden and preventing overfitting by capturing the most salient information.

By leveraging spatial relationships and exploiting the hierarchical structure of visual data, CNNs excel at tasks such as image classification. The utilization of pooling layers between convolutional layers further enhances the network's ability to capture abstract features while reducing computational overhead. Overall, CNNs represent a powerful paradigm in deep learning, capable of achieving state-of-the-art performance on various visual recognition tasks.

B. VGG16

VGG-16 is a convolutional neural network (CNN) architecture known for its depth and simplicity, introduced by the Visual Geometry Group (VGG) at the University of Oxford. Released in 2014, VGG-16 is part of the VGG family of models and is widely used for various computer vision tasks, particularly image classification.

One of the distinctive features of VGG-16 is its architecture, which consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers are stacked one after another, with small receptive fields (3x3 filters) and a fixed stride of 1 pixel. This uniform architecture with small filters allows VGG-16 to learn rich feature

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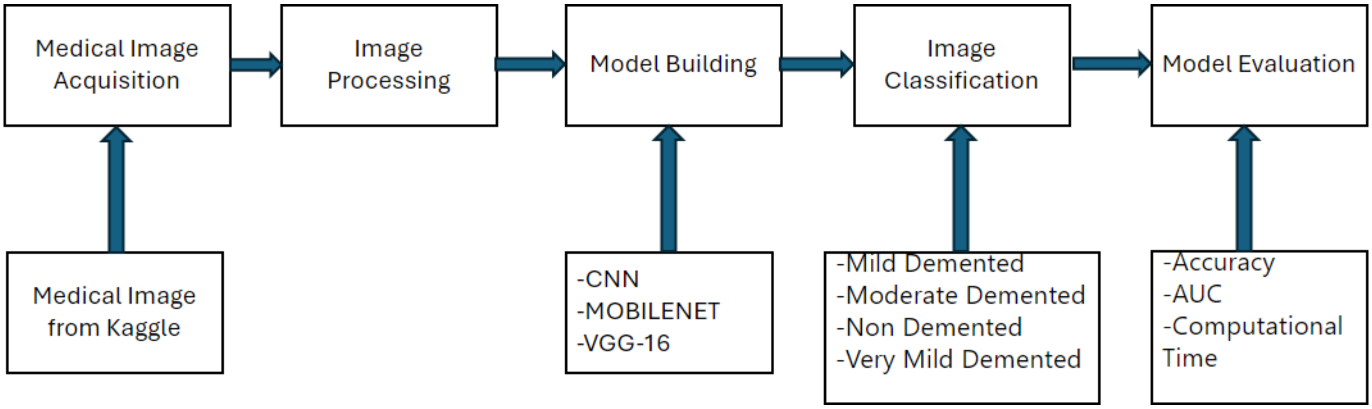

Fig. 2. Block diagram of the proposed methodology for Classification of Alzheimer's disease

representations at different spatial scales, contributing to its effectiveness in capturing intricate patterns in images.

Moreover, VGG-16 follows a straightforward design philosophy, where deeper networks are constructed by stacking more convolutional layers with smaller filter sizes. This simplicity makes VGG-16 easy to understand and implement, facilitating widespread adoption and experimentation in the research community.

Despite its simplicity, VGG-16 achieves remarkable performance on benchmark image classification datasets like ImageNet. Its deep architecture enables it to learn hierarchical features of increasing complexity, ultimately leading to high accuracy in recognising objects within images.

However, the main drawback of VGG-16 is its computational cost and memory requirements due to its depth and large number of parameters. Training and deploying VGG-16 may be resource-intensive, especially compared to more recent architectures optimised for efficiency, such as MobileNet.

In summary, VGG-16 is a classic CNN architecture renowned for its depth and simplicity, making it a popular choice for image classification tasks. While it may not be the most efficient model in terms of computational resources, its effectiveness in learning intricate image features has solidified its place as a fundamental benchmark in the field of computer vision.

C. MobileNet

MobileNet is a convolutional neural network (CNN) architecture developed by Google researchers, aiming to facilitate efficient execution on mobile and embedded devices constrained by computational resources. Introduced in 2017, MobileNet offers several distinctive features tailored for deployment on devices with limited power and memory capacities.

At the core of MobileNet's efficiency lies the concept of depthwise separable convolution. This technique decomposes the standard convolution operation into two distinct layers: depthwise convolution and pointwise convolution. The depthwise convolution applies a single filter to each input channel independently, significantly reducing computational complexity compared to traditional convolutions. Subsequently, pointwise convolution combines the resulting feature maps using 1x1 convolutions to create complex representations while further reducing the computational burden. mage label

MobileNet also introduces two key hyperparameters: the width multiplier and resolution multiplier. The width multiplier scales the number of channels in each layer, while the resolution multiplier decreases the input image resolution. These parameters offer a flexible trade-off between model size and accuracy, enabling customisation to suit specific resource constraints and performance requirements.

Moreover, MobileNet models are often pretrained on large-scale image datasets like ImageNet, providing a solid foundation for transfer learning and fine-tuning on domain-specific tasks. This pretraining strategy allows MobileNet to generalise well across diverse image recognition tasks while leveraging its efficiency advantages.

MobileNet finds applications in various computer vision tasks, including image classification, particularly in scenarios where real-time processing or deployment on edge devices is essential. Its optimised architecture strikes a balance between computational efficiency and performance, making it a popular choice for mobile and embedded applications.

IV. Results and Analysis

The graphical representations of the outcomes from the three Deep Learning models analyzed in this study were presented in Fig. 3. corresponding to the proposed CNN model, VGG-16, and MobileNet, respectively.

The loss function utilized in this study is Categorical Cross-Entropy Loss, which is suitable for multi-class classification tasks, extending binary cross-entropy loss to scenarios with more than two classes.

However, due to differences in units, computational time could not be visualized alongside these metrics.

The proposed CNN model demonstrates the highest accuracy on the test dataset, comprising 6400 images, with an accuracy rate of 99.18%, followed by VGG16 with 97.55%

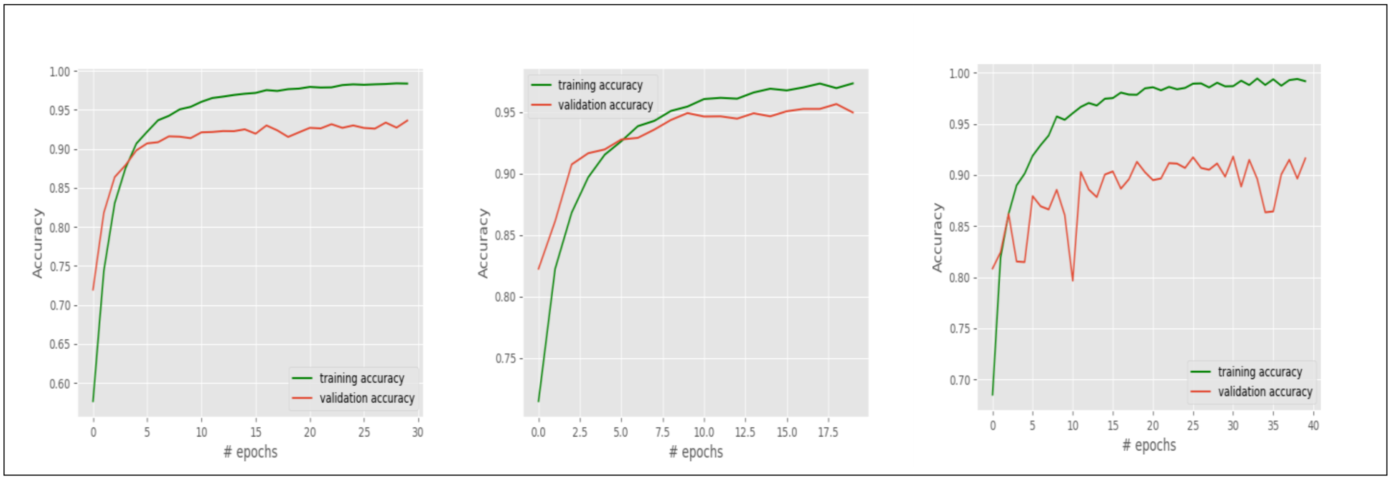

Fig. 3. Graphical Visualization of Accuracies of Deep learning models(Proposed CNN,VGG16,MobileNet respectively) on Alzheimer's Dataset

and MobileNet with 91.73%. Regarding the Area under the Curve metric, CNN achieves 99.89%, VGG16 attains 99.87%, and MobileNet reaches 98.23%. Furthermore, VGG16 requires more time for training on the dataset consisting of 33984 images, compared to MobileNet and CNN, in descending order.

V. Conclusion

In conclusion, this study has highlighted the effectiveness of deep learning models, namely CNN, VGG16, and MobileNet, in accurately classifying Alzheimer's disease from MRI scans. The proposed CNN model demonstrated superior performance in terms of accuracy and AUC, followed by VGG16 and MobileNet. These results emphasize the potential of convolutional neural networks for improving the accuracy and efficiency of medical image classification tasks, particularly in the diagnosis of complex neurological disorders such as Alzheimer's disease. Moving forward, future research endeavors should consider exploring alternative CNN architectures such as ResNet, and AlexNet, while also leveraging high-performance computing resources like GPUs and TPUs to further enhance classification performance.

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