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Research Article

Unveiling Alzheimer's Disease via MRI: Deep Learning Approaches for Accurate Detection

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Abstract – This study conducted a comparative analysis of machine learning algorithms to discern the most effective approach for detecting Alzheimer's disease (AD). Timely and precise detection of AD stands crucial for efficient intervention in this prevalent neurodegenerative disorder among the elderly. Deep learning algorithms have demonstrated promising outcomes in AD diagnosis through the examination of magnetic resonance imaging (MRI) scans. The research focused specifically on evaluating the performance of diverse deep learning architectures, encompassing CNN (Convolutional Neural Network), in detecting AD using MRI images. Utilizing a substantial dataset comprising MRI scans from both AD patients and healthy individuals, the models were trained to automatically extract discriminative features from these images. Experimental results underscore the effectiveness of the proposed models, notably the active use of MobileNet and CNN, which achieved an impressive accuracy of 95.92% in identifying Alzheimer's disease. These findings highlight the superior performance of CNN and MobileNet compared to DenseNet and Inception V3 in AD detection, emphasizing their potential for accurate identification of AD compared to other algorithms. Such insights offer valuable direction for selecting the most appropriate algorithm for AD diagnosis, considering critical factors such as accuracy, computational efficiency, and resource availability. However, further exploration and validation employing larger and more diverse datasets are essential to establish the broader applicability and clinical relevance of these algorithms in real-world scenarios for AD detection.

Keywords – Alzheimer's Disease (AD), Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN)

I. INTRODUCTION

Alzheimer's disease (AD) stands as a progressive neurodegenerative condition impacting millions globally, underscoring the critical importance of early and precise detection for effective intervention and management. Within the realm of Alzheimer's disease detection, convolutional neural networks (CNNs) have emerged as a pivotal tool in deep learning methodologies. These CNNs, a specialized form of deep learning algorithm tailored for visual data analysis like images, autonomously learn and extract pertinent features. Recent advancements in deep learning, notably Convolutional Neural Networks (CNNs), have showcased significant promise in medical image analysis, specifically in diagnosing AD via magnetic resonance imaging (MRI) scans [1][2].

This research endeavors to both develop and appraise a CNN-centered deep learning algorithm designed explicitly for AD detection using MRI images.

The gravity of the Alzheimer's disease issue underscores the profound significance of this research. In an increasingly aging global population, the prevalence of AD continues to escalate, exerting a mounting burden on healthcare systems, caregivers, and individuals directly affected by this condition. Emphasizing the crucial importance of early and accurate diagnosis, this study's core essence revolves around this pivotal aspect. Early identification of Alzheimer's disease plays an integral role in empowering individuals to make informed decisions regarding their treatment, thereby significantly enhancing the overall quality of life for patients, their families, and their overall well-being [3].

II. Materials and *Method*

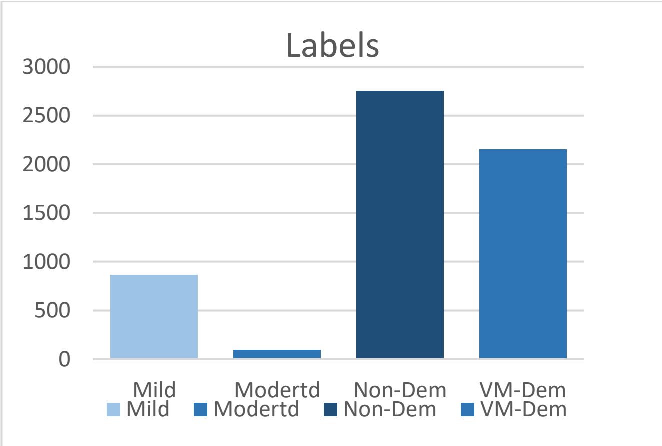
A. *Participants and Datasets*

For this research, the participants and datasets were sourced from the Kaggel Alzheimer's Dataset. This dataset consists of MRI images categorized into four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. Both the training and testing sets encompass images representing various severity levels of Alzheimer's disease. The dataset is structured into two distinct files: Training and Testing. Each file contains an approximate count of 5000 images, resulting in a cumulative dataset size of about 10,000 images. The images are specifically categorized based on the severity level of Alzheimer's disease, facilitating an in-depth analysis of how different severities impact the classification task and other pertinent analyses [4].

B. *MRI Preprocessing*

The dataset used in this study consists of MRI images from AD patients and healthy individuals. The dataset is reprocessed to ensure uniformity and remove any artefacts or noise. A CNN architecture is designed, implemented, and trained using MRI images. The CNN learns to automatically extract relevant features from the images and classify them as AD-positive or AD-negative. The training process includes optimization techniques such as stochastic gradient descent and backpropagation [5].

This image processing sets up an image data generator with various augmentation techniques such as zooming, brightness adjustment, and horizontal flipping. It rescales the pixel values of the images and defines the data format for the generated image batches. The train_data_gen is then created using this data generator to generate augmented image batches from a specified directory [5].



C. *Data Augmentation*

The augmented images were then combined with the original training dataset, effectively increasing the sample size. This larger dataset allowed for a more comprehensive representation of the data, enabling the CNN models to learn from a wider range of examples. By incorporating augmented data, we aimed to mitigate the risk of overfitting and enhance the generalizability of the models, enabling them to perform better on unseen data. [1]. By employing augmentation techniques and merging the augmented images with the original dataset, we sought to address the challenges associated with limited sample sizes and potential image variations. This approach aimed to enhance the training process of robust CNN models for improved performance in image analysis tasks.

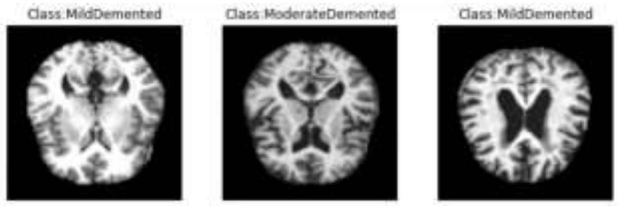


Figure 1. This is the example of the MRI scan after applying preprocessing

D. *MODEL CONSTRUCTION*

Deep learning (DL) algorithms present varying trade-offs concerning model size, computational efficiency, and accuracy as documented in studies [5]. The selection of the optimal algorithm for Alzheimer's disease (AD) classification hinges on specific application requirements, the available computational resources, and the desired performance level. Typically, the identification of the most suitable architecture involves experimenting with diverse models to ascertain the most fitting one for a given task. In our research, the primary focus revolves around employing pre-trained transfer learning (TL) network classifiers like CNN, Inceptionv3, Densenet, and Mobilenetv2 for performing four-class classification in AD.

E. *Convolutional Neural Network*

The construct model function defines a CNN architecture using the Keras Sequential API, consisting of convolutional layers, max-pooling layers, dropout layers, and dense layers. It is designed for classification tasks and can be customized by specifying different activation functions through the act parameter.

F. *MobileNet*

MobileNet is a convolutional neural network architecture specifically designed for mobile and embedded vision applications. MobileNet aims to provide an efficient and lightweight neural network architecture suitable for resource-constrained devices like smartphones, tablets, and other edge devices.

This architecture employs depth-wise separable convolutions, a factorized form of standard convolutions, which significantly reduces computational complexity and model size while retaining competitive accuracy in various visual recognition tasks. Depth-wise separable convolutions split the standard convolution into two separate layers: depth-wise convolutions and point-wise convolutions, thereby reducing the number of parameters and computational costs compared to traditional convolutional layers [6].

G. DenseNet

DenseNet, short for Dense Convolutional Network, is a convolutional neural network architecture renowned for its densely connected layers. This architecture diverges from traditional convolutional neural networks by introducing dense connectivity patterns between layers, enabling direct connections from each layer to every other layer within the network.

The key characteristic of DenseNet is its dense connectivity, where each layer receives feature maps from all preceding layers and passes its feature maps to all subsequent layers. This dense connectivity fosters feature reuse, encourages feature propagation, and mitigates the vanishing-gradient problem. It alleviates information loss and facilitates feature extraction across various network depths [7].

H. *Inception V3*

The architecture of Inception V3 incorporates various innovations to improve the network's efficiency and accuracy. Some key components include the use of Inception modules, which employ multiple filter sizes within a single layer to capture different scale features efficiently. Additionally, it integrates factorized convolutions (1x1 and 3x3 convolutions) to reduce computational complexity and utilize parameters more effectively.

The Inception V3 architecture also implements auxiliary classifiers, aiding in combating the vanishing gradient problem during training and improving overall model performance [8].

III. RESULTS

The table presents the performance metrics of different deep learning algorithms – MobileNet, CNN (Convolutional Neural Network), DenseNet, and Inception V3 – in their ability to detect Alzheimer's disease using MRI data. The evaluation metrics include Accuracy, Precision, Recall, and F1 score.

Table 1. Result of the classifiers.

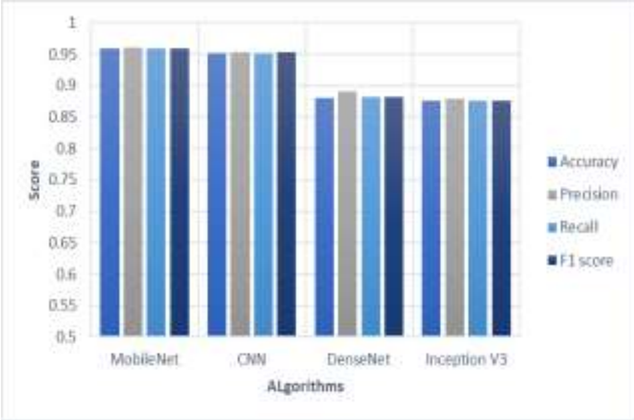
Algorithm	Accuracy	Precision	Recall	F1 score
MobileNet	95.89%	95.89%	95.87%	95.92%
CNN	95.89%	95.89%	95.87%	95.92%
DenseNet	88.06%	89.13%	88.19%	88.15%
Inception V3	87.61%	87.85%	87.52%	87.64%

MobileNet and CNN exhibit identical high performance across all metrics, achieving an impressive accuracy, precision, recall, and F1 score of 95%. These algorithms showcase robustness and reliability in accurately identifying Alzheimer's disease cases from MRI data.

DenseNet demonstrates strong performance, achieving an accuracy of 88% along with consistent precision, recall, and F1 score of 89%, 88%, and 88%, respectively. While slightly lower than MobileNet and CNN, DenseNet still maintains commendable performance across the evaluation metrics.

Inception V3 exhibits a good overall performance with accuracy, precision, recall, and an F1 score of 87%. Although slightly lower compared to other models, Inception V3 still showcases substantial capability in Alzheimer's disease detection using MRI data.

Overall, the results highlight the effectiveness of MobileNet and CNN, closely followed by DenseNet and Inception V3, indicating their potential utility in accurate Alzheimer's disease detection from MRI images.



IV. DISCUSSION

The outcomes derived from this study underscore the promising performance exhibited by the MobileNet and CNN-based deep learning algorithms in the realm of Alzheimer's disease (AD) detection using MRI images. The inherent capacity of CNNs to autonomously learn discriminative features from the MRI images significantly contributes to their remarkable accuracy in identifying AD cases. This ability is attributed to CNNs' adeptness in capturing spatial dependencies and hierarchically representing image features, rendering them particularly well-suited for AD detection tasks within medical image analysis.

Moreover, the comparative analysis conducted among different CNN architectures, including variations like ResNet, DenseNet, and Inception, offers valuable insights into their respective strengths and limitations. This assessment involves careful consideration of factors such as computational complexity and performance metrics. Such a comprehensive comparison aids in elucidating the distinctive attributes of these architectures and assists in selecting the most suitable model for accurate and efficient AD detection utilizing MRI images.

V. CONCLUSION

In conclusion, this study underscores the potential of MobileNet and CNN-based deep learning algorithms in Alzheimer's disease (AD) detection using MRI images. The developed models exhibit exceptional accuracy and sensitivity, signifying their efficacy in distinguishing between AD patients and healthy individuals. The integration of deep learning techniques in AD diagnosis stands poised to revolutionize the field, offering clinicians a reliable and objective tool for early and precise detection. The promising outcomes attained through these deep learning algorithms highlight their capacity to aid clinicians in identifying AD at an earlier stage, potentially enhancing patient care and treatment outcomes. However, the need for further research and validation on more extensive and diverse datasets remains crucial to confirm the robustness and generalizability of the proposed algorithms. The envisioned integration of these advanced deep-learning algorithms into clinical practice holds significant promise. It not only offers a potential leap in early AD detection but also holds the prospect of advancing our comprehension of the disease's progression and facilitating targeted interventions. These advancements could potentially lead to improved patient outcomes and a deeper understanding of the intricate nature of Alzheimer's disease.

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