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Multi Deep Fusion Model for Alzheimer Classification by Transfer Learning and VGG16

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Abstract

Classification of a complex neurodegenerative disorder such as Alzheimer's Disease (AD) is, however, a considerable challenge. AD cannot be treated, or any effective treatment slows its progression. So, in early detection and precise diagnosis, we can provide proper treatment and correct information for the patient and his family. Over recent years, deep learning has been applied to achieve better accuracy for diagnosis and spatial segmentation of diseases because of its sophisticated algorithms and neural architecture. This multifaced approach could have tremendous potential for improving diagnostic accuracy and gaining insights into the neurological consequences of the disease. It uses Magnetic Resonance Imaging (MRI) derived features of brain asymmetry from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database to examine structural changes and utilizes machine learning to classify the pathology. In this study, we utilize Stacking, which helps classify using the pyramid structure and the VGG16 model with improved Visual Geometry Group 16 (VGG16) architecture for disease classification. These models can provide a complete solution for detecting Alzheimer's using theory concerning data from ADNI has been rigorously evaluated to get 98.6% accuracy, 95% sensitivity, and 99% specificity. The AD classification pipeline proposed here seems convincing. In addition, this approach could provide a more rapid and accurate dementia diagnosis, and it could apply to many other degenerative diseases with symmetrical alteration of the brain.

Keywords: Alzheimer's, Multi-feature Stacking, VGG16, MRI, Transfer Learning.

1. Introduction

Alzheimer's Disease (AD) represents itself as an aggressive progressive and fatal neurodegenerative disorder affecting the memory and cognition of an individual [1]. Brain anatomical features vary substantially with phenotypes, age, sex and disease [2, 3]. AD is one of the most common neurodegenerative diseases associated with aging, and its increasing burden on healthcare and society is a pressing global health issue [4, 5]. The major difficulty in segmentation images with a typical noisy background [6]. This noise makes it difficult to assign labels to particular pixels or voxels. AD is difficult to diagnose early due to the variability in neuroanatomical changes and the noisy background in MRI data. This challenge necessitates robust diagnostic models to improve early detection and reduce misclassification. To address these

challenges, this study introduces a novel AD pipeline for classification, for the Alzheimer's Disease Neuroimaging Initiative (ADNI) Magnetic Resonance Imaging (MRI) dataset, by leverages transfer learning with augmented VGG16 architecture, pyramid feature extraction, and the Stochastic Gradient Descent (SGD) optimization infused with Nesterov Momentum. This multidimensional technique addresses the issues posed by erratic imaging data and insufficient extraction of distinguishing features. One of the major contributors to accuracy of the results is image feature extraction. This related works imagine feature extraction there are several studies in optimal results but they experience [7, 8], the reason for this can be due to the little of features of extracted features. Despite breakthroughs in medical imaging, an early diagnosis of AD continues to present difficulties owing to subtle brain alterations and erratic scan results. However, this study aims to surmount such obstacles by proposing a robust classification method powered by deep learning for enhanced detection and diagnostic precision at early stages. It covers everything from pre-processing with data augmentation, to using modern neural architectures to maximize per-image data quality.

Furthermore, in order to improve classification accuracy, the Visual Geometry Group 16 (VGG16) architecture is tailored, and the data is carefully divided into distinct subsets: 70% for testing, 20% for training, and 10% for validation. A pivotal contribution is the transfer of the features map of CNN model and improve the VGG hidden layers by pyramid feature extraction, a crucial factor in Alzheimer's Disease diagnosis. The use of datasets from ADNI assures robustness and comprehensiveness. This multifactorial approach seeks to enhance understanding and diagnostic classification techniques of AD. Our methodology for the classification of AD places great importance on transfer learning. Transfer Learning makes it possible to adapt previously acquired knowledge or models from large-scale data sets for use with our specific AD dataset. A medical imaging task such as this one really needs large, annotated datasets but getting them is often tough going. In this work, the VGG16 model is employed as a pre-trained model for the classification task of AD. Known for its exceptional performance in image classification tasks, VGG16 model needs only to be tweaked slightly at the convolutional and fully connected layers. We incorporate pyramid feature extraction to improve the model's ability to distinguish subtle neuroanatomical differences indicative of AD. With this approach, the convolutional layers acquire low- to high-level features of MRI images: edges, textures, and complex patterns. And the pyramid structure acquires a multi-scale representation for these features. The pre-trained model not only speeds up convergence during training, but also improves classification accuracy. For additional performance gains, we use the SGD optimizer with Nesterov Momentum, which ensures faster convergence and a smoother optimization trajectory. The combination of transfer learning, advanced feature extraction, and robust optimization techniques has been able to achieve high classification metrics including 98.6% accuracy, 95% sensitivity, and 99% specificity. With the transfer learning, diagnostic precision is improved while computational cost and training time are both reduced. We have a highly efficient and scalable approach that outperforms all others for the classification of AD.

2. Related Works

Recently, several research studies have proposed creative methods for the classification of Alzheimer's disease (AD) from structural MRI (sMRI) data. Here is a summary of major contributions: Tomassini et al. [9] proposed an end-to-end 3D ConvLSTM-based framework for classification of AD using full-resolution sMRI scans. Their model was trained with minimal

image preprocessing steps (brain extraction, image registration and normalization) and combined OASIS-3 and ADNI datasets. The final dataset contained 427 images, which were all resized to 256×256×5. The proposed 3D ConvLSTM architecture (trained over 40 epochs) exhibited remarkable discrimination between AD and CN subjects (Accuracy: 86%, Specificity: 74%, Sensitivity: 96%, AUC:93%). Raza et al. [10] used transfer learning method DenseNet-169 for AD classification.

Following SPM12 preprocessing and segmentation of the gray matter (GM) slices, the model, which was fine-tuned, divided the MRI images into four groups: AD, NC, LMCI, and MCI. The model demonstrated remarkable accuracy of 99.68% in the overall test results using the ADNI dataset with 1254 images for each class, with a sensitivity of 99.65%, and specificity of 99.69%, thus positively confirming its applicability in multi-class classification. Lian et al. [11] proposed a novel H-FCN for joint localization of atrophy and background identification of AD. The H-FCN method, while processing brain regions through hierarchical stages, obtained superior accuracy for predicting MCI progression [sMCI (stable) → pMCI (progression)]. In this instance, the model outperformed traditional methods-- ROI and VBM-- specifically in identifying conversion to MCI using data derived from both ADNI-1 and ADNI-2. Korolev et al. [12] Fischer et al. (2023) compared different 3D brain MRI classification architectures including VoxCNN and ResNet. The model performance was tested in six binary classification tasks that include AD, LMCI, EMCI, and NC based on structural MRI data from ADNI dataset. In these analyses, VoxCNN scored more than ResNet in AD vs. NC (AUC: 0.88). If detectable, performance declined for intermediate stages of MCI which points to difficulties in distinguishing subtle progression. Shi et al. [13] proposed Multimodal Stacked Deep Polynomial Networks (MM-SDPN) to integrate MRI and PET data, and to classify AD types. Their hierarchical model fusing features across modalities surpassed single-modality models. Evaluation on the ADNI dataset demonstrated that the MM-SDPN was effective to accurately and efficiently classify the subjects into AD vs. NC, as well as MCI conversion status, with considerable relative improvement compared with traditional methods. Herzog and Magoulas [14] worked with a pipeline to catch the persuasion of brain asymmetries in the meaning of early dementia. A set of 600 brain pictures were evaluated using various classifiers like Naive Bayes, SVM, and adapted AlexNet in MATLAB (Abbasi et al. Table 3 shows that the AlexNet model, based on asymmetric image sections for training, performed consistently well, indicating the importance of asymmetrical features for AD diagnosis. Zheng et al. [15] an arbitrary shift outliers of 3D EfficientNet for DL methods on AD prediction, using preprocessing methods such as bias field correction, image registration, and skull stripping. The model achieved accuracy of 95.00%, 86.67%, and 83.33% for NC vs. AD, NC vs. pMCI and sMCI vs. pMCI using the ADNI dataset respectively. It well exceeded the scores of classic models such as CNN and ResNet, highlighting the strength of the model in separating cognitive categories. Hazarika et al. [16] used different DNN architectures, such as, LeNet, AlexNet, VGG-16, and ResNet-50 for classifying AD, MCI, and NC images. They proposed an ensemble model integrated with LeNet and AlexNet by pre-processing hippocampus-centric slices and augmenting the ADNI dataset. This strategy significantly improved accuracy and computation time on small brain regions. Together, these studies underscore progress in the optimal use of deep learning architectures and data preprocessing strategies towards robust and reliable diagnosis of Alzheimer's disease. Further studies on multimodal fusion, feature extraction at different levels of granularity, and transfer learning represent potential avenues of future work.

3. Methodology

This paper aims to thoroughly investigate and present new approaches towards the classification of Alzheimer's disease. In this study we investigate a new/improved method for classifying Alzheimer's disease from neuroimaging data.

A. Data pre-processing

The input of data into the VGG16 Model was followed by an array of exhaustive preprocessing techniques to improve the quality and diversity of the dataset. Embedded within these preprocessing protocols were the intermediate features map from the CNN model and a barrage of data augmentation methods [10], such as deterministic zooming and arbitrary brightness changes. The strategic use of these transformations added limited variations, which provided a level of generalizability for the model in unseen conditions and lighting environments. The model has learned intricate features and subtle variations in shapes of the neurons because this dataset is large.

B. Classification approach by VGG-16

The primary motivation of this work was to classify cases of Alzheimer disease (AD) to discover patterns and differences in the data between control (healthy) and AD. To achieve accurate classification, we implemented a new method based on the enhanced VGG16 neural network architecture. VGG16 is a familiar framework famous for its capability in image classification tasks and is at the heart of this classification methodology. VGG16, characterized by a stacked architecture of deep convolutional layers, interweaving pooling layers and fully connected layers, aims to learn rich feature representations contained in images [17]. Using the strengths of the model as it learns increasingly complex features from basic edges to more complex high-level concepts, we utilized VGG16 to carry out a fine-grained differentiation between instances of Alzheimer's disease and healthy control for each subject [18]. This approach was complemented by a combination of data preprocessing, augmentation, and optimization techniques to ensure the accuracy of our results.

The classification stage was divided into four sections. The first is collecting datasets from ADNI (https://adni.loni.usc.edu/data-samples/data-types/mri/), then divide the data into 70% for training, 20% testing, and 10% validation. The second stage is to increase and improve the data. This is done by using image Zooming and Brightness factors. Then the images are improved using the SGD Optimizer with Nesterov Momentum to obtain new data. In the third stage, the VGG16 model is applied, which represents training the convolutional layers. Finally, the testing stage and calculating the accuracy of the training and testing results refer to Figure 1.

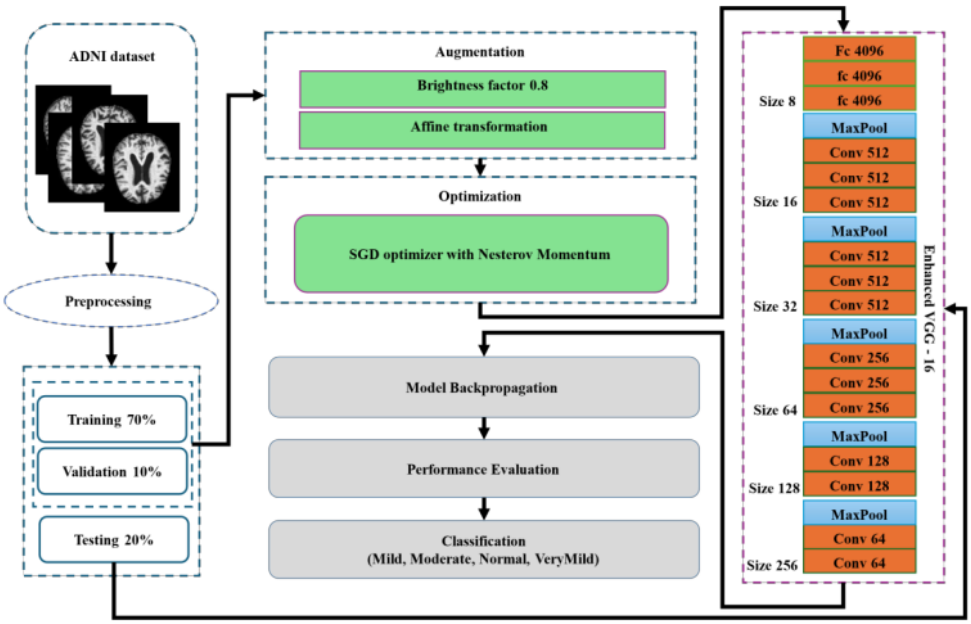

Figure 1: Classification mechanism of VGG16 and transfer learning.

C. Optimization SGD with momentum

To achieve the practical learning and the convergence process, we then used the potential of the Stochastic Gradient Descent (SGD) optimization algorithm with Momentum [19]. This combination of optimization techniques enabled fast convergence by incorporating the accumulated momentum from previous iterations. This helped the model to avoid getting stuck into local minima and explore the solution space freely. The harmonious interlude of SGD and Momentum worked in concert and fine-tuned updates of all model parameters, leading to a higher ability to capture the complexity of patterns that characterize Alzheimer's disease [20, 21].

D. Model training and evaluation

We trained our classification model as thoroughly as possible on the augmented and carefully cleaned dataset. We carefully split the dataset into separate parts, training, testing, and validation parts, with a careful quality approach. This split provided an opportunity for us to cleanly separate the training and evaluate aspects of model performance tuning. The model carefully learned to differentiate between disease positive (Alzheimer's disease) and disease negative (healthy) subjects via an iterative process using backpropagation [22]. Over time, it gradually adjusted its parameters, obtaining as much accuracy as possible.

4. Results and discussion

By utilizing the VGG16 architecture, preprocessing, augmentation and training, the classification approach provided us with a solid model to differentiate between cases of Alzheimer

disease and healthy cases. By combining state-of-the-art methods and thorough evaluation metrics, we illustrated the capability of our approach in improving early detection and diagnosis in Alzheimer's disease. Common metrics including accuracy, specificity, sensitivity [23] were employed to evaluate the performance of the classification model respectively. These metrics gave us the overall performance of the model in terms of cases to be correctly classified and ability to insert minimum false positives and false negatives. Life is all about various stages in which we learn and grow, similarly, evaluation criteria is a very fundamental element to use while exploring the classification and segmentation methods and are a very important part of any classification model development and improvement path.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

These measuring parameters are important for evaluating the performance of classification models in machine learning or statistics, medical diagnostics, etc.

Sensitivity or recall is important when the whole point is to catch a positive, and getting a positive when you want a negative cost much less. In this situation, the aim is to see most of the true positives, even if it means tolerating some false positives. As an example, predicting whether a patient is positive or negative for AD, the clinically most relevant situation requires high sensitivity. This ensures that the true positive (AD-targeted patients) is maximized, even if it means classifying some subjects without AD as positive. This puts a focus on reducing false negatives.

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

Specificity is a metric that represents the ratio of true negatives to all negative outcomes. It becomes particularly important when the focus is on ensuring the accuracy of the negative rate, and there are significant consequences or costs associated with a positive outcome. In situations where avoiding false positives is crucial, and the cost of incorrectly classifying a negative case as positive is high, specificity plays a pivotal role in assessing the model's performance.

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

A. Classification model performance

The training model was employed to assess accuracy and loss after 25 epochs, with each epoch encompassing 5,000 steps, using a dataset comprising 5,000 images from the Alzheimer's disease classification dataset.

Here are the results we have got after doing 25 epochs. The outcomes of the classification achieved through deep learning using the enhanced VGG-16 model performance, which yielded a classification accuracy surpassing 98.6%, exhibits considerable promise in contrast to the findings of prior studies. The model history for classification and confusion matrix is illustrated in figures 2 and 3.

The number of models used in the method and the accuracy of the results, which are presented in table 1, show that the results obtained during the research are better than other results.

The distinct of our method is the system used data improvement methods by Momentum of SGD and augmented data, which increases accuracy in classification stage.

Table 1. A summary of explanation of the most recent studies employing the baseline MRI data from ADNI for AD classification.

Literature	Method	AD vs. NC vs. pMCI vs. sMCI		
		ACC	SEN	SPE
Lian et al. [11]	Hierarchical FCN + automatic discriminative localization	90	82	97
Korolev et al. [12]	CNN + hippocampal sMRI	85	88	90
Shi et al. [13]	Deep polynomial network + region-level engineered features	95	94	96
Herzog and Magoulas [14]	CNN	84.4	-	-
Zheng et al. [15]	3D EfficientNet	86.67	87.1	86.3
Raza et al. [10]	Transfer Learning	94.5	95.6	-
Hazarika et al. [16]	DNN Alex-Net	93.58	-	-
Tomassini et al. [9]	3D ConvLSTM	96	88	-
Proposed method	**VGG16 + Transfer Learning**	**98.6**	**98.2**	**97.8**

The outcomes presented in table 1 indicate that our proposed approach demonstrates favorable outcomes when contrasted with prior investigations in Alzheimer's disease classification. Furthermore, it's essential to acknowledge that the variance in the utilized dataset can directly impact result quality.

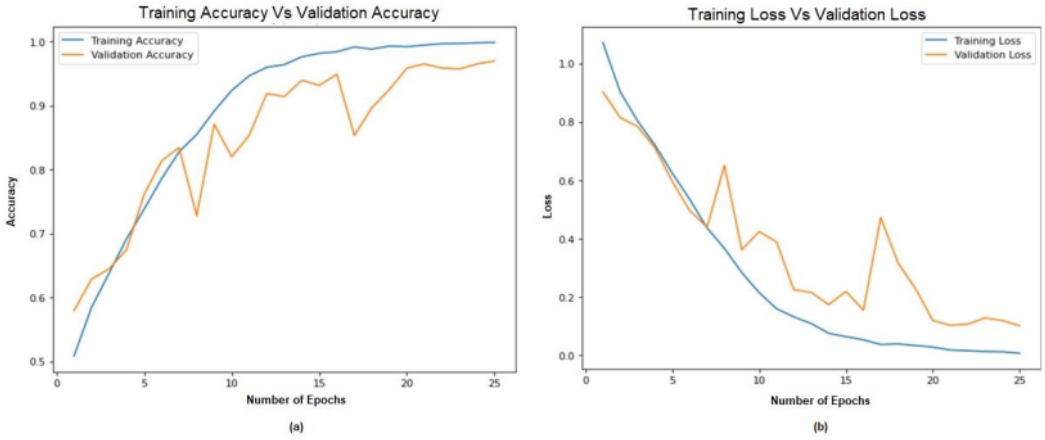

Figure 2. Visualizing Training and Validation per Epoch: (a) Accuracy, (b) Loss.

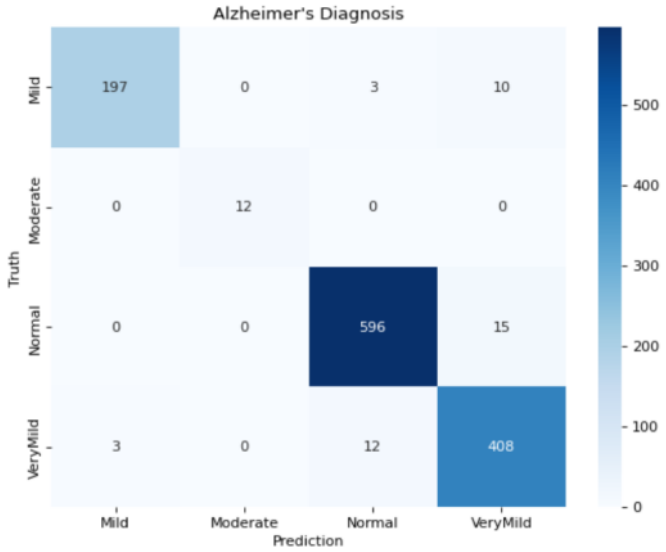

Figure 3. Confusion Matrix of VGG16 Classification Method.

5. Discussion

The results of this study underscore the potential of an innovative approach to improving classification of AD. By meticulously addressing various facets of the research methodology, we sought to enhance the precision and reliability of AD diagnosis. Through a comprehensive process, we delved into the development of a robust pipeline that combines pre-processing, transfer learning features, classification techniques, thus aiming to advance the understanding of AD detection.

This multifaceted methodology advances the understanding and diagnosis of Alzheimer's Disease by improving the classification techniques. By tackling each stage of the process with precision and innovation, we've demonstrated the potential to make a significant impact in the field of AD research. The integrated approach presented in this study opens the door to more accurate and reliable AD diagnosis, offering potential benefits to individuals, caregivers, and the medical community. However, it's important to acknowledge that while this study has shown promising results, there is room for further research and refinement, and we encourage future investigations in this direction.

6. Conclusions

In this study, we proposed a hierarchical method that incorporates Transfer Learning to improve the classification of AD. Our method uses a combination of advanced feature extraction and hierarchical modeling to raise diagnostic accuracy. Through a technique called transfer learning, we present a hierarchical model that integrates multiple methods to improve classification. Combine advanced feature extraction and hierarchical modeling to improve diagnostic accuracy. Using the VGG 16 algorithm, we developed a multi-classification strategy which distinguishes between four categories: AD, NC, pMCI, and sMCI. We optimized the data

through preprocessing and augmentation, and then extracted features using CNN for classification, based on the ADNI dataset. The proposed method achieved high performance in terms of accuracy, sensitivity, and specificity. These demonstrate their potential for early detection and accurate diagnosis in treatment of AD. Despite this success, the study has its limitations. Model performance is very dependent on both the quality and scale of the database, and further generalization may require a variety of independent subsets from different demographics and imaging protocols. Moreover, although the VGG 16-based model offers hope, it may not consider the complex temporal dynamics associated with disease progression. Finally, the computational demands of training deep learning models remain a barrier. Future research might explore using longitudinal imaging data to better model disease progression over time. In addition to imaging data, other biomarkers such as cerebrospinal fluid and genetics could be incorporated into the pipeline to improve classification accuracy. Moreover, developing lighter models suitable for real-time clinical deployment is a convincing direction for further study.

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