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A Light Weight Neural Network Model for Classification of Dementia

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Abstract

Dementia is a progressive neurodegenerative disease that is a major challenge to healthcare systems around the world and hence there is the need to have accurate and automated means of diagnosis. SMRI has become a useful modality for detecting neuroanatomical changes during the development of dementia, and yet, manual interpretation is tedious and prone to error. This paper will discuss a deep learning-based method of multiclass dementia classification based on a transfer learning model on the VGG-16 convolutional neural network. A big publicly available Kaggle data set comprising of about 44,000 T1-weighted brain MRI images was used, which comprised of four clinically relevant classes such as Non-Demented, Very Mild Demented, Mild Demented as well as Moderate Demented. All pictures were downsampled to the constant resolution size at 224 x 224 pixels and categorized as grayscale inputs to retain structural information and making them computationally efficient. A fine-tuning approach that was under a controlled strategy was used by unfreezing convolutional layers consecutively, allowing the detailed examination of convolutional layers parameter adaptation and generalization behaviours. The evaluation of the model performance was conducted based on accuracy metrics, learning curves, and analysis of the confusion matrix to present both quantitative and class-wise information. The final training accuracy of the proposed model was 89 percent and a validation accuracy of 76 percent which showed that the model converged well and the generalization was also good. The confusion matrix showed that Non-Demented cases were highly specific with potential difficulties likely to arise in making a distinction between the early stages of dementia since there were minor neuroanatomical overlaps.

INTRODUCTION

Dementia is a neurodegenerative condition that is marked by a progressive deterioration of cognitive abilities, memory and executive functioning which captivates a considerable impact on the quality of life and represents an increasing burden to global healthcare. The diagnosis of dementia at an early and accurate stage is important in order to provide timely clinical intervention, manage the disease, and delay the cognitive deterioration. Nevertheless, firm stage difference is difficult because of mild changes in the neuroanatomical patterns at the initial stages of the disease, as well as significant overlap between normal aging and pathological course. Magnetic resonance imaging is a major component of dementia diagnosis since it offers an in-depth structural data of the brain anatomy. The T1-weighted MRI scans, especially, allow visualizing the patterns of cortical thinning, enlargement of the ventricles, and atrophy in the areas related to neurodegeneration. Although diagnostic, manual analysis of MRI scans is time-consuming, open to inter-observer variability, and may not be good enough to identify cases at an early stage. This has triggered the growing appeal of automated and data-driven diagnostic methods. Principal Component Analysis and Support Vector Machines traditional machine learning methods have been studied in dementia classification with handcrafted features. Although these methods have shown relative effectiveness, they are constrained by reliance on manual feature engineering and ability to capture more complicated spatial relations among high-dimensional neuroimaging data. The deep learning models especially convolutional neural networks have demonstrated high performance in recent years whereby they automatically extract hierarchical feature representations without the need of human supervision or a priori intervention on the medical images.

VGG-16 is an example of the CNN architecture that has become one of the strongest and most popular bases because of its simple and deep architecture and powerful feature extraction ability. Whereas VGG-16 has already been effectively used to address a range of medical imaging tasks, the systematic analysis of VGG-16 on large-scale multiclass dementia classification, including controlled layer-wise fine-tuning and finer performance control by disease stage, has not been investigated so far. Furthermore, the existing studies mainly concentrate on binary classification or small size of data which does not apply clinically. It is in response to these gaps that this study suggests a transfer learning based VGG-16 model that can be used to classify multiclasses of dementia based on a large publicly obtainable T1-weighted brain MRI dataset. The assessment of the model is done based on four clinically meaningful categories such as Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Progressive unfreezing of convolutional layers is used as a controlled fine-tuning approach that allows the detailed characterization of parameter modification, learning behaviour, and generalization behaviour. Full assessment based on the confusion matrix analysis and learning curves is carried out to give clinically interpretable results about the strengths and limitations of the classification. By doing so, the research will define VGG-16 as an effective baseline in large-scale dementia classification and will help to identify the problems related to differentiating diseases in their early stages.

LITERATURE REVIEW

Deep learning has also contributed greatly to medical imaging in the last ten years, particularly with respect to neurodegenerative disorders such as dementia and Alzheimer disease (AD). A number of studies have examined the convolutional neural networks (CNNs) to determine dementia based on the structural and functional neuroimaging data.

In [2] the authors applied a 3D CNN that allows classifying between the Alzheimer disease and normal controls based on MRI scans and attain impressive classification accuracy, incurring high calculation costs. In the study by SUK et al. [3], the authors used a multimodal framework with MRI and PET capabilities by use of a highly sparse autoencoder to enhance accuracy of early disease detection. Another CNN-based framework proposed by Basie et al. [4] was used to differentiate the various levels of AD such as Mild Cognitive Impairment (MCI), with encouraging outcomes on differentiating progressive and stable MCI. New literature already began to examine lightweight models that can be used in real-time applications. By way of illustration, Mobile Net V2 was utilized by Islam et al. [5] to minimize latency, and computational expenses to ensure that dementia detection was practical on peripheral devices. Nonetheless, the majority of the current models are trade-offs between speed and accuracy, which restricts their clinical applicability. Xception model was proposed by Chalet [6] and it deploys deep separable convolutions to minimize parameters and still performs well in image classification tasks. The use of it in the medical imaging field is under-exposed to dementia classification. Our work will be based on this gap where we will be using the Xception architecture to classify dementia in real time and with accuracy using brain image data. Most recent progress in the detection of dementia and Alzheimer disease has involved machine learning (ML) and deep learning (DL) models, particularly those based on neuroimaging and electrophysiology measurements. Amin et al. [7] Showed a convolution neural network (CNN)-based strategy of detecting dementia through structural MRI with a strong focus on end to end deep learning pipeline, which does not require manual feature engineering but rather produces a high diagnostic accuracy, but does not include the explainability and early classification strength. Moreover, Iqbal et al. [8] suggested a hybrid approach, including the main component analysis (PCA) and CNN, in which PCA will be used to decrease the dimension and calculations of the data after which CNN can be used to classify the reduced data, thereby giving better performance than CNN alone. Wu et al. [9] allowed the application of ML to imaging, but by incorporating clinical, demographic, and imaging functions to forecast mild cognitive impairment (MCI) and dementia, they demonstrated the value of multimodal data combination in early disease detection. The authors of Mood Noor et al. [10] examined the EEG signals in classifying dementia using SVM and k-NN algorithms and offered an alternative non-invasive and cost-efficient route to diagnosing dementia. Their research was binary classification and did not include any temporary or cognitive context although it was promising. Lastly, a comparative analysis of the various ML algorithms and ensemble methods (Boost-based models using neuroimaging data) by Khan et al. [11] demonstrated that the use of structural MRI and biomarkers and cognitive scores together (combination), as opposed to separately, can greatly enhance classification performance, and thus clinical implementation will require multimodal and interpretable ML models.

Although the former research has demonstrated the potential of deep learning and hybrid machine learning models, there are still some research gaps that are of importance. Most of the works are very precise such as 3D CNN and multimodal MRI-PET but it is also very expensive to compute. This restricts their application in low-resource or real-time. In addition, the majority of the techniques target binary classification, e.g., distinguishing between Alzheimer s and healthy controls. They do not entirely touch upon multi-class classification or following the progress of the disease, which are key to individualized care. Also, less emphasis is put on the development of end-to-end diagnostic tools that are accurate, efficient, and understandable to be used in practice.

METHODOLOGY

The presented study carried out its experiments with a publicly available brain MRI dataset that was obtained on Kaggle[1] and included about 44,000 T1-weighted magnetic resonance imaging scans that were filtered to include automated dementia recognition. This data comprises four clinically significant cognitive classes that represent various disease stages, which are Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. In particular, it includes 12,800 images of cognitively normal individuals, 11,200 images of the Very Mild Demented, and 10,000 images of Mild Demented and of Moderate Demented people, respectively. This distribution guarantees sufficient coverage of all the classes and realistic imbalance of the classes in the real clinical environment. In order to have strong model assessment and avoid biased learning, the data set was segmented into training, validation, and test sets with the help of stratified sampling strategy as shown in “Fig 1”. This method maintains the original distribution of classes in each sub-set enabling the model to train representative features and equitable and unbiased evaluation of performance on unobserved data.

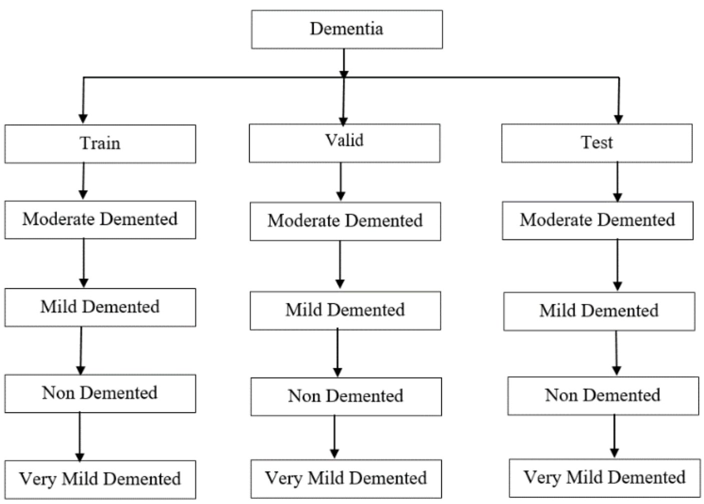

Figure 1: Arrangement of input files for testing

In contrast to classical pre-processing processes, this research does not make use of image cleaning such as denoising, contrast and brightness-enhancement. This choice is informed by the perception that pre-processing operations have a potential of losing finer-grain pixel-based details, which can have a negative impact on the capability of the model to identify early phase-detention details. A major objective of this work is to preserve the entire pixel level features to enhance the diagnostic sensitivity, particularly in the presence of very mild or early dementia.

All brain MRI images were downsampled to a spatial resolution of 224 x 224 pixels before training a model. The choice of this input size to the model was made to align with the standard input size of the VGG-16 architecture to allow pre-trained weights trained on large-scale image datasets to be used effectively. Image trimming to a standardized resolution guarantees that there is uniformity in the spatial representation of samples and sufficient anatomical detail is maintained to resolve structural brain patterns in dementia development. The selected resolution offers a good tradeoff between computational efficiency and the ability to retain diagnostics-relevant features including cortical contours and ventricular structures. VGG-16 architecture as stated in the below “Fig 2” is a deep convolutional neural network consisting of a hierarchical composition of convolutional, pooling, and fully connected layers that are trained on learning hierarchical feature representations of images. This hierarchical learning process is very useful in dementia classification with the help of brain MRI that is able to capture progressive structural changes with respect to various levels of cognitive impairment.

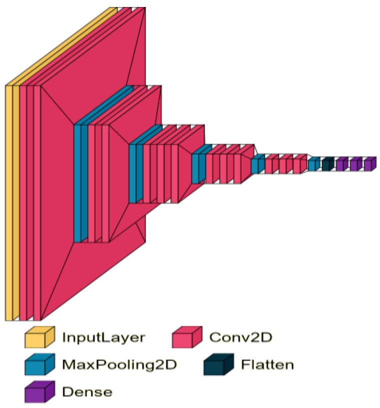

Figure 2: Model Architecture

The first and second convolutional blocks are defined by a shallow convolutional layer and few filters. The most basic visual features that are learned in these initial layers are edges, intensity gradients, texture boundaries and simple anatomical contours. The features in brain MRI images reflect cortical outlines, ventricular boundaries, and gross tissue contrasts between gray matter, white matter, and cerebrospinal fluid. The proper derivation of such basic features is extremely important in the differentiation between normal brain structure and pathologies. The number of filters is increased with the further development of the architecture into more convolutional blocks, and allows the network to learn more complex and abstract representations. These intermediate layers store structural patterns at region level like expansion of ventricles, thinning of the cortex and atypical shapes of the hippocampal. These properties are especially useful in distinguishing between Non-Demented subjects and those with Very Mild and Mild Demented ones where atrophy only starts to be observed in some regions specific atrophy. The deeper convolutional blocks concentrate on the high-level semantic representations through the combination of the information over the larger receptive fields. The layers store the global structural relationships and patterns of distributed atrophy of various regions of the brain. This abstraction level is critical to create the distinction between Mild and Moderate stages of Dementia when neurodegeneration has expanded and become more structural. The richness of VGG-16 is that the model is able to capture the progressive severity of the disease and not an isolated local feature. Between the convolutional blocks, there is a max pooling layer, which will decrease the spatial dimensionality and leave the most significant features. The operation enhances translational invariance and draws less attention to spatial changes in anatomical structures, which are present universally between MRI scans of different subjects. The aim of pooling is also to provide computational efficiency and avoid overfitting through the implementation of feature generalization. The flattening layer then transforms the multidimensional feature maps to a single dimension feature vector, after the convolutional feature extraction phases. This conversion allows the incorporation of spatially dispersed characteristics into a global expression of the brain structure, which is required in the decision-making process at the classification level.

The fully connected layers are high-level feature aggregators which learn intricate nonlinear connections among extracted features. These layers integrate the data of various brain regions to create the holistic virtualization of the state of thought. This integration is essential in the classification of dementia since the disease progression does not occur in brain isolated areas but instead in interconnected parts of the brain. This last dense layer, which is the final layer, makes use of the softmax activation function to make probabilistic predictions on the four classes representing the various stages of dementia.

RESULTS

The study presents a novel method of classifying dementia with the help of VGG-16 and four classes of dementia. The proposed deep learning approach is also more accurate in classification and less human-intervention, as compared to the conventional algorithms [7-11], such as the Principal Component Analysis (PCA) and Support Vector Machines (SVM). To evaluate its performance, the research adopted a pre-trained weight methodology with ImageNet, and the loss and accuracy of the training and validation were presented in "Fig 3b to d". A group of experiments were conducted to assess the behavior and capacity adaptation of the model by training it with various numbers of trainable layers but maintained at 138,357,554 total parameters.

TABLE 1: Summary of parameters with pre-determined weights

Details of the Experiments	Total Weights	Trainable Weights	Non-Trainable Weights
5 Trainable Layers	138,357,554	119,562,244	18,795,310
10 Trainable Layers	138,357,554	129,001,476	9,356,078
15 Trainable Layers	138,357,554	133,721,604	4,635,950

The parameter configuration analysis, as presented in Table 1 below demonstrates the effects of the progressive layer unfreezing on the learning capacity and the adaptable characteristics of VGG-16 model. The fixed number of parameters of all experimental settings is 138,357,554 which attest to the fact that the complexity of architecture is maintained, but the level of fine-tuning is only changed. Making five layers trainable results in the model having 119,562,244 trainable parameters and 18,795,310 non-trainable parameters and hence there is a significant amount of the pre-trained feature extractor that is frozen to maintain generic visual representations. Training more layers, ten will mean that the number of trainable parameters will be 129,001,476, and the number of non-trainable parameters will be 9,356,078, which is more adapted to the specifics of the domain. Additional unfreezing to fifteen layers gives 133,721,604 trainable parameters with 4,635,950 parameters fixed which, together with an additional unfreezing to the final 15 layers, allows more extensive optimization of high-level and mid-level convolutional filters. This gradual growth in trainable parameters increases the ability of the model to describe minor variations in the structure that are linked with the various stages of dementia and is stabilized by retaining only part of the previous weights. The distribution of parameters on the whole is an indication of a fine-tuning method that is controlled and allows representational flexibility, with generalization, which has led to a stable convergence and better classification in multiclass dementia recognition.

In the classification of multiclass dementia, the performance of the recommended VGG-16-based model was assessed based on the class-wise confusion matrix analysis and training and validation accuracy and loss curves to determine both discriminative and generalization functions. These findings combined will give a complete insight into the model efficacy and clinically significant constraints.

The confusion matrix presented in "Fig 3a", shows that the model has a high level of recognition of the Non-Demented category since 1550 samples are accurately identified. This means that normal brain patterns in learning are effectively learned and high specificity in the differentiation of cognitively normal individuals against the pathological ones is achieved that is of special significance in the minimization of false positive diagnoses in the clinical screening situation. The issue of classifying Non-Demented samples as either Mild or Very Mild Demented still has a restricted number of cases, and we can ascribe it to the age-based structural differences, which are partially similar to the initial neurodegenerative alteration. In the case of the Mild Demented sample, 375 samples were identified and thus it is true that the model is capable of detecting anatomical changes in the early stages of dementia. Nonetheless, the significant percentages of Mild Demented samples were incorrectly characterized as Non-Demented, which speaks to the delicacy of structural changes at the specified stage and their integration with the normal aging patterns. Further mis-classification in the category of the Moderate Demented is due to the progressive and continuous nature of dementia in that there are no sharp outlines between one stage to another. Moderate Demented class has 364 well-classified samples which are evidence of moderate sensitivity to more progressive neurodegenerative features. However, it is often misclassified as Non-Demented, which is an indication that still at this point, some MRI scans do not possess enough structural markers to be discriminated with a high level of confidence. This result highlights the natural challenging nature of using structural MRI characteristics to accurately classify stages. Very Mild Demented class is the most difficult to classify, as only 35 samples were classified properly and the rest were mistakenly classified as Non-Demented. This is a natural occurrence, because Very Mild Demented cases are the first form of cognitive impairment, in which the anatomical deviations are slight and could not be distinguished by a normal brain morphology. The fact that it is misclassified as the Mild Demented category is an additional indication of the gradual evolution of the stages of the disease instead of sudden pathological alterations.

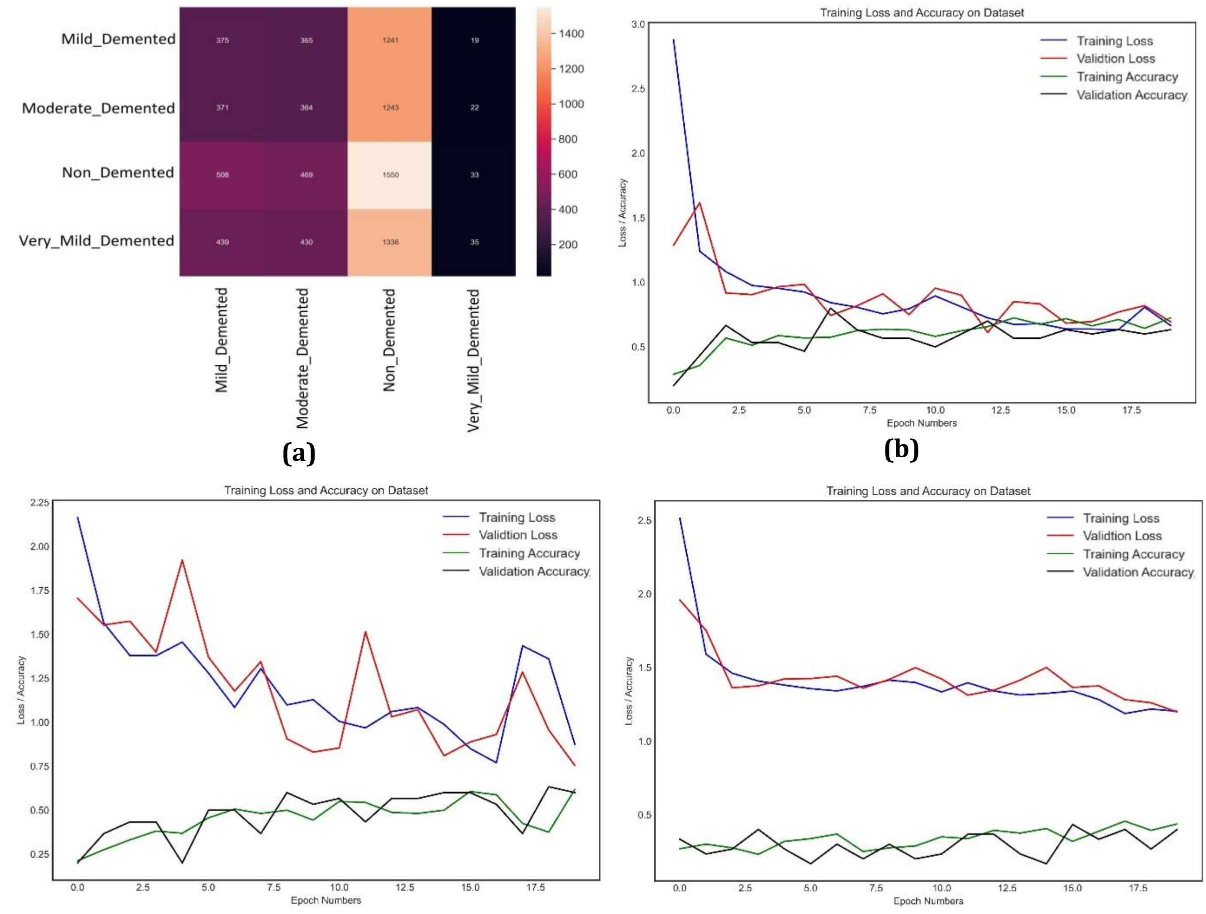

Figure 3: Learning Dynamics of the proposed model. a) Confusion matrix and Heat map. b) Accuracy and Training Loss on Dataset with Last 5 Trainable. c) Accuracy and Training Loss on Dataset with Last 10 Trainable. d) Accuracy and Training Loss on Dataset with Last 15 Trainable

These observations per class are in line with the learning curve analysis as it shows that there is a consistent convergence across training. In the early epochs, the loss of training is reduced at a high rate, which can be considered an evidence of effective adaptation of pre-trained convolutional filters to domain-specific MRI characteristics. A concomitant decrease of validation loss in this stage establishes the successful knowledge transfer and premature generalization to unobserved data. Training and validation loss curves become stable with some variation as the training continue, indicating that the model is not affected by a major overfitting. Training accuracy rises linearly with epochs, which is indicative of gradual improvement of discriminative representations in VGG-16 architecture. Moderate oscillations also follow this pattern in validation accuracy and they represent the response to multiclass dementia classification tasks, which have overlapping neuroanatomical patterns. The small difference between the training accuracy and the validation one also proves the strength of the learning process and the success of the chosen strategy of a fine-tuning. The model has a final training and validation accuracy of about 89 percent and 76 percent at convergence respectively. The result of this performance is that it shows good learning ability and reasonable generalization to unknowns of the MRI samples. The performance difference that is observed cannot be explained by the instability in training but rather the inherent complexity of separating the early and intermediate stages of dementia based on structural MRI data alone.

CONCLUSIONS

This paper proves that a transfer learning-based VGG-16 architecture is effective in performing multiclass classification of dementia with the help of structural brain MRI images in large-scale. The proposed methodology attains stable convergence and robust generalization in addition to the clinically significant distinction between cases of dementia and cognitively normal cases by systematic unfreezing of progressive convolutional layers and per-class analysis of performance. The learning curve analysis indicates a balanced optimization behaviour and slight overfitting, whereas the confusion matrix indicates high specificity of Non-Demented subjects and predicts difficulties in distinguishing between early and intermediate stages of dementia because of fine neuroanatomical overlap. The analysis at the parameter-level also shows that, the controlled fine-tuning increases the representational capacity with no notable impact on generalization. Altogether, the results prove that VGG-16 is a stable and scalable baseline model in dementia classification and can offer important findings to learn more about the trade-offs between the complexity of the model and the sensitivity of the diagnostic.

FUTURE ENHANCEMENT

The further development of this study can be aimed at overcoming the discrimination in early-stage dementia by using multimodal neuroimaging including functional MRI or PET in addition to structural MRI. Integration of attention processes with learning features that are region sensitive would further improve the capacity of the model to learn very subtle neuroanatomical alterations that accompany very mild and mild dementia. In addition to that, clinical interpretability and practical use can be improved by using longitudinal disease progression and lightweight or explainable deep learning models. Such developments can contribute to the enhancement of the reliability of diagnostics and the ability to transfer deep learning-based dementia screening tools in the everyday clinical practice.

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