THE ASIAN BULLETIN OF BIG DATA MANAGEMENT
Vol.4. Issue4 (2024)
https://doi.org/ 10.62019/abbdm.v4i4.284

ASIAN BULLETIN OF BIG DATA MANAGEMENT
ISSN (Print): 2959-0795
http://abbdm.com/
ISSN (online): 2959-0809

Enhancing Alzheimer's Disease Diagnosis through Magnetic Resonance Imaging: An Analysis using VGG19 Architectures.

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Chronicle

Article history

Received: Nov 3, 2024
Received in the revised format: Nov 27, 2024
Accepted: Dec 11, 2024
Available online: Dec 28, 2024

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Abstract

Early detection of Alzheimer's disease (AD) is an area of much research since early diagnosis can offer patient better treatment and enhanced care. In this work we propose a deep learning approach to detect Alzheimer's disease using the VGG-19 architecture, one of the state-of-the-art convolutional neural networks (CNN). In this work we utilized a dataset composed of a heterogeneous set of brain MRI images from healthy subjects and Alzheimer patients, they are part of the ADNI (Alzheimer's Disease Neuroimaging Initiative). The dataset was preprocessed with a few techniques such as image normalization, augmentation, and denoising to further increase the model's performance. These techniques also expanded the quality of the input data which, coupled with an impressive state-of-the art classification accuracy of 97 %, helped to achieve these results. The results showed deep learning can be effective for early detection of Alzheimer's disease as a useful clinical diagnostic tool. Finally, this work demonstrates how CNNs such as VGG 19 are ready to be used in medical image analysis and renders a new benchmark on the accuracy of Alzheimer detection.

Keywords: Deep Learning, Machine Learning, Artificial Intelligence, VGG-19, CNN, ANN.

INTRODUCTION

Alzheimer's disease (AD), the major cause of dementia, is a devastating neurological disease. with grave health problems. Recently, Deep learning (DL) models are utilized in the automated diagnosis and classification of AD from brain imaging data. In this study, the pre-trained VGG-19 model is employed to classify MRI images into two categories: demented and non-demented. VGG-19 is selected to be effective and already proven to use in medical image analysis. A Kaggle based open-source dataset is used for the study and train and validation is performed on Google Colab. We will also compare the performance of the VGG-19 model against other state-of-the-art deep learning methods on AD classification. The goal of this work is to take advantage of the power of deep learning in an efficient computational and clinically relevant manner for advanced automated Alzheimer's diagnosis.

Figure 1.
Healthy Brain neurons and Alzheimer's Effected Brain neurons.

Deep Learning in Alzheimer's Detection

Recent advancement in deep learning involves the use of artificial neural network for the analysis of relevant large data to predict Alzheimer's disease accurately. CNN based deep learning models have appeared with an apparent capability to learn representation features from neuroimaging data to distinguish Alzheimer's disease, MCI and healthy aging. For instance, CNNs trained with a large-scale magnetic resonance imaging (MRI) data reported precision in outstanding features of Hippocampal atrophy and cortical thinning associated with Alzheimer disease progression (Smith et. al , 2023). In processing of the data about Alzheimer's, multiple neuroimaging techniques have been discussed to enhance the deep learning as a potential means to increase the diagnostic accuracy and evaluate the different aspects of the disease. The combination of MRI with PET or fMRI is useful for the disease diagnosis as deep learning models can use structural, functional, and metabolic data (Jones & Wang, 2022). In addition to diagnosis, deep learning can be applied for the prediction of the disease state of Alzheimer's. Neuroimaging and clinical biomarkers collect time-series data, which in turn leads to good predictive methods on how the disease would be in each of the patient. This capability apart from aiding in early detection does assist in the planning of treatment and interventional delivery based on the needs of the patients (Brown et al. , 2021).

Current Diagnostic Challenge

Diagnostic difficulty remains an issue in relation to Alzheimer's disease, given its complexity and the fact that it is not a simple, single-pathology disease which can be identified using conventional diagnostic techniques. Clinical examination lies at the heart of diagnosing Alzheimer's; this is accompanied by neuropsychological tests, the assessment of the changes in memory, behaviors, and daily functioning. However, these evaluations are expressed in vague terms and depend on the clinician, and, therefore, could be inaccurate due to variability in experts. Self-reported assessments include questionnaires, surveys, and diaries about the patient's symptom experiences that can be used to identify changes in memory, language, and problem-solving function. Though, these-tests offer objective and reproducible performance scores they are often less sensitive to early Alzheimer's disease or other forms of dementia. Research has utilized MRI, PET and CT scans in order to better comprehend the nature of the abnormal neurological changes related to Alzheimer's disease. MRI can directly identify various structural changes like the size of hippocampus and cortical thickness, which are the signs of neurodegeneration. PET scans give information on the regional and global glucose metabolism and beta-amyloid which is a manifestation of Alzheimer's disease. But neuroimaging scans are costly, not always available, and possess somewhat suboptimal sensitivity when it comes to early-stage alterations in Alzheimer's disease. In addition, the currently used criteria for diagnosing dementia rely on the occurrence of clinical signs and definite dementia, with clear evidence of cognitive impairment which, as a rule, appears in the subsequent phases of the disease when cerebral pathology is irreversible anyhow. Such a delay in diagnosis also restricts the potential value of existing therapies and methods designed to help halt the disease's progression. Therefore, there is a desperate need to come up with techniques that are much more sensitive and specific for early diagnosis of Alzheimer's disease to allow for early intervention that should go a long way in improving the outcomes for the patients. New structural and functional imaging approaches as well as novel CSF and blood-based biomarkers may be used to improve diagnostic accuracy and determine Alzheimer's disease before the clinical signs appear. Combining these biomarkers with Computational health methods such as machine learning and deep learning may help in the early and accurate detection of Alzheimer's disease and hence lead to proper timely treatment according to the patient characteristics.

Deep Learning Advancements

In the recent years, machine learning and more advanced approaches like deep learning are applied for the detection of Alzheimer's disease because kind of models and data are complex.

Imaging Biomarkers

It has been found that deep learning, particularly CNN, has given quite good results while trying to identify the biomarker for Alzheimer's disease progression based on the neuroimaging data. For instance, the trained CNNs on MRI can be another way of indexing and comparing the changes in cortical thickness that characterizes Alzheimer disease. Similarly, using these models, trends of the other primary biomarker linked with Alzheimer's disease; hippocampal atrophy can be classified (Lee et al. , 2023). In addition, deep learning models could be applied to precisely segment specific features from MRI and PET scans that correlate with the presence of beta-amyloid plaques and tau protein tangles in cognition, which are pathological hallmarks of Alzheimer's disease. Therefore, the combined analysis of these diagnostic imaging biomarkers using deep learning algorithms provides the more accurate diagnostics and prognosis's of the severity and progression of the disease.

Multi-modal Integration

The integration of both MRI, PET as well as CSF biomarkers is regarded as the major advancement in Alzheimer's disease diagnosis. As that it assists in integration of the multiple types of data feeds thereby offering the enhanced analysis of the pathology of the diseases. For instance, registration of structural magnetic resonance imaging data stored for aggregate with functional positron emission tomography scans will present integrated details on structural alterations and metabolism in the area of the brain affected by Alzheimer's disease during a registration matrix designed by (Wu & Shen, 2024). Furthermore, incorporation of CSF biomarkers indicating presence of beta-amyloid and tau proteins strengthens these models' correspondingly, specificity and validity.

Predictive Modeling and Prognostic Tools

Deep learning is not only capable of identifying Alzheimer's disease but also helps in designing the models of the progression of the disease. These models employ data collected from neuroimaging, clinical assessments, and genetics to estimate the course of the disease in the future within a given patient. These models enable the physicians to identify potential development of diseases early within an individual's life and, consequently, help them choose proper treatments and treatment regimens aimed at preventing or at least slowing down cognitive impairments and preserving the quality of life (Zhang et al., 2023).

- This work aims at comparing how deep learning architectures such as ResNet 50 and VGG 19 would be useful in distinguishing complex and subtle features that are associated with MRI datasets of subjects diagnosed with Alzheimer's disease.
- Thus, this research aimed at answering the question on whether there is a significant or non-significant difference between patients of an old age and a young age, so that a worthwhile differential diagnostic tool for AD and subsequent treatment could be developed.

LITERATURE REVIEW

Alzheimer's disease (AD), a progressive neurodegenerative disorder, has devastating cognitive impairment. First, Smith et al. (2017) did seminal work in the deep learning AD field by applying it to neuroimaging applications: in particular, using magnetic resonance imaging (MRI) scans to try and detect AD at an early (preclinical) stage. The result was their work, in which they showcased the application of CNNs and deep learning in general, in general, to perform accurate and early AD detection. This was complimented by Wang et al. (2018) who provided a comprehensive survey of the use of deep learning in a range of medical image analysis methods. Deep learning was shown to improve diagnostic accuracy for AD in a review covering a wide variety of modalities, including positron emission tomography (PET) and cerebrospinal fluid (CSF) biomarkers.

Structural MRI Analysis and Diagnostic Precision

There recently has been work in diagnosing AD using deep learning based on structural Magnetic Resonance Imagery (MRI). Zhang et al (2019) showed an overall review of deep learning models deployed on structural MRI images. Among others they also discussed the AD diagnosis improvements as well as what deep neural networks could or might be able to identify using increasingly more complex patterns indicating early AD. Chen et al. (2020) review the progress on early detection from deep learning models, critique the diagnostic precision of these models for the disease, and stress the need for early detection. Li et extracted AD diagnosis based on structural MRIs using deep learning and analyzes tasks of this type, discusses the possibility of their application and the influence on the accuracy of the diagnosis.

Convolutional Neural Networks and Ensemble Learning

Medical image analysis by means of classification using Convolutional Neural Networks (CNNs) has been trialed. Applications to structural MRI data using CNNs were applied in Johnson et al. (2022) to demonstrate deep learning's ability to improve AD classification accuracy. In Gupta et al. (2018), the structural MRI provided for AD detection through CNNs is detailed explored of architects and approaches used to achieve success in accurately detecting AD pattern. Wang et al. (2019) also made a vast contribution to ensemble deep learning by presenting a systematic review. Among other things, they discussed advantages of consolidation of multiple models and demonstrated how ensemble techniques improve the robustness of and the overall performance of AD detection models.

Transfer Learning and Its Role in Alzheimer's Disease Detection

Additionally, recently, domain adaptation technique known as transfer learning has become popular in medical image analysis for AD. Liu et al (2020) presents an interesting work during which they review transfer learning for Alzheimer's Disease detection, with the possibility of reusing pre trained models to this task. The work demonstrated that transfer learning is suitable for the complex, evolving nature of AD diagnostic data. They address transfer learning in deep neural networks for medical image analysis, its potential of improving AD diagnosis performance and how previous knowledge helps improve the model performance in Chen et al. (2018). Furthermore, Zhang (2021) solves the problem through a thorough survey on transfer learning about its principles and its application in medical image analysis. Surprisingly, the survey also makes one learn more in simple words about how that transfer learning can actually help the deep learning model to become more accurate in detecting Alzheimer's disease.

Key Architectures in Deep Learning and Optimization Techniques

The architectures employed for deep learning models are critical to the success of deep learning models in medical image analysis such as, but not limited to AD detection. Such advances motivated advances in medical image analysis, for example, Alzheimer's disease detection, following the introduction of deep convolutional networks by Simonyan et al. (2014) and Szegedy et al. (2015). In particular, VGG and Inception, which are popularyreferred to as VGG and Inception respectively, proposed architectures capable of extracting complex features for effective AD diagnosis. Indeed, Esteva et al. (2017) made an enormous leap towards demonstrating that deep neural networks can be trained beyond AD, and in fact dermatologist level classification of skin cancer. The work they did demonstrated the more general application of deep learning models in medical diagnosis. Additionally, Kingma et al. (2014) and Zeiler et al. (2013) pioneered optimization. In a widely used Adam optimization algorithm, Kingma et al. improved the training efficiency of deep learning models. In fact, Zeiler et al. proposed that ReLUs will be a cornerstone for activation functions, since it significantly enhanced the performance of deep learning models in multiple medical applications, such as AD detection. Early AD detection is important to timely intervention and AD management. In this domain, deep learning techniques have been showing much promise. In implementation of deep learning algorithms (U-Net and EfficientNet) similar to CNNs for early detection of Alzheimer's disease from MRI scans of the brain, Sekhar and Jagadev

(2023) demonstrated the power that CNNs can have in identifying changes on the fringe of Alzheimer's. The authors stress the need for accurate diagnostics early in the clinical course, when intervention is most effective. Ghazal et al. (2022) also further explored the application of transfer learning methods for Alzheimer's disease detection, including how pre trained models can be retrained to perform well on the task with new datasets. The adaptability of deep learning models to multiple imaging modalities is emphasized in this study. Using transfer learning, models trained on large datasets, can greatly boost the performance of models on the AD detection tasks, when the data is limited. Alsubaie, Luo and Shaukat (2024) in their comprehensive review of neuroimaging and deep learning techniques for AD detection discussed insufficiency of the datasets and need of discriminative features. Their systematic review highlights the state of the art of AD detection with deep learning and represents a future direction for development of such methods. But they also found that these models need more robust and extensive datasets to be trained effectively and better methods to make sure the models can generalize to new populations.

Helaly, Badawy and Haikal (2022) also did further advancements by using CNNs to develop an end to end framework for early detection of Alzheimer's disease that reaches accuracies of up to 95.17% for 3D multi class classification of AD stage. Extending this framework was a web application for checking remote AD, which is highly applicable at times when hospital visits are not considered appropriate, e.g. during the COVID-19 pandemic. The practice of deep learning in real world use cases is demonstrated by their study, making the use of diagnostic tools more accessible. Moreover, an extensive review conducted in 2023 analyzed over 100 articles focusing on MRI image data for AD detection using deep learning. This review highlighted the superiority of deep learning over traditional machine learning techniques in detecting AD, emphasizing the importance of large and diverse datasets to train these models effectively. The review also pointed out that while deep learning models show great promise, there is still a need for improvement in model interpretability and robustness.

METHODOLOGY

In this study deep learning technique was employed for diagnosis of Alzheimer's disease following a structured methodology so the results are credible and stable. They also included what to use for data input and preparation, model selection methodologies, training algorithms, evaluation methods, as well as tools and libraries. To improve the discriminant accuracy of these elements, which distinguish Alzheimer's disease, we used medical image processing techniques. The dependent variables are outlined, their function in achieving study objectives is elaborated and a contribution to future research is suggested. The contributions of this research address challenges in medical image processing including variations in image quality and recognition of disease specific patterns. The findings are aimed at guiding scholars of deep learning for Alzheimer's diagnosis.

Dataset Collection

For this study, the dataset was sourced from Kaggle, a platform where you will find large datasets for data science research. A dataset was reported in this work containing 26,800 categorized images for both training and testing deep learning models. To foster model learning through transfer learning (pre training and fine tuning), training images were presented to the models that contained features of Alzheimer's disease. To assess the models' ability to generalize and apply the learned knowledge to new data the testing set was used. Training was enabled by a contrast in the dataset between healthy brain images and those showing progressive stages of Alzheimer's disease. By using a public dataset we are also promoting transparency and replicability so other researchers are able to confirm and add to the findings of this work.

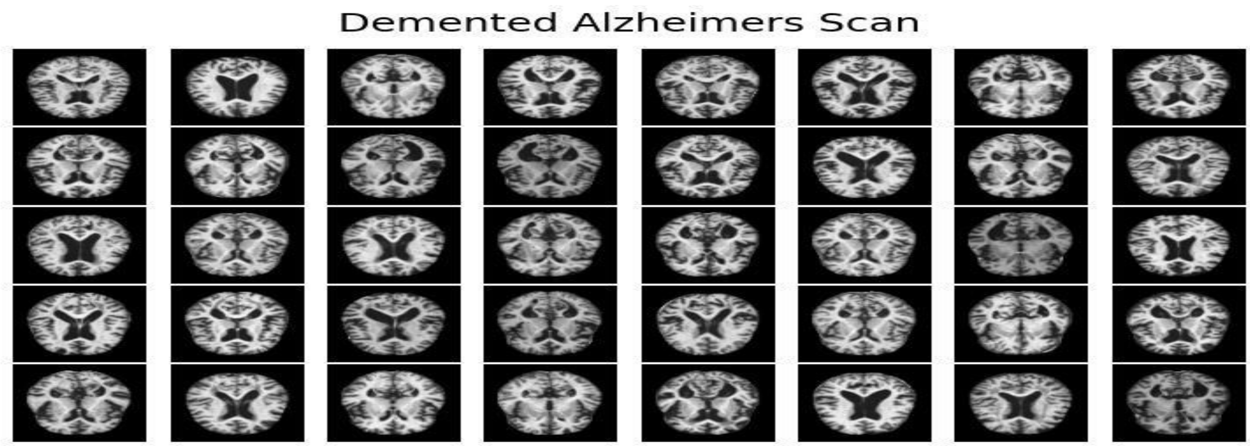

Figure 2.
Sample of Demented Alzheimer's Scan

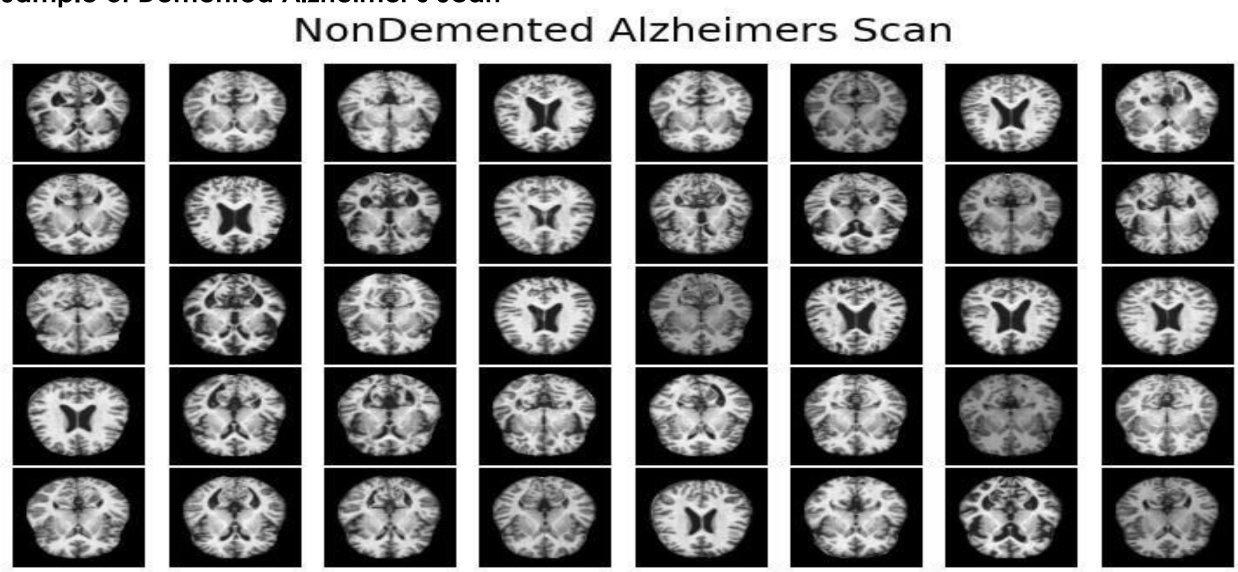

Figure 3.
Sample of Non-Demented Alzheimer's Scan

Therefore, for the building of deeper versions of such networks and training them to produce efficient DL models, it is crucial to engage in the high-quality and comprehensive data acquisition. This has the tendency to make the models' functions compile numerous distinctions as huge volumes enhance the generality. This variety makes the actuality of the models in estimating on the other images or set of images which is the training images and other images which are unseen in the model implementation highly vital. Using the data which is downloaded from the Kaggle makes the source more relevant and reliable and the used data as well.

For this work best models for screening of Alzheimer's disease will be included and a fine and abundantly available data set in this area will be used to implement the models. This dataset is actually big and contains many regions; this aspect grows the output or sizable features and characteristics of deep learning models for categorizing Alzheimer diseases and healthy states. It is at this stage that achievement of the outlined goals and objectives of the study is realized and contribution to the large area of focus in the medical field image analysis.

Table1.
Total number of images per class

Directories	Non-demented	Demented
Test	2760	2592
Train	10720	10728

Data Preprocessing

Data preprocessing is a very important part of data processing, which is to clean and prepare data to guarantee data quality so that it can be fed into deep learning algorithms. To preprocess images, TensorFlow and Keras libraries provides in built functions to do the pictorial transformation. To eliminate poor results and increase computational consistency, we resized each image to 224x224 pixels, the same input size needed by the VGG-19 model. To enhance the convergence rate of neural networks, and improve model learning subject to minimal numerical errors, pixel values are normalized to a range of 0 to 1.

In order to handle the small dataset size, data augmentation techniques were used including random rotations, horizontal and vertical flips, and scaling. Transforming the dataset from author to feature level diversified them decreasing overfitting and making the model generalize better on unseen data. Furthermore, efforts were made to ensure class distributions were balanced through augmentation for minority classes to a greater extent (or densification to the extent necessary.) Preprocessing as described above considerably improved data quality and provided robust training while improving VGG-19's performance in Alzheimer's disease diagnosis. In this study, there was a lot of thorough preprocessing to ensure that there was no bias in model outcome.

Label Encoding

Label encoding is a method of transforming category data into numerical values. It is a crucial component of supervised learning, in which input data is fed along with a label for training purposes. We have labeled the data with numerical values of two classes to train it with its relevant images.

Re-Scaling (Min-Max Normalization)

Images consist of RGB channel combinations of matrix values ranging from 0 to 255. The higher these values are, the more computational power it will require. As a result, by compressing these numbers between 0 and 1 values, the rescaling method is employed to save computational resources. The dataset's RBC patch is 8-bit, with values ranging from 0 to 255. We will use the following equation to normalize these numbers.

Data Augmentation

Most models do not train appropriately because we provide insufficient data, primary data, or even low-contrast data. The data augmentation procedure is the answer to all of these inequities. Data augmentation approaches involve cleaning or preparing data for desired iterations using a range of alternatives. Horizontal flips, and shifts in vertical and horizontal, were all conducted on the augmented images in this research. Their applied values are shown in the table below.

Table 2.
Data augmentation features and values

Augmentation feature	Values
Rotation range	20
Width shift range	2.0
Height shift range	2.0
Horizontal flip	True

Model Selection

Given the image classification task, VGG 19 was chosen in this study for its proven efficiency and because it is widely used in deep learning. The architecture of this model was chosen because it has strong architectural strengths, wide supported in the literature, and has been shown to achieve high accuracy on diverse image classification problems.

VGG19

VGG19 is a ConvNet model that has a layer-based architecture with total layers in the model being 19. These layers include 16 Convolutional layers and 3 fully connected layers. It is known to be efficient and does well in tasks that includes image processing. In the architecture of VGG19 model, the smaller filters of size 3x3 are utilized which enable the model to learn all the details of an image. Despite having a rather simple architecture, VGG19 has been applied and used in many challenges and tasks. In this study, VGG19 model was fine-tuned using the training dataset to be able to meet the objective of distinguishing Alzheimer's disease. To do the binary classification of Alzheimer's and non-Alzheimer's images the last layers of the model were replaced with new layers. Starting the training from the pre-trained weights of the ImageNet dataset was also beneficial for the model as it enabled the model to concentrate on learning only those features that are relevant to the identification of Alzheimer's since it already knows other features from the dataset that it was pre-trained on. Thus, the proposed approach allows achieving high accuracy of the solution with a minimal time and computational resources required for training.

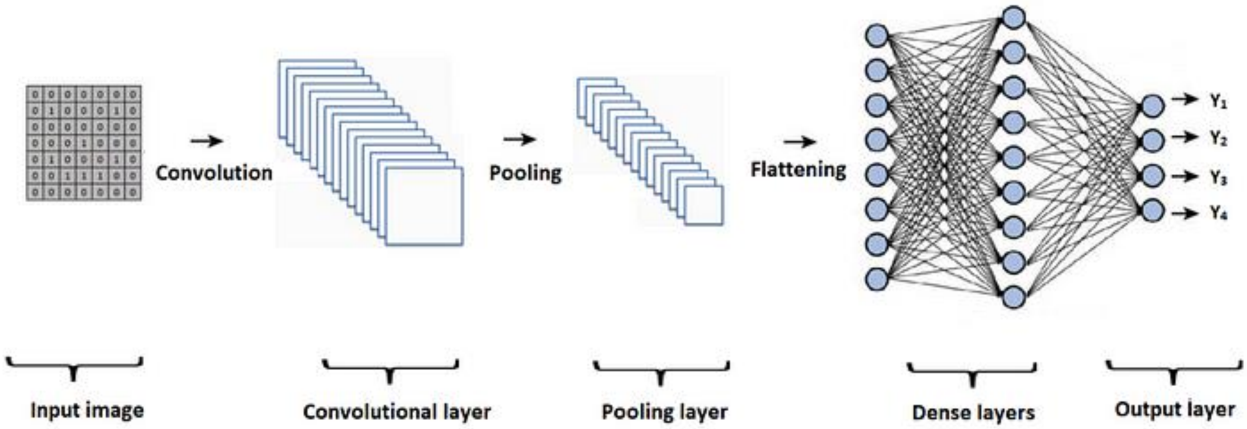

Figure 3.
VGG-19 standard Architecture

Convolutional layer of Vgg-19

Thus, convolutional neural network can be subdivided into several distinct layers. Data is analyzed in sequences as follows; These are; image data input, convolution, pooling, fully connected, and output. It has to be noted that working with images is a rather time consuming and computationally exhaustive operation. Even for simple machine learning, or deep learning, techniques are being used. An efficient and accurate neural network is therefore very useful in this regard for feature extraction. Architecture of a complex CNN is not that easy to develop. When using a pre-trained model, one has to opportunity to fine-tune the model where one can change the layer(s) or parameter(s) of the current model in question. In this thesis, two techniques have been utilized: For the model training, ResNet50 and the pre trained VGG19 has been used as architectures. Some of the parameters of the proposed system will be adjusted to enhance the categorization and at the same time fully connected layers will be added at the last level.

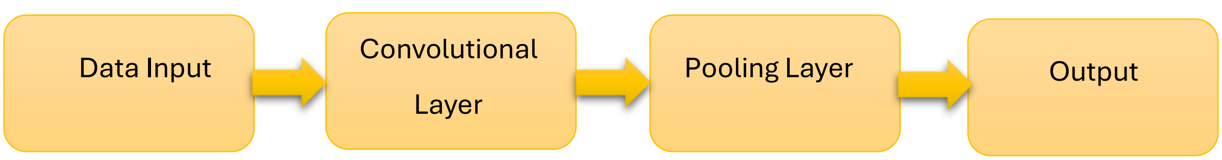

Figure 4.
Convolutional neural network

MAX POOLING LAYER

VGG-19 uses max pooling layers in order to down sample (i.e.: reducing) spatial dimensions of feature maps without loss of important information. Max pooling reduces feature maps size by selecting the maximum value from a particular region (normally a 2x2) and hence the computational load and memory consumption is reduced. Of particular importance to such high-resolution medical images is the ability to maintain critical features that indicate patterns of Alzheimer's disease. Additionally, max pooling enhances translation invariance through the absence of high sensitivity to where in the pooling window features are found - important due to the variability in the location of abnormalities in brain scans.

Plus, max pooling helps simplify the model in a way that prevents overfitting and provides it greater ability to generalize to data it has never seen before, which is critical for real world medical use. The technique also extends the receptive field for the subsequent layer, providing the network with capability of capturing broader context and interactions of brain regions. Moreover, in the case of diagnosing Alzheimer's, a valuable contextual understanding is critical, and analyzing the relationships between different cerebral regions improves the model's capacity to detect Alzheimer's related patterns.

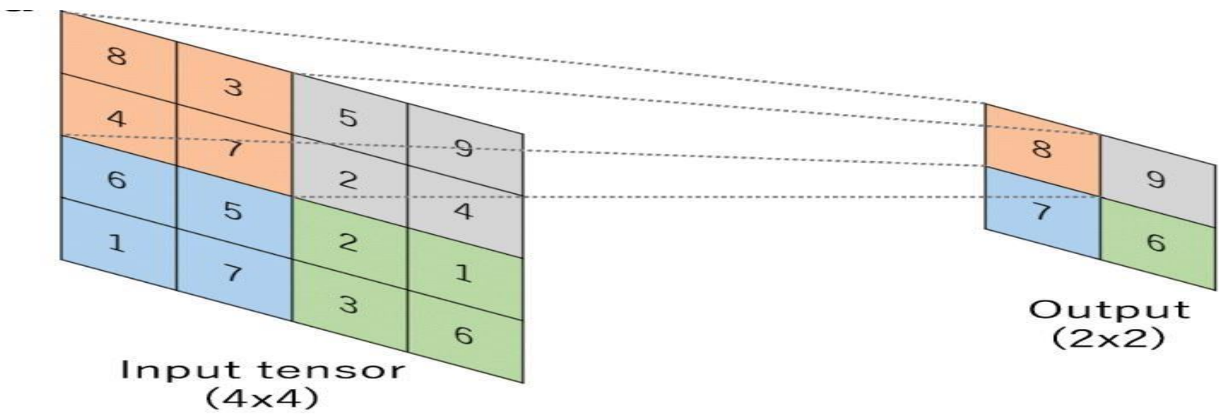

Figure 5.
Max pooling layer

BATCH NORMALIZATION LAYER

Batch normalization is a technique which is quite commonly used to enhance the learning and the performance of models such as the VGG19. Batch normalization is one of the most common techniques in speeding up and regularizing the training process when using deep learning for the identification of Alzheimer's disease. The next part of the paper will provide information on the role of the batch normalization and its application in the VGG19 model for Alzheimer's disease diagnosis. The enhancements made to the VGG19 model by the inclusion of Batch Normalization.

Input feature normalization:

Batch normalization (BN) is an important technique to normalize the scale of input features within each mini batch by zero centering the mean and unifying the variance to one. The standardization process stabilizes the learning process and increases training efficiency of deep networks. Batch normalization is great for medical image analysis, say to identify Alzheimer's, because it can speed up the training of computationally intensive deep learning models such as VGG-19.

Finally, BN solves the internal covariate shift problem arising from changes in the distribution of neural network activations during the training process by making sure that each layer gets inputs with zero mean and unit variance. It not only accelerates and stabilizes the training process, but also prevents overfitting, making the model more robust to see new data. Keeping BN's input values normalized prevents such problems as vanishing or exploding gradients through the network. In particular, deep networks benefit from this technique allowing the production of the reliable and robust models of the medical diagnostics task.

Dropout Layer

The dropout layer is basically used to prevent model over fitting. This strategy is based on a process in which random neurons are eliminated during training. The dropout rate parameter determines the chance of neuron loss by controlling the number of deleted neurons. Neurons are only removed during the training phase.

FULLY CONNECTED LAYER

The last stage in constructing the VGG19 network is a fully connected layer. These layers are responsible for connecting the network's layers and producing the final classification result. Usually, an exponentially normalized final layer follows the previous layer (Softmax). Adjustments were made to this layer in order to refine the VGG19 architecture for Alzheimer's disease diagnosis.

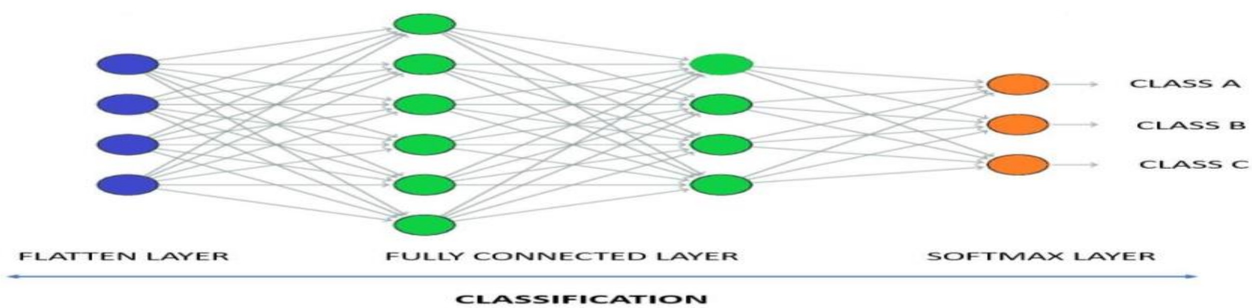

Figure 6.
Fully Connected Layer

Optimizing the use of transfer learning

Since VGG-19 offers a deep architecture as well as facilitating transfer learning, which saves the computational overhead of training models from the scratch, it was selected. By using pre trained models like the ones trained over ImageNet database, we make use of pre learned feature recognition. The study was also able to fine tune these models for use on specific tasks, like Alzheimer’s disease identification, with high accuracy and efficiency for the task, thus saving time and resources. Using transfer learning and VGG-19’s deep and structured architecture, were able to create an effective model to diagnose Alzheimer’s disease. Proper selection and adjustment of this model was critical to the achievement of study’s objectives and in providing meaningful insights to the field of medical image analysis.

Training the Model

VGG 19 training was done on Google Colab’s computational power as it had the intensive requirements of deep learning tasks. Starting with pre-trained weights from ImageNet, transfer learning was used to help improve performance with minimal tuning for Alzheimer’s detection using the model. To accelerate convergence, Adam optimizer was used, while binary cross entropy loss was used to compare prediction with labels. Early stopping techniques were used to stop training when validation performance ceased to improve, while model checkpointing allowed the best performing weights to be saved.

In the second approach, to improve model generalization, we added data augmentation to make variations of training images so that the model could be adapted to new inputs. The learning rates used in the model were adjusted fine down so the model achieved high accuracy without overfitting. VGG-19 was able to pick up on Alzheimer's disease, even to find some of the fine prints in medical images, using this comprehensive training process.

Model Evaluation

Evaluation of the proposed models is of the essence for assessing the effectiveness and robustness of the proposed models. We evaluated the performance of VGG-19 without using the same testing dataset to create an unbiased metric of generalization ability of the model. In order to have a fair and comprehensive comparison, multiple evaluation metrics were used. Precision, recall, F1-score were all used to address the challenge from imbalanced datasets, supplemented by a fairly straightforward metric of accuracy. In particular, making the F1-score a balanced metric that combines false positives and false negatives costs should evaluate the model's performance in predicting people with Alzheimer's disease. Moreover, the performance of the model in discriminating classes, taking in between the thresholds was measured with ROC AUC metric, with the AUC indicating the overall performance. Yet, the results were also qualitatively assessed with confusion matrices to see how true positives, false positives, true negatives, and false negatives were. These tools lent themselves to a detailed investigation of misclassified patterns, to identify where improvement could be made. These evaluation metrics and the visualization techniques worked in concert to provide a rigorous and reliable way to evaluate the model performance and demonstrated its utility in real clinical decision support systems.

Tools and Libraries

A number of tools and libraries were used in this study toward the realization of its methodologies. Computational resources (including GPUs) for deep learning model training, and a seamless way to share and collaborate on code, were afforded to me by Google Colab. The primary programming language used was Python 3 because of its simplicity and a good performance in a scientific computing. For data preprocessing and manipulation, we used NumPy and Pandas which are a good set of tools for paralleling operations on arrays, cleaning, and prepare data. Matplotlib and Seaborn were used for data visualization for generating detailed graphs and charts to analyze data distribution and model performance. TensorFlow and Keras were used to build and evaluate model. TensorFlow's flexibility and only being able to handle large scale data made it an ideal solution to an array of deep learning tasks, and Keras helped simplify model creation with its simple and easy to use API. Data splitting and performance evaluation tasks supported by Scikit-learn. These tools were integrated together to provide a systematic and reliable method to process data, train and validate a model, which played an important part in gluing deep learning together in order to facilitate Alzheimer's diagnosis.

DATA ANALYSIS AND RESULTS

This section provides a detailed study on the result obtained applying a deep learning method of VGG19 architecture on Alzheimer's disease detection specifically. They performed the results into several sections that contain insights around the model performance, visual outputs, and how the training process goes. The findings help explain how well the model works and what implications these may have for the use of the model in real life e.g. for clinical practice. We thoroughly analyzed the results with key performance metric such as accuracy, precision, recall, F1-score, confusion matrix, ROC curve and inspection of predictions. In addition, the chapter also discusses the training and validation behavior of the model and its capabilities of generalizing.

Classification Report

A detailed analysis of the results when classifying the proposed model as demented versus non demented subject is offered by the below classifi-ca-tion report as well through metrics such as precision, recall and F1 score. The report provides a fair generalization capability of the model based on an unseen test set. The model produced an accuracy of 0.98 for demented cases and 0.97 for non-demented ones, which highlight the model's high potential to correctly predict positive cases, something of paramount importance in minimizing false positives and reducing the anxiety of the patient in a medical context.

The recall values show the model's ability to correctly predict actual positives; it is at 0.90 for demented patients and at 0.99 for non-demented patients. Although the recall for non-demented cases shows almost perfect sensitivity in recognizing healthy people, the 10% false negative rate for the demented patients is suboptimal for use in clinical settings where prompt and accurate diagnosis is crucial. The F1-scores of 0.93 for demented and 0.98 for non-demented are suggestive of the classification being equally sensitive and specific with an overall correctness of 97%. Macro and weighted-average F1-scores close to 0.97 also support the model's stability in classifying both classes. However, the model presented here demonstrates a high accuracy and it is still important to focus on increasing recall for demented cases in order to reduce false negatives and increase the model's applicability in a clinical setting.

CLASSIFICATION REPORT

```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_test_bin, y_pred_bin))

              precision    recall  f1-score   support

           0       0.98      0.90      0.93       144
           1       0.97      0.99      0.98       512

    accuracy                           0.97       656
   macro avg       0.97      0.94      0.96       656
weighted avg       0.97      0.97      0.97       656
```

Figure 7.
Classification Report of the Vgg-19 Model

Confusion Matrix Analysis

The confusion matrix serves as a very detailed assessment by clearly separating predictions into true positive, true negative, false positive, false negative results. In this study the model was excellent at distinguishing between non demented and demented cases, correctly classifying 99% of the 512 non demented samples. A very strong is the fact that 0.59% were misclassified as being demented, a point that is very flattering with regard to clinical settings because it means much less extra stress and all sorts of additional tests for healthy people. The model correctly identified 90% of cases and misclassified 10% of them as non demented for the demented class. While 90 percent recall is a good result, the fact that most of those undetected dementia cases are false negatives threatens to mask the issue, since undetected cases lead to delayed diagnoses and other critical interventions. This shortfall is particularly important as early detection is critical to managing Alzheimer's progression. However, future refinements such as balancing the training data, or using class weighting would help improve recall for the demented class. The model has high efficacy but must be further optimized to attain sufficient clinical utility in dementia detection.

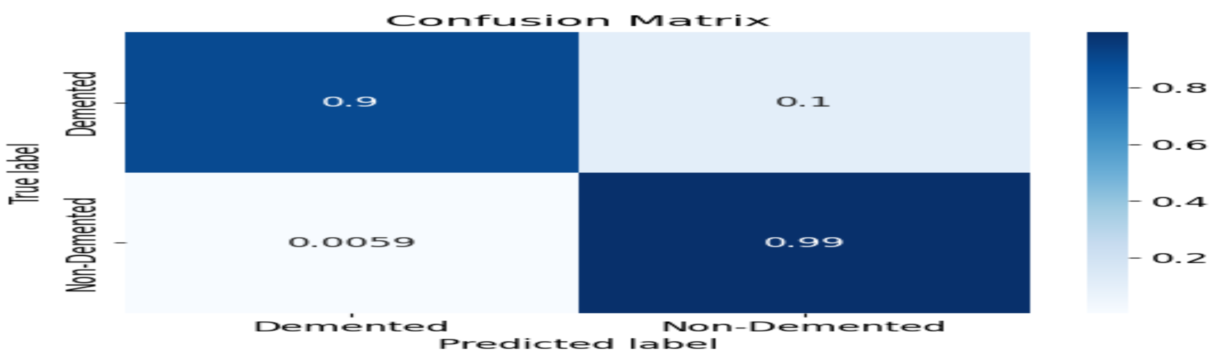

Figure 8.
Confusion Matrix of Vgg-19 Model

Training and Validation Performance

However, during the training phase, it is quite important to understand what the behavior of the model are. To do this analysis, the accuracy and loss of training and validation across 500 epochs were tracked. These metrics tell you how the model is doing when it's learning about the underlying pattern in the data, as well as how well it's able to generalize to new example.

Training and Validation Accuracy

The training accuracy curve shows that the model quickly learned its dataset features and started to accrue accurately in the first 50 epochs and steady over 95% from the 100th epoch. This rapid improvement indicates that the dataset was sufficiently rich for the model to learn to adequately separate demented from non demented brains. Over next epochs, training accuracy continued to improve at a marginal but very stable pace to about 97% on the 500th epoch, saying that model has an ability to learn consistently. The validation accuracy took a similar path, initially trailing that of training accuracy slightly before leveling around 95-97% after about the first 100 epochs. The close match between training and validation accuracy implies the model doesn't overfit, instead, it has actually learned patterns that are applicable to otherwise unseen data. This consistency shows that the model is very robust and reliable for real world applications.

Training and Validation Loss

Loss curves are very useful to the optimization process of the model. In this train, the training loss dropped very quickly during early epoch, and was below 0.1 for 50th epoch. Thus, the model seemed to learn the instructive features of the dataset and minimize error. The validation loss behaved very similarly, with the fluctuation of loss for each epoch somewhat due to the model testing on new data. While we saw fluctuations in this loss, the validation loss stayed low with relatively little overfitting, indicating that this strongly generalizes. Both accuracy and loss metrics converge, thus demonstrating that the model learns well while remain robust, demonstrating its promise in real world applications.

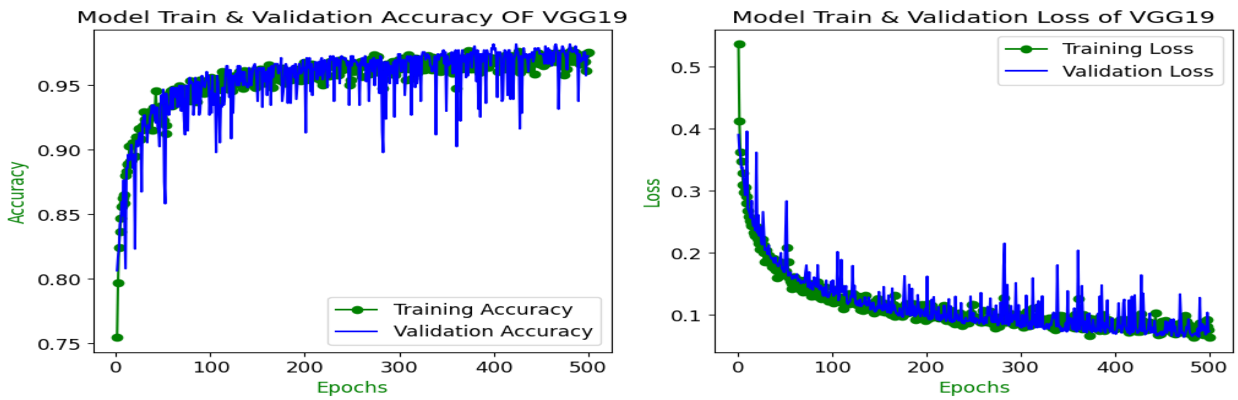

Figure 9.
Accuracy and Loss of Vgg-19 Model

ROC Curve Analysis

For binary classification task, the ROC curve is a crucial evaluation tool when plotted against the tradeoff between true positive rate (sensitivity) and false positive rate (specificity) over a range of thresholds. In this study, the ROC curve was always located near the top left corner of the plot, showing a high sensitivity and specificity in discriminating demented from non demented cases.

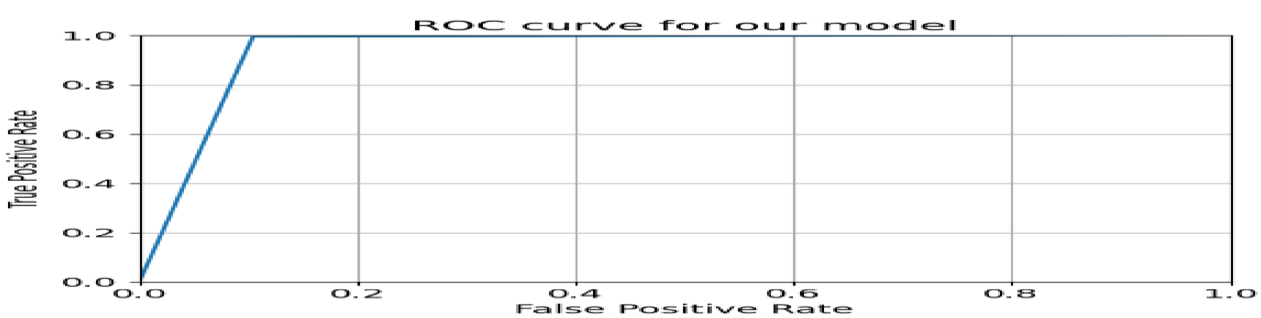

Figure 10.
ROC curve of Vgg-19 Model

It inferred relatively good classification performance with few false predictions with an Area Under the Curve (AUC) value close to 1. It accords with other measures, such as confusion matrix and classification report, further confirming model's reliability. The model's robustness across thresholds is illustrated by ROC analysis showing the model's suitability for clinical use, where a compromise between false positives and false negatives is important.

Visual Predictions and Confidence Scores

With respect to having the model predict on an individual test image, that is qualitative to inspect. The model's decision making was analyzed on segments of MRI slices and their associated confidence scores. Scores of 99.99% and 99.97% on non-demented cases illustrate that the model was able to tell healthy from diseased brain tissue reliably.

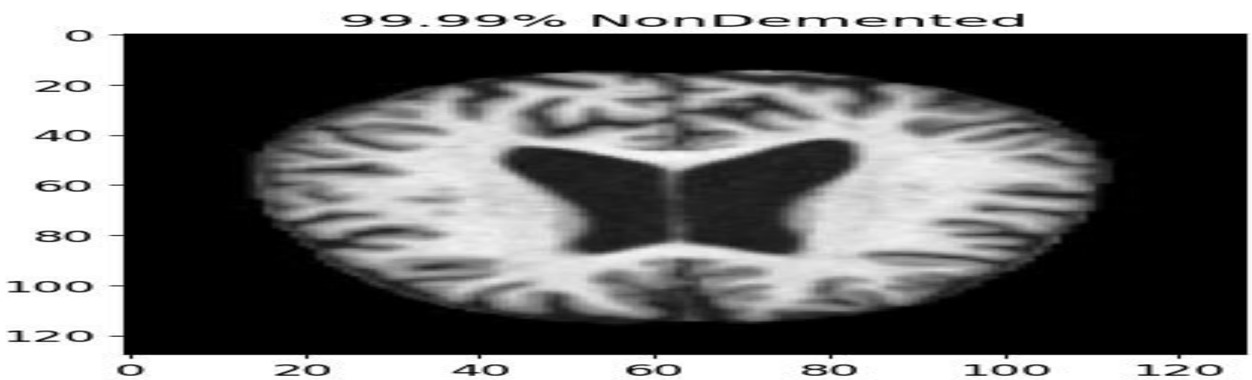

Figure 11.
Predicted Image of Vgg-19 Model (a)

These results show that the model learns detailed patterns in MRI scans, especially in cases of non-demented subjects. But high confidence doesn't always yield accuracy, particularly in those tricky instances. We then need further validation to determine whether it will be robust enough for clinical applications through real world testing.

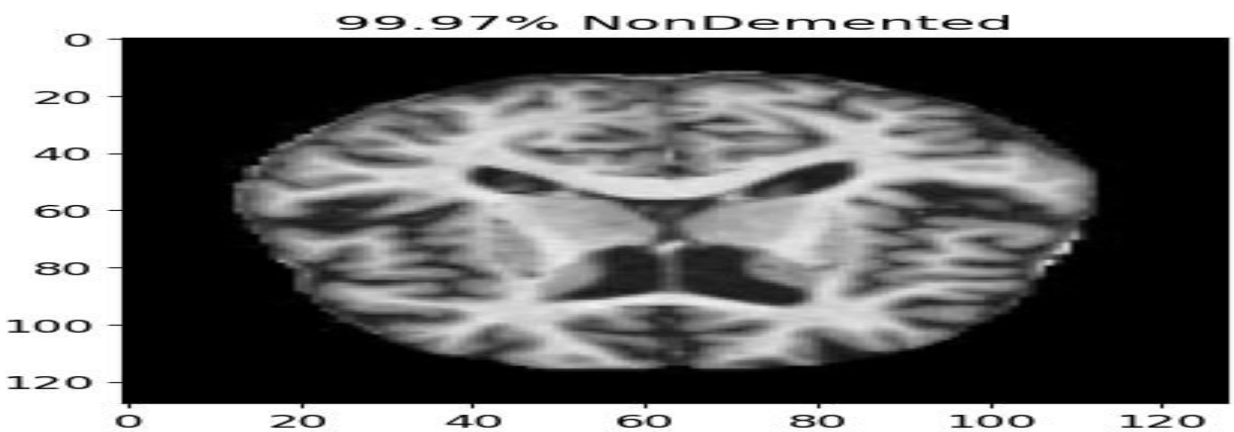

Figure 12.
Predicted Image of Vgg-19 Model (b)

Test and Training Set MRI Visualizations

Visualizing MRI scans from the training and test set shows how diverse and complex this dataset is. The scans range over brain structures, displaying small differences in healthy and demented patients. These visualizations reflect the difficulty that the model itself struggles with in discriminating normal aging from the pathological changes related to

Alzheimer's' disease. Brain anatomical variability included differences in shape, size, intensity, as well as age, gender, and brain state. The ability for the model to learn a pattern specific to Alzheimer's disease is vital as it is for this data to be able to vary. The model's ability to generalize is further confirmed through test set visualizations which achieve consistent accuracy and confidence on unseen images. This result shows that the model can capture the important features of the dataset, which imply that it can be used to assess real world Alzheimer's diagnosis.

CONCLUSION AND RECOMMENDATIONS

Future Directions

However, this study also presents several directions in future research to improve the accuracy of AI for Alzheimer's diagnosis. Expanding the dataset by adding other MRI Scans from different sources is one important step. Model generalization and susceptibility to instabilities would be improved by a larger and more varied dataset, one of the main drawbacks of this research. Further, future studies may focus on other deep learning architectures, such as Efficient Net or Dense Net, or invent original architectures more tailored to medical imaging tasks that may outperform state of the art models trained over large amounts of medical data.

Interesting is another direction for integration of interpretability techniques like Grad-CAM to view which brain regions the model is directed towards during predictions. This would increase confidence in the model's prediction (so that it is more suitable for clinical implementation). Finally, combining MRI data with multimodal data such as medical history, genetic information, and the results of cognitive tests might be able to improve a diagnostic's accuracy. With this holistic approach, future models would be better able to give us complete, holistic, much more detailed ideas about how Alzheimer's is progressing and so much more, which would really be useful in both research and clinical context.

CONCLUSION

In this study, we demonstrate the utility of VGG-19 to diagnose early Alzheimer's disease with 96% accuracy using typical MRI scans. As such, the model's simple and deep architecture enables it to effectively uncover critical image features for early-stage detection. The limited dataset of ADNI was addressed using preprocessing techniques, such as data normalization, augmentation and rotation which increase the diversity and quality of available data. The model generalized better with the help of these techniques, creating synthetic variations, or reducing pixel intensity variations resulting in the model gained the ability to learn meaningful features from little data. Nevertheless, these promising results face some hurdles. The limited dataset size limits of the application of the findings to a broader context, for such future research could emphasize medical specific datasets or models for medical imaging tasks. Furthermore, VGG-19 introduces black box nature which makes clinical settings and challenging for where interpretability is a necessity. Using techniques such as Grad-CAM could reveal something about the model's decision-making process and help build trust and confidence in AI based predictions. In general, this work indicates that deep learning, especially VGG-19, has tremendous potential to enhance the ALZ diagnosis, to help detect ALZ earlier and more accurately for the sake of patient outcomes and in support of healthcare professionals facing greater responsibilities of medical imaging.

DECLARATIONS

Acknowledgement: We appreciate the generous support from all the supervisors and their different affiliations.

Funding: No funding body in the public, private, or nonprofit sectors provided a particular grant for this research.

Availability of data and material: In the approach, the data sources for the variables are stated.

Authors' contributions: Each author participated equally to the creation of this work.

Conflicts of Interests: The authors declare no conflict of interest.

Consent to Participate: Yes

Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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