Demented and Non-Demented Neural Network Brain MRI Classification

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***Abstract* – Dementia, a neurological disorder impairing cognitive function and memory, poses significant challenges for precise diagnosis and classification. Existing detection methods often fall short, resulting in delayed treatment. This paper investigates the use of neural networks to identify and classify dementia using MRI brain scans from the Open Access Series of Imaging Studies (OASIS). Utilizing deep learning techniques, we aim to enhance classification accuracy. The proposed model employs ResNet-50 as the base model for each of the axial, sagittal, and coronal planes of MRI scans. The dataset is meticulously split to avoid data leakage, ensuring the reliability of the results. Our model achieved an accuracy of 59.58% on an unseen test dataset.**

Keywords: dementia, brain MRI, deep learning, classification

I. INTRODUCTION

A. Background

Dementia encompasses a broad spectrum of symptoms associated with cognitive impairments, predominantly affecting the elderly population. Accurately identifying and classifying dementia poses significant challenges for medical professionals. However, the development of neural networks capable of precise dementia classification holds the promise of facilitating earlier intervention than currently possible. Existing research has made strides in creating models to achieve this goal, generally utilizing data from well-established sources like OASIS and ADNI [1]. The following section provides a concise overview of the fundamental concepts employed in this research.

2.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a class of deep neural networks that have proven highly effective for analyzing visual data. CNNs are designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers. The primary advantage of CNNs is their ability to capture local patterns and features in images, making them particularly suitable for image classification tasks [2], [3].

2.2 ResNet

ResNet, or Residual Network, is a type of deep learning model that addresses the degradation problem in deep networks by introducing residual learning. The key idea is to allow the network to learn residual functions with reference to the layer inputs, which helps in training much deeper networks. ResNet has achieved state-of-the-art results in many image recognition tasks and is known for its simplicity and effectiveness [4].

2.3 Transfer Learning

Transfer learning involves taking a pre-trained model on a large dataset and fine-tuning it on a smaller, task-specific dataset. This approach leverages the feature representations learned on the large dataset, thus improving performance and reducing training time on the new task. Transfer learning is particularly useful when dealing with limited data availability, which is often the case in medical imaging [5], [6].

2.4 Ensemble Model

An ensemble model combines the predictions of multiple individual models to produce a more accurate and robust prediction than any single model. Ensemble methods, such as bagging, boosting, and stacking, have been widely used in machine learning to improve generalization and reduce the likelihood of overfitting. In the context of dementia classification, an ensemble approach can integrate different neural network architectures to enhance diagnostic accuracy [7], [8].

B. Literature Review

Previously, the most successful method to perform machine learning on images was to do feature extraction. However, the trend has changed since the success of AlexNet over the ImageNet competition. Since then, deep learning has taken over as it doesn't require manual feature extraction and provides better performance [9].
Pre-development of the neural network and during development, numerous papers were reviewed in order to collect information on how other papers have implemented a neural network for classification and the success each one had. This allowed for an amalgamation of these ideas and methods along with the clinical data supplied with the OASIS 1 dataset to develop this model. [10] used an Ensemble neural network method with voting using the DenseNet169 pre-trained model, as seen in **Figure 1**.

Class	precision	recall	f1–score	support
non-demented	0.97	1.00	0.99	73
very mild	1.00	0.33	0.50	6
mild	0.67	0.86	0.75	7
moderate	0.50	0.50	0.50	2
avg/total	0.94	0.93	0.92	88

Figure 1 *shows the performance of the proposed ensemble model on the OASIS dataset sed by [10]*

Rajendiran et al. introduced an alternative approach to analyzing the OASIS data by employing a transfer learning model. Their study involved evaluating various established models, including AlexNet, VGG-16 Net model, ResNet model, and Google Net model. Remarkably, the Google Net model outperformed the others in terms of accuracy, precision, recall, and f1-score, achieving values of 97.54%, 97.67%, 97.54%, and 97.55%, respectively [11].

A recent study by Khan et al. (2023) also proposed a transfer learning approach for multiclass classification of Alzheimer's disease using MRI images. The study focused on distinguishing between normal control (NC), early mild cognitive impairment (EMCI), late mild cognitive impairment (LMCI), and Alzheimer's disease (AD). They utilized gray matter extraction from MRI scans obtained from the Alzheimer's Disease National Initiative (ADNI) database to fine-tune a pre-trained VGG architecture. By freezing certain layers and adding new ones, the model was able to learn new features efficiently, resulting in superior performance. Extensive experiments demonstrated that their approach outperformed existing methods, highlighting the effectiveness of transfer learning in this domain [12].

Based on the literature review by Ashir Javeed and Arif Ali in their 2023 study, "Machine Learning for Dementia Prediction: A Systematic Review and Future Research Directions," it is evident that there is a significant gap in research using multimodal approaches for dementia prediction. Their review highlights the potential benefits of integrating various data types, such as imaging, clinical features, and voice data, to improve diagnostic accuracy and early intervention. This gap underscores the necessity for further research in this area to develop more robust and effective predictive models [13].

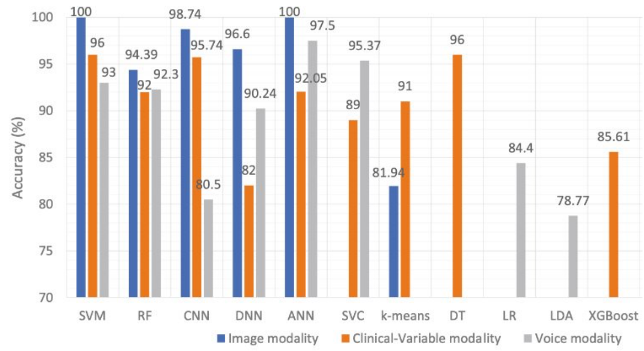

Figure 2 The performance of multiple machine learning models for dementia prediction. This chart was created from the use of multiple sources[13]

C. Motivations and Objectives

The motivation for this paper is to provide insight into the application of neural networks in providing medical professionals with better tools to detect early signs of dementia from MRI brain scans. The aim is that by creating a model that combines different approaches used in other papers, a more robust neural network can be developed to classify the intermediate states of dementia. This paper's objective is to build a model that can use the OASIS 1 MRI images to develop a competent model to classify dementia.

The organization of this research is as follows: Section II presents the Methodology, detailing the methods and specifics of the proposed model. Section III, Experiments, describes the training process and experimental setup. Section IV, Results, illustrates the outcomes derived from the experiments. Section V, Discussion, offers insights and interpretations of the findings. Finally, Section VI, Conclusion and Future Directions, summarizes the work and outlines potential directions for future research.

II. METHODOLOGY

A. Data collection and Processing

The data used for this research was sourced from the OASIS. OASIS offered 4 different datasets but for this paper only OASIS 1 was used. OASIS 1 was published in 2007 and contains MRI cross sectional scans of both demented and non demented adults from the ages 18+. Clinical data was also provided detailing information such as the patients social economic background, clinical dementia rating, score in a cognitive exam and education level [14]. The scans provided where collected using a T1-weighted scan to emphasize brain tissue over more water-based substances with raw images of the scan and processed images that normalized the brain scans to account for differences in brain sizes.

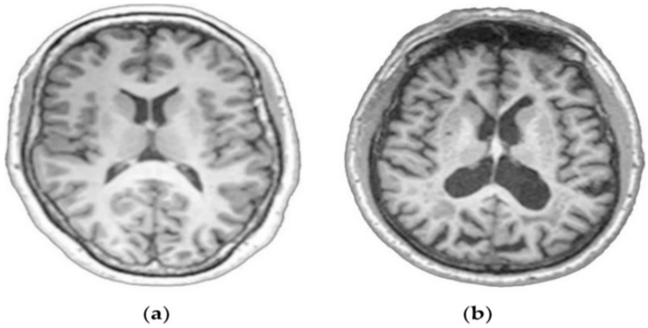

Figure 3 (a) Healthy Brain (b) Demented Brain

The dataset contains High Dynamic Range (HDR) files that need to be sliced to be processed. The same methodology proposed by [15] was used. Here, they found that the optimal number of images away from the center to reduce overfitting and noise was 20. Therefore, to reduce computational cost in finding the number of images, this same method was used. In a HDR image the total slices for a side view came to 176, 208 for front and 176 for top. The middle 40 were used in each section according to [15].

In total there were 436 patients. Patients that had a CDR value of "N/A" were excluded from the dataset resulting in a final sample size of 235 patients which leads to a more balanced dataset.

B. Neural Network Architecture

The neural network developed used 3 different angles of the brain for classification. It used a front(coronal), top(axial) and side(sagittal) view of the brain.

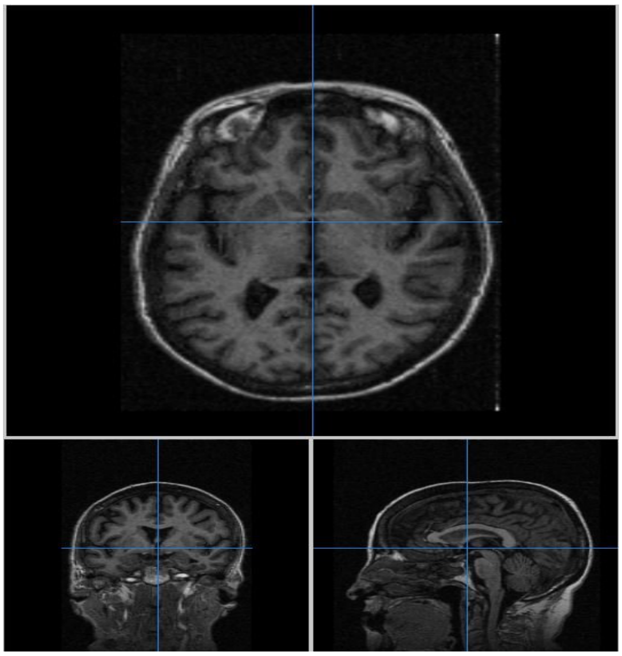

Figure 44 All 3 views used in the model

Across the entire dataset there were only two patients with "moderate dementia" leading to problems with training so for this model patients in classes 1.0 and 2.0 have been combined.

D. Network Training

The base model utilized is ResNet-50, pre-trained on the ImageNet dataset. The final fully connected layer of ResNet-50 was removed to expose the feature extraction layer, which was then concatenated with a dropout layer (rate of 0.4) to prevent overfitting. This modified layer was subsequently fed into a newly added fully connected layer, which reduced the dimensions to three target classes, using Leaky-ReLU as the non-linearity function.

Model training was conducted in two stages. The initial stage involved training the fully connected layer while using ResNet-50 solely for feature extraction, with its weights frozen. This stage lasted for 20 epochs. In the second stage, the entire network's weights were trained with a lower learning rate to fine-tune the model for this specific task.

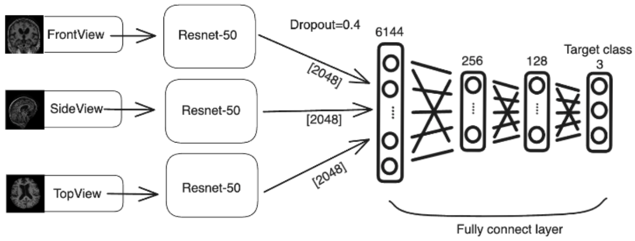

Figure 5 Network Architecture

The model used the following parameters:

Stage 1: Train fully connected layer
- Epoch: 30
- Optimisation: Adam
- Loss Function: Cross Entropy Loss
- Learning Rate: 1e-4
- Weight Decay: 1e-5
- Batch size: 8

Stage 2: Fine tune the whole network
- Epoch: 20
- Optimisation: Adam
- Loss Function: Cross Entropy Loss
- Learning Rate: 1e-5
- Weight Decay: 1e-6
- Batch size: 8

The development of the neural network was conducted using Kaggle for manging the dataset and programming the neural network. The network was codded using Python 3 with Py Torch being used as the neural networks back bone.

C. Image Transformations and Pre-Processing

This technique was adopted to reduce overfitting in the training set. The following transformations were applied to each image using PyTorch, displaying parameters after resizing each image to 224x224:

-Random crop to size 214,

-Padding of 5 with mode set to 'edge',

-Random rotations from –15 to 15 degrees.

The model split the data into a 70/20/10 ratio. That is 70% of the data was used for training, 20%

was used for validation and 10% was a hold-out test set. The core design of the network is illustrated below:

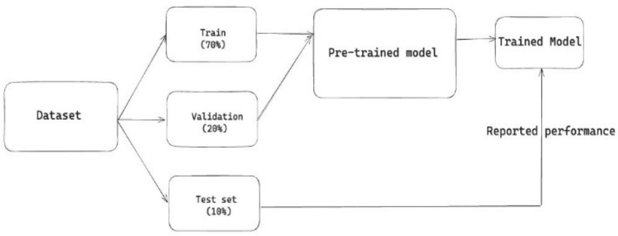

Figure 6 Dataset flow diagram

E. Extension – Ensemble Model

It was hypothesised that feeding all MRI views of the brain into one model would not be as effective as building one model for each view, resulting in an ensemble of 3 neural networks. The reasoning behind this comes from each image containing different details that are important for that specific view.

The inspiration behind this comes from [15] that outline a very similar approach in classifying dementia using the ADNI dataset.

III. EXPERIMENTS AND RESULTS

The proposed ensemble approach was trained using transfer learning and a ResNet architecture.

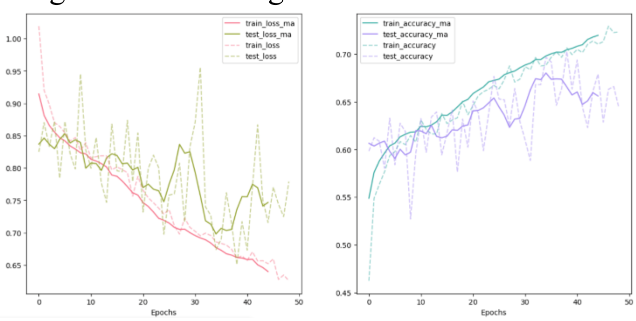

Figure 7 Network Performance. Left: Loss plots. Right: Validation

When generalising to unseen data (our 10% hold-out set), the model performs below expectations and reaches a final accuracy of 59.58%. This is better than random as we are classifying 3 classes. The confusion matrix in Figure 9 paints the full picture, where the model is shown to have troubles distinguishing between mild and moderate states of dementia.

Accuracy: 0.5958
Classification Report:

	precision	recall	f1-score	support
no demented	0.87	0.80	0.84	560
very mild	0.25	0.17	0.20	280
mild to moderate	0.29	0.62	0.40	120
accuracy			0.60	960
macro avg	0.47	0.53	0.48	960
weighted avg	0.62	0.60	0.60	960

Figure 8 Network results table

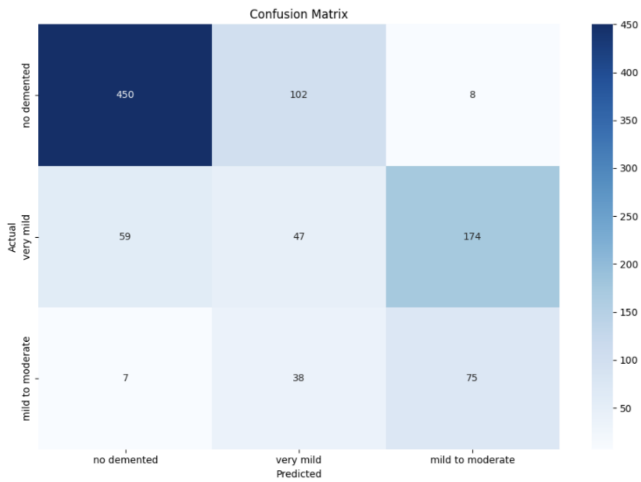

Figure 9 Confusion Matrix

IV. DISCUSSION

A. Results Interpretation

Figures 8 and 9 show the final performance of the model trained using the OASIS 1 dataset using a 3-view classification approach. The results achieved fell short of the goals due to complications and limitations faced during development with an overall accuracy of 60%. However, findings were still made, and some recommendations have been listed following the results of this model. The model performs well on predict non demented and mild to moderate class. However, it performs poorly on very mild class.

B. Key Findings

The key takeaway of this report is a highly advised recommendation into further research to be conducted into the application of multiple views to classify dementia with further adventures looking into the use of architectures such as U-Net based models. The findings also recommend an additional inquiry into the problem of overfitting and its implications on hindering the development of such networks and the lack of acknowledgement of the problem or how it is addressed in other models.

C. Limitations

Limitations on resources and time compromised the performance of the model. A major challenge faced during development was the limited dataset used to train the model resulting in issues of overfitting which could potentially be resolved with a larger dataset to train the network.

V. CONCLUSION AND FUTURE DIRECTIONS

In conclusion, this study aimed to classify dementia using a limited dataset of 235 patients. An ensemble approach of neural networks employing transfer learning was applied to each view in the OASIS 1 dataset, demonstrating promising results for future research. The proposed model achieved a final accuracy of 59.58% for three classes on unseen data. The confusion matrix indicated that the primary challenge lies in accurately distinguishing between mild and moderate dementia states.

Future research should consider exploring different architectures which have shown promise in medical imaging but were not feasible in this study due to resource constraints. Utilizing more data from subsequent versions of OASIS (2-5), subject to research approval, could potentially mitigate overfitting issues. The codes are available on https://www.kaggle.com/code/waritboonmasiri/3-views-model.

Additionally, implementing hyperparameter search techniques could help identify optimal configurations for the neural network models, further improving their performance. This could involve grid search, random search, or more advanced methods like Bayesian optimization or genetic algorithms, to systematically explore the hyperparameter space and enhance model accuracy and robustness.

By addressing these directions, future studies can build on the foundational work presented here, advancing the field of dementia classification through improved methodologies and comprehensive data utilization.

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