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**ASSIGNMENT: CET313 Assignment Report**

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CET313 AI Assignment

## Abstract

The number of Dementia and Alzheimer’s diseases patients has been growing rapidly over the years, in the UK alone the number of dementia patients is closing in on 1 million (NHS, 2023). In this study, a deep learning solution is developed and tuned. It will be able to use brain MRI scans, the deep learning model will be able to identify whether the patient is demented or not reliably. The data set used has over 80000 MRI samples that have been put together by Open Access Series of Imaging Studies (OASIS), the deep learning model used is ResNet50. The trained model managed to perform well yielding an accuracy score of more than 99% and only making mistakes in 5 out of the 3784 validation samples. To conclude, the results have been highly satisfactory, the model performs with great accuracy and provides a staggering amount of analysis feedback, the model tuning process was a great learning experience as was the literature review.

## Introduction

Alzheimer’s Disease is the main cause of dementia, both are significant public health challenges, with nearly 1 million individuals affected in the UK alone (NHS, 2023). Alzheimer’s disease, which accounts for 60–70% of dementia cases (Javeed et al., 2023), is a progressive brain disorder that gradually impairs memory, cognitive function, and the ability to perform daily activities. With misdiagnosis rates posing risks for treatment and care planning. This study leverages deep learning to classify brain MRI scans as demented or non-demented. By focusing on the OASIS dataset, which includes over 80,000 MRI samples, this research explores the potential of AI to enhance diagnostic accuracy and support early intervention strategies.

Convolutional Neural Networks (CNNs) are deep learning algorithms that excel at image classification by automatically picking up patterns during the training process. the chosen model for this study is a pretrained ResNet50 model. The aim here is to train a strong deep learning algorithm that will consistently classify MRI brain scans as demented and non demented correctly.

## Literature Review

**1.Image Classification in Medical Field**

Image classification has been gaining more and more traction in the recent years, Image classification has proven particularly useful in the medical field for performing complex tasks. For instance, (Yadav & Jadhav, 2019) discusses the application of CNNs in diagnosing pneumonia using X-rays. it is a very difficult task; it requires a professional radiologist which is very expensive and rare depending on where you are. This is where deep learning CNNs can fill the gap, such as when CheXNet (Rajpurkar et al., 2017) developed a 121-layer CNN capable of detecting pneumonia better than the average professional radiologist, such an incredible feat has inspired many including this study to dive into the world of AI for medical purposes.

**2.CNNs for Dementia Detection**

In the context of dementia diagnosis, MRI scans serve as a crucial tool, by picking the right model one is capable of producing a classification model, (Murugan et al., 2021) sought to create a machine learning algorithm called DemNet (Dementia Network) capable of early diagnosis for Alzheimer’s disease, they utilise MRI scans from 4 different stages of dementia to train their CNN, starting from *Mild Cognitive Impairment* to *Sever Dementia,* the results achieved in that study are very promising and give a great indication to the true capabilities of CNNs.

**3.ResNet50 Architecture and Capabilities**

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Description automatically generatedAs mentioned previously this study is going to utilise the ResNet50 CNN architecture as this architecture has the potential to produce state of the art results and is great at working with large datasets making it a perfect fit for this project, to put it simply the ResNet50 architecture is made up of 4 components (Kundu, 2023), the first being the convolutional layers responsible for feature extraction and It utilises the ReLU activation function, the 2nd and 3rd are the identity block and the convolutional block responsible that process and transform the extracted features and last but no least is the fully connected layers responsible for making the final classification.

**4.Significance of Large Datasets in DL**

Large datasets play a pivotal role in research, for example the CheXNet’s CNN was trained on 112,120 frontal-view chest X-ray images (Rajpurkar et al., 2017), the sheer size of the dataset allowed the model to gather enough information to produce the achieved results, OASIS provides the large dataset used for this project, the main idea of the OASIS project is to offer the community free neuroimaging dataset.

## Methodology

**1.Methodoly section topics**

This section discusses the approach adopted to train the DL model on the MRI scan. It showcases the used data as well as the preprocessing applied to the images, it describes the tools and libraries used, training process and the evaluation metrics.

**2.Dataset Information**

The dataset used in this study is sourced from the OASIS. It comprises over 80,000 MRI samples, sectioned into moderate dementia, mild dementia, very mild dementia and non-demented classes. The three classes used for this study are the moderate, mild and non-dementia classes. The data set has also already been segmented to show only the patient’s brain, the images were sliced on the z-axis into 256 images, and images ranging from 100 to 160 were selected from each patient.

**3.** **Hardware and Environment Setup**

As mentioned previously the dataset obtained is very large, the three classes used will have approximately 70000 images. Training a deep learning model with such scale, very powerful hardware is necessary. At first the idea was to use a 7900xt GPU to train the model locally, although a very powerful gaming GPU, AMD GPU’s are poor at training ML and DL algorithms, Nvidia GPU’s completely dominate the filed in that regard. Considering the computational power needed and GPU optimisation, one training run is estimated to have taken around a day. The solution chosen is to run the project on a Google Colab, using the pro version the user gets access to an Invidia A100 GPU, a state of the art GPU with 40 gigabytes of VRAM, the large VRAM allowed the training model to run with a batch size of 256 greatly speeding up the training process, the first run took just under 4 hours using a batch size of 128 and poor configurations. By the final run the configurations were adjusted and dataset was decreased in size, the run took only 30 minutes.

**4.Data Preprocessing**

Throughout the study many different configurations for data preprocessing were tested, this section will be split into two groups, the data preprocessing features that stayed consistent and the ones tested and removed. To begin with 4 data preprocessing steps stayed consistent throughout the project that were instrumental to achieving the final results:

* Image Resizing: all images were resized to 224x224 Pixels to match ResNet50’s requirements
* Normalisation: Pixel values were normalised to 0 or 1
* Grayscale conversion: All images were converted to Grayscale
* Splitting the data: the data was split into a train test split with slight variation in split ratios across experiment.

A screen shot of a computer program

Description automatically generated

A big issue arises when training the data was the huge imbalance in the data splits, here are the three data sets used:

* Moderate Demetia: 488 images
* Mild Dementia: 5002 images
* Non demented: 67222 images

This imbalance caused bias in the results and produced “padded” or “fake” results, to put it into prospective that is a ratio for moderate and non demented classes which were the only ones used until the final solution was 1:137, to deal with this issue three solutions were tested:

The first being Oversampling the demented class, this didn’t manage to fix the imbalance as the data was oversampled by a factor of 3 and increasing any farther would risk too much repetition and could cause overfitting (IBM, 2021). The second was data augmentation, which is basically the process of artificially increasing the image volume by applying some transformations such as rotating an image buy a certain degree or changing each image’s colour slightly. The third and final solution which proved effective and produced the best real results was Undersampling the non demented class to 9000 and adding the half the mild dementia data to the demented class making the ration 1:3 making the imbalance less significant.

**5.Model Selection & Training**

As mentioned previously the model used was a pretrained ResNet50 model imported through the Torchvision library, so no changes were made to the model itself but some parameters were adjusted such as the loss function, in the early iterations of the project while working with Oversampling and data Augmentation the loss function was made in a way that penalised the model more for making a mistake in the minority class (demented) while the majority (non demented) class has a smaller penalty/loss value, unfortunate this didn’t have much effect on the final results so the loss function was reverted to the default function.

Default loss function:

A screenshot of a computer

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A computer screen with green text

Description automatically generatedAdjustable loss function:

As can be see this loss function has been commented out as evidence of it being used in earlier iterations of the code but commented out later and replaced with the regular wight loss function.

**6.Evaluation Metrics**

A priority on the must have list for the model it is having a big range of evaluation metrics to analyse the models performance. These are the most important metrics included in the final code:

* Iteration loss and time
* Epoch training loss and accuracy
* Epoch validation loss and accuracy
* Epoch training time
* Confusion Matrix (validation)
* A screenshot of a computer

  Description automatically generatedClassification report (validation)

## Results and discussion

**1.Final Results analysis**

Here is a table with all the results from the best model:

|  |  |  |  |
| --- | --- | --- | --- |
| Epoch | Confusion Matrix | Epoch Train Accuracy | Epoch Validation Accuracy |
| 1 | [[ 819 6]  [ 0 2959]] | 92.52% | 99.84% |
| 2 | [[411 414]  [ 0 2959]] | 99.75% | 89.06% |
| 3 | [[ 753 72]  [ 4 2955]] | 94.56% | 97.99% |
| 4 | [[ 820 5]  [0 2959]] | 99.17% | 99.87% |
| 5 | [[ 817 8]  [4 2955]] | 97.63% | 99.68% |

The table showcases the system's performance progression across epochs. In the first epoch, the model delivered a relatively high validation accuracy, likely due to its initial ability to detect straightforward patterns within the validation data. At this stage, the model was still in its early learning phase, and while the results were promising, the possibility of minor overfitting cannot be ruled out.

In the second epoch, a sharp drop in validation accuracy occurred, with the model misclassifying 414 demented patients as non-demented. This indicates a momentary instability in the training process, possibly due to the model overfitting to patterns in the majority class (non-demented) caused by the class imbalance. However, the model adjusted and corrected itself in the following epochs, demonstrating its capacity to improve and generalize better over time.

From the third epoch onward, the system’s performance showed steady improvement, with both training and validation accuracy trending upward. By the final epoch, the model had nearly perfected its classification, misclassifying only 12 samples out of 3784. This significant improvement highlights the effectiveness of the preprocessing steps and training adjustments, such as balancing the dataset and optimizing configurations. Further examination of the misclassified samples might reveal insights into edge cases or inherent limitations in the data.

**2.Training Efficiency**

Using Google Colab Pro with an NVIDIA A100 GPU significantly reduced training time to 30 minutes for the final run compared to the first run which took 4 hours, thanks to optimized configurations and a batch size of 256 the model and setting the number of workers to 4.

**3. Discussion**

These results demonstrate the model’s ability to reliably classify brain MRI scans. The optimized preprocessing steps and class balancing strategies played a critical role in mitigating the impact of class imbalance on top of being the biggest learning experience. Additionally, leveraging state-of-the-art hardware accelerated the training process, making the project feasible within the given timeframe.

The high accuracy showcases the potential of pretrained CNN architectures like ResNet50 in medical imaging tasks, though the small sample size of moderate dementia cases suggests that future studies should focus on obtaining more balanced datasets to further enhance model robustness.

Furthermore, comparing the performance of a well-configured implicit neural network (INN) model would be an excellent direction for future studies. This comparison could reveal how both types of neural networks hold up against each other. Will the more complex INN, with its capability to represent functions in infinite dimensions, outperform a well-tuned CNN?

Important Links

**E-Portfolio: https://canvas.sunderland.ac.uk/eportfolios/17818/Week1**

**Dataset link:** **https://www.kaggle.com/datasets/ninadaithal/imagesoasis**

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