Group N

GROUP N : Deep Neural Network-based Medical Imaging through MRI Analysis

1. Problem Statement

The advancement of Artificial Intelligence has triggered a significant transformation in the field of Healthcare and **Medical Image Classification** has become critical in clinical diagnosis and treatment [13]. The traditional computer-vision methods have reached peak performance and become extremely specific and complex [6]. However, Deep Learning based Convolutional Neural Networks (CNNs) are superb when it comes to feature extraction. The performance can be enhanced by employing Transfer Learning, which utilize the knowledge from previous tasks to perform image analysis [5]. Thus, pre-trained CNNs for image classification tasks can bypass the need for complicated and expensive feature engineering [13].

There are numerous modalities of diagnosis that are available today for visualization of the patient's condition. In this project, our prime focus is to target medical diseases and disorders based on the patients' Medical Resonance Imaging (MRI), to provide diagnosis on the presence of Breast Cancer, types of Brain Tumor, and the stages of Alzheimer's in a patient. The aim of this project is to compare and contrast different Neural Network architectures, on the basis of their performance on three different datasets, thereby offering a way for diagnosing, that is quicker, more accurate, and consistent.

2. Image Dataset Selection

For the purpose of detecting a particular disease using Deep Learning, we need to obtain an ample amount of balanced and reliable data to enable the model to learn important information. Thus, we have selected the following datasets obtained from the same MRI modality.

2.1. Breast Cancer

Breast MRI is a frequently used type of imaging technique to evaluate the degree of cancer in the breasts of individuals with breast cancer [8]. The breast MRI dataset contains 922 patients gathered in Duke Hospital from 1 January, 2000 to 23 March, 2014 with invasive breast cancer and available pre-operative MRI at Duke Hospital [10] [9] [2]. It has 20,125 images in .dcm format with dimension 448*448.

2.2. Alzheimer's

The dataset contains MR images with five stages of Alzheimer's diseases and can be classified into Alzheimer's Disease (AD), Cognitively Normal (CN), Mild Cognitive Impairment (MCI), Early MCI (EMCI), Late MCI (LMCI). It has 1,296 images in .jpg format with dimensions 256*256, subclassified into training and test set. [1].

2.3. Brain Tumor

The MRI study for brain tumor diagnosis aims to identify the presence of the tumor, categorize its grade and type, and determine its location within the brain. The dataset contains 7023 MR images of human brain classified into 4 classes: Glioma, Meningioma, Pituitary, and No Tumor, in both .jpg and .tiff format, with dimensions varying from 520*520 - 3400*2800 [7].

3. Methodology

First, we perform Data Preprocessing to bring the data to the same format and size, by using resize, pad, normalize, autocontrast, hflip and vflip, to prepare the data to be utilised by the following pretrained models:

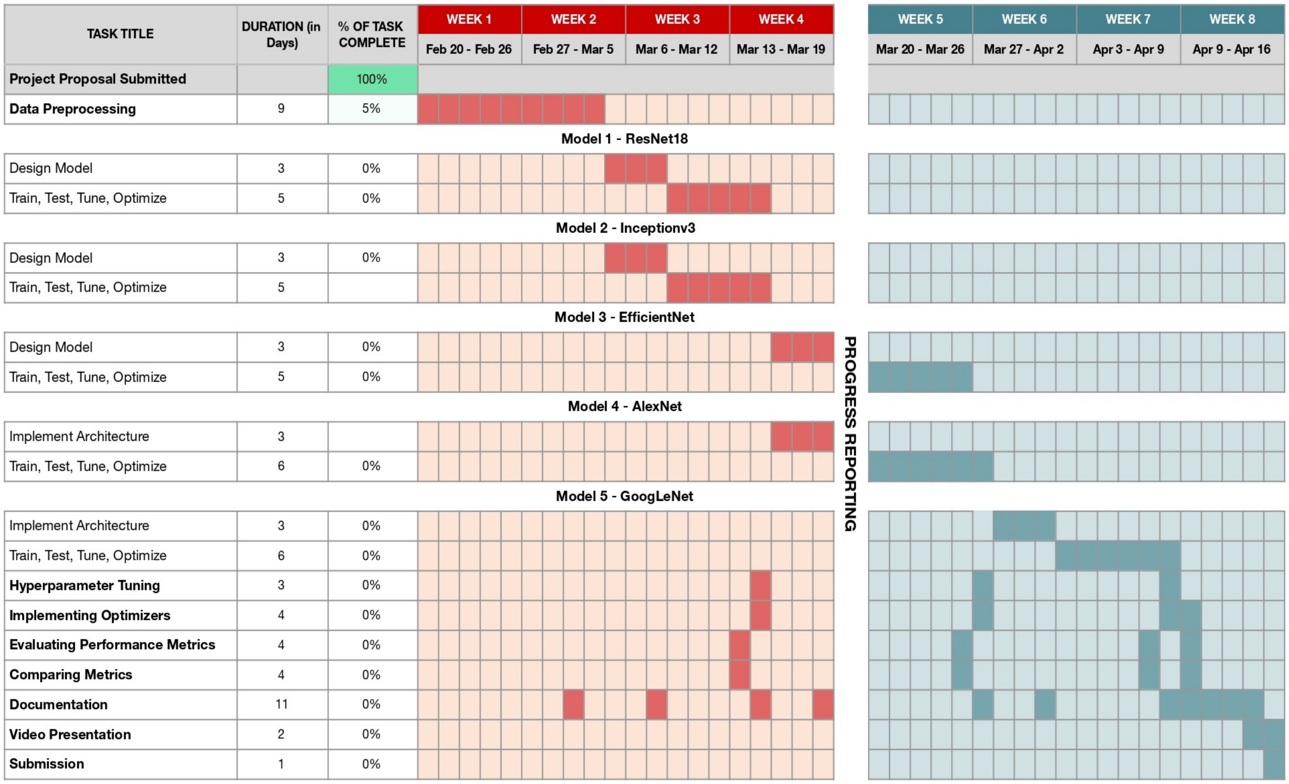
ResNet18: It is pretrained on the ImageNet dataset and produces an accuracy of 69.758%. It takes in data of size 224*224 and can classify objects into 1000 classes [4].
Inceptionv3: It produces an accuracy of 77.294% on the ImageNet dataset. It expects tensors with a size of 299*299. The model heavily applies batch normalisation to the activation inputs. Loss is computed using Softmax [11].
EfficientNet: It uniformly scales all dimensions using a compound coefficient. It produces an accuracy of 82.008% on the ImageNet and performs exceptionally on other datasets. It takes images of size 300*300 [12].
Each of these pre-trained models, will now be trained on all three of the datasets as they employ their learned model parameters to significantly reduce the training time. We also implement Transfer Learning using the AlexNet and GoogLeNet architectures of Pytorch and train them on the Alzheimer's and Brain Tumor datasets respectively.

By keeping the hyperparameters (epochs, batch_size, and learning_rate) constant during training for all models, we evaluate each model using the following metrics: Binary/Multiclass Accuracy, Confusion Matrix, Dice Similarity Coefficient, Specificity and Receiver Operating Characteristic, to measure the accuracy and localization correctness for Medical Imaging. To further boost the model performance, we tune the model hyperparameters and utilize the Adam optimizer, Backpropagation, or Stochastic Gradient Descent optimization.

Deep Learning enables researchers to develop new and more accurate imaging techniques, to provide earlier and more accurate diagnosis by detecting complex patterns and relationships in medical images, leading to focused, precise and personalized treatment. It has the potential to reduce healthcare costs, increase efficiency, and save lives [3].

Group N

4. GANTT CHART:



3.1. Project Timeline

Phase 1: The project proposal is submitted and the project is now initiated. The scope of the project is discussed. The team will perform literature review to identify the problem statement and corresponding datasets, to begin training and testing the models. The team now begins the project implementation. To make sure the data is suitable for use in the following phases, the team will perform Data Preprocessing in order to clean and format the data, remove noisy data, and manage any outliers. The models ResNet and Inceptionv3 are implemented. Initially the model is designed, and prepared for training. Following this, training, testing, debugging, hyperparameter tuning and model optimization is performed.

Phase 2: The team will implement the EfficientNet using pre-trained weights. The transfer learning models AlexNet and GoogLeNet will then be developed and implemented via their corresponding training, testing, tuning, and optimization steps. After each model is developed, the observations made from the model are documented and their performance is noted. In order to find the ideal optimization technique combination that yields the best performance, this stage entails experimenting with various combinations of hyperparameters. After this, the team will compare and contrast all necessary metrics across all of the models, then conduct a conclusive comparison to generate the results. The comparison's findings will be employed to determine the project's ultimate outcome.

Group N

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