Deep Learning Report

Abstract

This report explores the development of a deep learning model designed to detect brain tumors using Brain MRI images, a crucial tool for early diagnosis and improving patient outcomes. A Convolutional Neural Network (CNN) was created, and after optimizing the model's hyperparameters, it achieved an accuracy of around 90% . The architecture includes four hidden layers with filters (32, 64, 128, 128) and 128 neurons in the Dense layer, dropout rates of [0.1, 0.2, 0.3, 0.4], with an Adam optimizer at a learning rate of 0.005, and a batch size of 32. Throughout the process, challenges such as data quality, variability, and class imbalance were addressed through methods like data augmentation and hyperparameter tuning, which significantly improved the model's performance. These results highlight the importance of applying deep learning techniques effectively, especially in detecting brain tumors, where timely intervention is critical. The findings reinforce how deep learning can enhance diagnostic accuracy and play a significant role in better patient care.

1 Introduction

The healthcare industry, with its vast scale and predominantly analogy systems, presents a prime opportunity for leading global information technology (IT) companies. In 2018, investors in the United States invested over 11 billion US dollars in digital healthcare startups, reflecting a 16% increase from the previous year (ScienceDirect, 2022). As Geoffrey Hinton has pointed out, "We should stop training radiologists now. It's completely obvious that within five years, deep learning will outperform radiologists" (Fast Data Science, 2021). This highlights the transformative potential of AI in revolutionizing healthcare.

Each year, an estimated 2,900 people in the U.S. are diagnosed with brain tumors, with nearly 50% of them succumbing to the disease, while the UK reports around 4,200 new cases annually (Kim et al., 2011). Unfortunately, Early diagnosis of brain tumors significantly improves patient outcomes. Studies have shown that patients who undergo early surgical intervention have a postoperative survival period of 28.4 months, compared to 18.7 months for those with delayed surgery. Additionally, advancements in diagnostic tools, such as advanced magnetic imaging and artificial intelligence, have revolutionized neuro-oncology, leading to better patient outcomes (MDPI, 2021), particularly Convolutional Neural Networks (CNNs), have shown exceptional potential in quickly processing large volumes of imaging data.

Furthermore, so many studies did discuss the potential of deep learning (DL) and artificial intelligence (AI) in revolutionizing healthcare, particularly in medical imaging and computer-aided diagnosis (CAD). Deep learning has shown superior performance in tasks such as lesion detection and classification compared to traditional methods, even outperforming radiologists in some areas. The application of DL in CAD can provide valuable decision support to clinicians, improving diagnostic accuracy and efficiency, and enhancing various treatment processes (Chan et al., 2020).

This report details the development of a Convolutional Neural Network (CNN) model for detecting brain tumors from MRI images. The goal is to create a model capable of accurately identifying the presence of brain tumors in MRI scans, a critical step in early diagnosis and treatment planning. However, challenges such as variations in tumor location, image resolution, and the imbalanced distribution of tumor-present and tumor-absent categories in the dataset complicate this task.

Various deep learning techniques are explored, with CNNs selected for their proven effectiveness in image classification tasks. The report outlines the process of developing a robust model to identify brain tumors, overcoming dataset challenges. It includes an explanation of the model architecture, the rationale behind choosing CNNs, data preprocessing, training, and the evaluation of results. The findings from these experiments demonstrate the model's performance and effectiveness

2 Proposed Methodology

In this section, the deep learning methodology used to approach the problem of brain tumor detection will be outlined. The methodology consists of three main steps: data preprocessing to address challenges such as data quality and class imbalance, model construction, and optimization through hyperparameter tuning, followed by training and evaluation, as illustrated in **Diagram 1**.

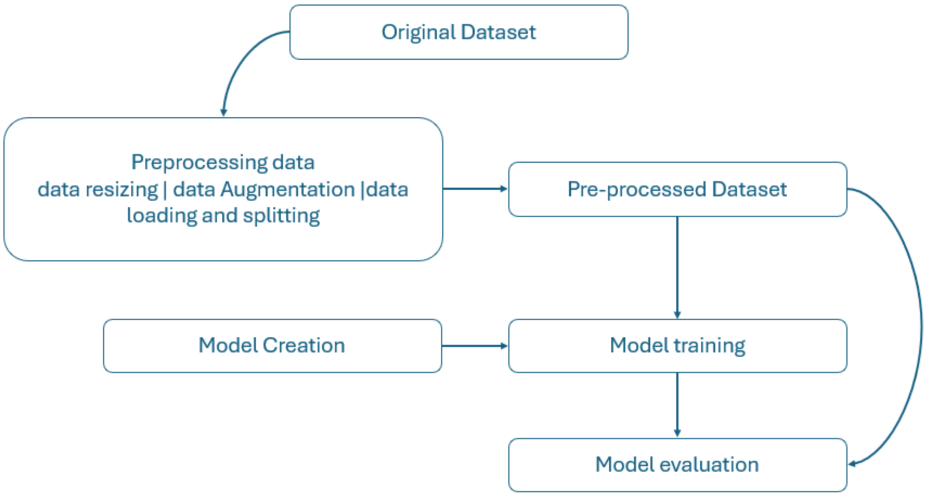

Diagram 1

In this process, the provided dataset presented significant consistency challenges, including variations in image resolution, which complicate the model's ability to generalize effectively. The Original dataset is labelled with 150 images in the "yes" folder (with tumors) and 73 images in the "no" folder (without tumors) as shown in **figure 1**, creating an imbalance in the dataset that poses an additional challenge for model training and evaluation. The images are in the acceptable .jpg format, suitable for training purposes.

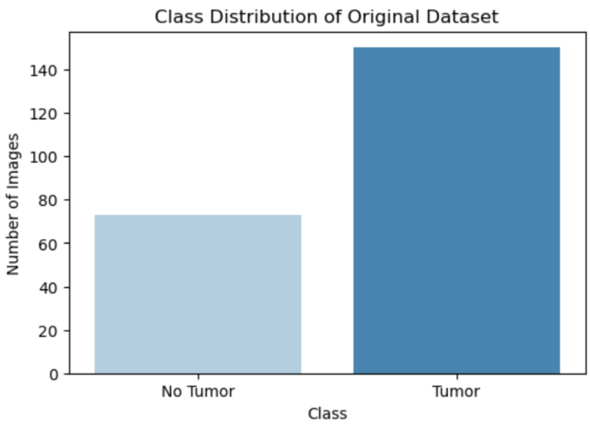

Figure 1

Preprocessing Step

To begin with, the data presented consistency challenges, including variations in resolution, which hindered the model's generalization. To address these, the images were resized to a consistent size of (224 , 224), ensuring a uniform format while preserving the aspect ratio to prevent stretching as shown in **figure 2**.

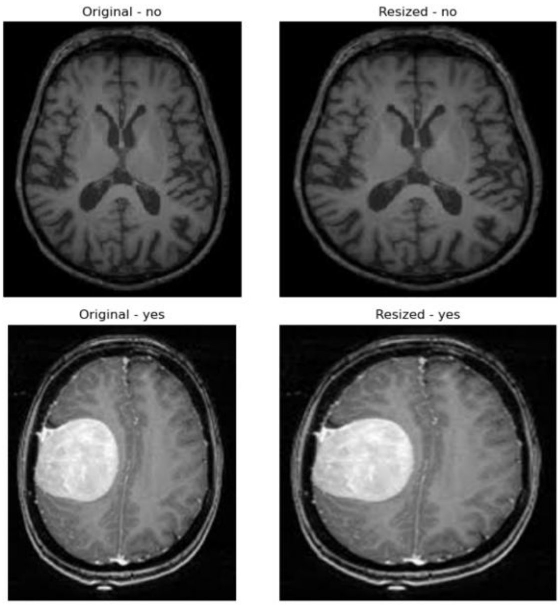

Figure 2

The dataset undergoes preprocessing steps such as normalization, and data augmentation including width and height shifts, shearing, zooming, and horizontal flipping. These transformations helped the model generalize better making it more robust to positional, scale, and orientation variations and balanced the dataset by providing a more even distribution of variations as demonstrated in **figure 3**. Additionally, pixel values are normalized to the [0,1] range, stabilizing training and improving convergence.

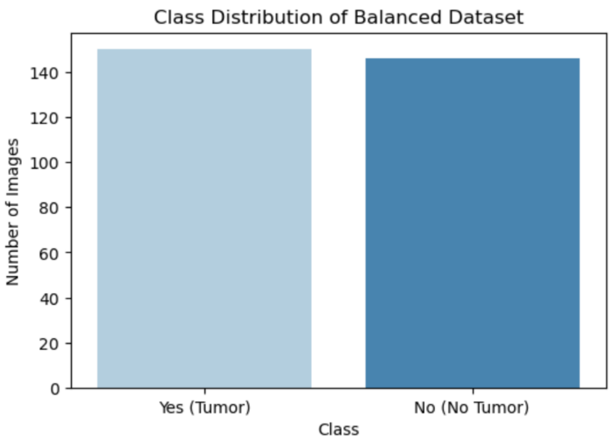

Figure 3

Finally, the balanced dataset is split into 80% training, 10% validation, and 10% test sets in a balanced way ensuring a structured learning process and comprehensive performance evaluation as presented in **figure 4**.

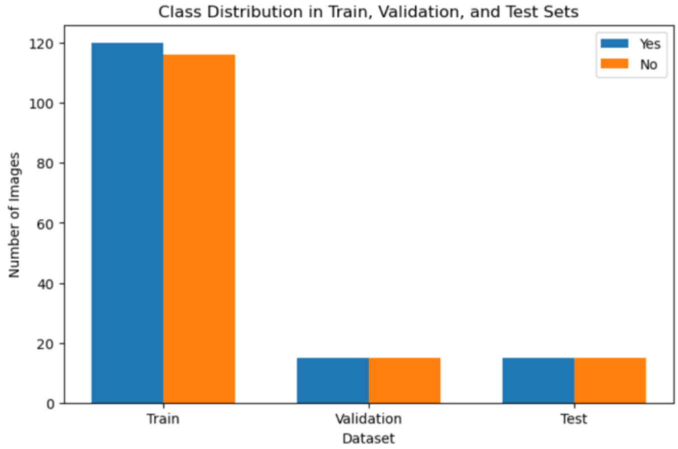

Figure 4

Model Architecture

The deep learning model was carefully designed by selecting an architecture that balances performance and generalization. Four convolutional layers were implemented, utilizing 32, 64, 128 and 128 filters, each followed by max pooling and dropout layers with rates of 0.1, 0.2, 0.3 and 0.4 respectively.

A fully connected Dense layer with 128 neurons was incorporated, with an additional 0.4 dropout rate to reduce overfitting. The Adam optimizer was employed with a learning rate of 0.005, and training was conducted using a batch size of 32. To further enhance generalization and address class imbalance ,data augmentation techniques were used such as width and height shifts, shearing, zooming, and horizontal flipping were applied, making the model more robust to variations in scale, position, and orientation.

Training and evaluating

the model was trained with the pre-processed dataset ensuring both classes contributed equally to the loss calculation. Early stopping, with a patience value of 5, halted training if the validation loss did not improve for five consecutive epochs, to prevent overfitting and reduce unnecessary training time, validation accuracy, along with model accuracy and loss, was monitored throughout the training process to assess the model's performance and generalization, as shown in **Figure 5**.

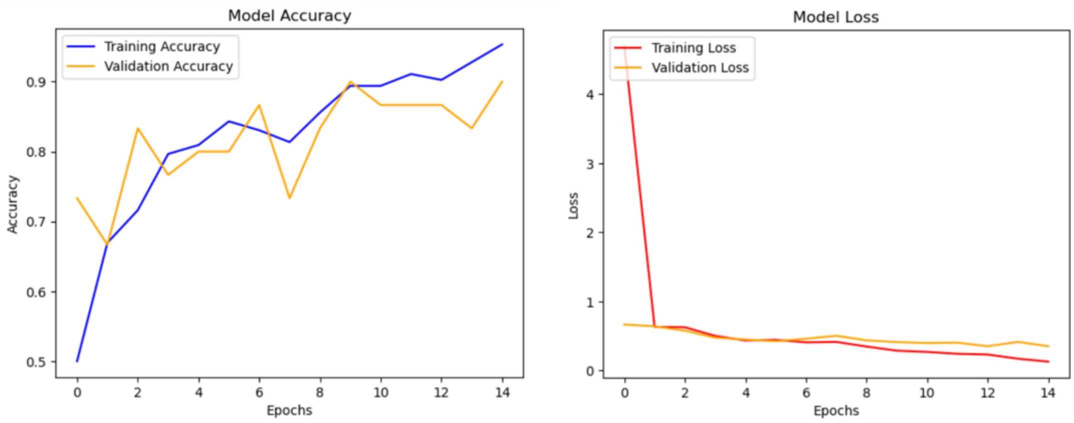

Figure 5

3 Experimental Results

This section explains the rationale behind the chosen hyperparameters by presenting the results that guided our selections. Our primary goal was to identify the hyperparameters that yielded the highest accuracy during the evaluation stage. Below, we provide a detailed analysis of the experimental setup, evaluation process, and the results that led to the final configuration.

Note : all those hyperparameters experiments where done in hyperparameter_selection.ipynb

Hyperparameter Settings

Initially, the model was designed with a progressively increasing number of filters (32, 64, 128 and 128) to ensure effective feature extraction. Low-level patterns are detected by the first layer, while deeper layers extract more complex shapes and high-level features. A **(3,3) kernel size** was selected to balance feature extraction and spatial preservation.

How were the learning rate, dropout rate, batch size, optimizer, and activation function chosen for the model?

In this process a **learning rate of 0.005** was chosen after testing **0.1, 0.05, 0.005, and 0.0005** across **20 epochs**. The highest accuracy (**82%**) was achieved using **0.005** over **0 epochs**, demonstrating its effectiveness in balancing convergence speed and model stability. This made it the most suitable choice, as illustrated in **Figure 6**.

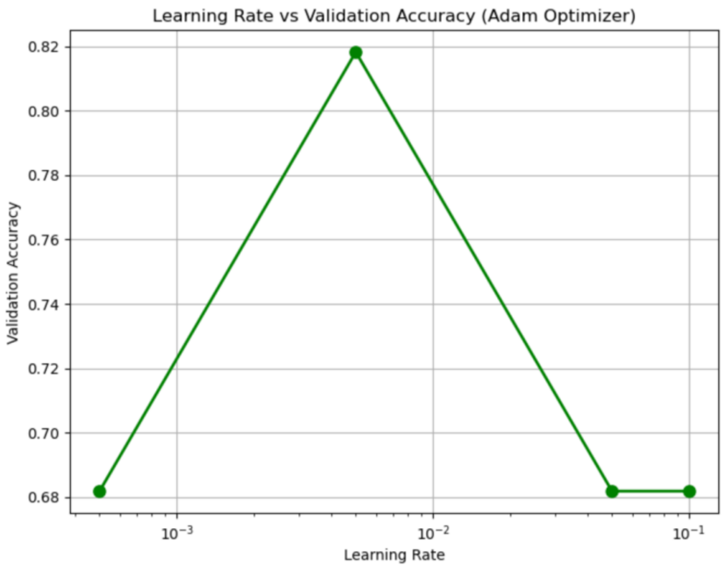

Figure 6

Next, the optimizer selected to enhance convergence and training efficiency was **Adam**, chosen over RMSprop and Adagrad, with the experimental results shown in **Figure 7**. Its adaptive learning rate and ability to combine Momentum and RMSprop provided more stability and efficiency during training.

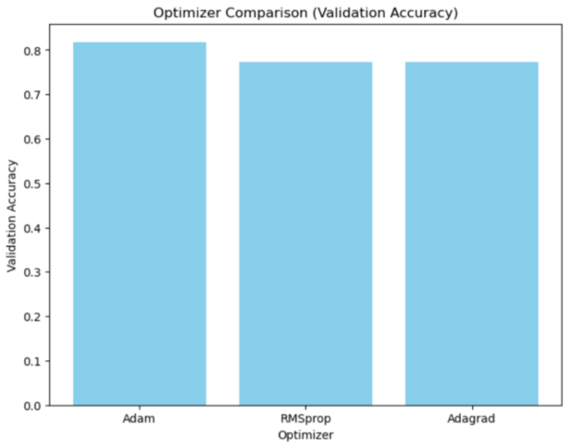

Figure 7

Then, the chosen **activation function** to introduce non-linearity and improve decision boundaries was **Sigmoid**, preferred over **ReLU** and **Tanh** for its suitability in binary classification, as it ensures the outputs stay between 0 and 1.

To prevent overfitting while maintaining performance, **dropout rates** of **0.1, 0.2, 0.3, and 0.4** were applied progressively across layers. This approach reduced reliance on specific neurons as the network deepened, leading to better generalization, as shown in **Figure 8**.

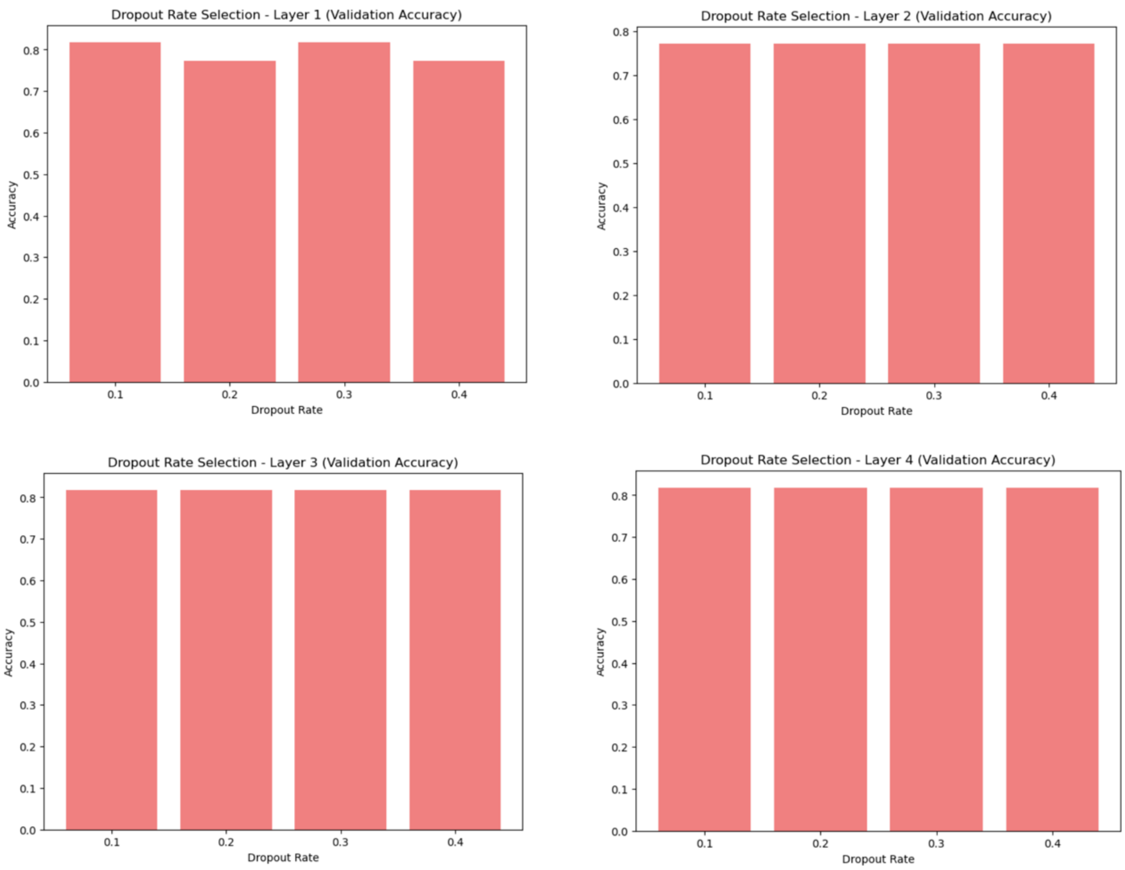

Figure 8

Lastly, a **batch size of 32** was selected to balance computational efficiency and model stability. Smaller batches, such as **16**, resulted in noisier updates, while larger ones, like **64**, increased memory consumption and risked poorer generalization. The choice of **32** ensured stable gradient updates and efficient training.

Evaluation model

The **Confusion Matrix** provides insight into the model's classification performance. The model correctly identified **13** "No Tumor" cases and **15** "Tumor" cases, demonstrating strong predictive capability. However, **2** "No Tumor" cases were misclassified as "Tumor," and **0** "Tumor" case was misclassified as "No Tumor." As illustrated in **figure 9**.

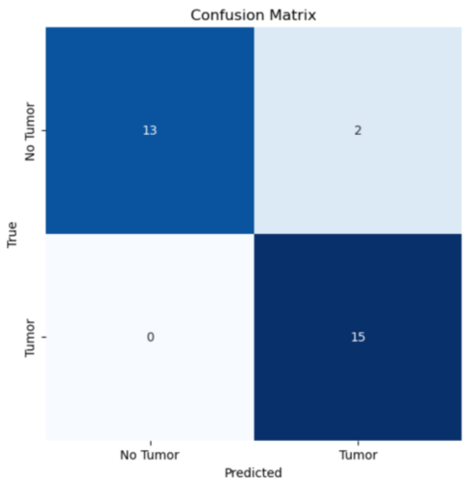

Figure 9

A typical medical image analysis system is evaluated by using different key performance measures such as accuracy, F1-score, precision, recall [5] as presented in **figure 10**, these measures are calculated did result on a **test accuracy of 90.00%**, the model performs well overall. The **precision of 0.88** indicates that **88%** of predicted "Tumor" cases were correct, while the **recall of 0.93** shows that **93%** of actual "Tumor" cases were correctly identified. The **F1 Score of 0.90** confirms a balanced performance, effectively handling both false positives and false negatives.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 10

Summary

This report presents a deep learning approach for brain tumor detection using Convolutional Neural Networks (CNNs), enhanced by transfer learning and data augmentation technique. Despite strong performance in classifying tumor and non-tumor cases, challenges such as variations in MRI resolution and class imbalance were addressed through preprocessing methods like image resizing, rotation, flipping, and brightness adjustments. Dropout layers were implemented to prevent overfitting, and data augmentation helped balance the class distribution. Extensive experimentation was conducted to reduce computational costs, with hyperparameters carefully optimized. Future work may explore transformer-based architectures and further dataset improvements to enhance model accuracy and reliability for real-world applications.

References

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