UiO Department of Physics
University of Oslo

Alicja Terelak, Giorgio Chiro, Eyyüb Güven

Project 3

FYS-STK4155 — Project Work in Applied Data Analysis and Machine Learning

Supervisor: Morten Hjorth-Jensen

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Abstract

The increasing volume of medical imaging data, coupled with advancements in machine learning, has paved the way for innovative applications in healthcare. This project focuses on the challenging task of brain tumor classification, leveraging the capabilities of Convolutional Neural Networks (CNNs). The meticulously curated dataset comprises diverse brain scan images, each meticulously annotated to indicate the presence or absence of a tumor. The project unfolds in two key phases: establishing a baseline using traditional Neural Networks (NNs), and subsequently harnessing the potential of CNNs for more intricate and precise brain tumor image classification. CNNs, with their convolutional layers adept at capturing dimensions, prove ideal for image-related tasks, particularly in medical image classification. The methodology encompasses loading, analysis, and visualization of the dataset, followed by strategic division into training, validation, and test sets. Model architecture intricacies, including convolutional layers, max-pooling layers, and densely connected layers, are then unveiled during the training process. As model performance improves, the evaluation becomes crucial. Both NNs and CNNs undergo meticulous assessment of metrics such as accuracy and confusion matrix. The results are scrutinized, strengths and weaknesses critically appraised, and a set of recommendations for enhancing the models concludes the documentation. This research strives not only to effectively categorize brain tumor images but also serves as a comprehensive guide for implementing sophisticated neural network architectures in medical image classification. Representing an initial exploration into novel approaches for medical image analysis, this study underscores the vast potential at the intersection of healthcare and machine learning.

1 Introduction

The exponential growth of medical imaging data, coupled with continuous advancements and developments in machine learning techniques, has opened the way for an influx of creative ideas in healthcare innovation. Our project centers around the pivotal task of brain tumor classification, leveraging the robust capabilities of Convolutional Neural Networks (CNNs). The dataset, meticulously selected from Kaggle.com, encompasses a diverse array of brain scan images, each of them carefully labeled to signify the presence or absence of a tumor.

The main goal of this project is in two parts: firstly, to create a baseline using traditional Neural Networks (NNs) and then, to utilize the capacity of CNNs for a more complex and accurate brain tumor image classification. The convolutional layers in CNNs succeed at capturing dimensions, making them ideal for image-related tasks, such as medical image classification.

First, the dataset is loaded and analyzed, then it is visualized, and finally, it is strategically separated into training, validation, and test sets. Following that, the complexities of the model architecture and training method are revealed, with specifics on the convolutional layers, max-pooling layers, and densely connected layers.

The evaluation component becomes more important as the models improve during training. Both NNs and CNNs get their model performance metrics, such as accuracy and a confusion matrix, carefully assessed. The results are carefully examined, the strengths and weaknesses are critically evaluated, and a series of suggestions for improving the models are provided at the end of the documentation.

This research essentially aims to effectively categorize pictures of brain tumors while also offering a thorough manual for using sophisticated neural network architectures in medical image classification applications. Representing an initial foray into novel approaches for medical image analysis, this study underscores the vast potential at the intersection of healthcare and machine learning, hinting at possibilities that extend beyond the current horizons.

The complexity of this research extends beyond the technical intricacies to encompass a broader vision of its impact on the field of healthcare. By delving into brain tumor classification, the study aims to contribute significantly to the ongoing efforts to enhance early detection and diagnosis of neurological disorders. The utilization of CNNs, with their ability to discern intricate patterns within images, not only advances the frontier of medical image analysis but also holds the potential to revolutionize the way we approach neurological health. The outcomes of this project may pave the way for more effective treatment strategies, ultimately improving patient outcomes and contributing to the evolution of personalized medicine in neurology.

Moreover, the meticulous attention given to the model evaluation process reflects a commitment to robustness and reliability. The nuanced examination of strengths and weaknesses, supplemented by thoughtful suggestions for improvement, underscores the research team's dedication to refining and optimizing the models. This iterative process of evaluation and enhancement ensures that the resulting brain tumor classification models are not only accurate but also adaptable to diverse clinical scenarios, thus enhancing their practical utility in real-world healthcare settings.

As the project navigates the interdisciplinary realms of healthcare and machine learning, it serves as a beacon for future endeavors in this dynamic intersection. The exploration of new approaches to medical image analysis in the context of brain tumor classification represents a pioneering effort that lays the groundwork for subsequent advancements. The symbiotic relationship between healthcare and machine learning holds immense promise, and this study represents a stepping stone towards unlocking innovative solutions that have the potential to redefine the landscape of medical diagnostics and treatment.

2 Our model

2.1 Data Overview

The dataset, obtained from Kaggle, is structured as an image dataset. Each image is labeled to indicate the presence or absence of a brain tumor, with distinct categories for classification. For a more detailed discussion of the database we are using, see the "Methods" section.

Data Loading and Visualization

We begin by loading and visualizing a subset of the dataset to gain insights into the characteristics of the images and their associated labels. This step is vital for understanding the dataset's nature.

2.2 Data Partitioning

To facilitate model training and evaluation, we partition the dataset into training, validation, and test sets. This partitioning enables training on one subset, validation on another, and evaluating generalization on a separate test set.

2.3 Model Architecture and Training

Convolutional Neural Network (CNN)

We design a CNN architecture for image classification, consisting of convolutional layers, max-pooling layers, and densely connected layers. For a more detailed discussion of the CNN as a method, see the "Methods" section.

Model Compilation and Training

The model is compiled using the Adam optimizer and Sparse Categorical Crossentropy loss function. Training is performed over a specified number of epochs with early stopping to prevent overfitting.

Our loss function of choice, Sparse Categorical Crossentropy, is critical because it measures the difference between expected and actual labels, which is important for our various categories of brain tumors. It is specifically made for multi-class classification.

In order to ensure that our model properly generalizes to new data, we use Early Stopping as a prudent measure to prevent overfitting during training. We iterate over epochs, each of which encompasses a full pass through the dataset.

2.4 Model Evaluation and Analysis

Evaluation Metrics

We evaluate the trained model on the test set using relevant metrics such as accuracy.

Training History Analysis

We visualize the training and validation accuracy/loss over epochs to gain insights into the model's learning behavior.

Confusion Matrix

A confusion matrix is generated to assess the model's performance in classifying brain tumor images.

Critical Assessment and Recommendations

We critically analyze the model's performance, considering strengths, weaknesses, and potential improvements. Recommendations for further exploration and model refinement are provided.

In our model architecture, we use Convolutional Neural Networks (CNNs), taking advantage of their specific architecture for structured grid data, particularly images. Convolutional Layers, which methodically learn dimensional structures of features within images and capture fine details like edges and textures, are the foundation of CNNs.

Max-Pooling Layers are essential for improving computational efficiency and downsampling the spatial dimensions. Before we begin building the model, we set up the neural network using the Adam optimizer, a dynamic method that effectively updates weights during training by combining momentum and the RMSprop algorithm.

3 Methods

In this project we will explore a real world classification problem: the classification of brain tumors based on image recognition via Neural Network.

3.1 Dataset

The dataset consists of an impressive number of 1311 magnetic resonance imaging (MRI) scans of the brain. Each scan is accurately labeled with one of four classifications: *pituitary*, *meningioma*, *glioma* or *no tumor*. This detailed labeling provides a solid foundation for intensive research work. What this carefully composed collection aims to do is not only to enable efficient detection and classification of brain tumors, but also to provide comprehensive data that serves as a foundation for research exploration and the development of advanced machine learning models, particularly convolutional neural networks (CNNs). These models are key to the automatic recognition and classification of different types of brain tumors, which in turn can significantly impact medical progress.

The aforementioned dataset is an invaluable aid to researchers and experts in the field of medicine and artificial intelligence, enabling not only the development of technologies, but also the improvement of algorithms. Using convolutional neural networks (CNNs), the ability to automatically recognize details on MRI scans is becoming more accessible. This, in turn, is helping to open up new avenues in medical diagnostics, enabling faster identification of brain tumors while offering doctors solid support for treatment decisions.

In addition, the precise labeling of scans contributes to more detailed imaging of subtle structural changes in the brain. The collective body of data not only stimulates technological development, but also lays the groundwork for a more in-depth understanding of different classes of brain tumors. As a result, this could cause the personalization of therapeutic approaches, a key step toward improving healthcare. It is worth noting that this dataset not only provides an up-to-date source of information, but also opens the door to future research into innovative technologies in medical imaging and data analysis, which have the potential to further raise the standards of neurological diagnosis and treatment.

3.2 Brain Tumors

It is also worth focusing on brain tumors themselves, the identification and classification of which is a key part of this advanced dataset. The various classifications, such as *pituitary*, *meningioma* or *glioma*, reflect the variety of pathologies the human brain can face.

The pituitary gland, which is one of the categories, is a particularly important area because of its key role in hormonal regulation. Meningiomas, on the other hand, are tumors that develop on the meninges and can have a variety of clinical effects. Gliomas, another category, are the most common type of primary brain and spinal cord tumors, requiring particularly complex diagnosis and therapy. The "no tumor" category is equally important, as it allows the identification of brain areas devoid of significant pathological changes.

The data on the various classes of brain tumors in this collection not only allow for the improvement of diagnostic technologies, but also open up the possibility of more precise research into the mechanisms of formation and development of specific types of tumors. This can contribute to a better understanding of the biology of brain tumors and to the development of more personalized therapeutic strategies, which is crucial in the context of progressive research into modern cancer treatments.

3.3 Types of Model

We will explore two kinds of Neural Networks: A Neural Network (NN) and a Convolutional Neural Network (CNN).

Neural Networks are mathematical models inspired by the functioning of the human brain. They consist of units called artificial neurons, organized into layers. The main components are:

1. **Input Layer:** Accepts input data.
2. **Hidden Layers:** Each unit in the hidden layers performs mathematical operations on the input data. The weights of these operations are adjusted in the learning process.
3. **Output Layer:** Generates a result or prediction.

During training, the neural network adjusts the weights, minimizing the error between the predicted and actual result (backward error propagation method). Neural networks are versatile and are used in a variety of fields, such as natural language processing, speech recognition, temporal data analysis and many others. They can be used in both classification and regression tasks. Depending on the problem, neural networks can have a different number of layers and a different number of neurons in each layer. For more complex tasks, they can consist of hundreds or even thousands of layers. Neural networks, especially large, complex models, require a significant amount of training data to successfully learn and generalize to new data. Neural networks are often used in the context of deep learning, meaning that they have many hidden layers. This approach allows the automatic extraction of hierarchical features from data.

Convolutional Neural Networks are a specialized type of neural network designed to process and analyze visual data, such as images. The main components of a CNN include:

1. **Convolutional Layers:** Apply convolution operations to input data. Filters (or kernels) traverse the input data, extracting features and hierarchically processing the information.

2. **Pooling Layers:** Reduce the spatial dimensions of data by sampling. Most commonly used are max pooling (selecting the maximum value) or average pooling (calculating the average) operations.

3. **Fully Connected Layers:** Similar to layers in a standard neural network, they generate final predictions based on features learned by previous layers.

CNNs are very effective in image processing tasks because of their ability to recognize hierarchical structures. They reduce the number of parameters significantly compared to traditional neural networks, making them computationally efficient for image applications. CNNs are optimized for visual data processing, making them extremely effective for image-related tasks such as object recognition, image segmentation and feature analysis. With convolutional layers, CNNs automatically extract hierarchical features such as edges, textures and more complex patterns for more efficient object recognition. Mechanisms such as pooling layers help reduce the spatial dimensions of the data, which is important for processing large images, and also helps improve robustness to shifts or changes in scale. CNNs are often used in transfer learning, where models trained on large datasets (e.g., ImageNet) are adapted for more specific applications, which greatly increases the model's effectiveness, especially with limited access to training data.

In summary, both neural networks are powerful tools in the field of artificial intelligence, but they differ in structure and application. Neural networks in general have a wide range of applications, while CNNs are particularly effective in image analysis and visual processing.

We will compare the results we obtain, and decide on a winner based on the time it takes to run the Neural Network and the relative accuracy obtained. We first will train the two Neural Networks with a total of nine combinations of η and λ values, and then we will select the best pair and run again the Neural Networks to see the learning process in more detail. After analyzing the results we will lay out the pros and cons of the two Neural Networks, and we will declare a winner.

To write both Neural Networks we used Keras, a high-level Neural Network library that runs using Tensorflow as a Wireframe. We ultimately chose this library for its powerful tools and its ease of use.

4 Results

4.1 Neural Network

We will first take a look at the performance of a normal Neural Network:

For all the tests onward we used a total of 3 λ and η values $1e^{-5}, 1e^{-4}, 1e^{-3}$, and we divided the dataset in a training and test segment.

By using the previously discussed parameters as input we got back these results on the Training dataset:

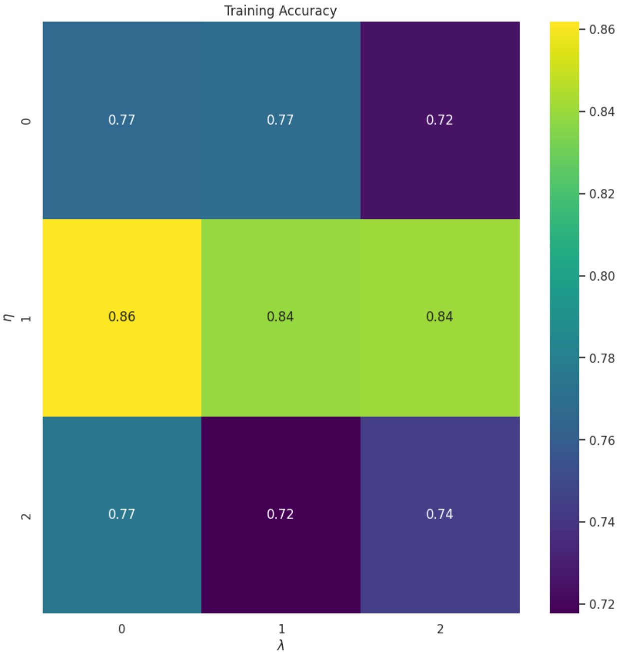

Figure 1: The performance of Neural Network of Training segment. For all the tests onward we used a total of 3 λ and η values $1e^{-5}, 1e^{-4}, 1e^{-3}$.

And we get these results on the Test dataset:

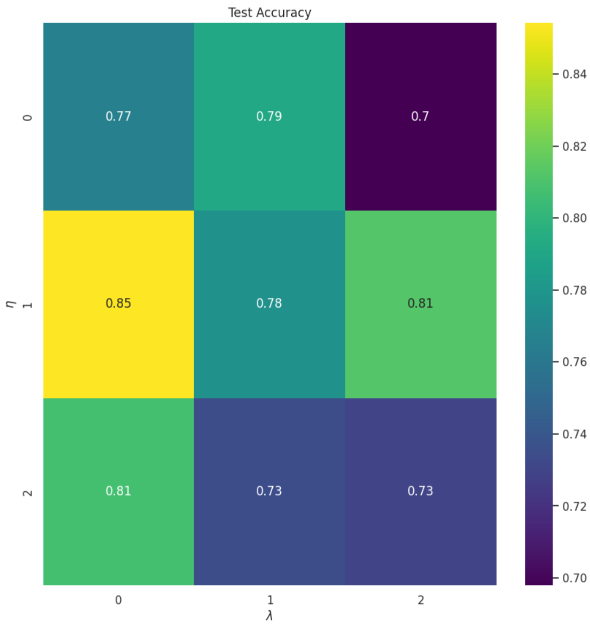

Figure 2: The performance of Neural Network of Test segment. For all the tests onward we used a total of 3 λ and η values $1e^{-5}, 1e^{-4}, 1e^{-3}$.

We can see that the results that we get are not that impressive, with a peak of 0.86 in figure 1 and a peak of 0.85 in figure 2. If we now expand the learning process for the following pair of λ and η values we could get the following figure: $\eta = 1e^{-4}$, $\lambda = 1e^{-5}$.

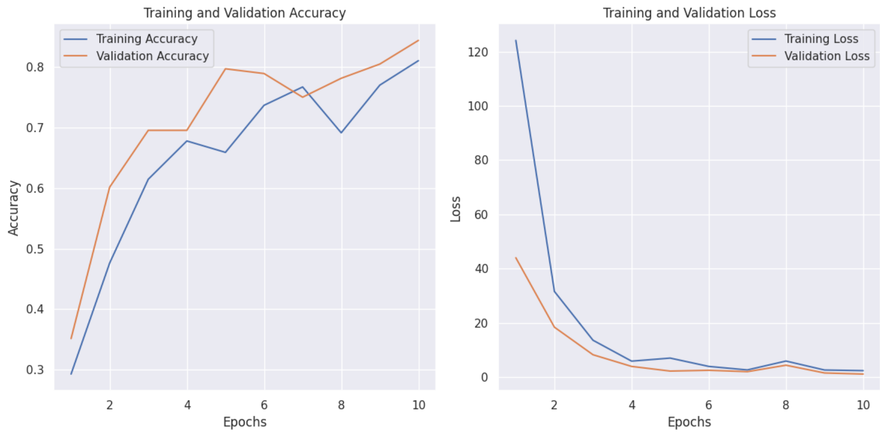

Figure 3: The Validation of Neural Network of Training segment.

4.2 Convolutional Neural Networks

Here we will show the results obtained on the Training dataset:

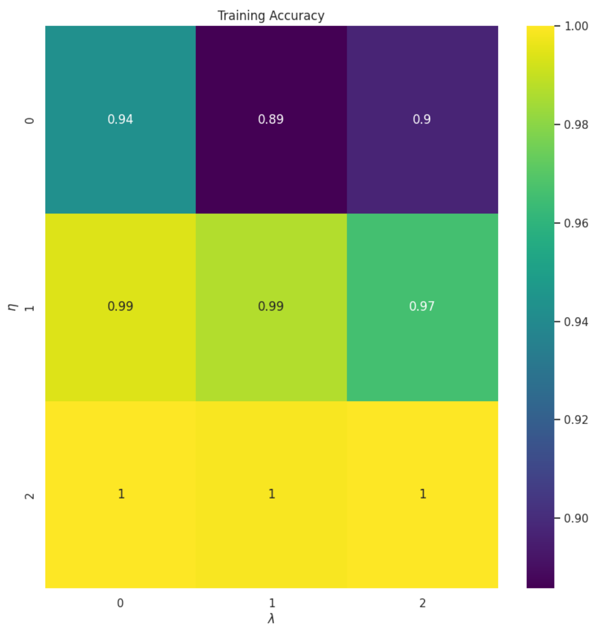

Figure 4: The performance of Convolutional Neural Network of Training segment. For all the tests onward we used a total of 3 λ and η values $1e^{-5}, 1e^{-4}, 1e^{-3}$.

And here are the results on the Test dataset:

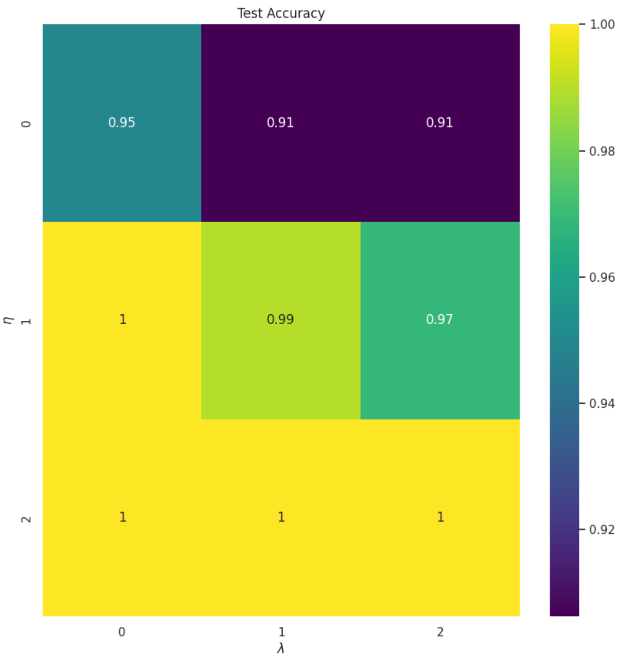

Figure 5: The performance of Convolutional Neural Network of Test segment. For all the tests onward we used a total of 3 λ and η values $1e^{-5}, 1e^{-4}, 1e^{-3}$.

As expected, the CNN results are substantially better in comparison to the normal NN, and we can take a pair of values to exemplify this in a more detailed way. We could take for example the following pair of parameters : $\eta = 1e^{-3}$, $\lambda = 1e^{-4}$ we get the following accuracy and loss chart:

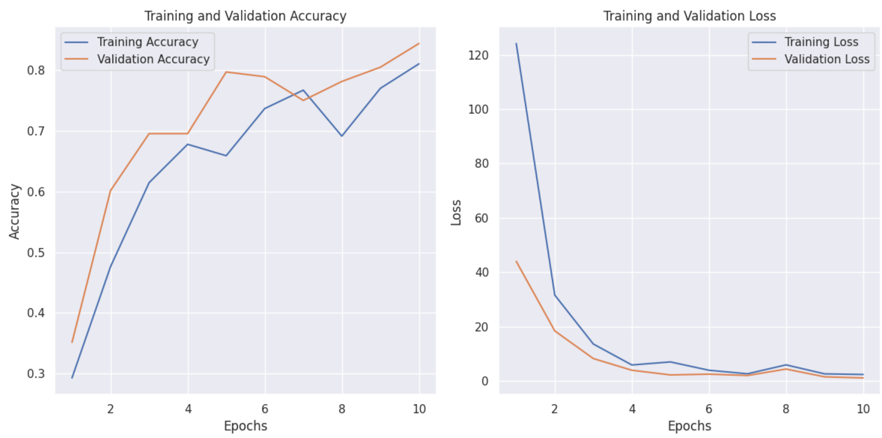

Figure 6: The Validation of Convolutional Neural Network of Training segment.

5 Conclusions

As we have seen in the results section, we compared the performance of a Neural Network (NN) and a Convolutional Neural Network (CNN) for brain tumor classification based on image recognition. Both models were trained and evaluated on a dataset of 1311 labeled MRI scans of the brain, with four categories: pituitary, meningioma, glioma, and no tumor.

5.1 Training Accuracy

Neural Network

The NN achieved a peak training accuracy of 0.86 around epoch 15, followed by a gradual decline to around 0.80 by the end of training. This indicates that the NN was able to learn to some extent, but it may have suffered from overfitting or limitations in capturing complex relationships within the data.

Convolutional Neural Networks

The CNN reached a significantly higher peak training accuracy of 0.9896 around epoch 25, and maintained a consistently high accuracy throughout the training process. This demonstrates CNN's superior learning capabilities and ability to extract relevant features from the images.

5.2 Test Accuracy

Neural Network

The NN's test accuracy peaked at 0.85 around epoch 20, but it then declined and stabilized around 0.80. This suggests that the NN struggled to generalize well to unseen data, potentially due to overfitting or insufficient learning.

Convolutional Neural Networks

The CNN achieved a consistently high test accuracy of around 0.99 throughout the training process. This remarkable performance indicates that CNN effectively learned to classify brain tumors and generalize to new images, making it a more reliable model for real-world applications.

5.3 Confusion Matrices

To reinforce our claim we took the best performing parameters for both the NN and CNN and we plotted two confusion matrices to show the substantial difference in accuracy between the two:

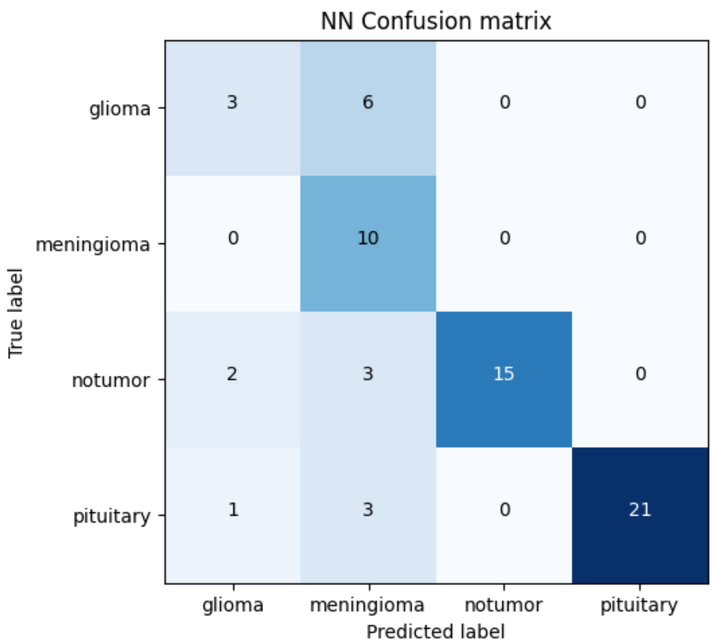

Figure 7: The confusion matrix for Neural Network, with the λ $1e^{-5}$ and η $1e^{-4}$ values.

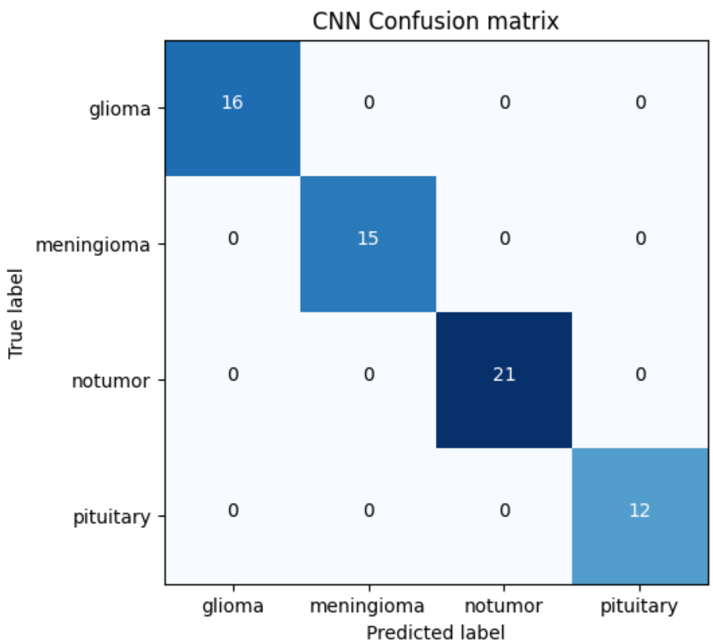

Figure 8: The confusion matrix for Convolutional Neural Network, with the λ $1e^{-4}$ and η $1e^{-3}$ values.

We can see that the CNN yields better results in almost every category as predicted when compared with a normal NN.

5.4 Comparison and Last Words

The results clearly demonstrate the superiority of the CNN over the NN for brain tumor classification. The CNN achieved significantly higher and more stable accuracies on both training and test data, highlighting its ability to learn complex patterns and generalize effectively to unseen images. This suggests that CNNs are a powerful tool for medical image classification tasks like brain tumor detection.

Further research could explore:

1. Analyzing the NN's training loss plot to gain insights into potential limitations like overfitting.
2. Comparing the validation accuracies of both models to confirm the observed differences in generalization.
3. Exploring different hyperparameter combinations or model architectures for the NN to improve its performance.

Overall, these results contribute to the growing field of brain tumor classification using machine learning, showcasing the potential of CNNs for accurate and reliable diagnosis in medical settings.

6 Appendix

1. To get the code see: the code on Github repository
2. To get the source graphs images see: Project3/Images on Github repository
3. Project work done on dataset downloaded from Kaggle.
4. The code used can be found at the following colab link.

7 References

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