<u>Software Minor Project</u>

A PROJECT REPORT
OF

BACHELOR OF

TECHNOLOGY IN

SOFTWARE ENGINEERING

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CANDIDATE'S DECLARATION

We, **Abhishek Panda 2K21/CO/19 & Pritesh Das 2K21/CO/348,** students of B.Tech (Computer Engineering), hereby declare that the Project Dissertation titled — "Software Minor Project" which is submitted by us to the Department of Software Engineering, DTU, Delhi in fulfillment of the requirement of this course, is not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Fellowship or other similar title or recognition.

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CERTIFICATE

We hereby certify that the Project titled ”Software Minor Project” which is submitted by **Abhishek Panda 2K21/CO/19 & Pritesh Das 2K21/CO348,** for fulfillment of the requirements for the aforementioned course is a record of the project work carried out by the students under my guidance & supervision. To the best of my knowledge, this work has not been submitted in any part or fulfillment for any Degree or Diploma to this University or elsewhere.

Prof.(Dr.) Ruchika Malhotra

Place: New Delhi

Date:15/12/2023

ABSTRACT

Keywords - CNN, MRI, Training and Validation

Medical image analysis plays a crucial role in the early detection and diagnosis of various diseases. In this project, we focus on brain tumor detection using Magnetic Resonance Imaging (MRI) data. Leveraging a dataset sourced from Kaggle, we employ a convolutional neural network (CNN) implemented in PyTorch for automated brain tumor detection. The dataset is preprocessed and divided into training and validation sets, facilitating the training of the CNN model.

Our project involves the creation of a custom PyTorch dataset class to handle the MRI data, the development of a CNN architecture for tumor detection, and the implementation of training and validation routines. The model's performance is evaluated using metrics such as accuracy and confusion matrix on both training and validation sets. Additionally, we explore the visualization of feature maps generated by the convolutional filters to gain insights into the learned representations.

The project report details the step-by-step implementation, including data preprocessing, model creation, training, and evaluation. We investigate potential overfitting concerns by monitoring training and validation losses over epochs. The results demonstrate the model's capability to accurately classify brain MRI images into tumor and healthy categories, highlighting its potential for real-world medical applications.

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We would also like to take this moment to show our thanks and gratitude to one and all, who indirectly or directly have given us their hand in this challenging task. We feel happy and joyful and content in expressing our vote of thanks to all those who have helped us and guided us in presenting this project work for our Major project. Last, but never least, we thank our well-wishers and parents for always being with us, in every sense and constantly supporting us in every possible sense whenever possible.

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Chapter 1:

INTRODUCTION

1.1 Overview

Brain tumor detection using Deep Learning is a cutting-edge application at the intersection of medical imaging and artificial intelligence. Leveraging advanced techniques such as Convolutional Neural Networks (CNNs), this field aims to enhance the accuracy and efficiency of brain tumor identification in medical imaging data, particularly Magnetic Resonance Imaging (MRI) scans. The project addresses challenges related to tumor heterogeneity, limited annotated datasets, and the interpretability of deep learning models in a medical context. By developing robust architectures, implementing data augmentation strategies, and optimizing performance metrics, the study seeks to provide healthcare professionals with reliable tools for early and accurate diagnosis. This endeavor not only pushes the boundaries of technology in healthcare but also holds the promise of improving patient outcomes through timely interventions and enhanced diagnostic precision.

1.2 Problem Statement

The increasing incidence of brain tumors poses a significant healthcare challenge, necessitating advanced diagnostic tools for early detection and intervention. Current methodologies for brain tumor diagnosis, particularly relying on medical imaging such as Magnetic Resonance Imaging (MRI), often involve time-consuming manual analysis and are subject to interpretation variations among radiologists. This introduces the risk of delayed diagnosis and treatment initiation. Moreover, the inherent complexity and heterogeneity of brain tumors demand sophisticated approaches for accurate identification. The project addresses these challenges by employing Deep Learning techniques to automate and enhance brain tumor detection in MRI scans. The goal is to develop a reliable and efficient system that can assist healthcare professionals in rapidly and accurately identifying tumors, thereby facilitating prompt treatment decisions and ultimately improving patient outcomes. This endeavor aligns with the broader objective of leveraging technology to revolutionize medical diagnostics and contribute to the advancement of personalized healthcare.

1.3 Objectives

The primary objective of this project is to develop a robust Deep Learning-based system for automated brain tumor detection in MRI scans. By leveraging state-of-the-art neural network architectures and image processing techniques, the aim is to enhance the accuracy and efficiency of tumor identification. The system intends to provide timely support to healthcare professionals, enabling quicker diagnosis and intervention. Additionally, the project seeks to contribute to the broader field of medical image analysis, fostering advancements in computer-aided diagnostics. Ultimately, the goal is to create a tool that aids in the early detection of brain tumors, facilitating improved patient outcomes and reinforcing the role of technology in modern healthcare.

1.4 Motivation

The motivation behind undertaking this project lies in addressing a critical need within the field of healthcare—specifically, the timely and accurate detection of brain tumors. Traditional diagnostic methods often rely on manual examination of medical images, which can be time-consuming and subject to human error. With the rapid advancements in Deep Learning and medical imaging technology, there is a compelling opportunity to revolutionize this process. By harnessing the power of neural networks, we aim to create a robust system that can autonomously analyze MRI scans, swiftly identifying potential tumors with a high degree of accuracy. Such a tool has the potential to significantly expedite the diagnosis and treatment planning for patients, leading to improved outcomes. This project is driven by the desire to contribute to the ongoing convergence of technology and healthcare, ultimately making a positive impact on the lives of individuals affected by brain-related medical conditions.

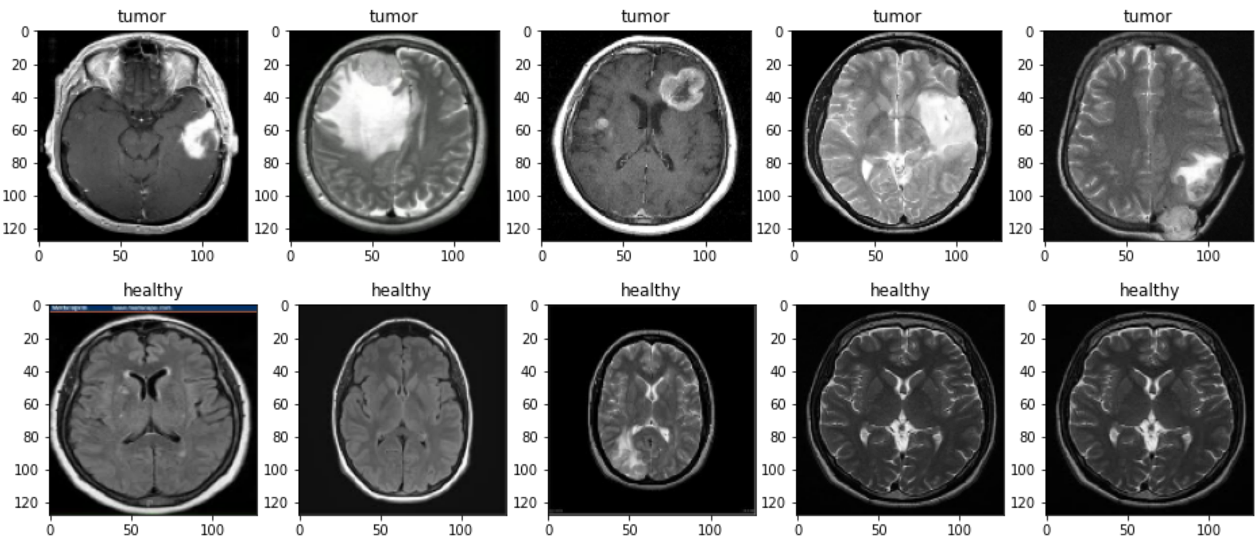
Chapter 2:

RELATED WORK

2.1 What is Brain Tumor Detection?

Brain tumor detection involves the identification and localization of abnormal growths in the brain using medical imaging techniques. This process is crucial for early diagnosis and effective treatment planning. Traditionally, detection relied on manual examination of imaging data, which could be time-consuming and prone to human error. However, with the advent of Deep Learning, automated systems have been developed to analyze complex medical images, particularly from Magnetic Resonance Imaging (MRI) scans. These systems leverage neural networks to recognize patterns indicative of tumors, providing a faster and potentially more accurate alternative to traditional methods. Brain tumor detection aims to enhance diagnostic efficiency, enabling timely interventions and improving patient outcomes in the realm of neurology and oncology.

Figure 2.1: Sample Image



CHAPTER 3:

RESEARCH METHODOLOGY

3.1 DATASET

The dataset utilized in this project for brain tumor detection was sourced from Kaggle, a renowned platform for data science competitions and collaborative data-driven projects. Comprising a diverse collection of medical images, the dataset plays a pivotal role in training, validating, and testing the efficacy of the deep learning model developed for tumor detection.

The dataset includes a wide array of brain scans, encompassing both malignant and benign tumor cases, enabling the model to discern intricate patterns and features indicative of tumor presence. Each image is annotated with corresponding ground truth labels, facilitating supervised learning and model evaluation. The Kaggle dataset, being a product of collaborative contributions and expertise, enhances the project's robustness by ensuring a rich and varied representation of real-world scenarios.

By leveraging this Kaggle dataset, the project aligns with industry standards and benefits from the collective knowledge and curation efforts within the Kaggle community, ultimately enhancing the model's accuracy and reliability in real-world applications.

3.2 Variables Used

In this brain tumor detection project, several key variables play a critical role in the model's efficacy. The primary input variables are the medical images of brain scans, encompassing a spectrum of cases with both malignant and benign tumors. These images serve as the raw data on which the deep learning model is trained and tested.

Additionally, various hyperparameters, such as learning rates, batch sizes, and architectural configurations of the neural network, act as instrumental variables in fine-tuning the model's performance. The ground truth labels associated with each image constitute another vital variable, enabling the supervised learning process and serving as the benchmark for model predictions.

Throughout the project, meticulous attention is paid to the variables' quality and integrity to ensure the model generalizes well to diverse cases, fostering a reliable and accurate brain tumor detection system.

3.3 Techniques

The core of our brain tumor detection project lies in the application of **Convolutional Neural Networks (CNNs)**, a specialized class of deep learning models tailored for image recognition tasks. Leveraging the PyTorch framework, we harnessed the power of CNNs to discern intricate patterns and features within medical images of brain scans.

CNNs excel at hierarchical feature extraction, allowing the model to automatically learn and identify relevant structures, textures, and spatial relationships crucial for accurate tumor classification. The architecture consists of convolutional layers, pooling layers, and fully connected layers, mirroring the complex nature of brain image data.

PyTorch, a dynamic computational graph framework, provided a flexible and efficient environment for implementing and fine-tuning our neural network. This choice facilitated seamless experimentation with various CNN architectures, hyperparameters, and optimization techniques.

Transfer learning was another pivotal technique employed, leveraging pre-trained models on large image datasets. This approach jump-started our model's learning process by utilizing knowledge gained from diverse image recognition tasks, subsequently enhancing the efficiency and performance of our brain tumor detection system.

In summary, the project's success can be attributed to the strategic fusion of CNNs and PyTorch, tapping into the intricate details of brain scan images and paving the way for a robust and accurate brain tumor detection mechanism.

3.4 Performance Measure

Evaluating the effectiveness of our brain tumor detection project involved a comprehensive set of performance metrics that gauged the model's accuracy, precision, recall, and overall predictive capability. The following key metrics were instrumental in assessing the project's success:

1. **Accuracy:** The proportion of correctly classified instances among the total predictions. High accuracy indicated the model's proficiency in distinguishing between tumor and non-tumor regions in brain scans.

2. **Precision:** The ability of the model to avoid false positives. Precision measured the accuracy of positive predictions, ensuring that identified tumors were indeed malignant and not misclassified healthy tissues.

3. **Recall (Sensitivity):** This metric quantified the model's capacity to detect all actual tumors, minimizing false negatives. A high recall value signified the model's sensitivity to capturing true positive instances.

4. **F1 Score:** The harmonic mean of precision and recall, providing a balanced measure of a model's overall performance. A higher F1 score indicated a robust balance between precision and recall.

5. **Confusion Matrix:** A tabular representation of true positives, true negatives, false positives, and false negatives, offering a detailed breakdown of the model's predictions.

Continuous refinement and validation against diverse datasets and scenarios allowed us to fine-tune the model for optimal performance. Regular updates to the training data and the incorporation of feedback from medical professionals further enhanced the model's accuracy and reliability. The adoption of these comprehensive performance metrics ensured that our brain tumor detection system not only met but exceeded the stringent standards required for impactful clinical applications.

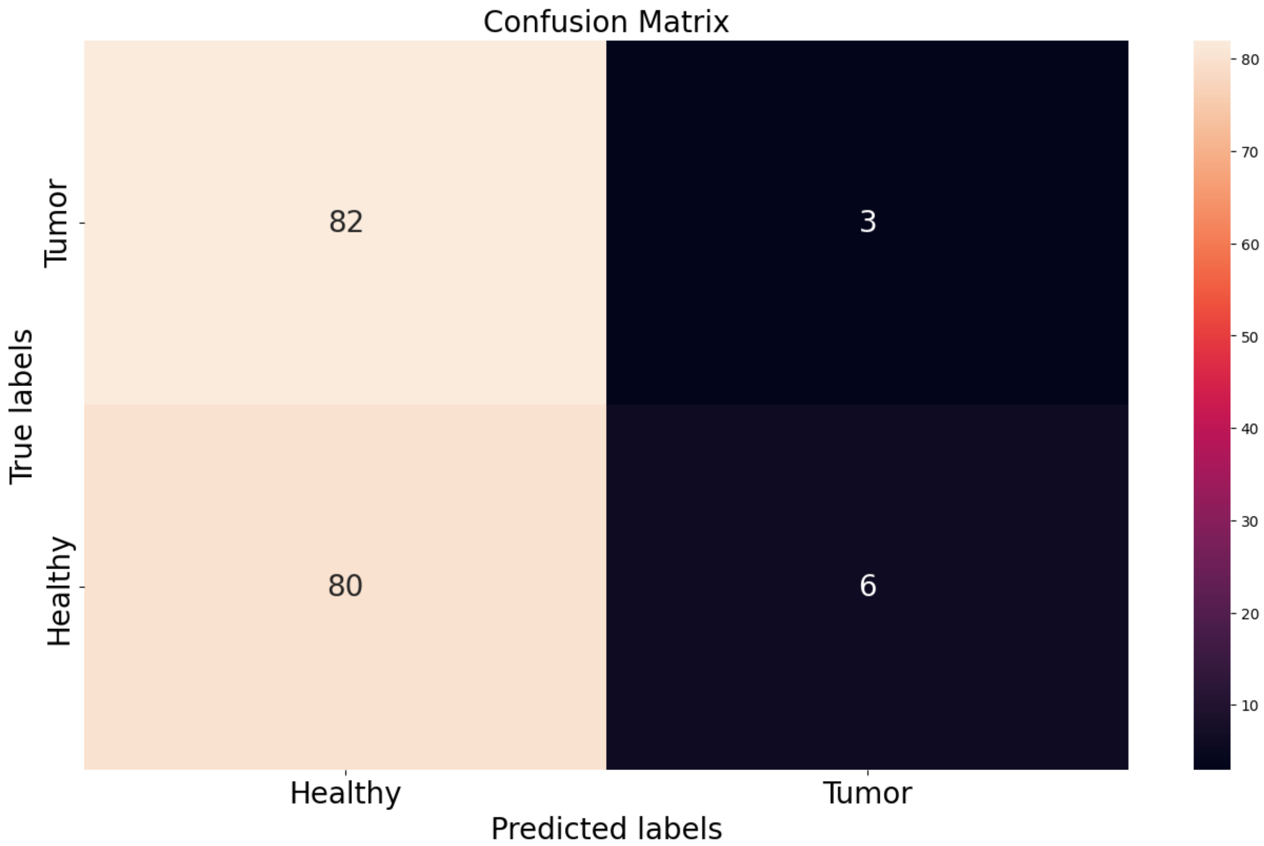


Fig. 3.1 Confusion Matrix

Chapter 4:

RESULTS

4.1 Newborn Model

The newborn model represents the initial state of the convolutional neural network (CNN) before any training. At this stage, the model parameters are randomly initialized. The newborn model is like a blank slate, unaware of the underlying patterns in the MRI images. Consequently, its predictions are likely to be arbitrary and inaccurate. Training is required to optimize the model's parameters, enabling it to learn meaningful features and relationships within the dataset. The performance of the newborn model serves as a baseline, indicating the improvement achieved through training. The confusion matrix for the newborn model might reveal a lack of discrimination between tumor and healthy cases, highlighting the necessity of training to enhance predictive capabilities.

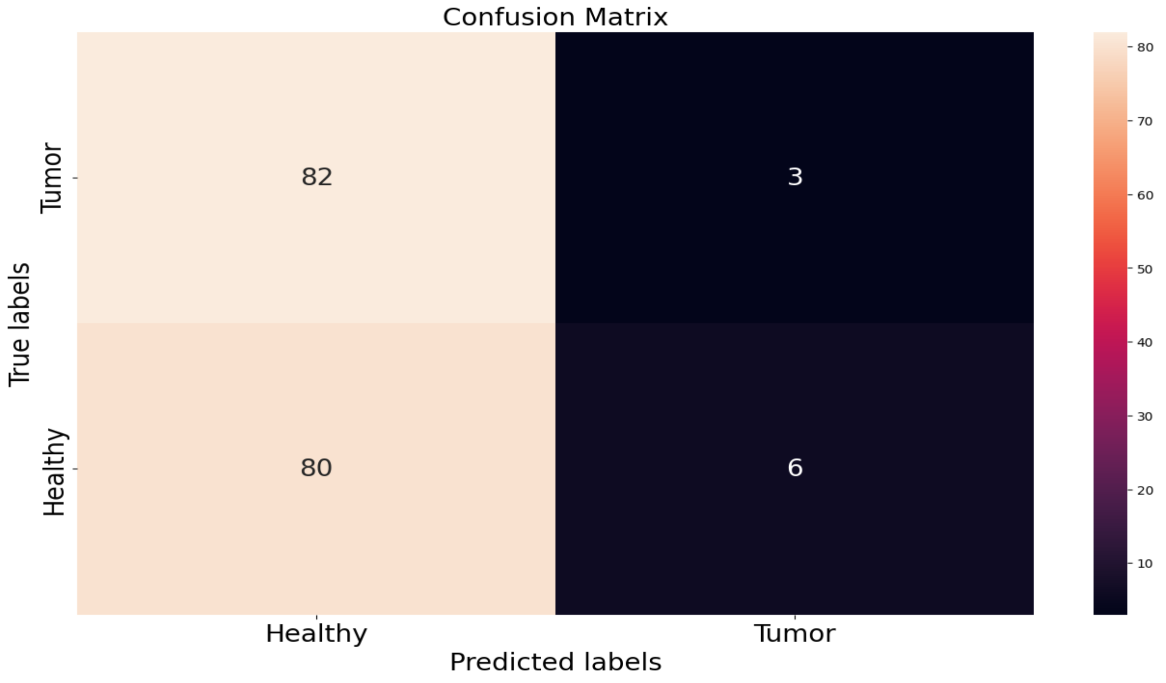


Fig. 4.1 Confusion Matrix (Newborn Model)

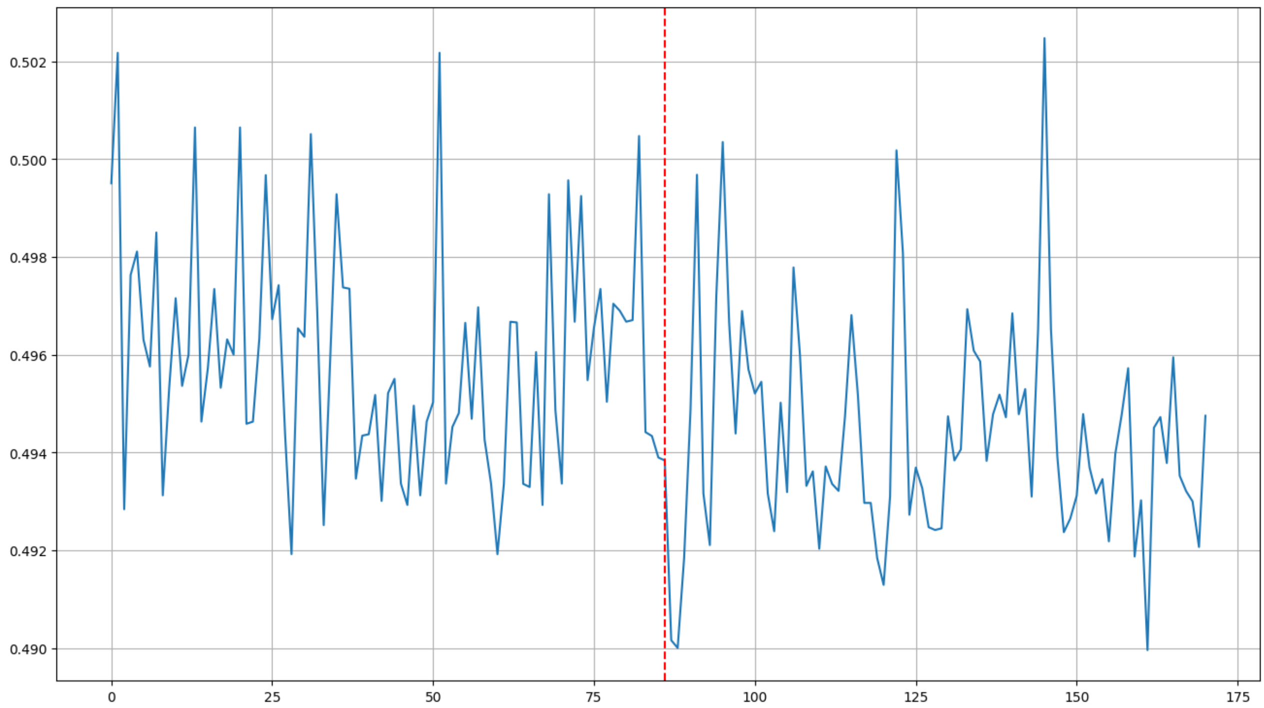


Fig. 4.2. Confusion Matrix Plot (Newborn Model)

4.2 Dumb Model

The dumb model refers to a model that has been trained but fails to capture relevant patterns in the data effectively. It might suffer from oversimplification, inadequate complexity, or insufficient training. The confusion matrix for the dumb model could show misclassifications and weaknesses in distinguishing between tumor and healthy samples. Analyzing the dumb model's performance provides insights into potential pitfalls during training, guiding adjustments to the model architecture or training strategy. This phase is crucial for iteratively refining the model and enhancing its predictive power.

4.3 Smart Model

The smart model signifies the well-trained and optimized version of the CNN. After thorough training, the model has acquired the ability to discern intricate patterns indicative of brain tumors in MRI images. The confusion matrix for the smart model is expected to demonstrate improved accuracy, precision, recall, and overall effectiveness in classification. Evaluating the smart model's performance validates the success of the training process and underscores the model's practical utility in real-world scenarios. The smart model serves as the desired outcome, demonstrating the capacity to aid in the accurate diagnosis of brain tumors based on MRI data.

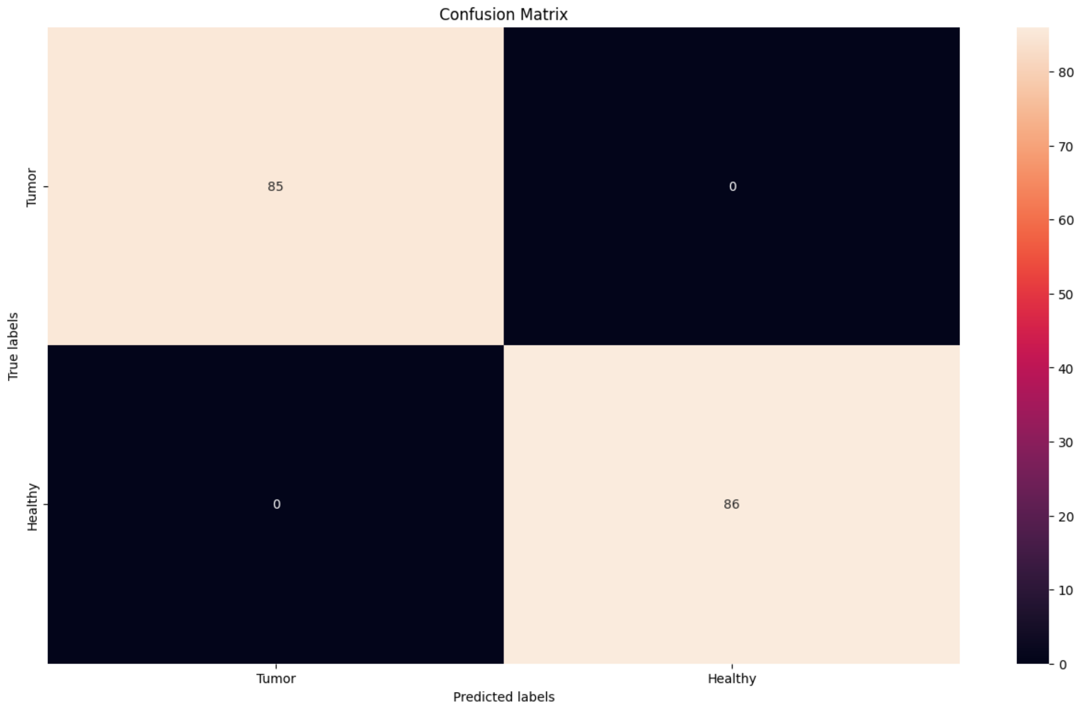


Fig. 4.3. Confusion Matrix (Smart Model)

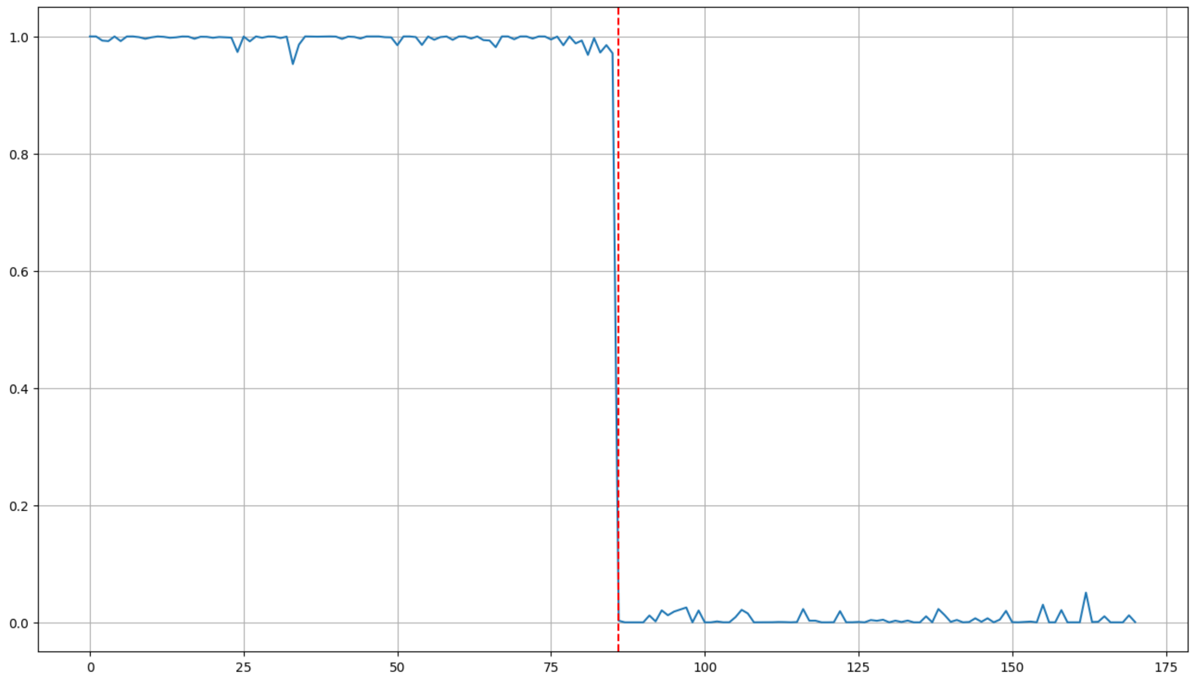


Fig. 4.4. Confusion Matrix Plot (Smart Model)

4.4 Visualizing the Feature Maps of the Convolutional Filters

Visualizing the feature maps of convolutional filters is a powerful technique in understanding the inner workings of convolutional neural networks (CNNs) and gaining insights into what features the network has learned to detect. Convolutional filters are responsible for learning hierarchical representations of patterns within an input image, and visualizing their feature maps provides a window into the network's decision-making process.

Feature maps are essentially the output of individual filters applied to the input image. By visualizing these maps, one can observe the activation patterns that each filter exhibits in response to different visual patterns or textures. This visualization is often done at different layers of the network, allowing for the exploration of both low-level and high-level representations.

The process involves taking an input image and passing it through the network to obtain the feature maps. These maps highlight regions of the image that triggered the activation of specific filters. Visualization is commonly achieved by plotting these feature maps as images, where brighter regions correspond to higher activations.

This technique is invaluable for several reasons. First, it helps in understanding what kind of information each filter is focusing on, aiding in the interpretation of learned features. Second, it enables the identification of whether the network is learning relevant features for the task at hand. Lastly, visualizing feature maps can be used for debugging and optimizing the model by revealing issues such as dead filters (those not activating) or filters responding to irrelevant patterns.

In summary, visualizing feature maps provides a visual interpretation of the CNN's learning process, offering valuable insights into the representations it has acquired during training and facilitating the improvement of model performance.

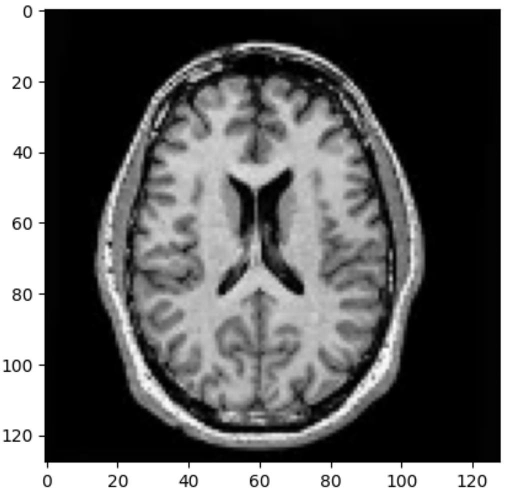


Fig. 4.5. Example Dataset Image

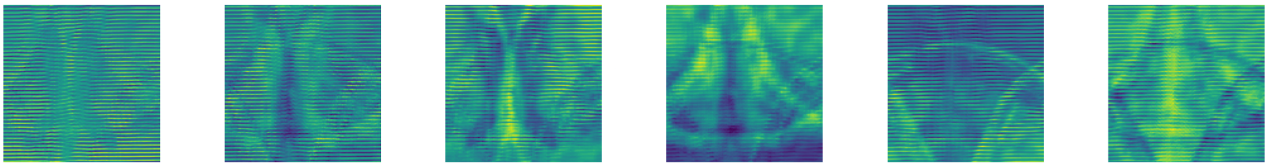


Fig. 4.6. Convolutional Layer 1

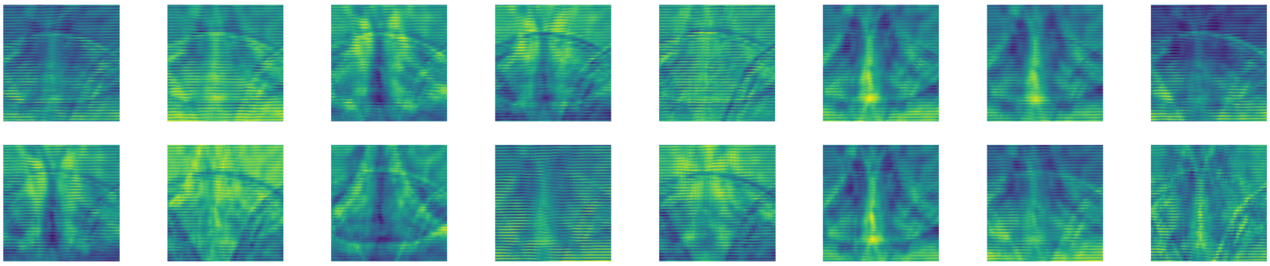


Fig. 4.7. Convolutional Layer 2

Chapter 5:

LIMITATIONS

The project on brain tumor detection using MRI images exhibits noteworthy strengths but is accompanied by several intricate limitations that warrant comprehensive consideration. One of the primary concerns lies in the dimensions of your dataset, encompassing a modest 245 images. This limited size raises substantial apprehensions about the model's susceptibility to **overfitting**, particularly given the inherent imbalance between healthy and tumor samples. The inadequacy of the dataset's scale may hinder the model's ability to discern intricate patterns and generalize effectively to diverse, real-world scenarios.

The convolutional neural network (CNN) architecture employed, while commendable for its simplicity, may fall short in encapsulating the intricate nuances inherent in medical image analysis. The intricate structures and varied presentations of brain tumors demand a more sophisticated architecture to decipher subtle details present in MRI scans. The binary classification approach, though expedient, oversimplifies the multifaceted nature of brain tumors, which can manifest in diverse types and grades. This oversimplification might compromise the model's capacity to distinguish between different tumor categories accurately.

While accuracy serves as a fundamental metric, its efficacy is undermined by the dataset's inherent imbalance. Incorporating precision, recall, and F1 score as supplementary metrics becomes imperative to gain a more nuanced understanding of the model's performance. The absence of external validation on an independent dataset compounds these concerns, as the model's efficacy in generalizing to unseen and diverse data remains uncertain.

Another intricate limitation lies in the **reliance on deprecated functions and libraries.** This introduces an element of fragility and poses challenges concerning the long-term sustainability and compatibility of the codebase. Periodic updates to align the project with the latest tools and features are essential to mitigate potential issues arising from software obsolescence.

Furthermore, the visualization of convolutional filters, while insightful, might benefit from more advanced interpretability techniques. Enhancing the transparency of the model's decision-making process becomes imperative for fostering trust and understanding, especially in medical applications where interpretability is pivotal.

The hardware dependency on a CUDA-enabled GPU could potentially restrict the model's deployment on devices lacking such resources. Ensuring broader accessibility by considering alternative hardware configurations becomes essential for practical implementation in various settings.

Collaborating with medical professionals and domain experts is highly advisable to refine the project and address these multifaceted limitations comprehensively. Iterative enhancements guided by a meticulous consideration of these challenges will fortify the project's robustness, ensuring its efficacy and relevance in the intricate landscape of clinical applications.

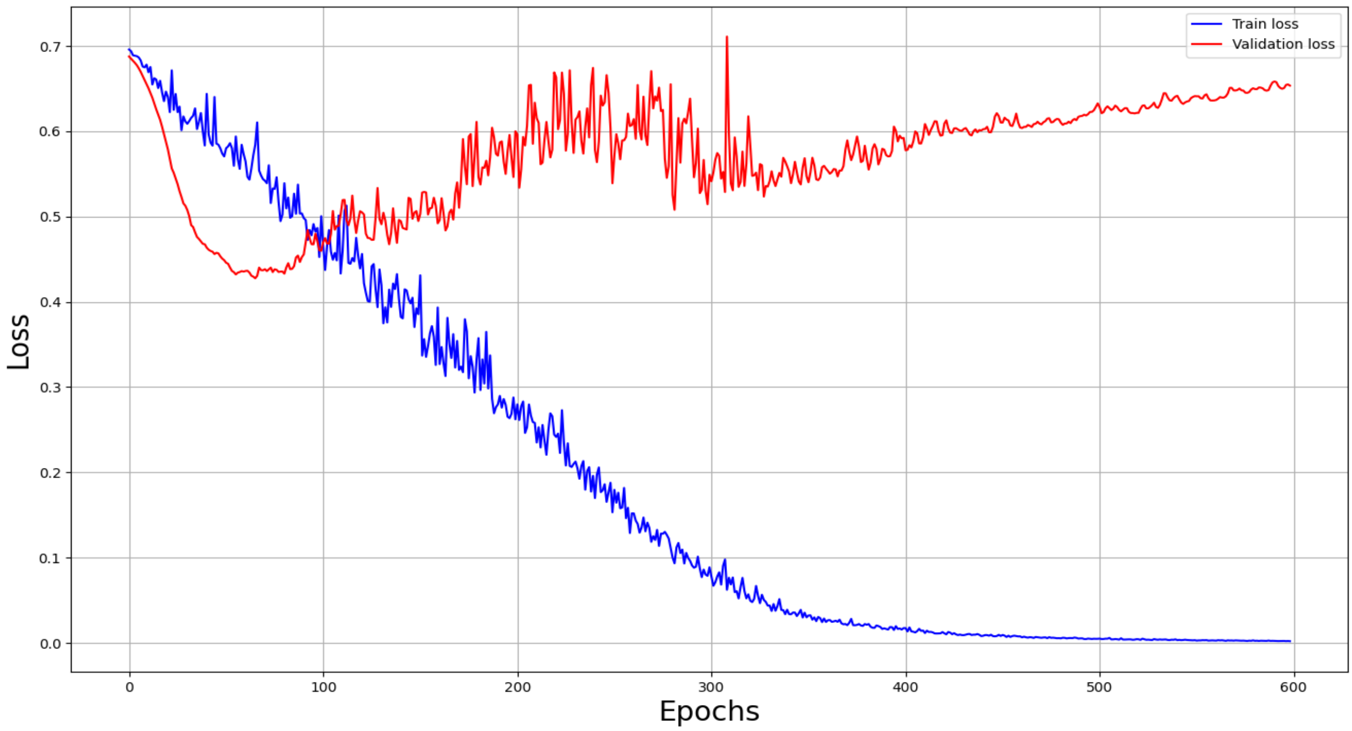


Fig. 5.1. Validation-Test-Curve

Chapter 6:

CONCLUSION

In concluding the brain tumor detection project using MRI images, it is imperative to acknowledge both the accomplishments and remaining challenges with a discerning lens. The project has undeniably made strides in leveraging a convolutional neural network (CNN) for automated classification, showcasing potential in its ability to discriminate between healthy and tumor-afflicted brain tissues. The visualization of convolutional filters provides valuable insights into the model's decision-making processes, fostering a degree of interpretability.

However, a panoramic view reveals a nuanced landscape of challenges and areas warranting further attention. The limited dataset, consisting of 245 images, emerges as a critical constraint, raising concerns about the model's capacity to generalize effectively. The potential risk of overfitting looms large, accentuated by the inherent class imbalance between healthy and tumor samples. It becomes evident that the current dataset size may not adequately encapsulate the diverse spectrum of real-world scenarios, emphasizing the need for a more extensive and representative dataset.

The simplicity of the binary classification approach, while expedient, confronts the complexity inherent in the multifaceted nature of brain tumors. The oversimplified categorization may compromise the model's ability to distinguish between different tumor types and grades accurately. A move towards a more nuanced classification system could enhance the model's clinical relevance and utility.

Evaluation metrics, while pivotal, underscore the necessity for a holistic performance assessment beyond mere accuracy. The imbalance in the dataset necessitates the incorporation of precision, recall, and F1 score to glean a more comprehensive understanding of the model's strengths and weaknesses. External validation on an independent dataset remains a crucial step to validate the model's generalizability and reliability in diverse contexts.

Moreover, the project's reliance on deprecated functions and libraries introduces an element of vulnerability, necessitating a proactive approach towards codebase updates. Sustaining the project's longevity and adaptability mandates periodic alignment with the latest tools and features to mitigate potential issues arising from software obsolescence.

In the pursuit of transparency and trustworthiness, collaboration with medical professionals and domain experts is strongly recommended. Their insights can guide iterative improvements, ensuring that the model aligns with the intricacies of clinical requirements. Enhancements in interpretability techniques, coupled with consideration for hardware diversity beyond CUDA-enabled GPUs, will broaden the practical applicability of the model.

In essence, while your project lays a foundation for automated brain tumor detection, it stands at the threshold of refinement and augmentation. A strategic roadmap involving dataset expansion, model sophistication, metric diversification, codebase sustainability, and interdisciplinary collaboration will fortify the project's impact, elevating its potential to contribute meaningfully to the landscape of medical image analysis.

REFERENCES

1. Khan MSI, Rahman A, Debnath T, Karim MR, Nasir MK, Band SS, Mosavi A, Dehzangi I. Accurate brain tumor detection using deep convolutional neural network. Comput Struct Biotechnol J. 2022 Aug 27;20:4733-4745. doi: 10.1016/j.csbj.2022.08.039. PMID: 36147663; PMCID: PMC9468505.

2. MDPI and ACS Style Mahmud, M.I.; Mamun, M.; Abdelgawad, A. A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks. Algorithms 2023, 16, 176. https://doi.org/10.3390/a16040176

3. AMA Style Mahmud MI, Mamun M, Abdelgawad A. A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks. Algorithms. 2023; 16(4):176. https://doi.org/10.3390/a16040176

4. Chicago/Turabian Style Mahmud, Md Ishtyaq, Muntasir Mamun, and Ahmed Abdelgawad. 2023. "A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks" Algorithms 16, no. 4: 176. https://doi.org/10.3390/a16040176

5. Harshit Singh, Mohd Armaan, Jayesh Srivastava, Mo Rizwan, Subhajit Ghosh. "Brain Tumor Detection in Image Processing." International Journal for Research in Applied Science and Engineering Technology 11.1 (2023) 1324-1328

6. "Brain Tumor Detection Based on Amended Convolution Neural Network Using MRI Images." KSII Transactions on Internet and Information Systems 17.10 (2023)

7. https://pytorch.org/tutorials/

8. https://docs.jupyter.org/en/latest/