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STUDY OF BRAIN TUMOR PREDICTION BY USING MACHINE LEARNING

Vishaya Ummaneni

STUDY OF BRAIN TUMOR PREDICTION BY USING MACHINE LEARNING

A Project

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Information Systems and Technology

by

Vishaya Ummaneni

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ABSTRACT

Technological advancements in deep learning and machine learning have greatly improved the diagnosis and analysis of medical images. This culminating experience project utilized the EfficientNetV2B3 model to predict brain tumors. The research questions are: (Q1) Does the study's deep learning model perform better than current methods when it comes to predicting brain tumor? (Q2) How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD? (Q3) Can the regularization method, such as dropout, enhance the neural network model's generalization? The findings are as follows: (Q1) Yes; the EfficientNetV2B3 model performs better than current methods. (Q2) Based on optimizer value, accuracy is varied: the Adam optimizer provides a higher performance compared to Adagrad and SGD optimizers. (Q3) (a) Yes, using regularization methods helps improve model generalization; (b) model performance is improved from 98% to 99% after using the dropout layer. Finally, the conclusion is that the EfficientNetV2B3 model performs well on brain tumor prediction.

ACKNOWLEDGEMENTS

The completion of this project journey has been marked by challenges, growth, and invaluable lessons. I am filled with so much gratitude to everyone who contributed to its comprehension. I would like to sincerely thank my committee chair cum advisor, Dr. Shayo whose continuous guidance, expertise and patience have been essential throughout this endeavor. Their mentorship not only shaped the focus of this research, but also helped me to become a better person and scholar. I'm indebted to my Principal Investigators, Dr. Molavi and Dr. Sirotnik, for the thoughtful feedback, helpful criticism, and ideas that have made a huge difference in the way I do this project. Furthermore, I would like to let everyone know that I appreciate every participant who shared their integral experience with us. They gave me access and support that no other person had. This would not have been possible without them. As they were major figures in the research, they greatly impacted and stabilized the study outcomes. Alongside, I feel indebted to my family that did not drop their steadfast assistance, love, and motivation. My mother's faith in me acted as a continuous undying motivator. Moreover, I thank my friends and companions for their advice and companionship, and Mr. X for his help by pointing with his fingers at places I needed to turn to, the meaning of which I did not fully understand, yet I cherished. They gave me the zeal and enthusiasm to make the whole long way much more significant and fun.

DEDICATION

With heartful thanks and immense love, I dedicate this project to my beloved parents, Chalapathi Rao Ummaneni and Sujatha Ummaneni, who are my pillars of strength and sources of inspiration. Even though we're far apart, your love goes beyond the distance, wrapping me in warmth and helping me wherever I go. This project is a way to show how thankful I am for your constant support, sacrifices, and endless love. Your advice has guided me through tough times with strong faith and strength. As I start this project, I remember the values, lessons, and dreams you've given me. Your unwavering belief in me has fueled my goals and pushed me towards success.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

Various medical imaging techniques can be used to investigate the body without the need for incisions or sedation. They encompass a wide range of procedures and modalities used to visualize the human anatomy for diagnostic and treatment purposes. Hence, medical imaging plays a vital role in improving people's health (Abdalla et al., 2018). In medical imaging, image segmentation is a process that involves identifying and characterizing the various parts of the body using a combination of deep learning techniques. Finally, the main goal of this process is to improve the accuracy and efficiency of brain tumor prediction by using image processing techniques.

The World Health Organization claims that around 400,000 individuals around the world are diagnosed with a brain tumor (Abdalla et al., 2018). In the US, it has been estimated that around 86,970 new cases of brain tumors will be diagnosed in 2019 (Abdalla et al., 2018). Most recent is in China, it has been estimated that around 24212 new cases of brain tumors will be diagnosed in 2023 (Xia et al., 2023). These include primary tumors, tumor of the malignant type and non-malignant type.

In the last 8 years, efforts have been given to using machine learning in a precise way to detect and predict tumors; (Hemanth et al., 2019). With this technique, diverse tasks like imaging and diagnosis of the tumors can be smoothly done, in a diagnostics fashion. But even though this technology has made a huge step forward, there are still areas of research that need to be studied. ((Hossain et al.,2019), (Gill et al.,2022), (Hemanth et al., 2019)).After reviewing the papers on this topic, some articles claim that using MRI images can help detect brain tumors (provide at least two references here) ((Hossain et al.,2019), (Gill et al.,2022), (Hemanth et al., 2019)), while others claim that the accuracy of model, we can improve through deep learning model (Part of machine learning). ((Hossain et al.,2019), (Gill et al.,2022), (Hemanth et al., 2019)). (again, provide at least two references here).

This project is focused on developing a method that uses both deep learning (customized EfficientNetV2B3) and MRI data. This involves training neural networks on large sets of data, such as images of brain tumors. The algorithms then extract various patterns and features from the data. After reviewing the literature on this topic, I decided to include a few research questions in the study. These are part of my research strategy to improve the accuracy of the model and make it more efficient. ((Hossain et al.,2019, (Gill et al.,2022), (Mahajani et al.,2013))

Although the initial studies on the use of machine learning in predicting brain tumors show the potential of this technology, they also highlight the limitations of this approach like efficiency of model and model accuracy ((Hossain et al.,2019), (Brindha et al.,2021)). By conducting a follow-up study, we can hopefully address these issues and contribute to the advancement of this technology. Previous studies highly recommended experimenting with advanced CNN models for achieving good amount of accuracy on brain tumor prediction.

The growth of tumors in the brain is one of the main causes of cancer fatalities around the world, affecting millions of individuals. Early detection of brain tumors can significantly improve the prognosis and help patients with their conditions. However, it can be quite a complicated and difficult process. That is why it is necessary that the patients get proper help from a team of doctors and other specialists (Gill et al., 2022). The machine learning field is showing the latest developments during the last few years. The field of healthcare has been one of the leading applicators of this emerging technology ever since its development began. Thanks to the implementation of machine learning methods, a more impartial and rapid option for document analysis will be made available. Using AI and machine learning tools it is possible to analyze a large variety of data and to identify hidden features and patterns of the data (Hemanth et al., 2019). Machine learning field will be expanding its algorithm' implementation and one day it will be powerful enough to distinguish and predict brain tumors more precisely. The implementation of machine learning in brain tumor treatment could represent a massive breakthrough in patient outcome prediction and could potentially help in saving lives (Sharma et al.,2022)

Problem Statement

The distracting brain tumor diagnosis study area has become an occasion for the long-awaited medical research breakthrough, requiring high accuracy and availability. Currently, most methods rely on CATs and MRI to find brain cancers, which have limitations in terms of accuracy (Sharma et al.,2022). Furthermore, these tools do not provide enough precision as needed isn't critical (Brindha, P and other writers., 2021). Furthermore, they are very likely to bring subjectivity into their analytical process, hence highlighting the need for more precise and neutral methods (Sharma et al., 2022). Recent imaging methods such as functional MRI have established details of how brain gliomas function actively. Despite their omnipresence in diagnostic tools and imaging which are a mainstay in the clinical practice, their use in a clinical settingis quite restricted (Brindha et al.,2021). The AI brain tumor detection development is closely connected with some limiting factors. These include the need for diverse and large datasets, privacy and consent issues, and algorithmicbiases. Despite the potential of AI in improving the efficiency and accuracy of brain tumor diagnosis, its clinical implementation remains a work in progress.

Due to the increasing demand for precise and early brain tumor diagnosis, the development of ethical and effective solutions is becoming more critical. This will allow for a paradigm shift in the way brain tumors are detected and treated. In this study, I am going to use machine learning techniques for brain MRI tumor detection. Now a days machine learning plays a vital role in the health care sector.

Areas of further studies of previous research work suggested to use explore different models and suggested to use optimization techniques to improve the model performance (Sharma et al.,2022), (Brindha et al.,2021).

In this research I am going to study brain tumor prediction by using machine learning. Several research papers are already published on this, but still there is a space for improvement for accurate prediction of tumors. In this research I am going to use EfficientNetV2B3 customized model to improve the models mentioned in Table 1 (Brindha et al.,2021).

Table 1. Summary of Previous Research Papers

Author Names	**Proposed Method**	**Accuracy**
(Jafari et al.,2012)	SVM	83.2%
(Hossain et al.,2019)	CNN	92%
(Rajeshwari et al.,2013)	DWT	88.6%
(Daljit Singh et al.,2012)	PCA and GLCM	91.67%
(Magboo et al.,2022)	CNN	85%
(Gill et al.,2022)	VGG19	79%
(Mahajani et al.,2013)	BPNN and KNN.	72.5%
(Bidkar et al.,2023)	CNN	90%

Research Questions

1. Does the study's customized EfficientNetV2B3 customized deep learning model perform better than current models when it comes to predicting brain tumor? (Jafari et al.,2012)
2. How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD? Can regularization method, such as dropout, enhance the neural network model's generalization? (Bidkar et al.,2023)
3. Will the implementation of the regularization method, such as dropout, enhance the neural network model's generalization?

Organization of the Study

The study is presented in several chapters, each of a different quality, to define the particular purpose. Chapter 1 looks at the start of the study by giving general information and a statement of the research questions that drive the process. After hanging this, Chapter 2 presents the Literature Review, where we expound on the previous studies that provide relevant knowledge on the same topic. Turner Chapter proceeds to focus on the Research Methodology, which encompasses the data collection process, model analysis tools and methods and the selection and evaluation of the model. In the fourth chapter of the research, we see the presentation of data analysis and findings, including tasks like data preprocessing, model performance evaluation and comparative studies of the different optimizers and their regularization methods. The last chapter, which is the fifth one, wraps it all up by providing a summary of the findings displayed, discussing their outcomes, and giving some suggestions for research that can be conducted in the future.

CHAPTER TWO

LITERATURE REVIEW

There is a need for more precise and reliable methods for detecting brain tumors. There have been several studies on deep learning's potential to improve the diagnosis and prognosis of brain tumors ((Jafari et al.,2012), (Hossain et al.,2019), (Rajeshwari et al.,2013), (Daljit Singh et al.,2012), (Magboo et al.,2022), (Gill et al.,2022), (Mahajani et al.,2013), (Bidkar et al.,2023)). However, there is a need to be a gap in the research's full potential. Although some of these studies have shown promising results, there needs to be a clear consensus regarding the optimal deep learning architecture, training methods, and input data types ((Rajeshwari et al.,2013), (Magboo et al.,2022)) Most studies on deep learning focus on a single type of brain tumor, such as meningiomas or gliomas. They need to provide an extensive evaluation of the capabilities of these models in identifying other types of tumors (Rajeshwari et al.,2013). Further studies on the accuracy and efficacy of brain tumor prediction techniques could lead to better outcomes and earlier detection for patients (Gill et al.,2022), (Mahajani et al.,2013), (Bidkar et al.,2023).

Question 1: Does the study's deep learning model perform better than current brain tumor prediction methods?

The research conducted by (Hossain et al.2019) investigates implementing CNNs in diagnosing brain tumors. It encourages deep learning to develop an algorithm to hone accuracy and cut out manual processes such as disease identification. The introduction of the study puts a lot of emphasis on the importance of early disease detection. The paper also deals with the necessity of automatic diagnosis, which the novel technology of CNN can solve. The authors talk about the deficiencies of traditional diagnostic methods when identifying certain diseases and how computational techniques can address those issues. It is striking that the implementation of CNNs is highlighted due to their competence in learning diverse features hierarchically, which is suitable for visual tasks (Hossain et al. 2019). The article describes the measures used to prepare the input for processing and proceeds. The study has experimental results supported by the proposed CNN method to validate the capability of detecting brain tumors. We will examine calibration metrics, especially Specificity, Sensitivity, Accuracy, and Area under the ROC curve, to measure effectiveness. The comparative analysis of the CNN approach with the existing benchmarks and methods can be a decisive factor in a thrilling novelty and efficacy tester.

The implications of the work will be analyzed in the discussion section, where the strengths and weaknesses of the proposed CNN model will be discussed (Hossain et al.,2019). The paper's concluding Section likely summarizes the study's findings and emphasizes the significance of the CNN-based method for identifying brain tumors (Hossain et al.,2019). The researchers may also talk about how their work has affected clinical practice. The paper should consider the broader scope of the literature on this subject. It should likely place itself within the framework of related works that examine the utilization of deep learning and machine learning in medical imaging. In addition, relevant studies on CNNs within neuroimaging may be presented to contextualize their novelty and significance. The study conducted by the researchers led by Hossain et al. provides valuable insights into the field of brain tumor diagnosis, leveraging CNN's capabilities to improve the accuracy of the diagnosis (Hossain et al.,2019). The findings show that integrating deep learning methods into medical imaging can yield significant benefits. This paper serves as a crucial step toward realizing the potential of such systems. Finally, they achieved 92% accuracy for a 70:30 training and testing split ratio.

Question 2: How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD?

The study by (Gill,2022) discusses using the VGG19 algorithm to detect brain tumors with the SGD Optimizer and the AdaDelta Optimizers. This work presented is not only one of the key acknowledgments of the creation of medical image analysis but also a nice starting point for everyone interested in the history of medical imaging. The authors present the VGG19 CNN model, which is state-of-the-art in image classification. Moreover, they run experiments to show good performance of shallow and deep networks using the SGD optimizer or AdaDelta solver. VGG19 selection and the diverse set of optimization methods are meant to add to the state-of-the-art representation by standardizing medical imaging.

The literature review of advanced learning in medial image analysis, which contributes to this study by discovering the importance of CNNs in merging multidimensional features out of images, is also being generated. Although the VGG19 architecture is employed these days very often in a variety of domains, such as image classification, there is a unique application of these optimizers for detecting brain tumors, as proposed by the authors here. The study reveals the main idea, which is that optimizers must be used to networks with depth accurately and innately.

Moreover, these results also give us specific knowledge of " VGG19 tumor model detection methods" efficiency. The research highlights the various steps taken that could have been used to derive the analysis, including instance preprocessing. I will thoroughly discuss the result in the Section of my paper. The scientists researched the topic as reported at an international conference. This brought the research disputes to the forefront of the global scientific discourse (Gill et al., 2022).

Further galleries showcased the newest breakthroughs of the time: space exploration, telecommunication, and electronics, among them. The work that Gill et al. have done has proven that deep learning and optimization algorithms play a role in the remarkable increase in the accuracy of brain tumor detection. Their findings are an important example of how computational methods in medical diagnostics are being refined. For the SGD optimizer, they achieved 79 % accuracy, and for AdaDelta, they achieved 74% accuracy.

(Bidkar et al.,2023) presented a method for developing deep learning capabilities for brain tumor classification using MRI images and has contributed to the advancement of medical image analysis. The paper's introduction emphasizes the need for efficient and accurate methods for identifying and categorizing brain tumors. It also positions the authors' work within the broader field of deep learning in medical imaging. CNNs play a vital role in automatically extracting complicated features from MRI data. The paper suggests a new way of optimizing the training process for brain tumor detection and classification using MR data. This approach is a blend of both Adam optimizer and the special will that Sewing Trust exposes. This landmark method is meant to enhance the model's efficiency, stability, and overall solution. It is worth noting that the papers reviewing brain tumor segmentation and recognition using MRI mainly focused on different CNN architecture designs, dataset options, and optimization methods. The authors' (model name) method is the alternative to traditional approaches, paving the way for deeper research. The technique-related part of the paper outlines the details of the experimental setup and preprocessing steps adopted and the architecture of the Convolutional Neural Network (CNN) (Bidkar et al.,2023). The choice of evaluation metrics plays an important part in assessing the method. The main evaluation metrics, namely the Dice coefficient for sensitivity, specificity, and segmentation accuracy, will also be used to assess the proposed method's performance. By including the comparative reviews of available methodologies, the conclusion of the hybrid Adam training method gets overshadowed by the assessment of its produced output. In this way, the authors have passed the boundaries of traditional methods in the medical image analysis sector. The authors' role in developing deep learning methods for diagnosing a brain tumor proves that they are buying into the idea of unceasing improvements in biomedical imaging, which is the only way to tackle the difficulties of tumor classification. The scientific community acknowledges this study's significance and serves as a valuable contribution to advancing computer-aided diagnosis. Finally, they achieved 90 % accuracy by using the Adam optimizer (Bidkar et al.,2023).

Question 3: Will implementing the regularization method, such as dropout, enhance the neural network model's generalization?

(Magboo et al.,2022) published a study that analyzed the detection of brain tumors using MRI scans. Another exhibition at the 8th International Conference on Artificial Intelligence, Machine Learning, and Deep Learning (IC2IE) emphasized using CNN's for diagnosing brain tumors. This endeavor aims to expose the range of CNN's used in medical pictures instead of their effectiveness and impact on brain tumor diagnosis. Moreover, it would present deep learning applications relevant to the medical imaging diagnostic requirements. Though the earlier studies have been done, the latest studies have worked on various types of CNN architectures and the manner of their preprocessing methods, intending to diagnose MRI scans. The evaluation metrics to test the performance of the CNN model include specificity, sensitivity, and accuracy. In addition, the literature on brain tumor detection will also show comparative studies' analyses of the existing methods, which are the strengths of the protocol (Magboo et al., 2022). The study conducted by Magboo provides valuable insights into the utilization of CNNs in detecting brain tumors. It also contributes to the discourse about the advantages of deep learning in medical imaging. The findings support the evolution of computational methods that can improve the diagnostic capabilities of healthcare institutions. The study's findings are expected to impact brain tumor detection significantly. It suggests integrating CNN technology into clinical workflows (Magboo et al.,2022).

In this research, I will study brain tumor prediction using machine learning. Several research papers have already been published on this, but there is still room for improvement in accurately predicting tumors. I will use the Ean fficientNetV2B3 customized model to improve the models I have mentioned clearly in Table 1 (Brindha et al.,2021).

CHAPTER THREE

RESEARCH METHODS

For this project, I collected datasets from the Kaggle platform and used Google Collab for the implementation. I have used Python language and TensorFlow framework for implementation.

The dataset comprises four categories: The four labels mentioned are Glioma, Meningioma, No tumor, and Pituitary. The project tests different neural networks to find out which one, including the EfficientNetV2B3 neural network, is more suitable for this task. Also, it compares the performance with different optimizers, such as Adagrad, Adam, and SGDO, & tries different approaches like dropout to improve model generalization capability.

This investigation aims to make the case that the EfficientNetV2B3 model offers some architectural advantage and denotes superiority to current methods in predicting brain tumor occurrence. To analyze the key structures, like generalization, scalability, and multi-tasking, the authors explain how it leads to performance enhancement, reduction of model size, and how fast the training is. Furthermore, the model is mentioned as one that is designed for diverse applications and can be reused using transfer learning. It is also described as one that excels in features like regions of interest detection and pixel indication.

The three optimizers used to assess the performance impact are Adagrad, Adam, and SGD, the last being normal gradient descent. The authors investigate the performances of these optimizers, trying to identify their strengths and analyze how they can perform with sparse and changing data by conducting experiments with them. The objective is to ascertain the optimizer that brings about the most advancement in brain tumor prediction accuracy.

Regularization dropout is done during the learning process to get the models a generalized form. One of the ways to do so is to randomly drop the neurons at every training epoch to combat the overfitting issue. These modifications will then be compared with other most utilized normalization techniques, such as L1 and L2 norms, via a series of empirical tests to determine the superiority of dropout in improving model performance better and faster generalization capability. The article brings up ideas for creating more efficient deep-learning models to develop more accurate brain tumor prediction models.

Does the study's deep learning model perform better than current methods when predicting brain tumors?

In this project, EfficientNetV2B3 model is used. The EfficientNetV2B3 is a very advanced deep learning model part of Google's EfficientNet family. The EfficientNet models are designed from a simple point of view to achieve human-like performances with fewer parameters. In 2021, a paper published by Google entitled "EfficientNetV2: "Improving the Efficiency ofTraining and Reducing the Model Size" conducted by Tan et al. 2021 was a study on a new scaling technique called the EfficientNetV2B3. This approach is about keeping a balance of a model's size and the force between its accuracy and descriptiveness. EfficientNetV2B3 is particularly useful for its scalable, efficient scaling. This involves the fluctuations of the base networks, like their image depth, resolution, and width, with additional components like the skip connections and the attention modules (Tan et al., 2021). The existing approach used by EfficientNetV2B3 contrasts with other scalability methods that emphasize the features, length, and depth of the system creation without assessing how these affects overall balance (Koonce,2021).

EfficientNetV2B3 has fewer parameters and lower computational costs than its generally high resource requirements. This allows it to perform better in real world scenarios. The multi-scale compound method is the principal way out of the EfficientNetV2B3 model. It, e.g., provides different scaling actions to be implemented on the network (Koonce et al.,2021). In contrast to the other scaling methods, only a particular fractional relation is used for all factors; EfficientNetV2B3 uses power scaling, i.e., the whole dynamic range of a parameter is exploited. This may establish a balanced network that can prove the equally strong performance of the factors (Koonce et al.,2021). The EfficientNetV2B3 model also includes the posture and efficient search methods with the neural network architecture, which can lead to the automatic creation of a network structure. The design of this model involves a mixture of dense and block inverting technology that helps the clamping effect and increases the speed of the process (Tan et al.,2021). The picture down there contains the advanced layers of the model with the MB con and Fus MB con; these layers are core parts of the EfficientNetV2B3 model.

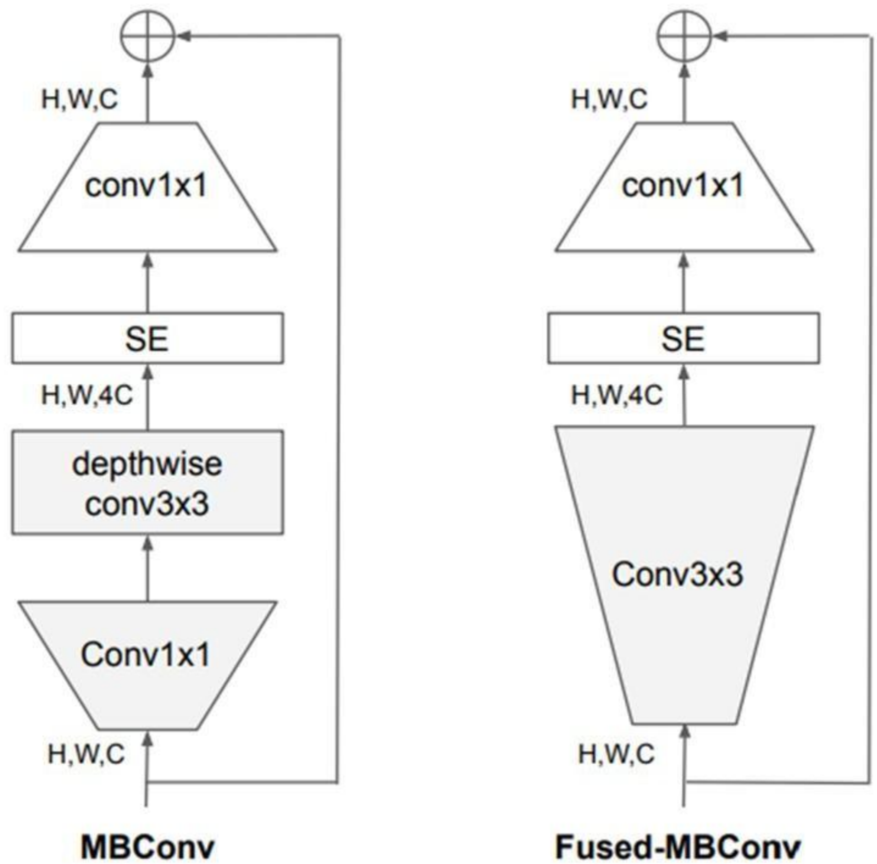

Figure 1: MBConv and Fused-MBConv layers (Tan et al.,2021).

The model also inserts a novel attention mechanism called SE attention, which the system utilizes to capture long-range dependencies. Besides its remarkable performance, the EfficientNetV2B3 has a faster training rate, which is more than previous models could have. The reason for its wide application is that it is compact in size and employable through a simple scaling method. The model of EfficineNetV2B3 can be applied rapidly for training sessions, and it can dynamically scale networks. So, this model is fit to develop demanding systems (Tan et al.,2021). The super transfer learning feature, indispensable for Effnet2B3, is undeniably important. Its feature of pre-training via developing transferable learning makes it fast to adapt to new applications.

These features were validated in some experiments in which the EfficientNetV2B3 achieved state-of-the-art results in classification (object detection) and other tasks (Tan et al.,2021). The EfficientNetV2B3 deep learning model introduced into the discipline of machine learning is revolutionary in the context of the efficiency and size of ML models because it attained higher performance. Its super-human skills are derived from utilizing a small body structure, pre-training on a big group of data sources, and compound scaling. The EfficientNetV2B3 model released recently has brought a new wave of progress in deep learning. It brings very extensive and versatile capacities for machine learning and AI. It achieved impressive outcomes and prospective training time. Compared to conventional systems, it is relatively more capable (Koonce et al.,2021).

How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD?

The project experimented with three optimizers, and the result was on the culminating experience. The adaptive gradient optimization algorithm, Adagrad, sometimes called dynamic learning rate, allows the adjustment of the learning rate for various weight parameters proportionally to their historical gradients. This optimization can increase the level of learning on the sparse dataset, which means that the dataset has fewer samples. With the help of Adagrad, the learning rate for the non-dominating factors will grow, and the popular components will decrease. This way, the model can concentrate on the underrepresented data in the training set. As it can handle nonstationary determining, Adagrad can also be used in neural networks with complicated data (Zitzler et al., 2003).

The Adam, another widely used optimization algorithm, uses properties of RMSprop and Adagrad in combination. It implements the principle of adaptive learning by having it alongside the element of momentum. Adam also occurs due to the degeneration of means of the past and the squared gradients and their momentum (Zillter et al., 2003). In this way, one can calculate the average slope of the gradient, which can help trace the exact shape of the gradient; therefore, the accuracy and speed in solving the problem will be improved. The Adam algorithm is characterized as robust when dealing with noisy or sparse gradient slopes; thus, it is periodically applied to deep neural networks (Zitzler et al.,2003).

The main underlying tenet and traditional algorithm used in optimization, SGD, performs an iterative update of the model parameters as the steepest slope of the descending loss function is considered (Zitzler et al., 2003). During epochs of SGD, the individual gradients of the training data points are calculated, and then the average of the gradient is used to update SGD. Unlike Adam and Adagrad, for which a separate learning rate is assigned to each parameter, SGD uses only a single learning rate per parameter, which can be difficult to implement with nonstationary functions. On the other hand, it represents a computationally straightforward technique that can accomplish satisfactory results in a large amount of data (Zitzler et al., 2003).

Simultaneously, the choice of an optimal algorithm can formidably affect the precision of a network's neural network (or Zitzler et al., 2003). The sparsity of data sets is a unique problem specific to AI, and the Adam algorithm and the Adagrad algorithm can successfully modify their learning rates to deal with sparse data sets. However, the more(S) widely adopted method, SGD, is known to be able to handle small datasets.

Sparse and nonstationary data sets are usually processed using Adad and Adagrad algorithms as they are more problem-oriented than SGD since they have learning rates. Moreover, this hill feature that can jump out of the local valley and get on the global optimum may result in better accuracy (Zitzler et al., 2003). Admittedly, the picky factor can be rationalized by different methods, like the kind of network and the complexity of data. Still, choosing the correct one in the long run is possible. This links various algorithms to implement processes that best apply to a given problem.

Can regularization methods, such as dropout, enhance the neural network model's generalization?

The facility configuration guarantees robustness to unseen issues in machine learning model prediction. It is a process aimed at avoiding the accidental learning of the features of the sample and having the model fitted to the sample. The process is profound in models based on strong and functional neural networks. It can be carried out by different means, whether it's L1 and L2 regularization and dropout (Girosi et al.,1995). The dropout technique is just among the exhaustive methods of essence in most recent times since it plays an imperative function in increasing the potency of a model of neural networks toward generalization. The dropout allows neural network cases to protect the models from undesirable relying on discriminant features (Baldi et al.2013). The other layer in the perceptron model called a neural network dropout layer, selects the randomly chosen nodes. It zeroes out set points or disables them and takes place during the testing; it brings about dropped units again (Baldi et al., 2013).

One target of the dropout technique is to ensure the model is overfitted. However, adaptation can occur when the neurons can adjust themselves. If a specific neuron set can be dropped, the other neurons in the network will have to accommodate them to bring good results. This allows the learning of generalized (Baldi et al.,2013) and robust features through a network of neurons instead of just one neuron using the task information. The simplification of the neural network model dropout method enhances the substantially deep features generally applied. The advantage of the dropout method is its combined ability to be easily integrated into every neural network model. For example, it can be brought to feedforward and convolutional networks such as pulses and impulses (Baldi et al.,2013).

The only requisite of designing a dropout layer is that its input and output dimensions are equal to the connected layer's input and output dimensions. The dropping technique in constructing a neural network model is especially ingressive in tasks of overcoming complexity in data. In line with this, it could help avoid overfitting the training data (Baldi et al.,2013). The possibility of eliminating separate units in a model for neural network purposes helps avoid learning about relationships among various available features for one portion of the data and use the model extensively. It can deactivate neurons in a neural network, which could be the source of the network's complexity, impeding faster training. It is especially advantageous when working with big data sets, as dimensions could be an issue, and training complex models may require a lot of time. One more of the benefits of dropout is that it allows clustering of something like contract learning (Baldi et al., 2013). For example, training a neural network will, in turn, lead to the formation of different subnetworks by dropping the units at once. Finally, we can combine these features to develop a broader model capturing vital and complex information.

Moreover, featuring several models to predict and average the predicted scores helps boost neural network performance. Whereas the dropout methods are very resourceful in handling the increased extent of complexity at the data level, small ones, however, can be best handled otherwise. Another example, exemplified by the algorithm, could be that the model could be faster operating if the data set is not very large or has a relatively low complexity level (Baldi et al.,2013). Moreover, the models that do not possess the given number of neurons will not excite the deactivation of the neurons in the model. Hence, the difficulty of the model might remain the same. In addition, the true class of neural network models can be altered by noise deactivation of neurons. Despite this, such minimum chess ability learning is still advantageous, making the model develop more generalized skills (Baldi et al.,2013).

The world of dropout methods to strengthen neural network models is priceless. It implies a kind of random dropping of groups (or "dropping of sets") of units during training, which, in turn, may create less complexity, enable the prevention of overfitting, and promote the development of more generalized functions. The dropout method looks very easy to implement and is reactionless to any neural network. It simplifies the delivery of different models' performance without requesting further settings. The efficiency of the dropout method can depend on the samples & the complexity of the model it is training (Baldi et al.,2013).

On the other hand, it is advisable to only go for such a single solution in some situations. Typically, with this method, neural network models can be enhanced to a higher level in a suitable context. Balance is a factor in developing a high-performance tool in machine learning because it is an important part (Baldi et al., 2013).

CHAPTER FOUR

TESTING

For data visualization, I visualized some images from the information set.

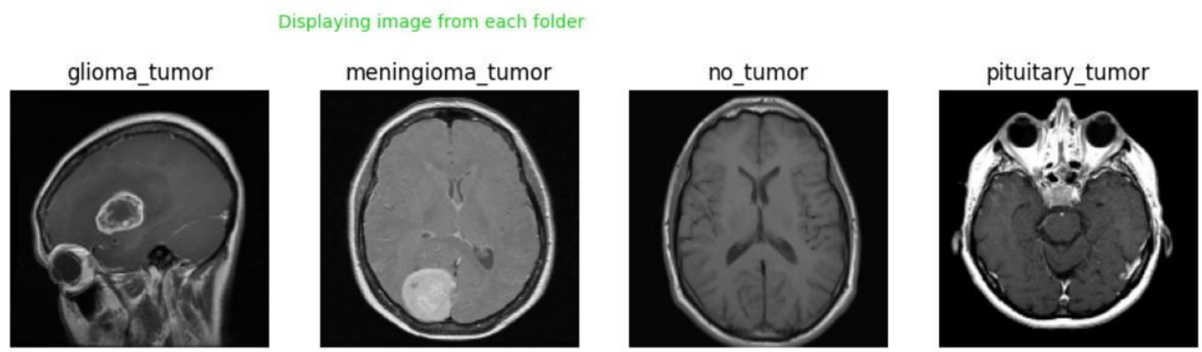

Figure 2: List of tumors in the dataset (From Code)

Does the study's deep learning model perform better than current methods for predicting brain tumors?

The study found that the deep learning model (EfficientNetV2B3) could perform better than the current techniques for identifying brain tumors. The findings were based on a comprehensive review of previous investigations, which also tried to develop similar models. In the literature review, the highest accuracy rate was reported at 92%. On the other hand, in this study, the model achieved a 99% accuracy rate (as seen in the figure below). The study utilized a larger dataset with an advanced deep learning method (EfficientNetV2B3). This may have resulted in the model's superior performance. The study shows that deep learning performed better than current techniques when identifying and predicting brain tumors.

	precision	recall	f1-score	support
0	0.98	1.00	0.99	97
1	1.00	0.99	0.99	88
2	1.00	0.94	0.97	49
3	0.98	1.00	0.99	82
accuracy			0.99	316
macro avg	0.99	0.98	0.99	316
weighted avg	0.99	0.99	0.99	316

Figure 3: Classification Report (From Code)

How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD?

The optimizer employed during the training process significantly impacts a model's overall performance. Research results indicated that Adagrad has the lowest accuracy at 88%, while Adam and SGD have higher accuracies at 99% and 95% (as seen in Figs 4,5 and 6).

Adagrad result:

	precision	recall	f1-score	support
0	0.91	0.90	0.90	97
1	0.90	0.74	0.81	88
2	0.85	0.92	0.88	49
3	0.85	0.99	0.92	82
accuracy			0.88	316
macro avg	0.88	0.89	0.88	316
weighted avg	0.88	0.88	0.88	316

Figure 4: Classification report (Using Adagrad optimizer - From Code)

Adam result:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	97
1	1.00	0.99	0.99	88
2	1.00	0.94	0.97	49
3	0.98	1.00	0.99	82
accuracy			0.99	316
macro avg	0.99	0.98	0.99	316
weighted avg	0.99	0.99	0.99	316

Figure 5: Classification report (Using Adam optimizer - From Code)

SGD result:

	precision	recall	f1-score	support
0	0.96	0.95	0.95	97
1	0.95	0.92	0.94	88
2	0.98	0.92	0.95	49
3	0.91	0.99	0.95	82
accuracy			0.95	316
macro avg	0.95	0.94	0.95	316
weighted avg	0.95	0.95	0.95	316

Figure 6: Classification report (using SGD optimizer - From Code)

The results indicate that different optimization methods can significantly impact the model's performance. Experimenting with different methods will help you find the best one for brain tumor prediction.

Can regularization methods, such as dropout, enhance the neural network model's generalization?

Neural networks utilize dropouts to prevent overfitting. Overfitting can occurif a model gets too complicated and stops learning the relationships and patternsit has trained on. This can result in poor generalization of new pieces of information.

In neural networks, dropout is used to improve the model's generalization. It can prevent the neurons from becoming dependent on one another, pushing them to learn more robust and independent features. As a result, the model is less susceptible to small data changes.

In my study, the model's accuracy improved from about 98 percent to 99% after implementing the dropout technique (as seen below in Fig. 7 and 8). This is because it allowed the model to learn new relationships and patterns in the data instead of just memorizing them. Although the training accuracy decreased, the test score also increased. This shows that the model became less focused on training data and improved its performance on new tests.

Without dropout layer:

	precision	recall	f1-score	support
0	0.95	1.00	0.97	97
1	1.00	0.95	0.98	88
2	1.00	0.94	0.97	49
3	0.98	1.00	0.99	82
accuracy			0.98	316
macro avg	0.98	0.97	0.98	316
weighted avg	0.98	0.98	0.98	316

Figure 7: Classification report (Without dropout layers - From Code)

With dropout layers:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	97
1	1.00	0.99	0.99	88
2	1.00	0.94	0.97	49
3	0.98	1.00	0.99	82
accuracy			0.99	316
macro avg	0.99	0.98	0.99	316
weighted avg	0.99	0.99	0.99	316

Figure 8: Classification report (With dropout layers - From Code)

CHAPTER FIVE

CONCLUSION AND FUTURE WORK

This study thoroughly evaluated and assessed the subject and has developed recommendations and findings.

Conclusion

Does the study's deep learning model perform better than current methods when predicting brain tumors?

The results of my study revealed that the deep learning method (EfficientNetV2B3) performed better than the current techniques when it came to identifying brain tumors. This finding is significant as brain tumors are among the most challenging types of cancer to treat. The accuracy and consistency of the deep learning model's predictions were better than those of traditional methods. This suggests that technology may improve the treatment and diagnosis of brain tumors.

How much does the model's performance change when using different optimizers such as Adagrad, Adam, and SGD?

Choosing the best model optimizer significantly impacts the model's performance. Throughout this experiment, I observed that the concluding accuracies of the three optimizers—SGD, Adam, and Adagrad—varied. A combination of this model and data set may be more effective than the others, as Adam's variation was the most accurate of the three.

Can regularization methods, such as dropout, enhance the neural network model's generalization?

Neural network regularization with dropout has been shown to enhance networks by reducing their overall risk or by allowing the regularization to generalize the network; this keeps the network from overfitting because the regularization may learn generalized patterns. One regularization technique involves excluding trained neurons and ignoring randomly selected neurons exclusively. This leads to the loss of all other parameters; however, it enables robust features that can help reduce the co-adaptation of neurons. Connected to this, the technique may also increase the precision of forecasts concerning unobservable samples.

These research results highlight how the fine-tuned EfficientNetV2B3 deep learning system is an effective tool for precise brain tumor prediction. It was proved to be powerful and accurate compared to traditional methods, reaching 99% accuracy. The research sheds light on how optimum selection can lead to better model performance, where the result of precision was led by the Adam optimizer.

This implies that the more powerful deep learning algorithms may not only bring novel technology in the medical diagnostics area but also lead other research researchers to stand that while deep learning progresses, it has significant potential to be applied to diagnosing and treating brain tumors. Therefore, the approach should be modified to provide more quantitative factors in the model design to achieve higher precision and efficiency. The research marks the basis for subsequent work towards building more accurate and time-based prediction models for clinical settings that will, in the long run, contribute to improving health outcomes relevant to the medical sector.

Future Work

The newly discovered results come up with future studies that are advanced and are supposed to be looking for better results by improving the neural network ability of the deep learning model for predicting brain tumors through regularization techniques other than dropout. Furthermore, looking into the effect of different architectures and parameters on model performance might aid the detection of key aspects of training that bring a rise in accuracy and efficiency. Additionally, studies could explore technologies based on developing user-friendly interfaces for deploying advanced deep-learning models in clinical settings. This would mean finding out what users need, which will be the starting point. This will enable the designing of user-friendly user interfaces and help healthcare professionals deploy and utilize predictive models seamlessly. It would be useful to leverage this research platform to develop the medical diagnostics discipline further and successfully apply new and advanced deep learning techniques in healthcare in the future.

The newly discovered results come up with future studies that are advanced and are supposed to be looking for better results by improving the neural network ability of the deep learning model for predicting brain tumors through regularization techniques other than dropout. Furthermore, looking into the effect of different architectures and parameters on model performance might aid the detection of key aspects of training that bring a rise in accuracy and efficiency. Additionally, studies could explore technologies based on developing user-friendly interfaces for deploying advanced deep-learning models in clinical settings. This would mean determining what users need, which would be the starting point. This will enable the designing of user interfaces that are friendly and that help healthcare professionals to deploy and utilize predictive models seamlessly. It would be useful to leverage this research platform to develop the medical diagnostics discipline further and successfully apply new and advanced deep learning techniques in healthcare in the future.

Kaggle References

https://www.kaggle.com/code/guslovesmath/tumor-classification-99-7-tensorflow-2-16

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APPENDIX A

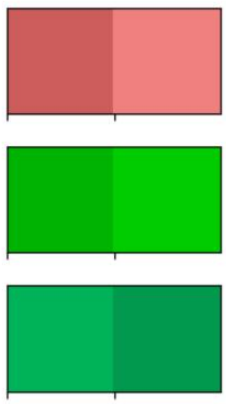
CODING

Importing Libraries

```
from seaborn import palplot as pp
import seaborn as sb
from os import path as P
from os import listdir as LD
from tqdm import tqdm as progress_bar
import cv2 as image_processing
import numpy
import matplotlib.pyplot as Mat_py
from sklearn.utils import shuffle as SH

from sklearn.model_selection import train_test_split as split
from tensorflow.keras.utils import to_categorical as categ

from tensorflow.keras.applications import EfficientNetV2B3

from tensorflow.keras.layers import GlobalAveragePooling2D as GAP
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Dense as D
from tensorflow.keras.models import Model as M

from tensorflow.keras.callbacks import ReduceLROnPlateau, ModelCheckpoint

from sklearn.metrics import classification_report,confusion_matrix
```

Data Loading

```
Maroon = ['#CD5C5C','#F08080']
Olive = ['#00b300', '#00cc00']
Teal = ['#00b359','#00994d']

pp(Maroon)
pp(Olive)
pp(Teal)
```



```
[ ] List_of_tumors_inside_dataset = ['glioma_tumor','meningioma_tumor','no_tumor','pituitary_tumor']
```

Image Loading

```
brain_tumor_images  = []
brain_tumor_labels =  []
image_dimension = 150
for T in List_of_tumors_inside_dataset:
    print(T)
    Dataset_path = P.join('/content/drive/MyDrive/BRAIN-MRI-II',T)
    directories = LD(Dataset_path)
    for DT in progress_bar(directories):
        images_location = P.join(Dataset_path,DT)
        image_process = image_processing.resize(image_processing.imread(images_location),
                                                (image_dimension, image_dimension))

        brain_tumor_images.append(image_process)
        brain_tumor_labels.append(T)
```

```
glioma_tumor
100%|██████████| 926/926 [00:12<00:00, 77.10it/s]
meningioma_tumor
100%|██████████| 937/937 [00:11<00:00, 81.14it/s]
no_tumor
100%|██████████| 396/396 [00:03<00:00, 117.07it/s]
pituitary_tumor
100%|██████████| 901/901 [00:11<00:00, 78.33it/s]
```

Data Processing

```
[ ] brain_tumor_images,brain_tumor_labels = SH(brain_tumor_images,brain_tumor_labels, random_state=101)
```

+ Code + Text

```
[ ] brain_tumor_images.shape

(3160, 150, 150, 3)
```

+ Code + Text

```
[ ] train_Brain_tumor_images,test_brain_tumor_images,train_brain_tumor_labels,test_brain_tumor_labels = split(brain_tumor_images,
                                        brain_tumor_labels,
                                        test_size=0.1,
                                        random_state=101)
```

```
[ ] Train_brain_tumor_labels = []
    for TL in train_brain_tumor_labels:
      Train_brain_tumor_labels.append(List_of_tumors_inside_dataset.index(TL))
    train_brain_tumor_labels = categ(Train_brain_tumor_labels)

    Test_brain_tumor_labels = []
    for TL in test_brain_tumor_labels:
      Test_brain_tumor_labels.append(List_of_tumors_inside_dataset.index(TL))
    test_brain_tumor_labels = categ(Test_brain_tumor_labels)
```

With Dropout Layer

```
base_weights = 'imagenet'
efficient_model = EfficientNetV2B3(weights='imagenet',
                    include_top=False,
                    input_shape=(image_dimension,image_dimension,3))

Efficient_model = efficient_model.output
Efficient_model = GAP()(Efficient_model)
Efficient_model = Dropout(rate=0.5)(Efficient_model)
Efficient_model = D(4,activation='softmax')(Efficient_model)
Efficient_model = M(inputs=efficient_model.input,
                    outputs = Efficient_model)
```

```
[ ] Efficient_model.compile(loss='categorical_crossentropy',optimizer = 'Adam', metrics= ['accuracy'])
```

Without dropout Layer

```
base_weights = 'imagenet'
efficient_model = EfficientNetV2B3(weights='imagenet',
                    include_top=False,
                    input_shape=(image_dimension,image_dimension,3))

Efficient_model = efficient_model.output
Efficient_model = GAP()(Efficient_model)
Efficient_model = Dropout(rate=0.5)(Efficient_model)
Efficient_model = D(4,activation='softmax')(Efficient_model)
Efficient_model = M(inputs=efficient_model.input,
                    outputs = Efficient_model)
```

```
[ ] Efficient_model.compile(loss='categorical_crossentropy',optimizer = 'Adam', metrics= ['accuracy'])
```

MODEL.H5

```
[ ] call_back_1 = ModelCheckpoint("model.h5",
                                  monitor='val_accuracy',
                                  save_best_only=True,
                                  mode="auto",
                                  verbose=1)
    call_back_2 = ReduceLROnPlateau(monitor = 'val_accuracy',
                                   factor = 0.3,
                                   patience = 2,
                                   min_delta = 0.001,
                                   mode='auto',
                                   verbose=1)
```

```
[ ] history_of_Efficient_model = Efficient_model.fit(train_Brain_tumor_images,train_brain_tumor_labels,
                                  validation_split=0.2,
                                 epochs =60, verbose=1,
                                 batch_size=60,
                                 callbacks=[call_back_1,call_back_2]
                                 )
```

```
Epoch 1/60
38/38 [==============================] - ETA: 0s - loss: 0.5625 - accuracy: 0.7978
Epoch 1: val_accuracy improved from -inf to 0.90685, saving model to model.h5
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.s
  saving_api.save_model(
38/38 [==============================] - 75s 446ms/step - loss: 0.5625 - accuracy: 0.7978 - val_loss: 0.2827 - val_accuracy: 0.9069 - lr: 0.00
Epoch 2/60
```

```
Count_of_EPOCHS = [E for E in range(60)]
image , ordinate = Mat_py.subplots(1,2,figsize=(12,12))

brain_tumor_training_accuracy , brain_tumor_training_loss = history_of_Efficient_model.history['accuracy'] , history_of_Efficient_model.history
brain_tumor_validation_accuracy ,brain_tumor_validation_loss = history_of_Efficient_model.history['val_accuracy'] , history_of_Efficient_model.

image.text(s='Training and Validation Accuracy/Loss vs Epochs',size=18,color=Olive[1],y=1,x=0.28,alpha=0.8)

sb.despine()

ordinate[0].plot(Count_of_EPOCHS, brain_tumor_training_accuracy, marker='>',markerfacecolor=Teal[1],color=Olive[1],
           label = 'Training Accuracy')
ordinate[0].plot(Count_of_EPOCHS,brain_tumor_validation_accuracy , marker='>',markerfacecolor=Maroon[1],color=Maroon[0],
           label = 'Validation Accuracy')
ordinate[0].legend(frameon=False)
ordinate[0].set_xlabel('Epochs')
ordinate[0].set_ylabel('Accuracy')

sb.despine()

ordinate[1].plot(Count_of_EPOCHS, brain_tumor_training_loss, marker='<',markerfacecolor=Teal[1],color=Olive[1],
           label = 'Training Loss')
ordinate[1].plot(Count_of_EPOCHS,brain_tumor_validation_loss , marker='<',markerfacecolor=Maroon[1],color=Maroon[0],
           label = 'Validation Loss')
ordinate[1].legend(frameon=False)
ordinate[1].set_xlabel('Epochs')
ordinate[1].set_ylabel('Loss')


image.show()
```

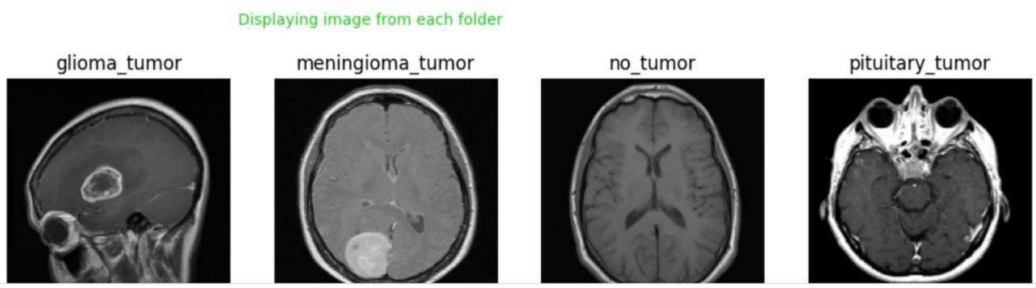
APPENDIX B

DATA VISUALIZATION

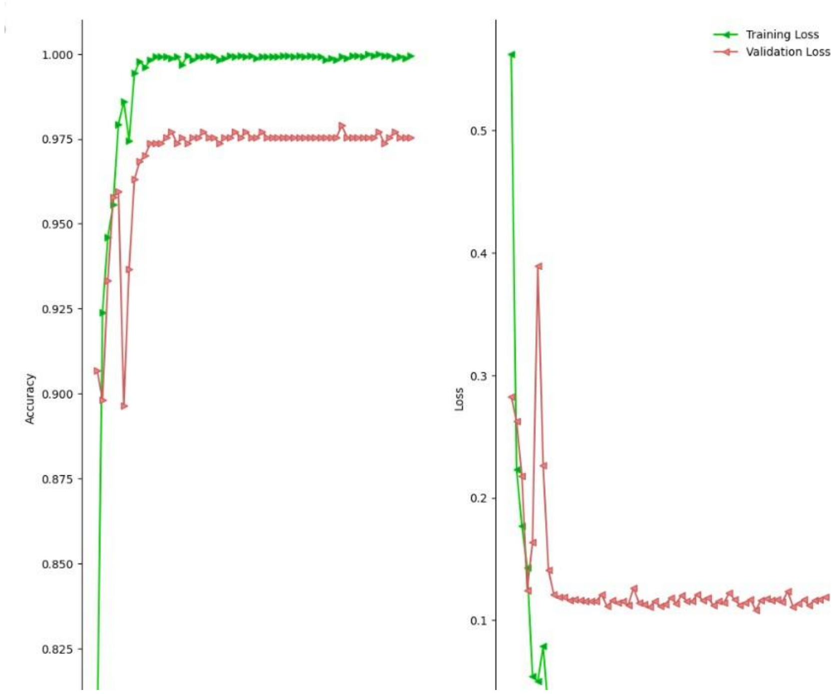
Displaying the Tumors

```
[ ] brain_tumor_images , brain_tumor_labels  = numpy.array(brain_tumor_images) , numpy.array(brain_tumor_labels)
```

```
[ ] image , ordinate = Mat_py.subplots(1,4,figsize=(12,12))

    image.text(s='Displaying image from each folder',size=10,color=Olive[1],y=0.62,x=0.3,alpha=0.9)
    global_var = 0
    for Dis in List_of_tumors_inside_dataset:
      Variable = 0
      while True:
         if brain_tumor_labels[Variable]==Dis:
              ordinate[global_var].imshow(brain_tumor_images[Variable])
              ordinate[global_var].set_title(brain_tumor_labels[Variable])
              ordinate[global_var].axis('off')
              global_var+=1
              break
         Variable = Variable + 1
```



Training and Validation Loss



APPENDIX C

RESULTS

Model Summary

```
Efficient_model.summary()
```

```
Model: "model_1"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_2 (InputLayer)           [(None, 150, 150, 3)]  0         []

 rescaling_1 (Rescaling)        (None, 150, 150, 3)  0           ['input_2[0][0]']

 normalization_1 (Normaliza     (None, 150, 150, 3)  0           ['rescaling_1[0][0]']
 tion)

 stem_conv (Conv2D)             (None, 75, 75, 40)   1080        ['normalization_1[0][0]']

 stem_bn (BatchNormalizatio     (None, 75, 75, 40)   160         ['stem_conv[0][0]']
 n)

 stem_activation (Activatio     (None, 75, 75, 40)   0           ['stem_bn[0][0]']
 n)

 block1a_project_conv (Conv     (None, 75, 75, 16)   5760        ['stem_activation[0][0]']
 2D)

 block1a_project_bn (BatchN     (None, 75, 75, 16)   64          ['block1a_project_conv[0][0]']
 ormalization)

 block1a_project_activation     (None, 75, 75, 16)   0           ['block1a_project_bn[0][0]']
  (Activation)
```

Classification Report

```
print(classification_report(test_brain_tumor_labels,brain_tumor_test_predictions))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99        97
           1       1.00      0.99      0.99        88
           2       1.00      0.94      0.97        49
           3       0.98      1.00      0.99        82

    accuracy                           0.99       316
   macro avg       0.99      0.98      0.99       316
weighted avg       0.99      0.99      0.99       316
```

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