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A Robust Two-Stage Method for Accurate Brain Tumor Detection and Classification using Convolutional Neural Network and ResNet50

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Abstract: **Brain tumors are a serious health concern that can affect individuals of all ages, and their diagnosis and treatment require prompt and accurate identification. Brain tumors are often diagnosed using magnetic resonance imaging (MRI), which is an extensively utilized diagnostic technique, but interpreting these images can be challenging and time-consuming for medical professionals. Recent advancements in machine learning techniques, particularly deep learning, have demonstrated potential for increasing the precision and effectiveness of brain tumor diagnosis. This study presents a two-stage approach using a convolutional neural network and transfer learning with fine-tuning in ResNet50 for identifying and categorizing brain tumors. The initial stage of the proposed approach involves the identification of brain tumors in the provided scan, while the second stage involves categorizing the tumors into one of three types: pituitary tumor, glioma, or meningioma. To train detection model, this study employed a dataset comprising 4,600 grayscale images of brain tumors. Meanwhile, for the classification model, the dataset is obtained from Figshare(a reputable data-sharing platform) which includes T1-weighted contrast-enhanced scans obtained from a total of 233 patients, with a total of 3,064 scans diagnosed with glioma, meningioma, and pituitary tumor. Specifically, the dataset contains 1426 scans from patients with glioma, 708 scans from patients with meningioma, and 930 scans from patients with a pituitary tumor. This study's goal is to evaluate the efficiency of machine learning methods in enhancing the detection and classification of brain tumors. We believe that our findings have significant implications for the development of tools and technologies that can aid medical professionals in accurately diagnosing, making decisions, and treating brain tumors, potentially leading to improved patient outcomes.**

Keywords - **brain tumor, magnetic resonance imaging, resnet50, convolutional neural network**

INTRODUCTION

Medical advances in recent years have empowered us to conquer a wide range of disorders. Cancer, on the other hand, remains a plague to humanity owing to its unpredictability. Cancer of the brain is one of the most lethal and quickly spreading illnesses. The brain is a complicated organ made up of nerve cells and tissues that govern vital bodily functions such as breathing, muscular movement, and senses. Tumor tissues are formed by abnormal cells that lose their ability to function and proliferate uncontrolled. Cancerous brain tumors are caused by the uncontrollable and abnormal proliferation of brain cells, making them one of the most dangerous and deadliest malignancies There are two major categories of brain tumors: benign tumors and malignant tumors. Benign brain tumors are non-cancerous growths that do not spread to other parts of the body. They can still cause symptoms and health problems, depending on their size and location in the brain. In contrast, malignant brain tumors are cancerous and have the ability to infiltrate and damage healthy brain tissue close to the tumor, and they can also metastasize or spread to other areas of the brain or the body. They are generally more aggressive and more challenging to treat than benign brain tumors. Brain tumors are classified into several types, including glioma, meningioma, and pituitary tumors. The brain and spinal cord are encased with fragile membranes that frequently give rise to non-cancerous tumors known as meningiomas. Gliomas, on the other hand, are a group of tumors that form inside the brain's tissue. High-grade gliomas are some of the most aggressive types of brain tumors, having a median survival rate of 2 years. Pituitary tumors are atypical growths that originate from brain cells in the pituitary gland and can appear elsewhere in the brain. They have an inherent character and are often consistent in shape. Because of heterogeneity, hypo-intense characteristics, isointense, and associated perilesional edema, which casts doubt on the categorization process, it is challenging to categorize brain tumors. Primary tumors such as meningiomas, pituitary tumors, and gliomas are frequently classified using T1-weighted contrast-enhanced imaging. Features are taken from the complex architecture of various tumors on brain MRI to classify brain tumors. Instead of feature extraction and classification, traditional approaches for classifying brain tumors use region-based tumor segmentation. Deep learning algorithms for categorization have nevertheless become the new paradigm.

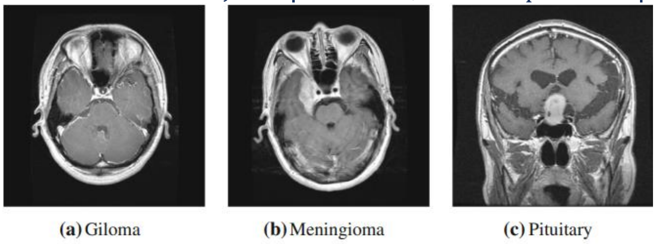

Figure 1 Types of Brain Tumors

Because of heterogeneity, hypo-intense characteristics, isointense characteristics, and associated perilesional edema, which cast doubt on the categorization process, it is challenging to categorize brain tumors. Primary tumors such as meningiomas, pituitary tumors, and gliomas are frequently classified using T1-weighted contrast-enhanced imaging. Features are taken from the complex architecture of various tumors on brain MRI to classify brain tumors. Instead of feature extraction and classification, traditional approaches for classifying brain tumors use region-based tumor segmentation. Deep learning algorithms for categorization have nevertheless become the new paradigm. An effective treatment strategy and better patient outcomes depend on the early diagnosis and categorization of brain tumors. Convolutional neural networks (CNNs) in particular have attracted a lot of attention recently for their potential to improve the precision and effectiveness of brain tumor diagnosis and classification. Machine learning algorithms are a useful tool for medical image analysis because they can efficiently analyze vast and complicated datasets. CNNs can automatically learn and extract characteristics from medical pictures, such as magnetic resonance imaging (MRI), to properly categorize tumors in the context of brain tumor detection and classification. It has been demonstrated that transfer learning, which uses pre-trained CNN models as a starting point for creating new models, increases the precision and effectiveness of classifying brain tumors. Because of their heterogeneity, hypo-intense characteristics, isointense characteristics, and associated perilesional edema, which casts doubt on the categorization process, it is challenging to categorize brain tumors. Primary tumors such as meningiomas, pituitary tumors, and gliomas are frequently classified using T1-weighted contrast-enhanced imaging. Features are taken from the complex architecture of various tumors on brain magnetic resonance imaging to classify brain tumors.

The main contributions of this paper include proposing a two-stage approach for brain tumor analysis using transfer learning from pre-trained CNN models. This approach demonstrates the effectiveness of CNN and transfers learning to brain tumor segmentation and classification.

NEED OF THE STUDY

Given the rising prevalence of brain tumors and the potential severity of the condition, research into the identification and classification of these tumors using machine learning (ML) is crucial. For prompt and successful treatment of brain tumors, accurate diagnosis and classification are essential. By assisting radiologists in spotting patterns and abnormalities in medical pictures, ML systems can increase the precision and effectiveness of diagnosis. The identification and categorization of brain tumors using machine learning has the potential to support the creation of individualized treatment programs, eventually improving patient outcomes and furthering the study of medical imaging.

RELATED WORK

K. He. et al. [1] This research introduces a new deep learning architecture that has demonstrated exceptional performance in various image recognition tasks, including the challenging ImageNet dataset. The study addresses a crucial issue in deep learning frameworks, specifically the difficulty of training deep neural networks due to the problem of vanishing gradients. The authors suggest using residual connections to overcome this limitation by allowing the direct flow of information between layers. The experimental results presented in the study demonstrate that the ResNet architecture surpasses other architectures in multiple image recognition tasks, thus establishing a new state-of-the-art performance. Moreover, the research provides a critical evaluation of the ResNet architecture and its impact on the fields of deep learning and image recognition. The paper discusses the limitations of current deep learning frameworks and highlights the advantages of ResNet's approach. Additionally, the research identifies areas that require further exploration and research in the field. The authors of this paper present a comprehensive analysis of the ResNet architecture, providing an in-depth explanation of its advantages over other deep learning frameworks. ResNet's residual connections enable the direct flow of information between layers and overcome the challenge of vanishing gradients, enabling the training of much deeper neural networks. Furthermore, the authors offer a detailed examination of the ResNet architecture's performance across various layers and its efficacy in minimizing training errors. In summary, this research provides a detailed examination of the ResNet architecture and its potential impact on the fields of deep learning and image recognition. The empirical results demonstrate the architecture's exceptional performance in achieving state-of-the-art outcomes across multiple image recognition tasks. Additionally, the study offers a critical evaluation of architecture's contributions to the field, providing insights into its benefits and limitations.

A. Kumar Singh et al. [2] This research used a publicly accessible dataset of 3064 brain MRI slices for an experimental investigation to compare the effectiveness and performance of three alternative CNN architectures for classifying brain tumors: GoogLeNet, AlexNet, and VGG16. The dataset, which was broken down into 70% training, 15% validation, and 15% testing, included 930 slices for a pituitary tumor, 1426 slices for a glioma tumor, and 708 slices for a meningioma. Two transfer learning approaches, fine-tune and freeze, were looked into for all three CNN architectures to meet the study's goal. Six different experiments were conducted to compare the results obtained from each approach. In the case of fine-tuning, GoogLeNet achieved a test accuracy of nearly 98% with augmented data. Meanwhile, the best results for the freeze approach were obtained using GoogLeNet with Inception 4b-Output features, achieving 94.55% accuracy. For AlexNet, the best results were obtained using Conv5 features with a 94.79% accuracy. Finally, for VGG16, the best results were obtained using fine-tuning with augmented data, achieving a 98.6% accuracy. These findings indicate that transfer learning techniques are effective in brain tumor classification, and the choice of CNN architecture and features can significantly impact classification accuracy. The results of this research contribute to the advancement of brain tumor classification methods and have practical implications for medical diagnosis and treatment planning.

A. Rehman et al. [3] This study provides a brand-new convolutional neural network (CNN) approach for classifying multi-grade brain tumors. The method uses considerable data augmentation approaches to properly train the system and utilizes deep learning methodologies to differentiate tumor locations from MR images. An already-trained CNN model is adjusted with new information to categorize the grades of brain tumors. On both the original and the augmented data, an experimental assessment of the suggested system is done, showing superior performance to the current approaches. In this research, the Radiopaedia dataset was utilized, consisting of 121 MR images depicting brain malignancies. These images were classified into four categories based on their respective ground truth labels, as reported in the WHO's annual publication. Different methods were used to create an additional 30 pictures from each MR scan because there weren't many images available for each grade before data augmentation. Additionally, the quantity of freshly created samples for each grade is also documented in this study. Both the Radiopedia and brain tumor datasets were used to assess the suggested technique. The accuracy obtained for the dataset from Radiopedia was 96.7%, whereas the accuracy gained for the dataset from brain tumors was 94.5%.

M. Sajjad et al. [4] The analysis of medical pictures using deep learning techniques, in particular convolutional networks, is covered in detail in this study. The review covers more than 300 contributions to the field and explores how deep learning is used in tasks like medical image analysis, including classification of the image, detection of the object, segmentation, registration, and others. In addition, the authors provide concise summaries of studies in various application areas, including neurology, ophthalmology, pulmonology, digital pathology, breast imaging, cardiology, abdominal imaging, and musculoskeletal imaging. The research emphasizes how deep learning has the potential to enhance clinical decision-making in medical image analysis in terms of accuracy and speed. In addition, the study looks at the difficulties and constraints of using deep learning in medical image analysis, including the need for large datasets, the interpretability of the findings, and the danger of overfitting. The authors also discuss the potential of transfer learning and adversarial training to mitigate some of these obstacles and highlight the importance of using larger and more diverse datasets, as well as addressing the ethical and regulatory concerns associated with the implementation of deep learning techniques in healthcare. Overall, this study provides a valuable resource for professionals and researchers in the field of medical image analysis.

G. Litjens et al. [5] The importance of identifying critical features for image classification and the impact of noise on classifier performance is the key focus of this study. The research suggests an experimental evaluation of the classification accuracy of a neural classifier under three different scenarios, including images with no noise, images with noise removed, and images with unknown noise. A supervised learning model is employed in the proposed method for computer vision, where the system's performance is evaluated on input photos after training on features extracted from example images. The quality of the classifier is heavily dependent on the features extracted from the image. Three separate experiments are used in this study: the first classify images with noise using a data set that includes original images from sixteen distinct categories; the second classifies images with noise; and the third determines the type of noise affecting the image by applying an appropriate filter before classifying it. A picture with a resolution of 128x128 is broken into sixteen blocks, each of which has a size of 32x32 pixels, to obtain statistical moments-based texture characteristics from the image blocks. Next, six statistical texture features are extracted from each block, resulting in a total of 96 features for each image. These features are utilized during both the testing and training phases of the analysis. For each experimental iteration, a feedforward backpropagation neural network (BPNN) is constructed with 15 hidden layers and 16 outputs. Supervised learning is utilized to train the classifier, with a feature vector consisting of 96 values as input. The neural network employs the backpropagation learning model and receives the feature vectors along with their corresponding labels during the learning process. Once the input image's features have been extracted for evaluation, a prediction model is utilized to forecast the label.

T J. D. Berstad et al. [6] In this research, the advantages and disadvantages of utilizing a classification approach like multiple binary classifications and single multiclass classification were analyzed. Different neural network models, namely DenseNet, Xception, Inception, ResNet v2, Inception v3, NASNet, and MobileNet, were utilized in the study. To analyze the performance of the mentioned models, the classification speed and accuracy metrics were compared using both classification techniques during the training and testing phases. To categorize medical images into 8 categories, the study used 99 networks in total, comprising 88 single binary networks and 11 multiclass networks. The results demonstrated that employing several binary classification networks produced a model with less variation and a higher degree of trustworthiness for the task at hand. However, compared to a single-network multiclass technique, the multi-network method conducted classification on average 7.6 times more slowly. The study's findings indicate that both strategies may be used in modern neural network designs since employing multiple binary networks can increase the accuracy of classification and robustness but at the price of resource consumption and classification speed.

A. Kabir Anaraki et al. [7] In this study, the authors propose a CBIR method to identify brain tumors in T1-weighted contrast-enhanced MRI images. To aid in clinical decision-making, the medical industry is quickly embracing content-based image retrieval (CBIR) technologies. When the user approximately delineates the tumor location, the system is programmed to obtain photographs of brain tumors of the same pathogenic kind as the query image. Since there are few brain contrast-enhanced MRI (CE-MRI) slices accessible in clinical settings with considerable slice gaps, the suggested approach is based on 2D slices. A dataset of 3064 publicly accessible slices from 233 people who had been diagnosed with pituitary tumors, gliomas, and meningiomas was used in the study. The tumor margins were precisely marked by radiologists in each slice. In this study, a three-stage feature extraction approach is provided. The initial phase entails improving the tumor area to include pertinent background data. The enhanced tumor region has been subdivided into subareas based on intensity ranking, and the second stage entails extracting local features from each subdivision. Concatenating the Fisher vectors (FVs), which are calculated for each subregion, results in the final feature representation. A closed-form metric learning technique is used to determine how similar the query picture and the database images are after feature extraction. On the provided dataset, the suggested approach was thoroughly evaluated, and the resultant mean average accuracy was 94.68%. When compared to comparable state-of-the-art procedures, these results show that the recommended strategy is successful.

J. Cheng et al. [8] The study proposed a technique that uses CNN and genetic algorithms (GA) to classify various grades of gliomas in MRI data in a non-invasive manner. The authors employed GA to develop the CNN architecture, resulting in a significant reduction in computational costs compared to current approaches that use trial and error or predetermined common structures to select network architectures. The network architecture factors included the number of max-pooling and convolutional layers, the number and size of filters, the number of fully connected layers, the activation function, the frequency of dropouts, the optimization technique, and the learning rate. (Kaiming He, 2016) The authors trained 50 random parameter networks using 80% of the collected data. The genetic algorithm (GA) decided which networks to keep or discard based on validation accuracy for the next generation. To reduce the variance of classification error, the authors also employed bagging, an ensemble approach that combines multiple classifiers to decrease generalization error. The proposed technique successfully classified brain cancers in MRI images, achieving 90.9% accuracy for three glioma grades and 94.2% accuracy for glioma, meningioma, and pituitary tumor types. This approach can enable the early detection of brain tumors.

DATASET PREPARATION

This study, uses separate datasets for brain tumor detection and classification as 2-stage method is employed. For brain tumor detection, publicly available dataset from Kaggle[9] is used. This dataset had a total of 4600 samples from the scan of the brain. Out of that, 2513 samples had a brain tumor, and 2087 samples were healthy. The dataset is split into training and validation based on the 80-20 rule.

For the brain tumor classification, publicly available dataset from Figshare[10] is used. This dataset has a total of 3064 MRI samples of the 233 patients' brains diagnosed with a brain tumor. Out of this dataset, 708 slices were meningiomas, 1426 slices were gliomas, and 930 were pituitary tumors. These samples were found in .mat (MATLAB) format, and each sample had five attributes, namely a patient ID, an image of a scan with 512*512 dimensions, a label from 1–3, which indicates the type of tumor, a tumor border, which indicates the coordinates of the tumor present in the image, and a tumor mask, which is a masked version of the tumor. Only the image and label out of all the attributes is extracted for this task. As the dataset collected for classification is small, the augmentation is done on the dataset where the rotation at 8 different angles, 0, 45, 90, 120, 180, 270, 300, and 330 is applied.

METHODOLOGY

The methodology proposed for detecting brain tumors consists of two stages, utilizing separate detection and classification models to achieve accurate results. In the first stage, the input image undergoes detection using the designated model. If a tumor is detected, the image is then fed into a classification model to determine its specific type, which could be a meningioma, glioma, or pituitary tumor. However, if no tumor is detected in the initial detection stage, the image is classified as healthy.

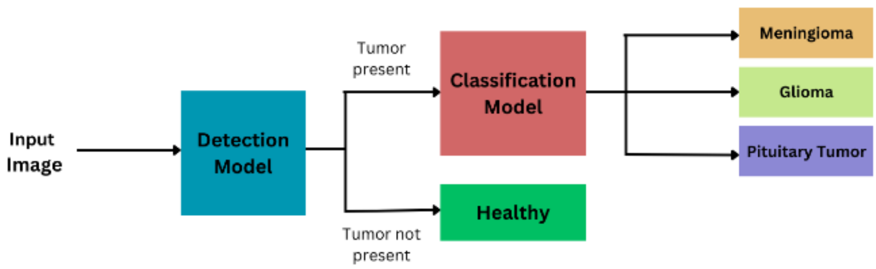

Figure 2 Flowchart of the Proposed Methodology

5.1 Training Brain Tumor Detection Model

The proposed convolutional architecture for training the brain tumor detection model, i.e. Fig. 3 includes 11 layers, excluding flatten and input layers. The input for the first Convo2D layer is an image of dimension 256*256. Features are extracted using this convolutional layer in the form of a feature map. The first Convo2D layer has 32 filters with a kernel size of 3*3 pixels. Non-linearity is introduced into the model using ReLU (Rectified Linear Unit) activation. The output of the Convo2D layer is then given to the MaxPooling2D layer to reduce the spatial dimension of feature maps. The output of MaxPooling is then given to the second convolutional layer with a reduced dimension of 128*128 and then the result is given to the second MaxPooling layer. The generated feature maps are then given to the fully connected layers, in this case, it is the dense layer. The fully connected layer needs input in terms of vectors (1D). So, the flattened layer is used to convert the output of previous layers into vectors. The first dense layer in the proposed architecture has 128 neurons and a ReLU activation function. This layer learns to combine features learned by convolutional layers and produce a high-level representation of the input. Then, the batch normalization layer is used to improve the stability of the model during training and to avoid overfitting. To introduce randomness into the model, a dropout layer is used with a dropout rate of 0.3, which means that this layer randomly drops out 30% of neurons in the layer during training. To further enhance the performance, a new dense layer similar to the previous dense layer with 64 neurons was included, along with an additional batch normalization layer and dropout layer, serving the same purpose as the previously mentioned layers. A dense layer with a sigmoid activation function and a single neuron is the final layer that outputs the predicted probability of whether the input image belongs to a specific class, such as tumor or healthy. The model is compiled using the Adam optimizer with a rate of learning of 0.001, utilizing the accuracy metric and the binary cross-entropy loss function as the assessment criteria.

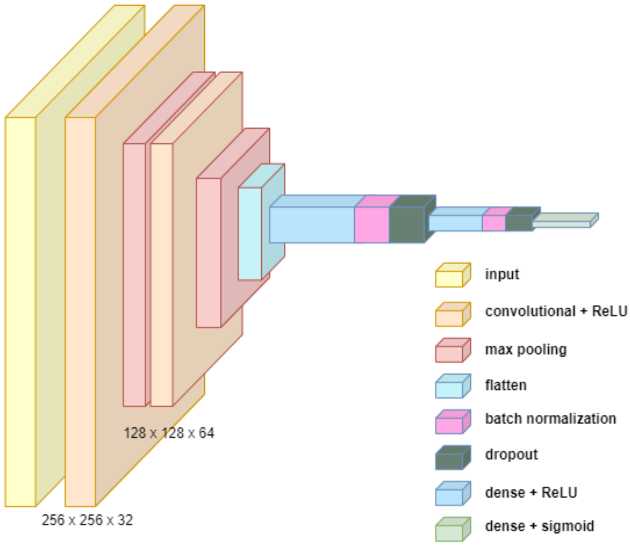

Figure 3 CNN Architecture of Detection Model

5.2 Training Brain Tumor Classification Model

To train the brain tumor classification model, this study employed the approach of transfer learning with finetuning in ResNet50, as presented in Fig. 4. In this approach, the fully connected layer is redefined, where the original fully connected layer, which was designed for ImageNet classification, is replaced by a new one consisting of three linear layers with 2048 units each, separated by SELU activation functions, and followed by dropout layers with a probability of 0.4. The final layer uses the LogSigmoid activation function to produce the model's output. After modifying the network, all parameters (including those in the original ResNet model and the new fully connected layer) are set to be trainable so that the optimizer can update their weights during training on the new dataset. The training is done in batches, with the number of images per batch being 4 and the number of augmentations per image being 8. For each batch, the image sample is forwarded through the model, the loss is calculated, and backpropagation is performed to update the model parameters.

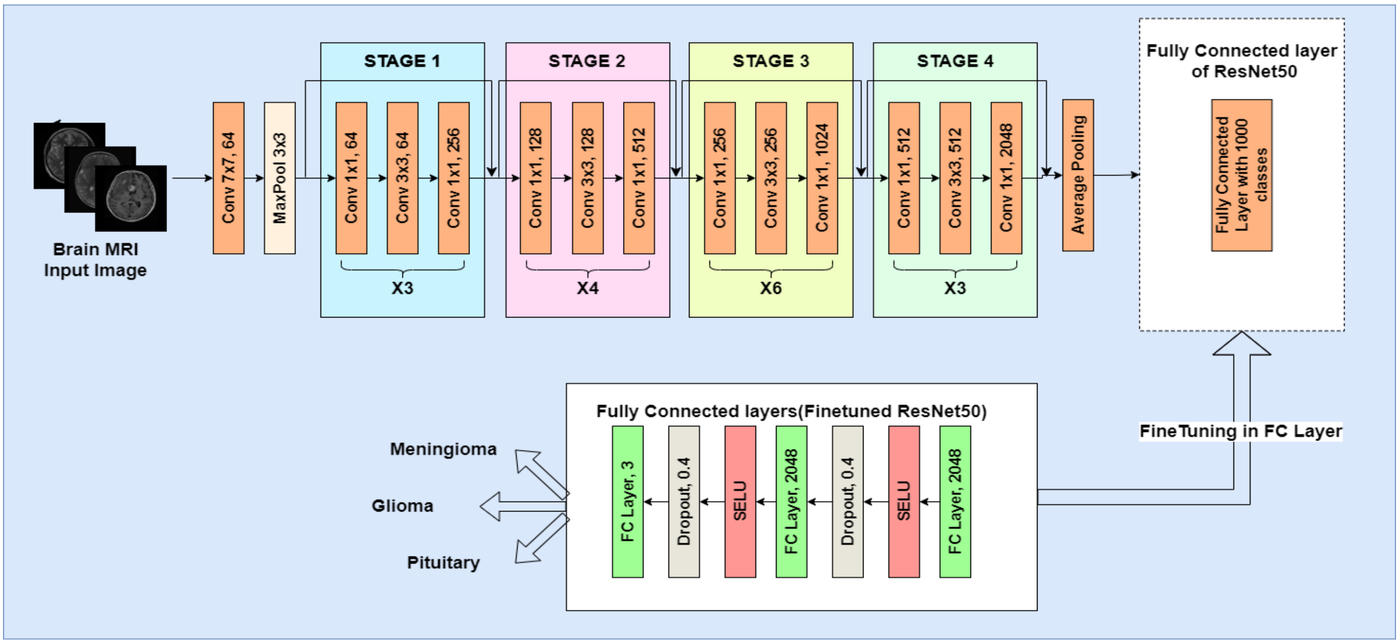

Figure 4 Finetuned ResNet50 Classification Model

RESULTS

The model for detecting brain tumors was able to achieve a very high level of accuracy in both training and validation. The model specifically obtained 99.92% training accuracy and 99.35% validation accuracy. The graphs in Fig. 6 show that both the training and validation accuracy steadily increased with each epoch until they reached a plateau after epoch 7. Notably, the validation accuracy did not decrease as the epochs increased, indicating that the model can generalize well to new data.

Moreover, Fig. 5 demonstrates that the training loss and validation loss gradually decreased over time and eventually stabilized. The small gap between the validation loss and the training loss suggests that the model is not overfitted and is capable of accurately detecting brain tumors in new data as well.

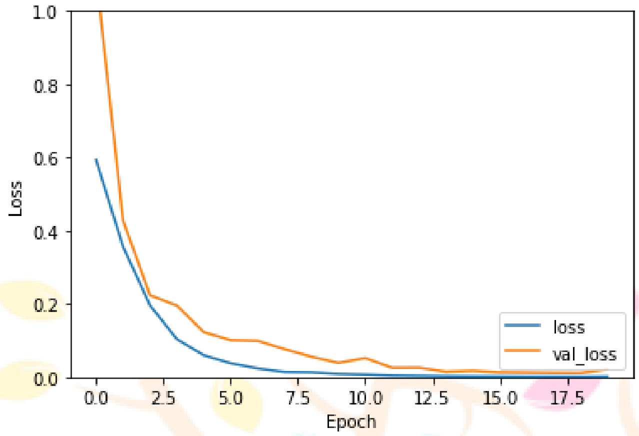

Figure 5: Loss Metrics for the Detection Model

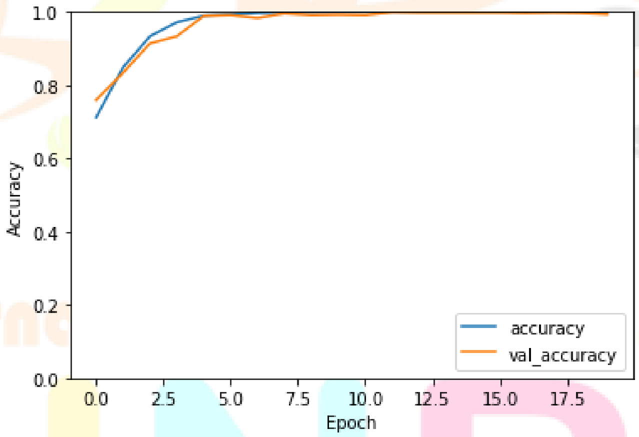

Figure 6 Accuracy Metrics for the Detection Model

The classification model, which is a fine-tuned ResNet50 model, has achieved a test accuracy of 99.32% and a validation accuracy of 98.88%. It is evident from Fig. 8 that both training and validation accuracy improves over time as the training progresses. By epoch 4, the model's accuracy has reached 88.46%, and the validation accuracy is 89.91%, which is a good indication that the model is learning to generalize well. The accuracy keeps improving, with a significant jump after epoch 8 when the accuracy reaches 95.27% and the validation accuracy reaches 95.94%. This jump is due to the model learning some key patterns or features from the data. The validation accuracy continues to improve until epoch 22, where it reaches its peak of 98.27%. And even after epoch 25, the model is still learning and improving its performance on both the training and validation datasets. Fig. 7 shows that validation loss is higher in the beginning. However, as the number of epochs increases, the validation loss starts to decrease and become closer to the training loss, which better indicates that the model is becoming better at generalizing and performing well on unseen data.

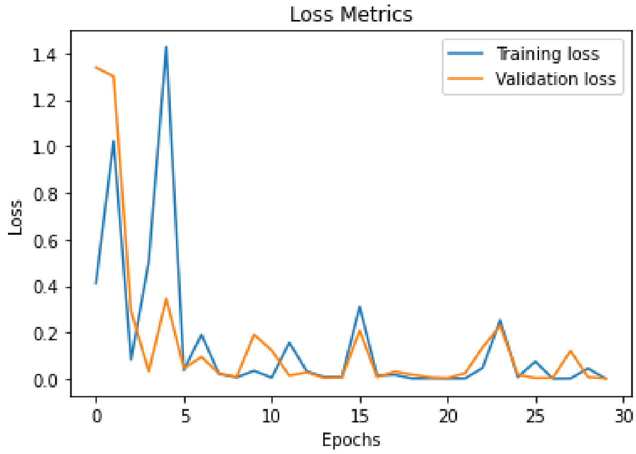

Figure 7 Loss vs Epochs Curve for Classification Model

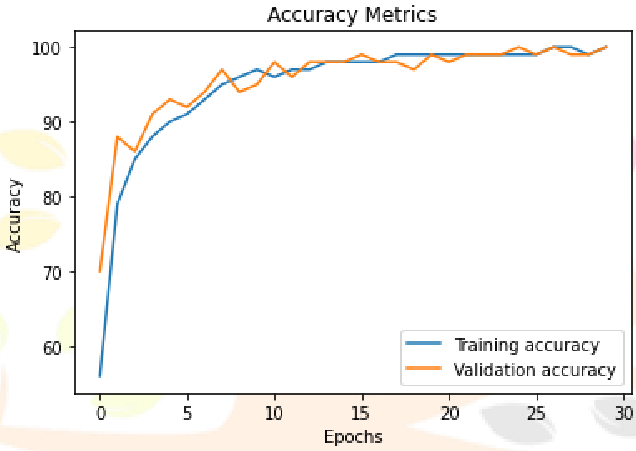

Figure 8 Accuracy vs Epochs Curve for Classification Model

To gain a more thorough understanding of how the model performed in each class, a detailed breakdown is provided in Fig. 9 using a confusion matrix. The confusion matrix clearly illustrates the model's performance across all classes, and it is apparent that the model performed robustly in all cases and is likely to be effective in real-world applications.

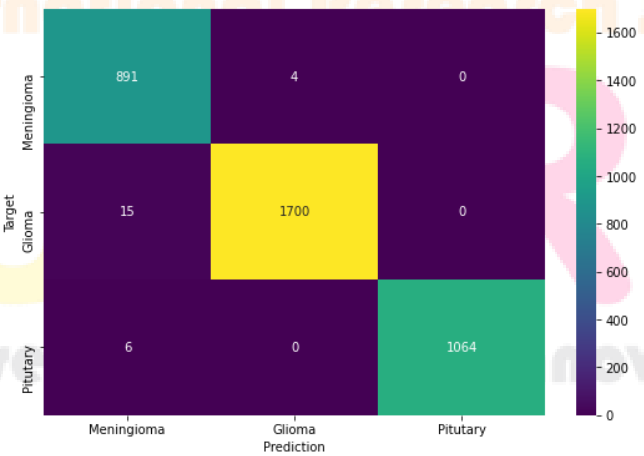

Figure 9 Confusion Matrix for the Classification Model

The performance of the classification model in classifying each of the three types of tumors is given below in Table 1.

Table 1 Report of the Classification Model

Classification	**Evaluation Metrics**		
	Precision	**Recall**	**F1-Score**
Meningioma	0.98	1.00	0.99
Glioma	1.00	0.99	0.99
Pituitary	1.00	0.99	1.00

CONCLUSION

To summarize, the proposed two-stage approach utilizing CNN and fine-tuning the ResNet50 network to detect and classify brain tumors has achieved high accuracy rates and demonstrated robustness against different types of brain tumors. In light of these findings, This study shows that deep-learning techniques can significantly increase the reliability and accuracy of brain tumor diagnosis. We hope that our work will contribute to the ongoing efforts to improve brain tumor diagnosis and treatment and, ultimately, help save more lives.

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