MRI-Based Brain Tumor Classification Using Inception Resnet V2

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ARTICLE INFO | ABSTRACT

Brain tumors are one of the most fatal disorders owing to the uncontrolled proliferation of abnormal cells inside the brain. Digital images are obtained using Magnetic Resonance Imaging (MRI), which is a medical instrument that can assist doctors and other medical personnel in assessing and diagnosing the presence and type of brain tumors. However, manual and subjective classification is time-consuming and error prone. Hence, an objective, automatic, and more reliable method is needed to classify MRI images of brain tumors. Artificial intelligence is considered appropriate to determine the type of brain tumor via MRI images to overcome the constraints of conventional testing methods. One method for performing automatic classification is the Convolutional Neural Network (CNN). This work demonstrates how the Inception Resnet v2 architecture in CNN is utilized to classify MRI brain tumors into four categories via transfer learning, namely glioma tumors, meningioma tumors, no tumors, and pituitary tumors. The accuracy value of the generated model reached 93.4% after running for 20 epochs. It infers that artificial intelligence is beneficial in identifying a brain tumor objectively to help doctors and radiologists in the medical field.

1. Introduction

Brain tumor is one of the deadly diseases caused by abnormal cells growing uncontrollably in the brain. The uncontrolled multiplication of cells causes the tissue to grow abnormally without physiological function inside the brain. The central nervous system, which regulates the core of human activity and existence, comprises soft support tissue and brain nerve cells attached to the spinal cord. Thus, the presence and growth of brain tumors will cause the brain to swell and block the flow of cerebrospinal fluid, which undoubtedly disrupts the neurological system [1]. As a result, headaches, nausea, sensory problems, memory issues, personality changes, and other symptoms that can lead to death can arise depending on the type and size of the tumor.

There are two types of brain tumors: benign and malignant [2]. Referring to John Hopkins Medicine, benign tumors typically have slow growth, are localized, and rarely spread. In comparison, malignant tumors have rapid growth, invade the surrounding brain structures, and are considered cancerous. Some primary brain tumors are gliomas, meningiomas, and pituitary tumors. Meningioma and pituitary are typically benign, while gliomas are most commonly malignant. If the tumor is large enough and interferes with healthy tissues, it may start causing symptoms, depending on where it is located inside the brain. Thus, detecting and analyzing the types of tumors precisely plays a significant role in enhancing the practical assessment of patients [3].

Imaging technologies to produce medical images are called modalities, in which Magnetic Resonance Imaging (MRI) is one of the non-invasive methods. It is commonly used and considered better because such modalities are preferred to avoid harmful effects on body tissue, especially inside the brain [4]. An attractive feature of MRI is that it can efficiently obtain contrasts between tissue types, such as white and gray tissue. As a result, MRI has become a superior technology for studying the human brain in recent years. This non-invasive technology can provide high-resolution spatial pictures using radio frequency signals with a powerful magnetic field [5] and deliver rich information content that can be used to create automated diagnostic tools that can support medical professionals make faster and more accurate judgments about the brain disease under investigation.

Early detection of brain tumor whereabouts and its classification is vital to improve the treatment outcome and increase the patient's survival rate [6]. However, tumor type recognition by manual judgment from the radiologists is a challenging, error-prone, and time-consuming process and it highly depends on the radiologist's skill and experience [7]. This matter triggered researchers to develop advanced classification for classifying brain tumors in medical image analysis. As the technology develops, the computerized brain tumor has come to the surface to diagnose the presence of the tumor, its location, and type. Therefore, automatic or computerized methods are expected to reduce manual diagnosis errors and provide information that leads to the correct diagnosis and treatment.

Radiological examination using MRI brain tumor images can be generally classified into binary and multi-class classification. In contrast, the binary one, known as brain pathology detection, determines whether the brain is normal. Because of the tumor characteristics, such as location, form, and size, thus, the multi-class classification aims to detect both brain pathology and the tumor type [8]. This paper covered the three primary types of tumors: meningioma, glioma, and pituitary tumor.

Many researchers are implying deep learning models based on Convolutional Neural Network (CNN) to solve the classification system, as they do not require manually split regions and necessary feature extraction. But the limited availability of large datasets becomes a problem as CNN requires massive data to train [9]. These two opposed circumstances can be tackled using the transfer learning approach [10], where a deep pre-trained CNN model for another related application can be used for further research.

Technological advances like classification modeling are needed to assist doctors in verifying the presence of tumors in the brain. In general, image classification models are obtained using several methods such as Logistic Regression, Naïve Bayes Classifier, Support Vector Machine (SVM), Decision Tree, Artificial Neural Network (ANN) to CNN. These models aim to accelerate the detection of tumor types in the brain so that doctors can carry out appropriate medical treatment for patients.

This study aims to determine the type of brain tumor that attacks the patient through the classification of MRI images. However, image data requires certain analytical techniques to distinguish between normal brain conditions, brain tumors with meningioma, pituitary, and gliomas. Furthermore, the conventional machine learning-based models have their drawbacks, such as the necessity for manual segmentation and feature extraction, leading to a decrease in performance

accuracy and efficiency. Thus, this study employs CNN as one of the deep transfer-learning-based algorithms to address these challenges by performing feature extractions automatically utilizing various convolutional layers. As a result, the extracted features should produce a robust result for later classification [11]. The Inception Resnet v2 architecture is used to capture MRI patterns to determine if a patient is classified as one of the four categories mentioned. The benefit of the research is that it is hoped that this research can provide a classification of the types of brain tumors that attack patients so that they can contribute to the medical field.

The remainder of the paper is organized as follows. In Section 2, we introduce and review several previous works of classification using deep learning models, especially CNN and PNN. Section 3 describes the data and methodology, specifically deep learning architecture that we use in this study. In Section 4, we discuss the result of the Inception Resnet v2 analysis process and performance evaluation of the brain tumor classification. Lastly, we conclude the paper and future direction in Section 5.

2. Related Works

In recent years, a number of researchers have developed a number of methodologies with solutions for detecting brain tumors using MRI data. From conventional machine learning algorithms to deep learning models, these methodologies are diverse. On the classification of brain tumors using deep learning, we review several international journals.

N. Abiwinanda, M. Hanif, S.T. Hesaputra, A. Handayani, and T.R. Mengko used a convolutional neural network with five distinct architectures to identify the three (3) most frequent forms of brain cancers, namely Glioma, Meningioma, and Pituitary [12]. The second architecture with the highest accuracy is the best architecture. Two convolutional layers, a ReLU layer, and a max-pool layer are followed by 64 hidden neurons in the architecture. The highest accuracy obtained is 98.51% for training and 84.19% for validation.

E. Irmak used a convolutional neural network to create a multi classification of brain tumors for the purposes of early diagnosis (CNN) [13]. For three different classification tasks, three different CNN models were proposed. One of the classifications used in this research is Classification-2, which divides brain cancers into five types: normal, glioma, meningioma, pituitary, and metastatic brain tumors. There are 25 weighted layers in the proposed CNN model for Classification-2 (1 input, 6 convolutions, 6 ReLU, 1 normalization, 6 max pooling, 2 fully connected, 1 dropout, 1 softmax and 1 classification layers). This model gets an accuracy value of 92.66%.

Rehman *et al.* conducted a study using CNN to classify the three categories of brain tumors [11]. This classification is performed with softmax layers using a pre-trained network using fine-tune features. The VGG16 architecture of CNN is implemented using a fine-tuned approach to learn the effectiveness of transfer learning methods that achieved 98.69% accuracy on the test set. The training automatically stopped as it reached the best network committed at epoch 7 with SGDM solver with a batch size of 10.

The proposed transfer learning model from [9], InceptionV3 using a proven softmax classifier, was also used to classify brain MRI images into three categories. Some modifications were made to fit the objectives, such as modifying the final three layers, replacing the average pooling layer with a flattened layer, and replacing InceptionV3's fully connected layer with a new layer. Finally, the softmax activation layer was also altered and replaced. This study reveals that the validation accuracy of the proposed InceptionV3 model hit more than 99% and more than 98% on every aspect of performance metrics.

Abir *et al.* researched the use of probabilistic neural networks to analyze a novel MRI-based brain tumor classification PNN [14]. Brain tumors are divided into three categories: benign, pre-malignant, and malignant tumors. In preprocessing, they used image filtering, sharpening, resizing,

and contrast enhancement, as well as extracting GLCM features. They utilized thirty brain MRI samples to train the PNN classifier, and tests were done on twelve sets of images to see how accurate the classifier was. As a smoothing factor, the constructed classifier was tested with various spread values. The experimental results show that the PNN classifier is usable, with accuracy ranging from 83.3% to 72% depending on the spread amount. A spread value of 15 resulted in a maximum accuracy of 83.33%.

Table 1. Related works of Brain Tumor Classification

Author	Year	Objective	Method	Accuracy (%)
Abiwinanda *et al.*	2019	Brain tumor classification using convolutional neural network	CNN	84.19%
E. Irmak	2021	Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework	CNN	92.66%
Abir *et al.*	2018	Analysis of a novel MRI based brain tumor classification using probabilistic neural network (PNN)	PNN	83.33%
Soumik and Hossain	2020	Brain Tumor Classification with Inception Network Based Deep Learning Model Using Transfer Learning	CNN	99.44%
Rehman *et al.*	2020	A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning	CNN	98.69%

3. Materials and Methodology

This section describes the data, the analysis steps, and the methods used in this research.
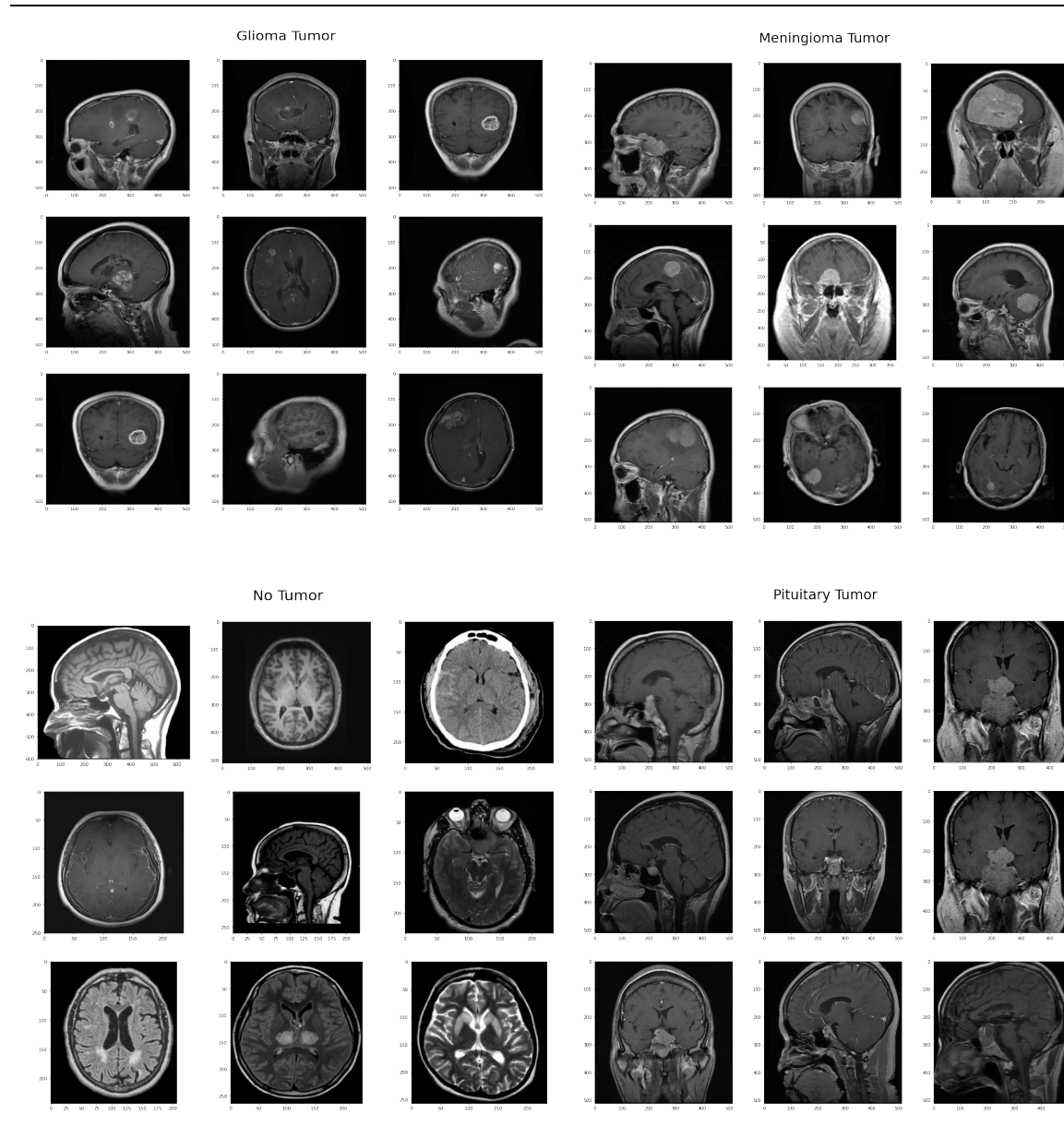
3.1. Data

This study uses MRI images as the main input. Image defined as still images (photos) or moving images such as video. Digital image means that image/image processing is done digitally using computer assistance. Mathematically, the image is a continuous function with light intensity in a two-dimensional plane. In order to be processed by a digital computer, an image must be represented numerically with discrete values. The representation of a continuous function into discrete values is called image digitization. An MRI image is a digital image that is output from a scanner (imaging system) in the form of an MRI device. The scan result is a grayscale image with a certain size in dicom or dcm format. Changes in the MRI image format can result in a change in the color channel of the image to RGB (Red Green Blue), so that a pixel in the image has a red color intensity

The dataset used in this study is from kaggle.com entitled Brain Tumor Classification (MRI), which contains 3265 MRI images. There are four categories in the dataset used in this study, namely:
a. glioma tumor (926 images),
b. meningioma tumor (937 images),
c. pituitary tumor (901 images)'
d. brain without tumor (501 images).

Table 2. Sample Data for Each Label

3.2. Methodology

This research begins with splitting the data for training and validation. At this step, the data will be divided into 70% for training and 30% for validation. The next step is analyzed using proposed algorithms, Inception Resnet v2 frozen layer and with all layers unfrozen. The algorithm with the highest accuracy value will be evaluated by metric evaluation. The flow of research conducted can be seen in Fig. 1.
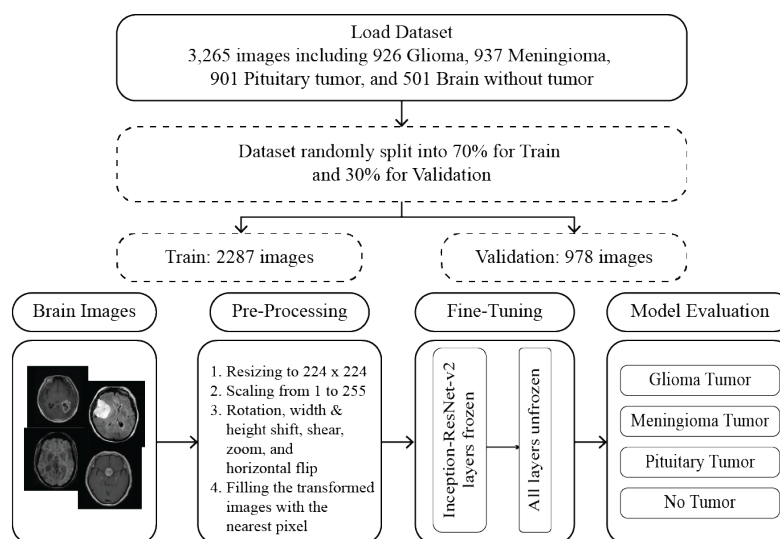
Fig. 1 Research flow.

3.2.1 Splitting Data

This splitting is performed on all the data that have class label (dependent variable). The purpose of separating the data into a training set and a validation set is so that researchers can assess the performance of the model in the classification. The training set is the data section used to build the model, while the validation set is the data section used to assess the model's performance. The model built from the training set is used to predict the images included in the validation set. After modeling, the model is assessed by comparing the prediction results with the label validation set. The more images that are properly classified, the better the performance of the model. Separation of training and validation data is done randomly by maintaining the proportion of labels on the training data.

The dataset is divided into 2,287 training data and 978 validation data. Samples of MRI images can be seen in Table 3. The distribution of training data and testing data in each category can be seen in the following table.

Table 3. Data Distribution

Class	Data Training	Data Validation
Glioma Tumor	649	277
Meningioma Tumor	656	281
No Tumor	351	150
Pituitary Tumor	631	270
Total	2287	978
	3265	
Glioma Tumor	649	277

3.2.2 Data Preprocessing

Data preprocessing in question is the stage to transform data into a form that can be used for analysis. The simplest step of medical image analysis is the preprocessing and enhancement stage, designed to decrease noise and improve the image's resolution and contrast [15]. Image preprocessing methods such as changing the image shape, rescaling, and image augmentation are implemented to train and input the data into the model.

The data obtained has a pixel size that varies from one another. Therefore, it is necessary to standardize the pixel size first so that the model can process the input data. Some types of CNN architecture have a specific pixel size on the input layer. On this model, each image is resized to 224 × 224 pixels, and each pixel's value is scaled, ranging from 1 to 255. Image augmentation is also

applied. Image augmentation is a machine learning technique that is used to improve sample data and train neural networks to focus on the features and features of the image by performing image transformations such as reflection, shift, and rotation of the image [16]. Preprocessing is done using the TensorFlow Image Data Generator, which automatically divides and processes the previous data because manually editing it is considered time-consuming.

3.2.3 Convolutional Neural Network (CNN)

Proposed method in this research is the deep convolutional neural network to classify the MRI brain tumors into four categories via transfer learning, namely glioma tumors, meningioma tumors, no tumors, and pituitary tumors. CNN is a type of neural network commonly used to process images. CNN is generally used to detect and recognize objects in an image. Although broadly speaking, CNN is not much different from a neural network, CNN consists of neurons that contain weight, bias, and activation function. CNN generally consists of convolution, pooling, and fully connected layers.

Convolutional Layer serves to capture specific patterns from an input image with the help of filters. This goal is achieved by perform the convolution technique as illustrated in Fig. 2.
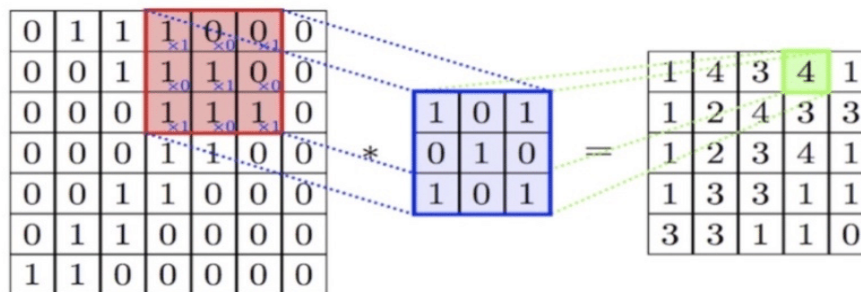

Fig. 2 Calculation process of a filter in the convolutional layer [17].

In addition to capturing certain patterns (feature extractor), convolutional techniques also function to reduce the dimensions of the input image so that computations can be performed more efficiently. In most CNN models, there is more than one convolutional layer so the resulting dimensions will be smaller as well. The output obtained from the convolution stage then becomes the input for the fully connected layer.

Furthermore, a comparison of methods is carried out based on the fulfillment of assumptions, model performance and speed of assumptions. The assumptions and performance of the model are important because an accurate model is needed to convey a diagnosis, and computational speed is important to provide an accurate diagnosis in the field. This comparison is also based on a comparative survey of methods in image classification analysis by Dhaware and Wanjale [18].

Table 4. Table of Comparison Methods

Method	Fulfilment of Assumptions	Model Performance	Speed of Assumptions
Logistic Regression	Yes	No	Yes
Naive Bayes Classifier	Yes	No	Yes
Support Vector Machine	No	Yes	No
Decision Tree	No	No	Yes
Artificial Neural Network	No	Yes	No
Convolutional Neural Network	No	Yes	Yes

3.2.4 Architecture Model

After preprocessing the data, the modeling is carried out. This study uses the Inception Resnet v2 architecture to perform the modeling. Inception Resnet v2 is a CNN that is built from the Inception

architecture family but includes residual connections to replace the filter concatenation stage of the Inception architecture. Residual connections create shortcuts in the model to train the neural network more deeply, which improves model performance. It also significantly simplifies the inception block that was present in Inception v3. As a result, Inception Resnet v2 is more accurate than the previous model. Inception Resnet v2 has better performance than earlier models, including Inception Resnet v1 which has a lower computational load but lower accuracy [19]. Inception Resnet v2 architecture diagram can be seen in Fig. 3.
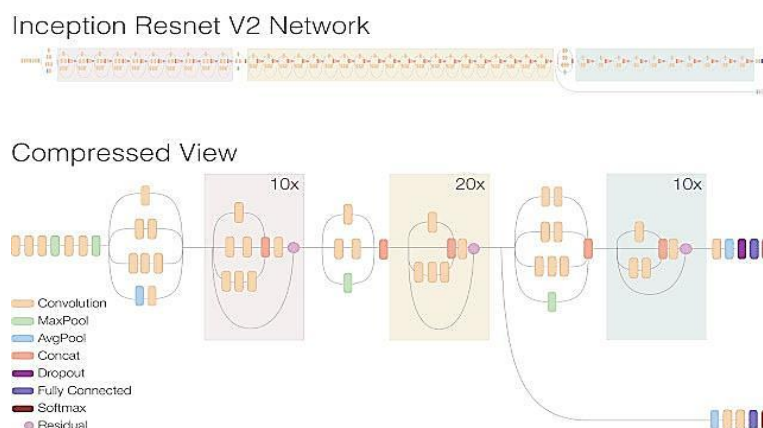
Fig. 3 Inception Resnet v2 diagram [20].

3.2.5 Training Model

The model is then compiled with the Adam optimizer using a learning rate of 1e-4, batch size of 64, and decay of 5e-6. The training model is set to 20 epochs and uses a checkpoint model during model training to get the model with the highest accuracy by monitoring validation accuracy and using the maximum mode. The training for this model is carried out in two stages. First, Inception Resnet v2 with a frozen layer allows for retaining weight and bias from the dataset. The only layer being trained is the layer added after Inception Resnet v2. Second, the training model is carried out with all unfrozen layers. This method allows for faster training time and ensures restoring the best weight possible. Two dropout layers of size 0.5 are used in both stages of model training to prevent the model from overfitting.

3.2.6 Model Performance Evaluation

The model is then assessed using a confusion matrix, which produces assessment metrics including accuracy, sensitivity, precision, recall, and f1-scores. This metric is used to evaluate the quality of the model and whether the model is feasible to use.
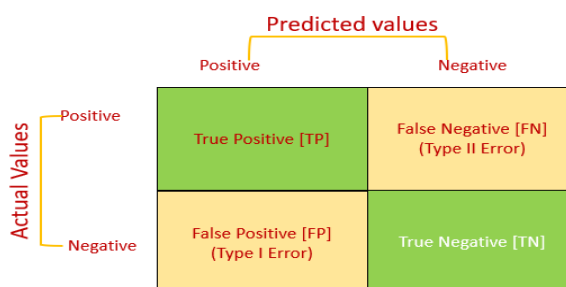
Fig. 4 Confusion matrix.

The confusion matrix measures the prediction performance by calculating the level of truth from the classification process. This measuring tool compares the results of the model classification with the actual classification results. Within the framework of the confusion matrix, there are four terms,

namely true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) as illustrated in Fig. 4. TP is the actual positives that are correctly classified. TN is the actual negatives that are correctly classified. FP is when the positives are classified as negatives. And the last, FN is when the negatives are incorrectly classified as positives. In this research, the performance of the model can be calculated using the following metrics:

1. Accuracy

A value that represents the accuracy of the model in classifying objects correctly. Accuracy for binary classification can be expressed in the following formula.

$$accuracy : \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision

A value that represents the model's accuracy in predicting a condition by comparing the amount of relevant information with the total amount of both relevant and irrelevant information.

$$precision : \frac{TP}{TP + FP} \tag{2}$$

3. Recall or sensitivity

A value that represents the model obtaining information by comparing the amount of relevant information with all relevant information taken or not taken by the system.

$$recall : \frac{TP}{TP + FN} \tag{3}$$

4. F1-score

A value obtained from the comparison between the average value of precision and recall.

$$f1\ score : \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{4}$$

5. Loss

The term "loss" refers to the magnitude of the "error" during the data training stage. The greater the loss, the more likely the model failed to recognize the pattern in the inputted data. The loss function is a function that is used to evaluate how well a model captures patterns in data. The loss function's value increases as the model's ability to capture the pattern decreases. The cross-entropy function is commonly used as a loss function in classification analysis, with the formula:

$$CE = -\sum_{i}^{c} p_i log(x_i) \tag{5}$$

4. Results and Discussion

This chapter will discuss the process of classifying brain tumors based on MRI output and outcomes. The classification method used is Convolutional Neural Network (CNN) with Inception Resnet v2 architecture. The experiments are performed using the Keras TensorFlow library and the python language. Model experiments are done twice, first with the Inception Resnet v2 layers frozen, the second with all layers unfrozen. The network architecture is set with the first layer being our proposed model. Two dropout layers with size 0.5 are added, and a flattened layer in between. The last layer using Softmax activation is an output layer with four neurons. Then, the Adam optimizer is used for optimization with a learning rate set to 1e-4. The number of epochs is set to 30 with a batch size of 64. Finally, model checkpoint is applied by monitoring validation accuracy with mode max to save the best model possible

4.1. Result

The first round of model training was set by 20 epochs, resulting in a maximum validation accuracy of 0.7906. The second round also had 20 epochs and a maximum validation accuracy of 0.9344. Fig. 5 illustrates the model plots of the second-round model used.
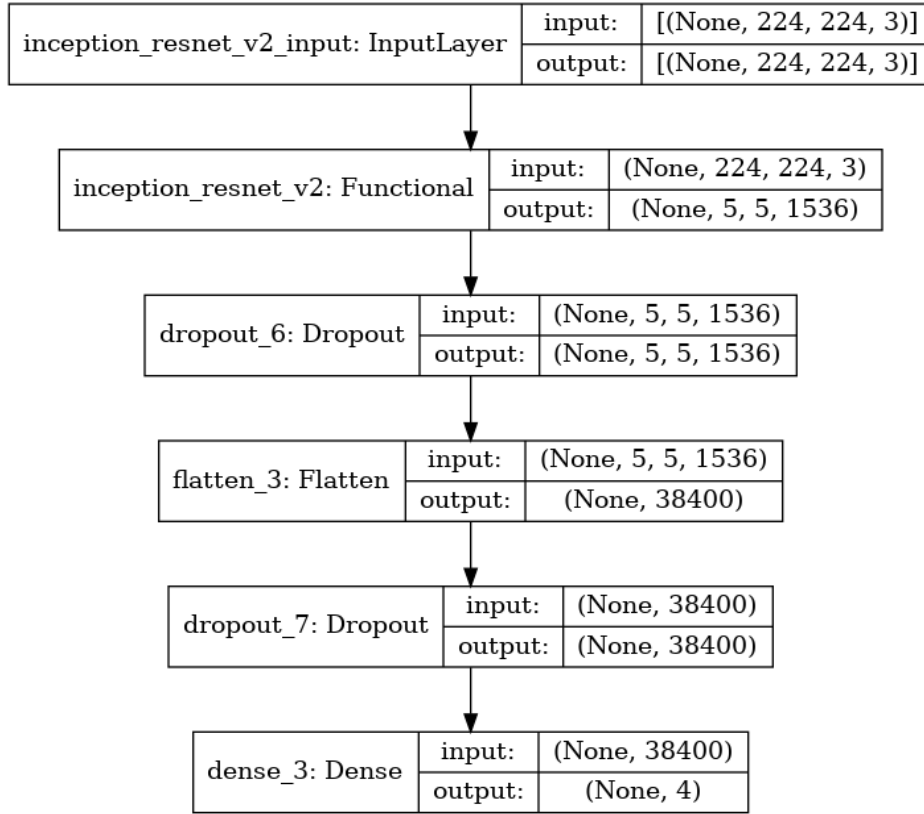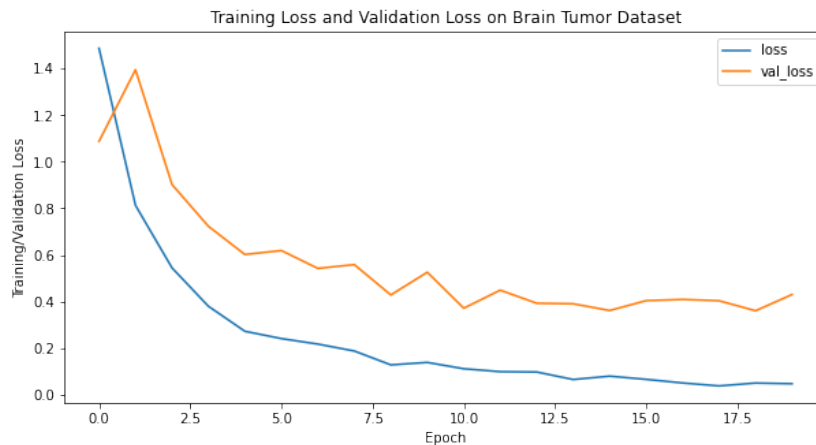
| inception_resnet_v2_input: InputLayer | input: | [(None, 224, 224, 3)] |
| | output: | [(None, 224, 224, 3)] |

| inception_resnet_v2: Functional | input: | (None, 224, 224, 3) |
| | output: | (None, 5, 5, 1536) |

| dropout_6: Dropout | input: | (None, 5, 5, 1536) |
| | output: | (None, 5, 5, 1536) |

| flatten_3: Flatten | input: | (None, 5, 5, 1536) |
| | output: | (None, 38400) |

| dropout_7: Dropout | input: | (None, 38400) |
| | output: | (None, 38400) |

| dense_3: Dense | input: | (None, 38400) |
| | output: | (None, 4) |

Fig. 5 Plot model.

The validation loss and validation accuracy graphs in Fig. 6 below show that they perform better at each run epoch. The validation loss graph shows a decrease, and the validation accuracy graph in Fig. 6 shows an increase indicating better results.
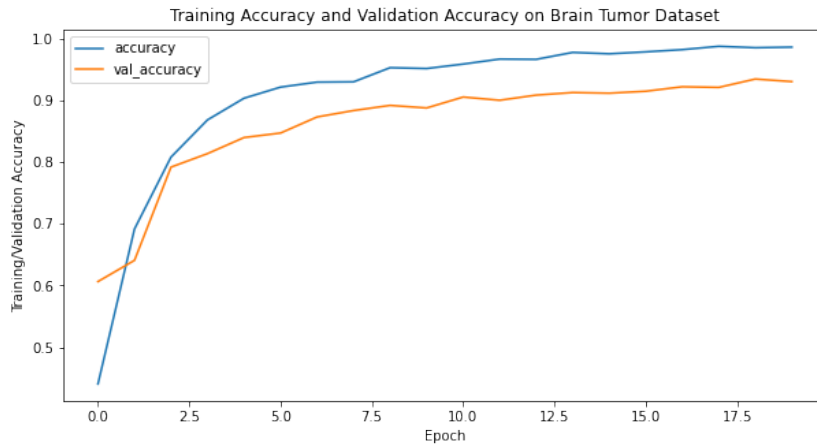
Fig. 6 Training and validation loss and accuracy

4.2. Model Performance Evaluation

Fig. 7 displays a heatmap of the confusion matrix that shows the performance of the model on the validation dataset.
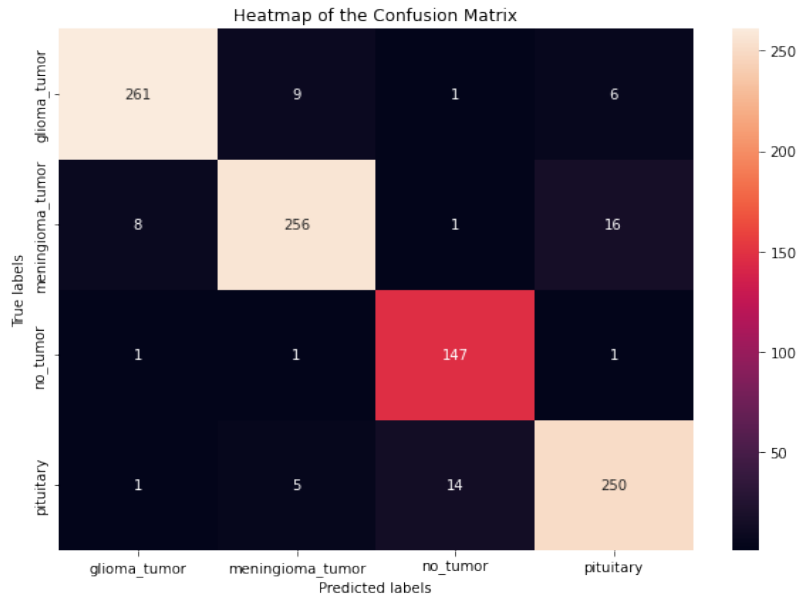

Fig. 7 Heatmap of the confusion matrix for validation set.

Based on the information obtained from the confusion matrix, we can see that the type of meningioma tumor is the most challenging type of tumor to be recognized by the model. In contrast, no tumor image is the class that is slightly misclassified.

Table 5. Model evaluation

	Precision	Recall	F1-Score
Glioma Tumor	0.96	0.94	0.95
Meningioma Tumor	0.94	0.91	0.93
No Tumor	0.90	0.98	0.94
Pituitary Tumor	0.92	0.93	0.92
Accuracy	0.93	978	
Macro Avg	0.93	0.94	0.94
Weighted Avg	0.94	0.93	0.93

The classification report table shows that the model is better at classifying images of glioma tumors compared to other classes based on precision and F1-Scores. From the recall metric, pituitary tumor is an image that can be classified better than other classes. The overall accuracy of the model is 0.9344.

5. Conclusion

In this study, researchers used the Inception Resnet v2 architecture, part of an excellent transfer learning technique for image classification analysis. By using only 20 epochs, the model has succeeded in achieving the highest maximum validation accuracy value of 0.9344 and validation loss of 0.3129. After completing the data analysis stage, there are several conclusions that can be drawn. First, glioma tumor was the most difficult tumor type to be recognized by the model because there were 57 observations that were not properly classified. Of the 57 observations, 43 were meningioma tumor MRI, 14 observations were tumor-free MRI. Second, meningioma tumor and tumourless images are images that can be recognized well by the model because there are only two errors in the prediction of the tumor type.

From the conclusions above, the accuracy obtained is 93.4%. This means that the model formed is good enough in classifying MRI images of brain tumors, but it would be better if the accuracy value was higher to minimize errors that occurred in the classification. It is recommended to get a better model, it can be done by multiplying the MRI images of the brain because the more data that is processed, the more likely it will be to produce a better model.

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