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Comparative Analysis of Convolutional Neural Network and MobileNet Models for Brain Tumor Classification

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Abstract

One of the main causes of cancer deaths in the world today is brain tumors. Brain tumors are very dangerous because there are more than 200 different types and they are difficult to treat. MRI (Magnetic Resonance Imaging) is a technique that is increasingly used to detect and analyze brain tumors without surgery. However, manual analysis of MRI by radiologists is very time consuming and depends on their experience, which can cause treatment delays. Convolutional Neural Networks (CNN) are very good at learning patterns from images. Lighter models such as MobileNet are designed for real-time applications on small devices. We compared the performance of standard CNN models with MobileNet for classifying brain tumors. We collected 7,023 brain MRI images categorized into four main tumor types: glioma, meningioma, pituitary, and no tumor. To improve data quality, we use techniques such as data augmentation, data transformation, and data normalization. The CNN and MobileNet models were trained using 80% training data set and 20% testing data set. We adjust the model's performance using accuracy, loss, precision, recall, and F1-score. The CNN model achieves a peak performance in instruction of 99.27% and a peak performance in testing of 98.29%. Conversely, the MobileNet model achieves higher training accuracy, specifically 99.79%, but lower training accuracy, specifically 98.15%.

Keywords—MRI, CNN, MobileNet, Brain Tumor, Brain Tumor Detection

Keywords:

1. Introduction

Brain tumors is a serious threat to global health and because of it the rate of the death is high. A brain tumor itself is an abnormal growth of brain cells [1]. Mostly, around 70% of tumors are benign, while the remaining 30% are serious [2]. Benign tumors have the same structure and do not contain active cells, while malignant tumors contain active cancer cells and have a non-uniform structure [1]. The exact cause of the tumor is still unknown, but several risk factors that can increase a person's chances of having a brain tumor are exposure to radiation, a family history of brain tumors, and genetic disorders. Every year, there are around 7 to 11 cases of brain tumors per 100,000 individuals in various age ranges and it is estimated that as many as 227,000 people die every year from this terrible disease [3]. Riddhi Chawla et Al [4] also said that around 69,720 new cases of brain disease were discovered in 2013, both malignant brain tumors (14,770 cases) and benign brain tumors (around 32,100 cases). Statistical data from CBTRUS 2012 shows that brain tumors are the second highest cause of cancer-related deaths in children under 20 years of age and in men aged 20-39 years (with leukemia as the main cause). In addition, brain tumors are also the fifth leading cause of cancer-related deaths in women aged 20-39 years.

A researcher named Shenbagarajan Anantharajan et Al found a fact that [3], brain tumors represent a complex diagnostic challenge because they are protected by the “Blood-Brain Barrier (BBB)”. MRI scanning is considered the most effective diagnostic method for detecting disorders of the BBB and has been a popular research topic since the 1980s. But noise makes it hard to identify afflicted areas in MRI images, which frequently can lack the good contrast [5]. When the diagnosis is delayed and adequate treatment ensue from this, making it more difficult to detect brain cancers. Furthermore, since accuracy is so important in medical systems, the usefulness of models in creating machine learning algorithms is a significant concern. The necessity of creating efficient machine learning algorithms to raise the accuracy of medical systems is highlighted by this.

Brain tumor is not only a deadly disease, but also attracts attention because of its broad impact and challenging complexity. Md. Saikat Islam Khan et Al research’s [2] said that more than 120 different types of brain tumors have been identified, including meningiomas, gliomas, and pituitary tumors, which are the most common brain tumors. Our research also uses these three forms of brain tumors to classify the types of brain tumors. Meningiomas, which affect the membranes of the brain, are the most dominant type and affect the brain and spinal cord. Glioma is originates from astrocyte glial cells and can grow slowly and become one of the most serious brain tumors. Meanwhile, pituitary tumors, which are caused by excessive growth of brain cells in the brain's pituitary gland, are also one of the types of tumors discussed.

We are employing MobileNet architecture as the primary strategy in the analysis process in conjunction with the plain Convolutional Neural Networks (CNNs) with 5 convolutional and 2 fully connected layers in order to accomplish this goal. Firstly, we use CNNs' inherent capabilities to extract pertinent characteristics from intricate MRI pictures. After processing the data and normalized the pixel values, we feed the modified photos into the CNN model with the aim of reducing noise and increasing contrast. Furthermore, we implement a lightweight CNN version called MobileNet, which may speed up inference by lowering model complexity. This is expected to have benefits for large dataset management and real-time brain tumor detection applications. When combined with preprocessing methods such as data augmentation, pixel value normalization, and image size modification, it is expected that this approach will enhance the diversity of the training dataset, decrease model overfitting to noise, and improve the quality of the data representation.

2. Related Works

There are many studies that have been conducted in the literature regarding the classification of brain tumors. The following is some of the research that has been discussed. S. Shanthi et Al [6] proposed the use of Automated Hybrid Deep-Deep Neural Networks (OHDNN) for brain tumor classification in the field of medical imaging in her paper. They performed two main phases: image pre-processing, including quality enhancement and noise removal, and classification using OHDNN, which combines CNN and LSTM. The use of an adaptive driver optimization (ARO) algorithm helps improve the performance of OHDNN. By testing on a dataset of MRI images, this approach achieved a maximum accuracy of 97.5%. For the investigation, they used “512×512” brain MRI images collected from various clinics in Karnataka. The dataset consists of 1000 images, with 600 used for training and 400 for testing.

Takowa Rahman et Al [7] said in the research that the utilization of a novel structure in parallel convolutional neural networks (PDCNN) to extract global and local features from two parallel stages, thereby overcoming the overfitting problem. This was achieved by combining dropout regularization and batch normalization. Because of the input image is resized and transformed to grayscale to reduce complexity. Subsequently, data augmentation is employed to increase the available dataset size. The advantage of this parallel path lies in the fusion of two parallel CNNs with different kernel sizes, enabling the model to capture both local and global information. The efficacy of this approach was evaluated using three distinct types of MRI datasets. Consequently, the binary tumor identification dataset-I, Figshare dataset-II, and multiclass Kaggle dataset-III achieved accuracy rates of 97.33%, 97.60%, and 98.12%, respectively.

Atika Akter et Al [8], in his research proposed a deep Convolutional Neural Network (CNN) based architecture for automatic classification of brain images into four classes and a U-Net based segmentation model. Using six benchmark datasets, classification models were tested and segmentation models were trained, allowing comparison of the effects of segmentation on tumor classification in brain MRI images. Accuracy, recall, precision, and AUC are classified in the two classification methods. It showed that the highest accuracy of 98.7% for combined dataset and 98.8% with the segmentation approach for the classification model, with the highest classification accuracy reaching 97.7% among the four individual datasets.

Brain tumors can be different in size and it also have different small details from patient to patient, it makes the radiologist difficult to diagnose and classify them from multiple images. P.M. Siva Raja et Al [9] in his research said that an innovative approach in brain tumor classification in this complexity. This approach combines Bayesian fuzzy cluster-based segmentation with the use of autoencoders in hybrid circuits. The step involves pre-processing the image using a non-local mean filter to reduce noise. After that, the segmentation was carried out using a Bayesian fuzzy clustering approach to identify brain tumor areas. The feature extraction process is then carried out using powerful features such as information size, scattering transform (ST), and Tsallis packet wavelet entropy (WPTE). Finally, tumor classification was carried out using a hybrid scheme of autoencoder in JOA (Jaya optimization algorithm) with softmax regression techniques. The implementation of this approach was carried out in the MATLAB environment and the simulation results obtained from the BRATS 2015 database showed that the proposed approach achieved a high classification accuracy rate of 98.5%, outperforming other recent methods, in line with the findings in previous studies.

Although, a researcher named Zaka Ur Rehman et Al found a fact that [10], Leave-one-out cross validation (LOOCV) technique can also be used to identify brain tumors in MRI images. Using the dataset (BraTs 2012), bilateral filtration was applied to reduce sound interference. After that, they used a Gabor filter to create a text map from the image. Then, the image is divided into small parts called superpixels, and basic features are extracted. Although the basic features are not that important for finding a brain tumor, they are integrated with the text map image to enhance its meaning. The results of this analysis are then used to classify images into two categories, namely tumor and non-tumor areas. The technique successfully found brain tumors with an accuracy of about 88%, which is good enough to complete the MICCAI BraTS challenge.

3. Methodology

The steps of dataset collection, size adjustment, value normalization, data transformation, data augmentation, dataset sharing, classification output, and model performance evaluation involved in the research methodology. The steps are include the collection of relevant datasets that followed by size adjustment and value normalization to ensure data consistency. Data augmentation is then utilized to raise the sample size and avoid overfitting, and data transformation is applied to broaden sample variety. Subsequently, the dataset is split into subgroups for training and testing models. The efficacy of plain CNN and MobileNet models in brain tumor classification is revealed by evaluating the classification results using performance criteria including accuracy, precision, and recall. The steps of this investigation are depicted in Fig. 1.

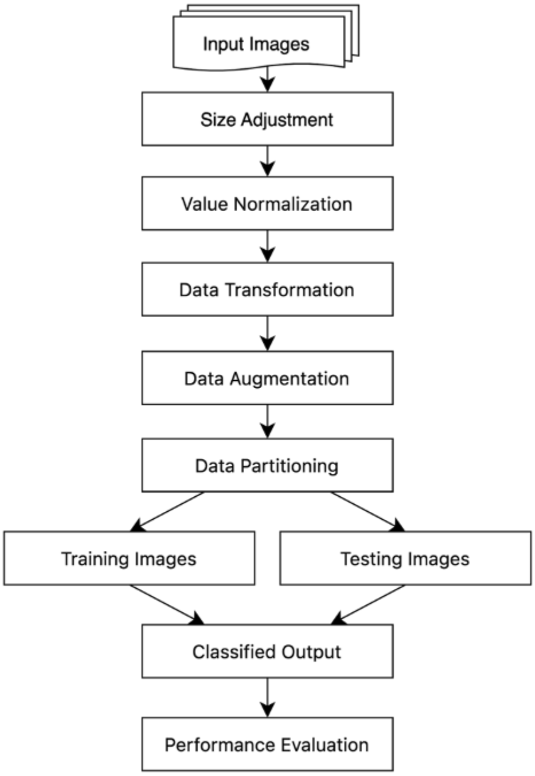
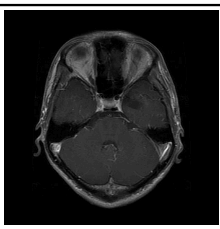
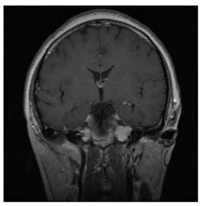
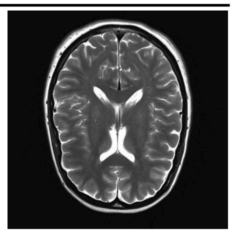


Fig 1. The framework of the proposed approach.

3.1. MRI Dataset

We utilize an MRI dataset that is the combined result of Figshare, SARTAJ, and Br35H sources accessible through the Kaggle platform in this study. The dataset includes 7023 human brain MRI images that have been classified into four main categories: glioma, meningioma, no tumor, and pituitary. The images of the no-tumor class were obtained from the Br35H dataset. Each MRI image in this dataset is represented in three different views, namely axial, coronal, and sagittal. Table 1 shows examples of the datasets we use.

Table 1. Dataset of MRI Brain Tumor.

	Glioma Tumor	**Meningioma Tumor**	**Pituitary Tumor**	**No Tumor**
MRI Brain Pictures				

3.2. Pre-processing

Before using the brain MRI image data to train the plain CNN (our model) and MobileNet models, it must first undergo a series of crucial procedures in data preprocessing, which are included in the code above. The images are first read and adjusted to a consistent size of 150 × 150 pixels. After that we can see that the pixel values of the images were normalized to fall within the range of 0 - 1. There are a moment that the data was reshaped according to the format accepted by the plain CNN and MobileNet models. And finally, the class labels of the data are converted to one-hot encoding for model training purposes.

3.3. Data Augmetation

Data Augmentation is an important technique in training plain convolutional neural network (CNN) and MobileNet models, especially when the available dataset is limited. At this stage, we apply various transformations to the training images, such as rotation, horizontal and vertical shifts, and horizontal flips. So it will increase the variety of data which used to train the model and prevent overfitting. We also use the ImageDataGenerator module of Keras to perform data augmentation automatically during the model training process in our implementation. So a more general and robust representation of brain MRI images will improving the generalization ability and performance of the model in classifying new images with data augmentation can be learned by the model.

3.4. Model Planning

We propose the plain CNN and MobileNet architecture models consisting of multiple convolution layers and dense layers. The model is designed to accept images of 150 x 150 pixels in RGB format. This CNN architecture consists of multiple convolution layers with ReLU activation function, followed by a max pooling layer to reduce feature dimensionality. We also applying the dropout in some layers to reduce overfitting. The model ends with several dense layers that connect the results of the convolution layers to an output of size 4 (corresponding to the number of classes to be predicted about glioma_tumor, meningioma_tumor, no_tumor, and pituitary_tumor) using a softmax activation function.

The next step is to use the pre-prepared training data to train the plain CNN and MobileNet models. We also used the Adam optimizer with a pre-defined learning rate and the categorical crossentropy loss function to evaluate the performance of the models on the multiclass classification problem. And then, we specified the number of epochs (50) and the batch size (32) for the training process. During the training process, we applied data augmentation using ImageDataGenerator to increase data and prevent overfitting. We also added a callback to stop training if the training and validation accuracy had reached a value of more than 97%. After the training was complete, we recorded the time taken for the training process using the time module. So it will show that the training process of plain CNN and MobileNet models for brain MRI image classification can be considered complete, and the models are ready to be tested on never-before-seen data. And the details about the proposed plain CNN model are represented in Table 2, while information about MobileNet can be found in Table 3.

Table 2. Proposed CNN model.

Layer (type)	**Output Shape**	**Param #**
conv2d (Conv2D)	(None, 150, 150, 64)	4864
max_poling2d (MaxPooling2D)	(None, 75, 75, 64)	0
dropout (Dropout)	(None, 75, 75, 64)	0
conv2d_1 (Conv2D)	(None, 75, 75, 128)	73856
max_poling2d_1 (MaxPooling2D)	(None, 37, 37, 128)	0
dropout_1 (Dropout)	(None, 37, 37, 128)	0
conv2d_2 (Conv2D)	(None, 37, 37, 128)	147584
max_poling2d_2 (MaxPooling2D)	(None, 18, 18, 128)	0
dropout_2 (Dropout)	(None, 18, 18, 128)	0
conv2d_3 (Conv2D)	(None, 9, 9, 128)	147584
max_poling2d_3 (MaxPooling2D)	(None, 9, 9, 128)	0
dropout_3 (Dropout)	(None, 9, 9, 256)	0
conv2d_4 (Conv2D)	(None, 4, 4, 256)	295168
max_poling2d_4 (MaxPooling2D)	(None, 4, 4, 256)	0

dropout_4 (Dropout)	(None, 4096)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 1024)	4195328
dropout_5 (Dropout)	(None, 4)	0
dense_1 (Dense)		4100
Total params: 4868484 (18.57 MB)		
Trainable params: 4868484 (18.57 MB)		
Non-trainable params: 0 (0.00 Byte)		

Table 3. Proposed MobileNet model.

Layer (type)	**Output Shape**	**Param #**
dobilenet_1.00_244 (Functional)	(None, 4, 4, 1024)	3228864
dlatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 1024)	16778240
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 512)	524800
dense_2 (Dense)	(None, 256)	131328
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 4)	1028
Total params: 20664260 (78.83 MB)		
Trainable params: 17435396 (66.51 MB)		
Non-trainable params: 3228864 (12.32 Byte)		

4. Result and Discussion

4.1. Classification result

The use of plain CNN and MobileNet involved in the proposed two-model architecture for brain tumor classification. Then, the plain CNN is using the dataset that divided into two parts, namely for training and testing. The dataset division ratio is 80:20, where 80% of the data is used for training and 20% for testing. The brain tumor classification accuracy using the plain CNN model for the 80:20 ratio is shown as follows. The number of epochs used is 50, and the total execution time required is 665 seconds. The maximum of accuracy that achieved by the plain CNN model is 97%.

The same purpose for comparising was also used in the MobileNet model. The same dataset was used for training and testing with the same split ratio of 80:20. The MobileNet model was trained with 50 epochs with an execution time of 300 seconds and achieved a maximum accuracy of 90% was trained in the MobileNet. We used an architecture consisting of five convolution layers with ReLU activation function, followed by a max pooling layer to extract features from brain tumor imagesfor the implementation of plain CNN and MobileNet models. We also apply a dropout layer to reduce overfitting of the model additionally. After the last convolution layer, we use a fully connected layer with 1024 units followed by dropout and a softmax output layer with four classes for brain tumor classification. The total parameters that can be set in this model are 4,868,484.

4.2. Classification result

We are using a confusion matrix for classification system results. So, here are the following factors is used to evaluate performance [7]. A comprehensive measure of a model's performance by evaluating its overall correctness in classification tasks is provided by calculating the accuracy. After that, Precision is for insight into the reliability of the model's positive class predictions, expressing the proportion of true positives among all instances predicted as positive. Recall, also known as sensitivity, assesses the completeness of positive events correctly identified by the model, indicating the proportion of true positives correctly classified among all actual positive events. The F1 Score, which is the harmonic average of precision and recall, offers a balanced assessment of model performance, especially useful when there is a need to achieve a balance between precision and recall, ensuring high precision in identifying positive events and comprehensive coverage of all events. positive event.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{1}$$

$$\text{Precision} = \frac{TP}{(TP + FP)} \tag{2}$$

$$\text{Recall} = \frac{TP}{(TP + FN)} \tag{3}$$

$$\text{F1-Score} = \frac{2 * Precision * Recall}{(Precision + Recall)} \tag{4}$$

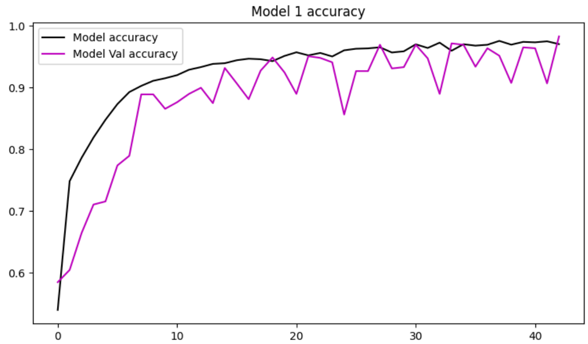


Fig 2. Accuracy of CNN.

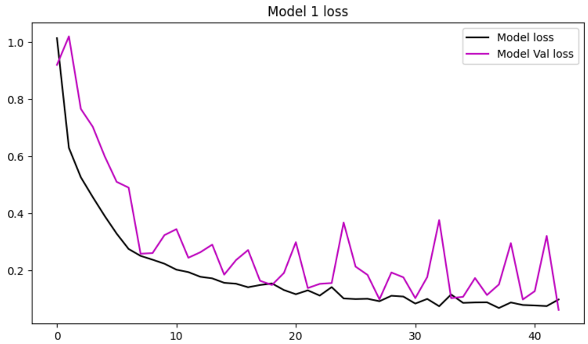


Fig 3. Loss of CNN.

Figure 2 is showing the change in accuracy of CNN and figure 3 is showing the change in model loss during the training process using plain CNN. While the magenta colored lines represent the values in the validation data, The black colored lines in both graphs represent the values in the training data. The increase and the decrease in accuracy and loss for both datasets as the period of progresses indicates an improvement in the performance of the plain CNN model.

Table 4. Model evaluation training and testing using CNN.

	precision		**recall**		**f1-score**	
	train	**test**	**train**	**test**	**train**	**test**
glioma	1.00	0.99	0.98	0.96	0.99	0.97
meningioma	0.98	0.96	0.99	0.98	0.99	0.97
notumor	1.00	0.99	1.00	0.99	1.00	0.99
pituitary	0.99	0.99	1.00	0.99	1.00	0.99
micro avg	0.99	0.98	0.99	0.98	0.99	0.98
macro avg	0.99	0.98	0.99	0.98	0.99	0.98
weight avg	0.99	0.98	0.99	0.98	0.99	0.98
samples avg	0.99	0.98	0.99	0.98	0.99	0.98

The model evaluation for training and testing data summary using CNN is provided in table 4. Metrics such as precision, recall, and F1-score for each classified class, namely glioma, meningioma, no tumor, and pituitary is included in this evaluation. Precision results show the accuracy of the model when identifying a particular class, even though the model's ability is to find all instances of the class within the recall measure. A more comprehensive picture of the model's performance, and F1-score combines precision and recall into a single value are included.

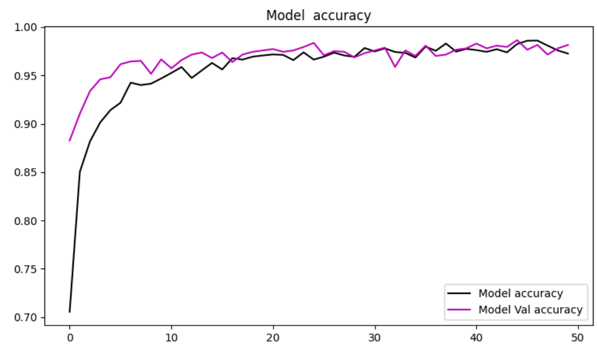


Fig 4. Accuracy of MobileNet.

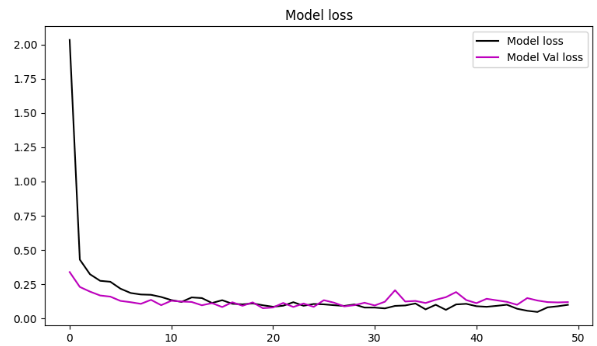


Fig 5. Loss of MobileNet.

The changes in model accuracy is showed in figure 4 and loss during the training process using MobileNet is showed in figure 5. The black line in the third graph represents the values in the training data, while the blue line represents the values in the validation data. An improvement of the MobileNet performance is indicates the increase and the decrease in accuracy and loss for both datasets as the period of progresses.

Table 5. Model evaluatiom training using MobileNet

	precision		recall		f1-score	
	train	test	train	test	train	test
glioma	1.00	1.00	0.99	0.97	1.00	0.98
meningioma	1.00	0.96	1.00	0.97	1.00	0.97
notumor	1.00	1.00	1.00	0.99	1.00	0.99
pituitary	1.00	0.97	1.00	0.99	1.00	0.98
micro avg	1.00	0.98	1.00	0.98	1.00	0.98
macro avg	1.00	0.98	1.00	0.98	1.00	0.98
weight avg	1.00	0.98	1.00	0.98	1.00	0.98
samples avg	1.00	0.98	1.00	0.98	1.00	0.98

Meanwhile, an overview of the model evaluation on the training and testing data using MobileNet is provided in table 5. This evaluation is similar to table 4, which includes the same metrics and results from training the model using MobileNet.

4.3. Classification result

Table 6. Suggested tumor type categorization outcomes using CNN and MobileNet.

Method	Dataset	Accuracy (%)	Loss (%)	Time (s)
CNN	Train	99.27	2.79	665
CNN	Test	98.29	6.22	665

MobileNet	Train	99.79	0.65	455
MobileNet	Test	98.15	11.93	455

After we saw the table 6, it showed the performance of the plain CNN and MobileNet models on the training and testing data. The plain CNN model achieved an accuracy of 99.27% with a loss of 2.79% in the training data, and about 665 seconds in the training time. The plain CNN model still maintain good performance with an accuracy of 98.29%, although with a slightly higher loss of 6.22% on the test data.

The MobileNet model also showed higher performance in period of training data accuracy, reaching 99.79% with low loss of 0.65% and shorter training time of around 455 seconds. However, we can see that the accuracy of the MobileNet model is slightly lower than that of the regular CNN model, in 98.15%, while the loss is higher, reaching 11.93% on the test data. This also shows that the MobileNet model tends to slightly overfit the test data compared to the plain CNN model.

The model performance additional information's on the test data is provided by the confusion matrix in figure 5. The confusion matrix is also can help to evaluate the extent so that the model can classifying each class correctly and identifying potential classification errors that need to be corrected.

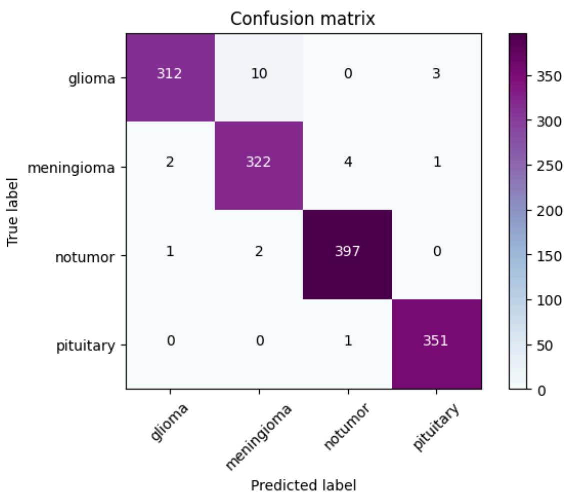


Fig 5. Confusion Matrix using CNN.

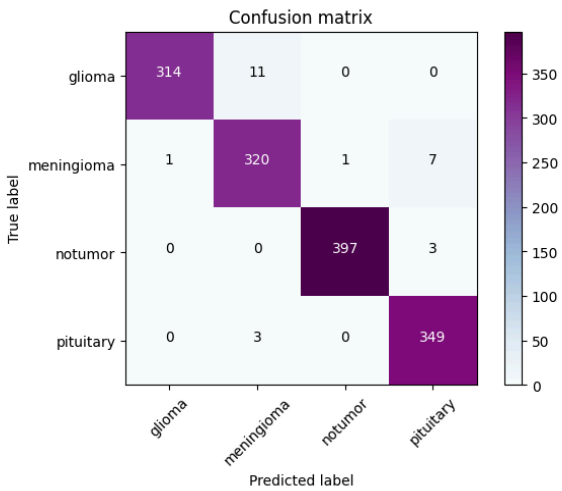


Fig 6. Confusion Matrix using MobileNet.

5. Conclusion and Future Work

We apply and compare the plain CNN and MobileNet models for brain tumor classification using MRI images in our paper, showing the results. Both models were trained and evaluated on a combined MRI dataset consisting of 7,023 images classified into four main categories. 99.27% is the maximum accuracy on the training set and 98.29% on the test set, with training times of around 665 seconds for the plain CNN model. Meanwhile, the MobileNet model provided a higher training accuracy of 99.79% but a slightly lower test accuracy of 98.15%, with shorter training times of around 455 seconds. Overall, both models show that the results are very promising for brain tumor classification. But the plain CNN model still exhibits slightly better generalization ability than MobileNet based on test set performance. This research demonstrates the feasibility of applying deep learning for automated brain tumor diagnosis and classification using MRI images.

There are some potential areas for future work. More specialized MRI brain tumors and larger datasets can be utilized to improve model training. Progressive data augmentation and preprocessing techniques may enrich the data representation. Ensemble or multimodal learning of MRI by combining with other modalities such as CT scans can be explored. Provides insights into model decisions; machine learning methods can be interpreted. By deploying trained models on edge devices, we enable real-time mobile applications. Continuous learning approaches that allow models to learn from new data can help improve diagnosis over time. Overall, for further research in hospitality or medicine, deep learning has the potential to truly impact healthcare.

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