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Article

Early Detection of Brain Tumors: Performance Evaluation of AlexNet and GoogleNet on Different Medical Image Resolutions

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Abstract: Early detection of brain tumors through medical imaging is crucial to improving treatment success rates. This study aims to classify brain tumors using two deep learning models, AlexNet and GoogleNet, by testing three image sizes. The dataset used consists of four classes: glioma, no tumor, meningioma, and pituitary. The test results show that the AlexNet model achieves the best accuracy of 98% at a resolution of 150x150, while GoogleNet shows stable performance with the highest accuracy of 96% at both 150x150 and 200x200 resolutions. The medium resolution (150x150) proves to be optimal for both models, providing the best balance between visual information and processing efficiency. This study highlights the potential use of AlexNet and GoogleNet in brain tumor classification, with opportunities for performance improvement through further development, such as ensemble techniques and the use of a larger dataset.

Keywords: AlexNet; Brain Tumor; Classification; CNN; GoogleNet

1. Introduction

According to the World Health Organization (WHO) [1], brain tumors are the second most lethal disease worldwide [2]. Brain tumors result from the abnormal growth of cells within the brain [3], which can disrupt the normal functioning of the nervous system. Brain tumors are classified into two categories: malignant and benign. Benign brain tumors grow more slowly and are less likely to spread to surrounding tissues, whereas malignant brain tumors can spread and damage adjacent tissues. The exact causes of brain tumors remain unknown; however, several studies have identified factors involved in tumor formation. These factors include exposure to ionizing radiation, a family history of brain tumors, and certain rare genetic conditions. Nevertheless, most brain tumor cases have no clear risk factors and may occur sporadically. The symptoms of brain tumors vary depending on their location, size, and type. Common symptoms include worsening headaches, vision disturbances, seizures, limb weakness, changes in behavior or personality, speech difficulties, and cognitive impairments. These symptoms may develop gradually or appear suddenly, depending on the tumor's characteristics.

The diagnosis of brain tumors involves a series of tests and procedures. Imaging techniques such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans are used to obtain detailed views of the brain and identify the presence of tumors. Another common diagnostic method is a biopsy, which involves taking a tissue sample from the tumor for microscopic analysis. This procedure is often performed to determine the type and malignancy of the tumor; however, it is timeconsuming and incurs significant costs [4]. Treatment for brain tumors depends on the type, size, and location of the tumor, as well as the patient's overall health condition. Additionally, brain tumor patients often undergo therapy. Common therapeutic approaches include tumor removal surgery to reduce tumor size, radiotherapy using high-energy X-rays or particles to destroy tumor cells, and chemotherapy with anticancer drugs to inhibit cell growth. In some cases, a combination of several treatment methods is required [5].

Brain tumors can have a significant impact on the lives of patients and their families. Patients require strong physical, emotional, and social support, which includes assistance from doctors, nurses, and other healthcare professionals, as well as support from family and close relatives. This support is essential to help patients cope with the challenges they face during diagnosis, treatment, and recovery. The prognosis and life expectancy of brain tumor patients vary widely depending on several factors, including the type of tumor, its severity, and the patient's response to treatment. Some benign brain tumors that can be completely removed through surgery have a favorable prognosis. However, malignant brain tumors have a poorer prognosis due to their aggressive growth and spread. Brain tumor patients require long-term monitoring and follow-up care to manage tumor growth and minimize the risk of recurrence.

The issues outlined above highlight the importance of properly addressing brain tumors. Early diagnosis of brain tumors is crucial as it determines the type of treatment required if a brain tumor is detected. Therefore, there is a significant need for precise and accurate diagnostic techniques for brain tumors. Doctors typically diagnose brain tumors by analyzing MRI and CT scan results. This analysis is often performed manually, which increases the likelihood of diagnostic errors [6]. Manual analysis involves observing images produced by MRI or CT scans. Another diagnostic method, biopsy, is also commonly used; however, this approach requires a considerable amount of time and incurs high costs, whereas timely and accurate treatment is critical for patients with brain tumors. Biopsy involves extracting brain tissue for microscopic examination [7]. This underscores the need to develop accurate and reliable brain tumor classification techniques. One promising approach is to leverage classification methods using machine learning, a branch of artificial intelligence [8].

Brain tumor classification using machine learning is a highly effective approach for diagnosing and categorizing brain tumors. Brain tumors exhibit various types and complex characteristics, making accurate identification and classification a challenging task for doctors and radiologists. Therefore, the use of machine learning [9] techniques can provide significant assistance in understanding and classifying brain tumors by recognizing patterns within medical images.

Machine learning, a branch of artificial intelligence, enables computers to learn from data and make decisions or predictions without being explicitly programmed [10]. In the context of brain tumor classification, machine learning can be applied to analyze medical data, including MRI images, CT scans, and clinical patient data, to identify patterns associated with specific types of brain tumors. One commonly used machine learning approach for brain tumor classification is the application of deep learning algorithms, such as artificial neural networks and Convolutional Neural Networks (CNNs) [11]. These algorithms can learn to recognize critical features within image data and extract relevant information to differentiate between various types of brain tumors. The development of a brain tumor classification model using machine learning requires a large, high-quality dataset. This dataset should include medical images accompanied by precise annotations detailing the type and characteristics of the brain tumors. MRI images are particularly valuable in this context, as they provide high-quality imaging that facilitates machine learning [12] algorithms in accurately classifying brain tumors [13]. Based on this premise, the images used in this study consist of brain tumor medical images produced by MRI.

2. Related work

Research on medical image classification has become increasingly popular as it helps to reduce errors in disease diagnosis. Numerous studies have integrated machine learning with medical imaging, demonstrating that machine learning can be effectively applied in the healthcare field. Research utilizing medical images is particularly compelling as it assists doctors in making diagnoses. Additionally, diagnoses become highly accurate with the aid of machines capable of recognizing patterns in each medical image. One of the most accurate studies used medical images of women's breasts to detect breast cancer, achieving a classification accuracy of 99.7% [14]. This study classified 261 images with breast cancer and 745 images without breast cancer. Figure 8 in the article shows that 245 healthy images were correctly classified, with only one misclassification. Meanwhile, 60 breast cancer images were correctly classified without any misclassification in that category. These findings confirm that disease diagnosis using machine learning is highly feasible and can significantly enhance diagnostic precision [9].

The classification of brain tumors using CNN is not a novel area of research; numerous studies have been conducted to diagnose brain tumors using MRI-generated brain images. Shafi et al. (2021) [15] classified glioma, meningioma, pituitary, and multiple sclerosis brain tumors. Table 1 of their study presented a dataset comprising 2,399 brain images obtained from MRI scans. The algorithm

Table 1. Related work using machine learning.

Authors	Deep Model	Dataset	Dataset Size	Accuracy
M. Alqhatani (2022)	CNN	Breast Cancer (MRI)	1006	99.70%
Shafi et al., (2021)	SVM	Brain Ttumor (MRI)	2399	97.74%
Inan et al., (2023)	KNN, XgB, SVM, LR, MLP, TabNet	Breast Cancer (MRI)	767	91.39%, 94.90%, 91.56%, 90.33%, 92.44%, 96.99%
Kabir Anaraki et al., (2019)	CNN	Brain Tumor (MRI)	3064	94.20%
Baranwal et al., (2020)	CNN, Linear SVM, Poly Nomial SVM	Brain Tumor (MRI)	3064	94.00% 81.00% 84.00%

chosen for their research was Support Vector Machine (SVM). The results showed training and testing accuracies of 97.95% and 97.74%, respectively. This study stands out as one of the highest accuracy achievements using SVM. However, the study did not specify the division between training and testing datasets. Their research achieved a higher accuracy in brain tumor classification using SVM compared to the study by Inan et al. (2023) [16] which reported an accuracy of 91.56% for their SVM model (Table 7 in their study).

Another study on the use of CNN was conducted by Kabir Anaraki et al. (2019) [17], focusing on the classification of brain tumor medical images. This research classified three types of brain tumors: glioma, meningioma, and pituitary tumors. The study utilized two different feature extraction models, as shown in Figure 8 of their research. The distinction between the models lies in the input image sizes: the first model used 48x48 input images, while the second model used 128x128 input images. The study achieved an accuracy of 94.2%, which is higher compared to the research conducted by Baranwal et al. (2020) [18]. Baranwal et al.'s study also classified brain tumor medical images using a CNN model. Their research utilized 3,064 MRI-generated brain tumor images. The original image size of 512x512 pixels was resized to 384x384 pixels. The accuracy obtained in their study was 94%.

Previous research highlights the role of machine learning in diagnosing diseases from MRI-generated images. A summary of these studies can be found in Table 1.

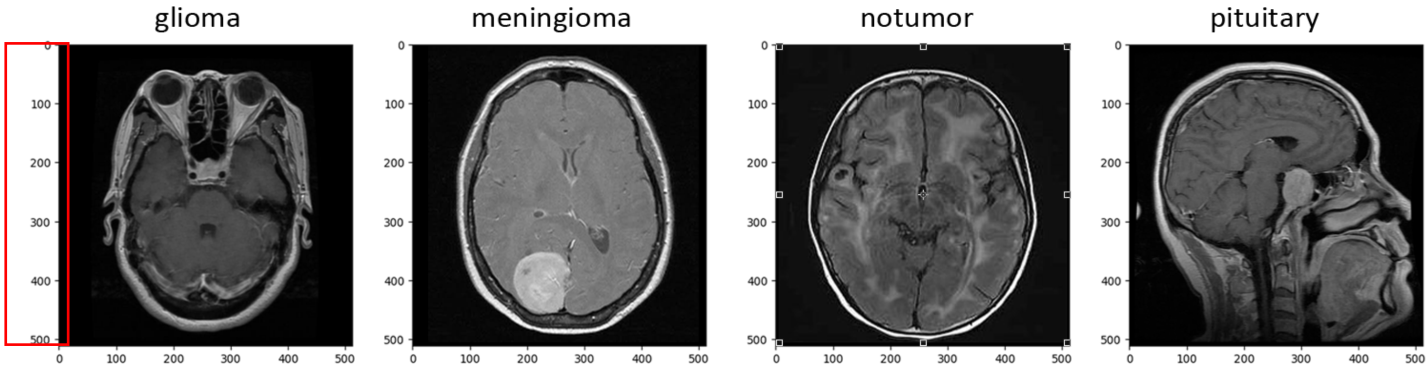


Figure 1. Before preprocessing datasets.

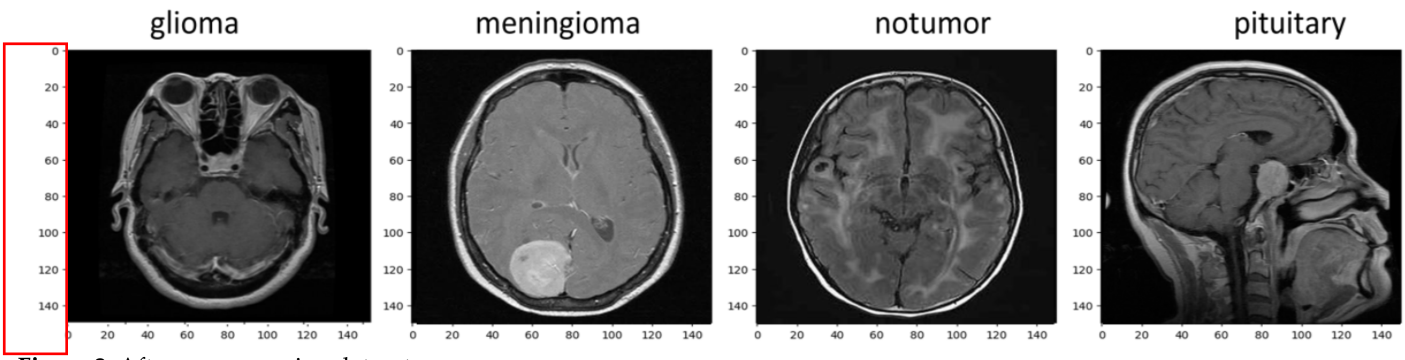


Figure 2. After preprocessing datasets.

Previous research, as shown in Table 1, demonstrates that medical images can be classified using machine learning. Various machine learning architectures are employed to classify diseases in humans. One of the most commonly used medical images for disease classification is brain tumor images obtained from MRI scans. The machine learning architectures frequently used for disease classification based on images are CNN and SVM. Based on this, we conducted a study on medical image classification using CNN, but with a larger dataset compared to previous studies. Our research focuses on analyzing the use of input image sizes, emphasizing the importance of selecting the right image size to ensure precise and accurate diagnosis, particularly for brain tumor classification.

3. Proposed Methodology

Based on the related work, the classification of medical images using CNN in machine learning has been more widely applied compared to other architectures, which is why this study uses CNN. This research tests the performance of CNN in classifying brain tumors with a large dataset. Several CNN architectures that can classify images with large amounts of data include AlexNet, GoogleNet, and VGG. This architecture can extract features very clearly [19][20]. These architectures have been proven to successfully classify images with large datasets and numerous classes, as they have won the ImageNet classification contest. Therefore, these architectures are highly suitable for this research. However, these architectures are designed to classify images with a large number of classes. Thus, this study will analyze the performance of the architecture used to classify images with fewer classes and under different image size scenarios.

3.1 Brain Datasets

The development of a machine learning model for brain tumor classification requires a dataset containing accurately labeled medical images of brain tumors. This dataset plays a crucial role in training and testing the machine learning model to recognize patterns associated with specific types of brain tumors. The brain tumor dataset includes various types of tumors, both benign and malignant, with variations in size, location, and morphological characteristics. High-quality and representative data is essential to ensure that the machine learning model can learn and generalize effectively on unseen data. A rich and diversified dataset allows the model to learn the distinctive visual features of brain tumors, such as shape changes, texture, and intensity distribution in medical images. In addition to medical images, the brain tumor dataset for machine learning can also include clinical patient data, such as age, gender, health history, and results from additional tests like biopsies and genetic analysis. Integrating this clinical data can help enhance brain tumor classification by considering other factors that may influence the tumor's characteristics and development. High-quality and representative brain tumor datasets play a critical role in developing machine learning models for tumor classification. The collection of well-rounded and diverse datasets enables the model to learn and recognize the distinctive patterns that can assist in diagnosing and grouping brain tumors more accurately.

The collection of brain tumor datasets for machine learning in Indonesia is challenging due to the need for collaboration between medical institutions, research agencies, and experts in radiology and oncology. Additionally, acquiring MRI scan images of the brain in Indonesia requires consent from the patient or their family. Since the collection of brain tumor data must be done with respect to privacy and ethics, patient data must be kept confidential in accordance with applicable guidelines and regulations for medical data protection. Given these challenges, acquiring a brain tumor dataset became a significant obstacle for this research. Therefore, we decided to use a dataset provided by Kaggle. The datasets available on Kaggle can be freely downloaded and used for research purposes in various fields of machine learning, including healthcare. The dataset collected consists of 7,023 brain images across four classes: glioma, meningioma, no tumor, and pituitary. Brain images without tumors are included to help the model learn to distinguish between tumor and non-tumor images. The entire dataset was split into training and testing data. The training dataset consists of 90% of the total dataset, while the testing dataset makes up 10%. A larger portion of data is allocated to training because the model requires more data to learn and recognize patterns effectively.

3.2 Image Preprocessing

Image preprocessing is a crucial step in preparing image data before it is processed by a machine learning model. The purpose of image preprocessing is to enhance the quality and representation of image data, making it easier for the model to recognize patterns and features in the brain images. The first step in preprocessing is labeling the images according to their respective classes. Labeling images is a critical step in machine learning model development because the quality and accuracy of labels directly impact the model's ability to understand and differentiate objects or patterns in the images. The labeling process is performed according to the categories in the dataset, which are glioma, meningioma, no tumor, and pituitary. By providing these labels, the model can learn to recognize visual patterns corresponding to each class. This allows the model to classify the images correctly during both the training and testing phases. Proper labeling ensures that the model can distinguish between the different types of brain tumors and identify non-tumor images effectively.

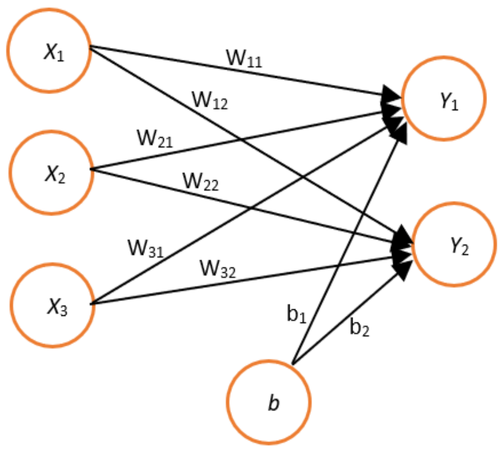


Figure 3. Fully connected layer.

One of the crucial steps in the image preprocessing phase is resizing the images. This process ensures that all images have uniform dimensions, facilitating the model's ability to efficiently extract features from the images. Resizing also reduces computational complexity, thereby speeding up the training and testing processes of the model. As shown in Figure 1, the original image size is quite large (greater than 500x500 pixels), requiring considerable computational time for both training and testing. Therefore, resizing techniques are applied to adjust the image dimensions to better suit the model's needs, enabling it to recognize patterns in the images more swiftly. In this study, three different resizing scenarios are tested: 100x100, 150x150, and 200x200 pixels. While these resized images are smaller than the original size, they retain all the critical information within the images, and no significant features are lost. Figure 2 demonstrates an example of an image resized to 150x150 pixels. Despite the reduction in size, the image still retains all necessary information for tumor classification. Smaller image sizes enable the model to process images more rapidly, without compromising the time required for diagnosis. This resizing technique proves to be beneficial in optimizing the performance of the machine learning model, without diminishing the accuracy of brain tumor classification.

3.3 Feature Extraction

The use of feature extraction in brain tumor classification must employ an architecture capable of working with high-dimensional images to produce accurate diagnoses. The feature extraction proposed in this study is CNN, as this architecture is capable of extracting each feature present in the image. The neural network in CNN contains neurons that are interconnected. In general, CNN has several layers, namely convolutional layers, pooling layers, and fully connected layers.

3.3.1 Convolution Layer

The convolutional layer serves as the first layer in extracting the input image. The convolutional layer shifts the filter used according to the given stride (s) value until the entire matrix is passed by the kernel. This is done repeatedly using different filters to obtain accurate information from the input image. The following is the mathematical Equation 1 for performing convolution [21].

$$\mathrm{x} = \varphi(W * Y_{(ij)} + b) \tag{1}$$

The value of x in equation (1) represents the output of the neuron, φ is the activation function applied to the argument within the parentheses, W is the weight matrix used to multiply the input $Y_{(ij)}$, and $Y_{(ij)}$ is the input of the node or neuron. This can be the output from the previous layer or the original input, depending on the position of the formula in the network architecture, and b is the bias (bias vector) added to the result of the multiplication $W * Y_{(ij)}$.

3.3.2 Pooling

The convolutional layer produces a feature map that is still quite large. This affects the computation speed during training. The pooling layer is one way to address this issue. The main function of the pooling layer is to simplify the image or feature representation by taking the maximum or average value from a specific region within the input matrix. Pooling layers in deep learning are usually applied after the convolutional layer to reduce the size of the feature map and eliminate some irrelevant spatial information. The mathematical equation to compute the new feature map can be used in Equation 2.

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{S} \right\rfloor + 1 \tag{2}$$

The value n_{out} represents the new feature map value generated by each convolution, n_{in} is the input layer or the size of the image used, p is the padding size applied during convolution, k is the size of the kernel used, and S is the stride value, which refers to the horizontal or vertical movement of the kernel. The research we propose will use different input images, resulting in different feature maps generated from the convolution process.

3.3.3 Fully Connected Layer

The Fully Connected (FC) layer, also known as the Dense layer, is a key component in the architecture of artificial neural networks. The Fully Connected layer is where each neuron in this layer is directly connected to every neuron in the previous layer. In other words, each neuron in the Fully Connected layer receives input from all neurons in the previous layer. The main function of the Fully Connected layer is to combine the information extracted from the previous layers and perform a linear transformation on the input. Each connection between neurons in this layer has a weight and bias that represent the importance of each feature in the data. During the training process, these weights and biases are adjusted so that the model can learn to represent complex patterns in the data and produce an output that is aligned with the given task. The Fully Connected layer is typically followed by an activation function such as ReLU, Sigmoid, or Softmax to introduce non-linearity into the model. This non-linearity allows the neural network to represent more complex patterns and capture non-linear relationships in the data. While the Fully Connected layer has been successfully used in various tasks such as image classification [22], natural language processing, and speech recognition, it also has its drawbacks. One of them is the very large number of parameters, especially in models with deep architectures. This can lead to overfitting and requires a larger amount of training data. Below is Figure 3 showing the process of the Fully Connected layer performing classification.

Based on Figure 3, it can be concluded that Equation 3 is:

$$\begin{aligned} Y_1 &= [(W_{11}.X_1) + (W_{21}.X_2) + (W_{31}.X_3)] \\ Y_2 &= [(W_{12}.X_1) + (W_{22}.X_2) + (W_{32}.X_3)] \end{aligned} \tag{3}$$

Equation 3 can be represented in a matrix form as follows in Equation 4:

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} W_{11} & W_{21} & W_{31} \\ W_{12} & W_{22} & W_{32} \end{bmatrix} . \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \tag{4}$$

Equation 4 shows that the input significantly influences the output. The use of brain tumor image size will affect the accuracy and precision in diagnosing brain tumors. To better illustrate the impact of input on output, we attempt to present it in Figure 4.

Figure 4 shows that the value X represents the input image, the value W represents the weight of the input image, and b is the bias value resulting from the mathematical operation between the input and the weights. Meanwhile, Y represents the output of the classification result after the image has passed through each stage of feature extraction. The results obtained are analyzed by comparing the labels of the given image.

3.4 Model evaluation

The results of the testing are displayed in a confusion matrix, which facilitates the analysis. The confusion matrix used is shown in Table 2 [23].

The confusion matrix is a commonly used evaluation tool in modeling and classification. It serves to analyze the model's performance by comparing the model's predictions with the ground truth. The confusion matrix has four main components: True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP). TP represents the number of positive observations that were correctly predicted by the model. In classification, TP indicates the number of positive cases that were correctly detected as positive by the model. TN represents the number of negative observations that were correctly predicted by the model. In classification, TN indicates the number of negative cases that were correctly detected as negative by the model. FN represents the number of positive observations that were incorrectly predicted as negative by the model. In classification, FN indicates positive cases that were not detected as positive by the model. FP represents the number of negative observations that were incorrectly predicted as positive by the model. In classification, FP indicates negative cases that were incorrectly detected as positive by the model. Based on the values of TP, TN, FN, and FP, precision, recall, F1-score, and accuracy can be derived. These results are obtained using formulas 5-8 [24][25].

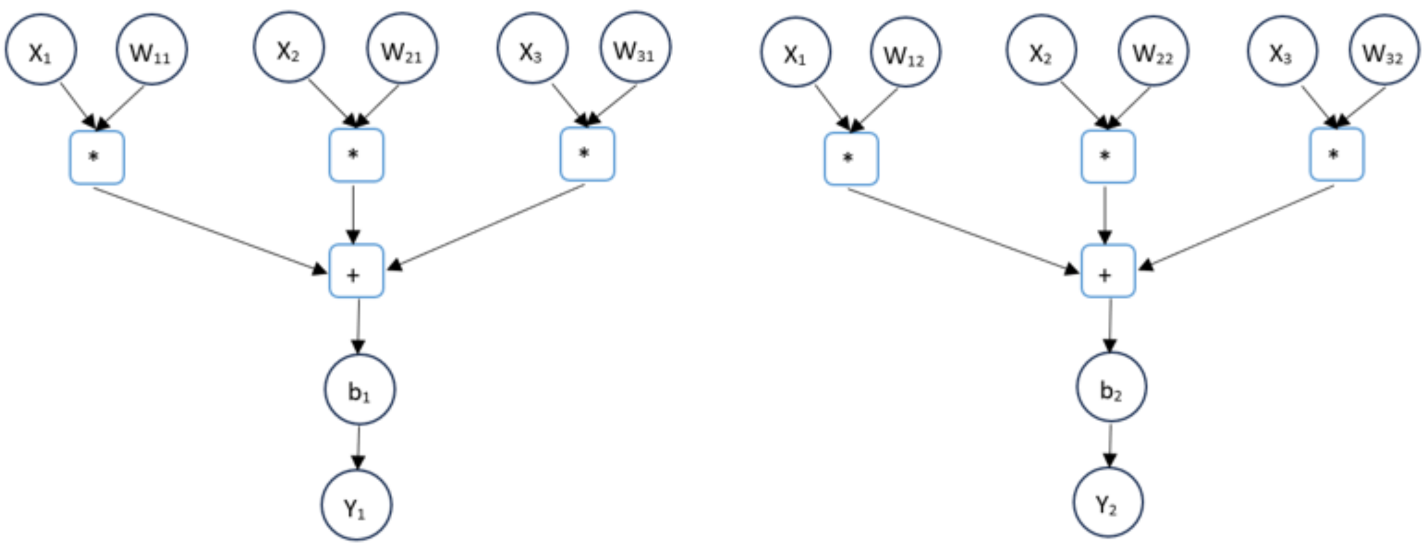
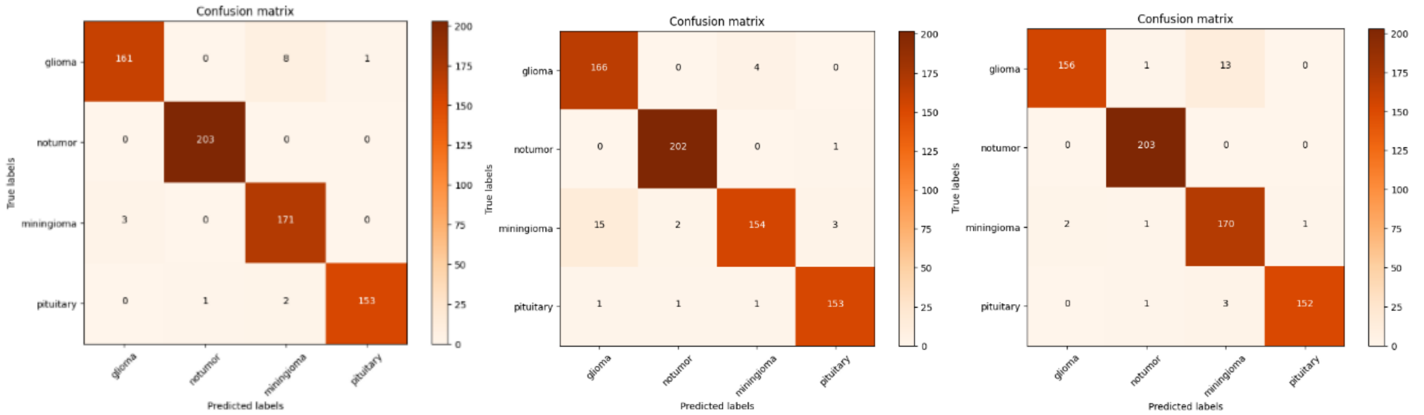


Figure 4. backpropagation illustration.



a) X = 100x100   b) X = 150x150   c) X = 200x200

Figure 5. Confusion matrix result of AlexNet Architecture.

Table 2. Confusion matrix.

		Prediction	
		0	**1**
True	**0**	TN (True Negative)	FP (False Positive)
	1	FN (False Negative)	TP (True Positive)

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 - Score = 2\ X\ \frac{Precision\ X\ Recall}{Precision + \ Recall} \tag{7}$$

$$Accuracy = \frac{\sum TP}{Total\ Data} \tag{8}$$

4. Result and Discussion

This study focuses on the use of Deep Learning methods in brain tumor classification, which presents a significant challenge in the field of medical science and healthcare technology. Brain tumor diseases are among the most serious and complex health problems, affecting the quality of life and life expectancy of patients. In an effort to improve diagnosis and treatment, medical technology has shown rapid advancements, and particularly, Deep Learning technology has garnered attention due to its remarkable ability to process complex medical data. This research presents the latest results from the use of Deep Learning algorithms in classifying brain tumors based on medical images generated from MRI scans. This method promises great potential for ensuring more accurate tumor identification, reducing diagnostic errors, and facilitating more precise decision-making in treatment planning. By using extensive and high-quality patient data, we trained and evaluated various deep neural network architectures, including CNN. This training process allows the algorithm to understand the distinctive features of brain tumor images, enabling it to distinguish between images with tumors and those without.

4.1 Result

This study analyzes the results of the influence of input image size on the accuracy level in classifying brain images using neural networks, which can assist doctors in diagnosing brain tumors. The neural network architectures tested are AlexNet and GoogleNet. The training process for both architectures was conducted in the same manner, using a batch size of 32 and 20 epochs. The input image sizes (X) tested were 100x100, 150x150, and 200x200.

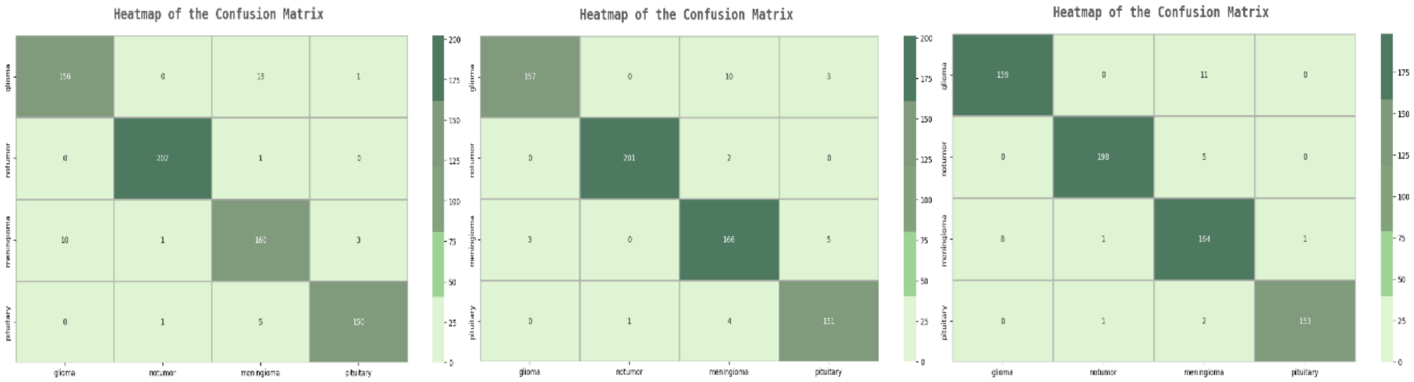
4.1.1 AlexNet Model

This study focuses on analyzing the results of testing the effect of input images on the accuracy of classifying brain tumor medical images. Figure 5 shows the testing results of the AlexNet model using a 10% dataset from 7023 images.

Figure 5 shows the brain tumor classification results based on previously unseen data. The data indicates that the AlexNet architecture can predict medical images with and without tumors. With an input size of 100x100, the AlexNet model correctly predicted 202 images and

Table 3. Testing result of AlexNet.

Classes	**X = 100x100**			**X = 150x150**			**X = 200x200**		
	TP	**FP**	**FN**	**TP**	**FP**	**FN**	**TP**	**FP**	**FN**
Glioma	166	4	16	161	9	3	156	14	2
No tumor	202	1	3	203	0	1	203	0	3
Meningioma	154	20	5	171	3	10	170	4	16
Pituitary	153	3	4	153	3	15	152	4	1



a) X = 100x100 b) X = 150x150 c) X = 200x200

Figure 6. Confusion matrix result of GoogleNet Architecture.

Table 4. Testing result of GoogleNet.

Classes	X = 100x100			X = 150x150			X = 200x200		
	TP	FP	FN	TP	FP	FN	TP	FP	FN
Glioma	156	14	10	157	13	3	159	11	8
No tumor	202	1	2	201	2	1	198	5	2
Meningioma	160	14	19	166	8	16	164	10	18
Pituitary	150	6	4	151	5	8	153	3	1

Table 5. Result of AlexNet model.

Image Size	Precision	Recall	F1-Score	Akurasi
100	96%	96%	96%	96%
150	98%	96%	97%	98%
200	97%	97%	97%	97%

Table 6. Result of GoogleNet model.

Image Size	Precision	Recall	F1-Score	Akurasi
100	95%	95%	95%	95%
150	96%	96%	96%	96%
200	96%	96%	96%	96%

misclassified one image in the "no tumor" class. Meanwhile, for input sizes of 150x150 and 200x200, the model was able to correctly predict all images without brain tumors. These results demonstrate that AlexNet can accurately predict both brain tumor and non-tumor images, which is highly beneficial in assisting doctors with precise brain tumor diagnoses.

Table 3 shows excellent accuracy for the "no tumor" class with an input size of 150x150. The 200x200 input size yielded the same result for the "no tumor" class, but for the glioma, meningioma, and pituitary classes, the 150x150 input size demonstrated higher accuracy compared to the 200x200 input size.

4.1.2 GoogleNet model

The development of the model for image classification using GoogleNet went through the same preprocessing steps, with three different models created based on varying image sizes: 100x100, 150x150, and 200x200 pixels. Therefore, the resulting models consist of three models based on image size groups. The Figure 6 shows the training results of the model using the GoogleNet architecture.

Based on Figure 6, the results show the classification outcomes for each class of images with different sizes. These results indicate that there is an impact on the classification outcomes based on the varying image sizes. Table 4 shows the distribution of results based on formula 8.

The results of the tests show the model's performance in classifying brain tumors into four classes (glioma, no tumor, meningioma, and pituitary) using three different image input resolutions: 100x100, 150x150, and 200x200 pixels. Each class has varying values of True Positive (TP), False Positive (FP), and False Negative (FN), which reflect the model's sensitivity to changes in image resolution. Overall, the model demonstrates consistent results in detecting tumors with relatively low error rates, although there are performance differences between classes and resolutions. For the glioma class, the model shows improved performance at the 150x150 resolution, with the highest TP of 157 and the lowest FP of 13. However, at the 200x200 resolution, while TP increases to 159, there is a rise in FN to 8, indicating that increasing the resolution might cause the model to miss some truly positive samples. This could be due to the increased texture complexity in the glioma class, which is more effectively captured at the medium resolution.

The meningioma class shows the best performance among all classes, with the highest TP (202 at 100x100) and very low FP (only 1 at 100x100). Although there is a slight decrease in TP at the 200x200 resolution, FP remains low (5 at 200x200). This indicates that the model has a good ability to recognize specific patterns in meningioma, even with varying resolutions. For the pituitary class, the model shows significant performance improvement at the 200x200 resolution, with TP reaching 153 and the lowest FP of 3. FN also decreased significantly compared to other resolutions, indicating that this class is more sensitive to high resolution. In contrast, the no tumor class shows more stable results, with only slight variation in FN and TP across resolutions. In conclusion, the input image resolution has varying impacts depending on the complexity of patterns within each class, and medium to high resolutions tend to provide better overall results.

4.2 Discussion

Model training is performed to assess the performance of each generated model. This serves as a reference in making decisions to determine the appropriate image size for classification tasks. Based on Table 5, the results of testing the model using AlexNet are presented.

Table 5 shows the results of testing the AlexNet model with three different image input sizes, highlighting variations in performance across the metrics of Precision, Recall, F1-Score, and overall accuracy. In general, the model performs well across all image sizes, with accuracy values above 96% for each size. However, there are some significant differences that require further analysis regarding the impact of image resolution on the model's classification ability. For the 100x100 image size, the model achieves consistent metric values, with Precision, Recall, and F1-Score each at 0.96, and an overall accuracy of 96%. This indicates that the model is able to make fairly accurate predictions at a lower resolution. However, this resolution may not be sufficient to capture more complex details of brain tumor patterns, which is why the metric values are slightly lower compared to higher resolutions.

The 150x150 image size yielded the best performance, with Precision increasing to 0.98, while recall remained at 0.96. The F1-Score improved to 0.97, and the overall accuracy reached 98%. This indicates that the medium resolution allowed the model to capture more relevant visual information without significantly increasing the error rate. These results suggest that the 150x150 size provides the best balance between model complexity and available image information. At the 200x200 image size, all metrics (Precision, Recall, and F1-Score) were recorded at 0.97, with an overall accuracy of 97%. Although this performance was slightly lower than at 150x150, the increased resolution still provided consistent results. However, this resolution increases likely added complexity to the model without delivering significant improvement in classification performance. This suggests that the model may have reached its optimal capability in capturing patterns at the medium resolution. Overall, the test results indicate that the 150x150 image size is the optimal resolution for the AlexNet model in this brain tumor classification task. This resolution offers the best combination of processing efficiency and prediction accuracy, which could be an important consideration in real-world model deployment.

Table 6 presents the results of the GoogleNet model testing with three different input image sizes (100x100, 150x150, and 200x200). The performance across all sizes was excellent, with Precision, Recall, F1-Score, and overall accuracy ranging from 95% to 96%. Although the differences between the metrics were small, the analysis of each image size provides insight into the effect of input resolution on the model's effectiveness. At the 100x100 image size, the model achieved Precision, Recall, and F1-Score values of 0.95, with an overall accuracy of 95%. Although the performance is high, this resolution may not be optimal for capturing the complex details of brain tumor images. GoogleNet, with its deeper and more complex architecture, likely requires a slightly higher resolution to fully utilize its ability to recognize patterns. The 150x150 image size showed an improvement in all metrics, with Precision, Recall, F1-Score, and accuracy reaching 0.96. This improvement suggests that the medium resolution allowed the model to capture more visual information, leading to more accurate predictions. This resolution appears to strike a good balance between data complexity and the model's ability to process information. At the 200x200 image size, the metric values remained consistent with those of the 150x150 resolution, all at 0.96. This indicates that the increased resolution did not provide significant additional benefits to the model's performance. The additional information obtained from this higher resolution might not have been significant enough to enhance the model's ability, or the model may have reached its optimal limit in utilizing the visual features of the data. Overall, the GoogleNet model showed stable and reliable performance across different image sizes, with the best results achieved at both 150x150 and 200x200 resolutions. This suggests that medium to high resolutions are well-suited for the architecture of this model in the brain tumor classification task. Considering processing efficiency, a resolution of 150x150 can be regarded as the optimal choice for implementing the GoogleNet model for this task.

5. Conclusion and Future Work

Based on the test results of the AlexNet and GoogleNet models with three different image input sizes, both models demonstrated excellent performance with accuracy above 95% for all resolutions. The AlexNet model achieved optimal performance at a resolution of 150x150, with an accuracy of 98%, while GoogleNet showed stable performance at both 150x150 and 200x200 resolutions, with an accuracy of 96%. The medium resolution (150x150) proved to offer the best balance between visual information and processing efficiency for both models. For future research, it is suggested to test other models with more modern architectures or utilize ensemble techniques combining AlexNet and GoogleNet to improve accuracy. Additionally, using a larger and more diverse dataset could help enhance the generalization of the model, leading to better performance across various tumor classifications and conditions.

5. Conflicts of Interest

The authors declare no conflicts of interest.

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