Jurnal Infotel
Vol. 17, No. 1, February 2025, pp. 81–95.
doi:10.20895/infotel.v17i1.1262

Research Article

Brain Tumor Detection Through Image Enhancement Methods and Transfer Learning Techniques

Afandi Nur Aziz Thohari[1,*], Patricia Evericho Mountaines[2] and Mohd Rizal Mohd Isa[3]

[1]Informatic Engineering Study Program, Politeknik Negeri Semarang, Semarang 50275, Indonesia
[2]Computer Engineering Department, Universitas Diponegoro, Semarang 50275, Indonesia
[3]Faculty of Defense Science and Technology, National Defence University of Malaysia, Sungai Besi 57000, Malaysia

*Corresponding email: afandi@polines.ac.id

Received: October 28, 2024; Revised: December 2, 2024; Accepted: December 3, 2024.

Abstract: A brain tumor is dangerous and must be treated immediately to prevent worsening. The identification of brain tumors can be performed by more in-depth examination by specialists or by using artificial intelligence technology through MRI datasets. Several studies have examined how artificial intelligence could be used to find brain cancer in MRI images. The algorithm usually used is CNN with an addition of transfer learning. Previous studies have produced very high accuracy, but the accuracy value can still be improved. In this study, MRI image quality is improved as a new input for modeling. The test results show that the proposed CNN Model produces an accuracy of 98.50% on the test data. This result is higher than the baseline method of 98.45%. Analysis of other metrics, such as precision, recall, and F1-score, indicates consistent performance across classes. These findings suggest that using preprocessing to improve image quality can improve Model performance. Using CLAHE and median blur to improve image quality can improve accuracy by 14.5%. This study contributes to identifying an effective combination of Model optimization techniques for image classification tasks.

Keywords: brain tumor, CNN, image quality, MRI, optimizer

ISSN: 2085-3688; e-ISSN: 2460-0997

1 Introduction

Brain tumors represent atypical proliferation that occur within the brain or its adjacent structures. Neoplasms result from unregulated proliferation of cerebral cells. Intracranial tumors can develop from brain cells (primary brain tumors) or malignant cells that have metastasized from other regions of the body (secondary brain tumors). Numerous diagnostic modalities exist to identify brain tumors, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT) Scans, biopsy procedures, and comprehensive neurological assessments. MRI is the most proficient method for detecting brain tumors among these modalities. MRI demonstrates considerable efficacy in identifying cerebral neoplasms due to its superior image resolution capabilities, soft tissue sensitiveness, non-radiation, and higher contrast [1].

Diagnosis of brain tumors using MRI requires deeper examination by a specialized doctor. Nevertheless, due to the swift advancements in technology, the identification of brain tumors can now be achieved using Artificial Intelligence methodologies. Deep learning is a technology of Artificial Intelligence that can detect and classify objects in MRI images [2]. The predominant deep learning algorithms employed for image detection and classification tasks are called Convolutional Neural Networks, abbreviated as CNN. Some researchers have researched to detect and classify brain tumors using CNN algorithms. CNN algorithms have proved to be able to detect brain tumors quickly and accurately [3]. Several studies have used the transfer learning of CNNs to accelerate training time and improve classification performance [4, 5]. In transfer learning techniques, previously trained models are used to improve the effectiveness of the training procedure. A pre-trained model is defined as one that has been constructed using comprehensive datasets while achieving a high degree of accuracy.

Various types of pre-trained models can detect brain tumors in images. However, from different pre-training models, three types of pre-training models have the optimum performance to detect brain tumors in MRI, ResNet152V2, DenseNet121, and InceptionV3 [6]. The investigation into the identification of brain tumors via MRI technology with ResNet152V2 produces 98.9% accuracy in test data [7]. In the meantime, the model accuracy of the DenseNet121 model was 97.39% [8]. In addition, using InceptionV3 to identify brain tumors on MRI gives 98% accuracy [9].

In previous research, the accuracy value for detecting brain tumors on MRI could have been more optimal. The accuracy and precision of the model can still be improved, thereby reducing errors in predicting brain tumors. Another gap is that previous studies used MRI with standard quality, and there was still noise. In this research, improvements have been made to the quality of MRI for detecting brain tumors. Besides that, this research put forward multiple strategies to augment the effectiveness of brain tumor detection models. One method proposed is to add optimizers. Research shows that optimizers increase model accuracy [10]. The research uses five optimizer types: AdaDelta, AdaGrad, Adam, SGD, and RMSProp. Afterward, tests will be conducted to compare the five optimizations to obtain the highest accuracy.

The subsequent approach involves enhancing the caliber of the MRI through the application of advanced image processing methodologies, namely median blur and CLAHE. This process is intended to determine the influence of improving image quality on the accuracy of the results. In previous studies, image quality improvement techniques have been applied to reduce the median blur and increase contrast with histograms [11]. The

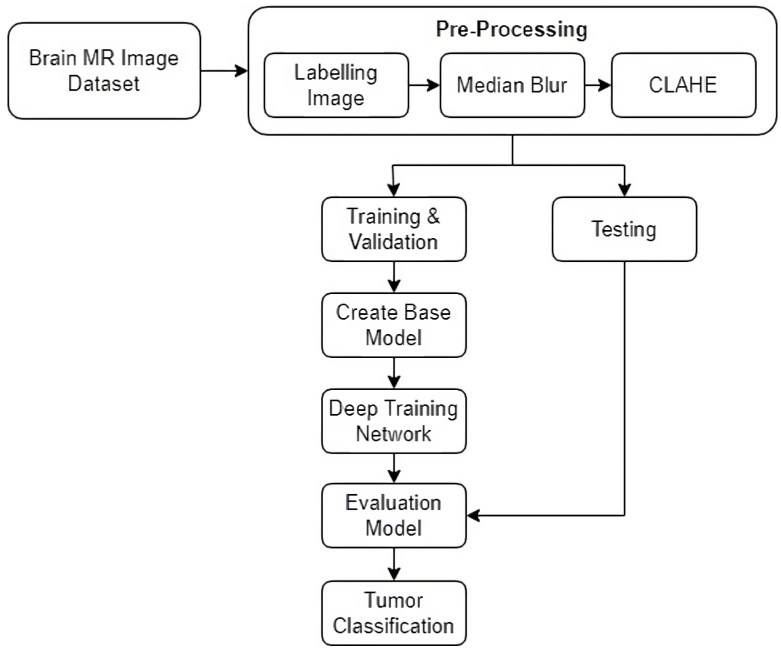


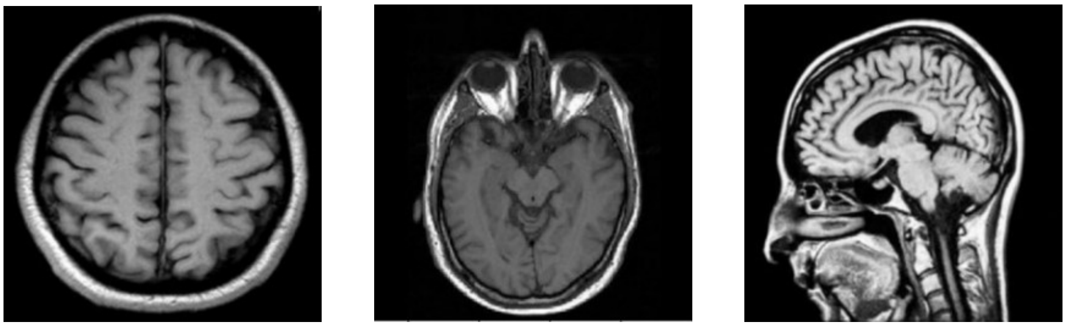
Figure 1: Proposed method for identification of brain tumor.

model accuracy was 95.8%. The research uses median blur to reduce noise, while CLAHE increases the sharpness of the image. The techniques used in this research are expected to produce more accurate models than in previous studies. The results of brain tumor detection have a significant impact on the actions taken by the patient. Consequently, model accuracy is essential and needs to continue to be improved.

This research contributes to providing a new method for brain tumor detection. This research provides a new approach to obtain a high-accuracy brain tumor detection model. The research methodology adds pre-trained models using CNN algorithms. In this study, several optimizers will be compared to achieve optimal accuracy. Subsequently, the quality of the MRI images was enhanced by applying advanced image processing methodologies, including median blur and CLAHE. Enhancements in the quality of training images are anticipated to elevate the model's accuracy and differentiate it from current research endeavors.

2 Research Method

Numerous research endeavors have been undertaken to investigate the identification of brain tumors utilizing artificial intelligence methodologies. However, this model still needs to produce optimal performance. These studies also used artificial intelligence technologies, *i.e.*, algorithms for the CNN and additional methods to optimize model performance. In addition, image processing techniques should be applied to improve the quality of the MRI image. Then select an optimizer and divide the data set to improve model accuracy. The detailed methods and phases of this research are shown in Figure 1.



(a) (b) (c)

Figure 2: Brain tumor MRI image.

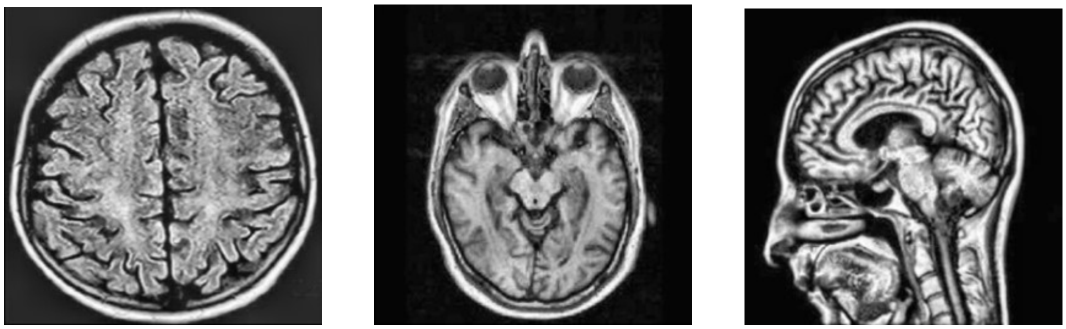
2.1 Gathering Data

The initial stage of the research was to collect brain tumor data sets. This dataset has been sourced from Kaggle and comprises a collection of MRI data that are divided into four categories: glioma, meningitis, pituitary, and no tumor [12]. The aggregate count of images within the dataset is 3,264, which consists of 2,764 tumor images, including glioma, meningitis, pituitary, and 500 non-tumor images. This study classified two categories, namely tumor and non-tumor, so 500 tumor and 500 non-tumor data were extracted from the dataset. Selecting 500 tumor data to avoid the data imbalance between tumor and non-tumor. The selection of 500 tumor data was made randomly, consisting of 167 glioma, 167 meningioma, and 166 pituitary images. Figure 2 shows the sample MRI in the dataset used in this research. Figure 2a is a view of the brain from above at 2x zoom. Figure 2b is an image of the brain in standard view, and Figure 2c is a view of the human head from the side.

2.2 Preprocessing

In this study, Kaggle's datasets are not used directly to extract features. However, improving the image quality of a set of images is carried out to make image characteristics and characteristics more easily recognized. At this stage, three activities have been undertaken, including the following.

1. Labeling Image
   The first phase of preprocessing is to select data and label image data. Image labeling technology uses an Excel file containing image IDs and image labels. There are two labels: label 0, which means non-tumor, and label 1, which means tumor.
2. Median Blur
   This research advances the amalgamation of imaging processing techniques designed to improve the quality of the source images. Among the processed images, median blur and CLAHE techniques are utilized. The median blur eliminates noise from the image [13]. Meanwhile, CLAHE improves the image sharpness. The addition of CLAHE has been proven to improve image quality and increase image classification accuracy [14, 15].



(a) (b) (c)

Figure 3: Median blur and CLAHE processing results.

3. CLAHE
   CLAHE is an image-level optimization algorithm that automatically optimizes the histogram for a small image area to increase its contrast. CLAHE is an advanced image enhancement algorithm that executes automatic optimization of the histogram for localized regions of the image to enhance its contrast [16]. CLAHE represents an advancement of the Adaptive Histogram Equalization (AHE) technique, which involves segmenting images into smaller sections (tiles) and optimizing their equivalence within each segment [17]. CLAHE operates by partitioning the image into smaller segments called tiles and blocks. Subsequently, it implements local histogram equalization on each tile to enhance contrast. Perform a contrast limit (clipping) to avoid noise by limiting the maximum number of pixels with a specific intensity value. The calculation of the histogram threshold or clip limit is defined in (1).

$$\beta = \frac{M}{N}(1 + \frac{\alpha}{100}(S_{max} - 1)) \tag{1}$$

with variable M denotes the area size and N signifies the grayscale value with an upper limit of 256. S_{max} indicates the maximum slope of the image, and α is the clip factor that represents the threshold value to incorporate a limit within a histogram ranging from 0 to 100. Equation (1) determines the clip limit value to indicate that there are excess pixels. The remaining excess pixels are distributed to areas below the clip limits to make the histogram even. Figure 3 illustrates the outcomes of image processing conducted through the application of median blur and CLAHE techniques. Figure 3a, Figure 3b, Figure 3c are visual views of the human brain seen from above and from the side.

2.3 Data Preparation

Preprocessing using median blur and CLAHE increases the quality of MRI images used as datasets. Then, the dataset is then divided into training, validation, and test data. The dataset is segmented into two distinct scenarios. In the initial scenario, the dataset is allocated as 60% for training, 10% for validation, and 30% for testing (60:20:10). Conversely, in the second scenario, the dataset is allocated as 70% for training, 10% for validation, and 20% for testing (70:20:10).

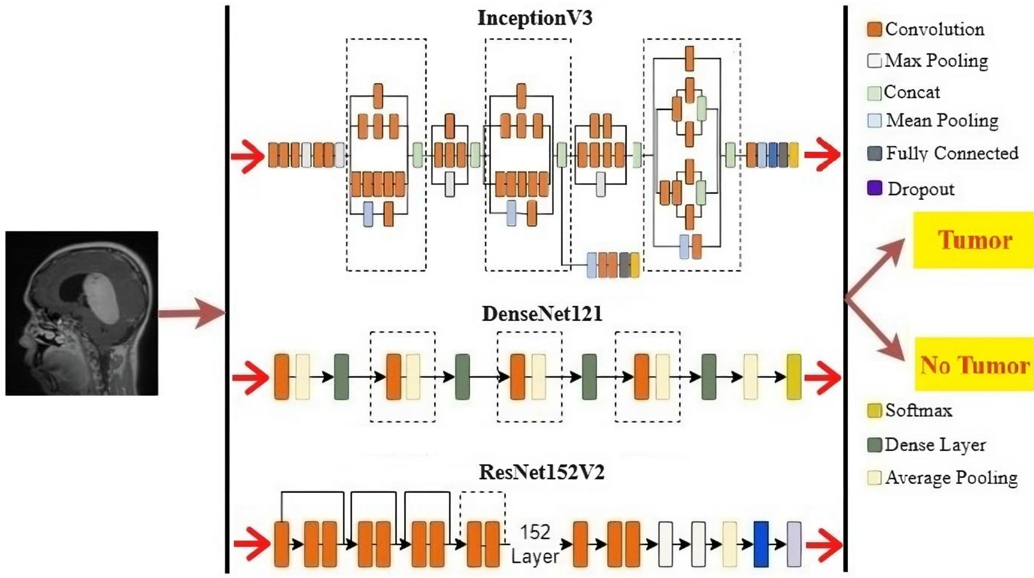


Figure 4: InceptionV3, DenseNet121, and ResNet152V2 architecture for brain tumor detection.

2.4 Create Base Model

The research used a pre-trained CNN model to construct a classification model. The model was created using three pre-trained CNN models, including the DenseNet121, InceptionV3, and ResNet152V2. The three pre-trained models are proven to be accurate in classifying images because they have proved to be accurate [18,19]. This pre-trained model is employed in the feature extraction procedure and generates a feature map. Each pre-trained model has its own unique and different working methods.

a) The InceptionV3 architecture uses an initial block composed of several convolutionary layers, the main concept of which is used. The primary aim of the InceptionV3 architecture was to minimize the number of parameters and computations while preserving a high level of accuracy [20]. To minimize the quantity of parameters in InceptionV3, it is advisable to partition the cone matrix into two distinct segments. For example, the 5×5 convolution is divided into two 3×3 convolutions. In the InceptionV3 architecture, the middle of the network has an additional classification to speed up the training process and prevent excessive installation.
b) DenseNet121 is a model composed of multiple parts, including a dense layer, a bottleneck layer, and a transition layer [21]. Dense layers are used to strengthen the learning process of features. This layer is processed by convolution and grouping. By using a 1×1 and 3×3 convolution, the bottleneck layer reduces the number of parameters. The transition layer is used to reduce the dimension and prevent the network from becoming too large.
c) ResNet152V2 is an advanced version of the Residual Network (ResNet) architecture which has 152 layers [22]. ResNet152V2 includes many residual blocks, bottleneck blocks, batch normalization, and ReLU activation functions. Improved architectural

design improves training stability and enables deeper training of networks without performance degradation problems.

Table 1: Hyperparameter in the model training process

Hyperparameter Tuning	**Value**
Dropout	0.5
Activation Function	Softmax
Batch Size	64
Epoch	20
Learning Rate	0.01
Pooling Layer	GlobalAveragePooling2D
Optimizer	AdaDelta, AdaGrad, Adam, SGD, and RMSProp

The MRI image is processed using each pre-trained model architecture. Afterward, pooling, dropping, and adding the softmax activation function are performed. The final result produces a single-dimensional matrix feature. A comparison of the architectures of InceptionV2, DenseNet121, and ResNet121V2 is shown in Figure 4.

Figure 4 shows the stages or processes of each pre-trained model used to obtain brain tumor prediction results. It can be seen in Figure 4 that the InceptionV3 Architecture uses the Inception Block to combine several filters in parallel. The DenseNet121 architecture uses the Dense Block to combine all previous layer outputs. Each block is usually followed by a transition layer operation that includes pooling and bottlenecks to control feature size. Then ResNet152V2 is the most profound architecture, namely 152 layers. Using a vast number of layers makes the accuracy of ResNet152V2 even better.

2.5 Deep Training Model

Model training uses a fully connected layer of neural networks. Since the model classifies only two classes, binary cross-entropy is used as a loss function. Then use the optimizer to update the model's weight. Optimizers are a very important component of modeling training processes because they minimize the loss function [23]. This is important because it ensures that the models learn from the data provided and improve their predictions over time. This study used five types of optimizers: Adam, SGD, RMSProp, AdaGrad, and AdaDelta. The five optimizers have their characteristics and advantages. Five optimizers were tested to determine which optimizers would produce the optimum model performance for evaluating brain tumor images. All models are tested using the same hyperparameter value. Table 1 displays the hyperparameters employed during the training procedure.

2.6 Evaluation Model

The assessment of the model's efficacy may be conducted through the implementation of a confusion matrix. This matrix is characterized by a 2×2 configuration that delineates the quantities of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The information extracted from the confusion matrix can subsequently be employed to calculate the model's recall, precision, accuracy, and F1 score. Equations (2) to (5) are utilized to derive the metrics for recall, precision, accuracy, and F1 score.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4}$$

$$\text{F1} - \text{Score} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

The precision of the model serves as an indicator of the accuracy in predicting tumors that do not belong to any class. Concurrently, recall assesses the model's effectiveness in accurately identifying tumor classes. The combined metrics of accuracy and F1-Score represent the integration of precision and recall. The optimal model for brain tumor detection is the one that achieves the highest F1 score and accuracy.

3 Results

This study divides the dataset with a percentage of 70% training data, 20% testing data, and 10% validation data. The technique used to evaluate the model's performance is K-Fold cross-validation. The purpose of using K-fold cross-validation is to reduce overfitting and maximize the use of data both as training and test data. The dataset is divided into three folds (K = 3) to reduce the computational process. The greater the folds, the heavier the computation that is run. The free version of Google Colab is limited to a maximum RAM capacity of 12.7 GB. There is an additional early stopping setting to stop training when the validation loss value increases. Early stopping will be active if there is no reduction in the validation loss value by five epochs.

3.1 Evaluation of model performance

There are 15 training result models with five types of optimizers. The number of epochs used is 20, with an average training time per epoch of 50 seconds. The evaluation results of the training process can be seen in Table 2. The InceptionV3 Model with the RMSprop optimizer has the most optimal performance with accuracy and F1-Score values of 0.985 each.

The evaluation of Model performance in Table 2 is performed using K-Cross Validation. This method provides a more accurate estimate of model performance than dividing the dataset only once. This is because all data can be used as training data or test data, and no part of the dataset is only used for testing. In Table 2, the InceptionV3 Model with the RMSprop optimizer produces the most optimal performance. The performance of the InceptionV3-RMSProp Model can be analyzed using the confusion matrix shown in Figure 5.

The confusion matrix in Figure 5 is the result of Model testing using testing data. The total amount of testing data is 200. The evaluation uses K-fold cross-validation, with a total of 3 folds. The model training process using cross-validation produces three models with

Table 2: Performance testing results of the brain tumor detection model

Model	Optimizer	Performance			
		Accuracy	Precision	Recall	F1-Score
DenseNet121	AdaDelta	0.80	0.817	0.817	0.817
	AdaGrad	0.784	0.67	0.924	0.777
	Adam	0.875	0.80	0.99	0.887
	RMSProp	0.835	0.881	0.828	0.853
	SGD	0.95	**1**	0.916	0.956
ResNet152V2	AdaDelta	0.915	0.972	0.883	0.926
	AdaGrad	0.9	0.917	0.901	0.909
	Adam	0.665	0.89	0.638	0.743
	RMSProp	0.88	0.917	0.87	0.893
	SGD	0.935	0.982	0.901	0.909
InceptionV3	AdaDelta	0.91	0.908	0.925	0.917
	AdaGrad	0.64	0.422	0.836	0.561
	Adam	0.94	0.972	0.922	0.946
	RMSProp	**0.985**	0.981	**0.99**	**0.985**
	SGD	0.905	0.862	0.959	0.908

different evaluation results. This result happens because each fold's training and validation data differ. The results of Model training with cross-validation are shown in the graph in Figure 6.

Figure 6a shows the accuracy value at each epoch that the Model produces. The accuracy value increases with the increasing number of epochs. The maximum number of epochs in the training process is 20. Fold 1 can complete 20 epochs because the validation loss value constantly improves. However, the training process on fold 2 stops at the 17th epoch, while fold 3 stops at the 15th epoch. This result happens because the validation loss value does not improve for five epochs. If the validation loss value is not improved for five epochs, it will activate early stopping. Figure 6b shows the loss value from the training process. The loss value decreases with the increasing number of epochs. Based on Figure 6, it is known that fold 1 shows the most optimal model performance.

4 Discussion

The research also tested the effects of image preprocessing to improve model performance. The image preprocessing techniques used are median blur and CLAHE. The preprocessing of images will eliminate the noise of the MRI image and increase the clarity of the MRI image. Previous tests have shown that the InceptionV3 model is best optimized using RMSProp optimizers. Consequently, experiments have been conducted to compare the model with a model that has not gone through a preprocessing process. The testing process is repeated three times to verify the validity of the results shown. The outcomes of the assessment are presented in Table 3.

According to the empirical data delineated in Table 3, the utilization of median blur and CLAHE markedly augments the accuracy of the model. In the scope of this research, the execution of pre-processing methodologies culminated in an enhancement of 14,5% in the

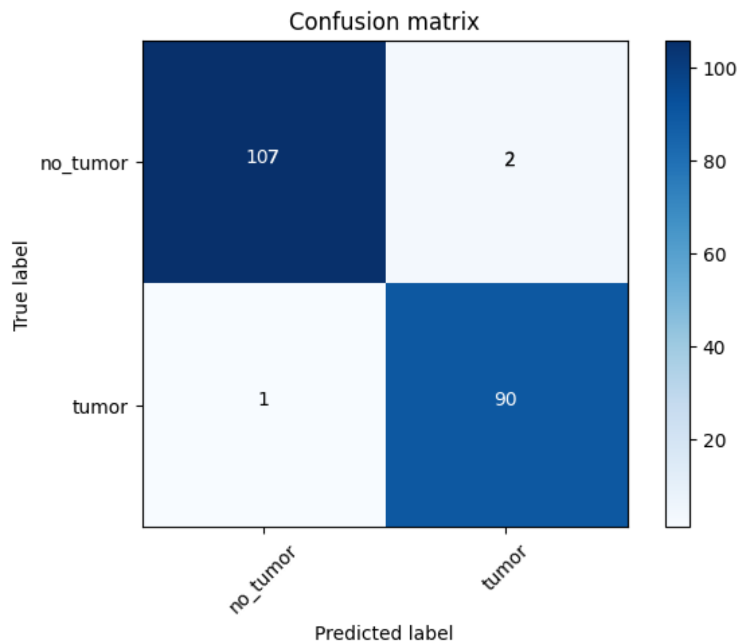
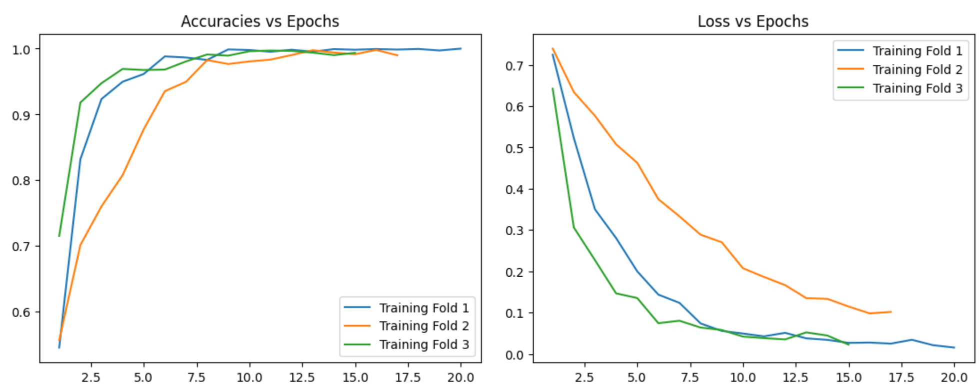


Figure 5: The confusion matrix model InceptionV3 – RMSProp model.



(a) (b)

Figure 6: The training performance graph of the InceptionV3-RMSProp model.

accuracy of the model. These results elucidate that the caliber of the input image can exert a significant influence on the performance of the model.

Figure 7 illustrates the outcomes of the visualization of the confusion matrix model that underwent no preprocessing. Based on the data derived from the confusion matrix, it is evident that the model struggles with tumor predictions. The false negative rates in this instance are significantly high, recorded at 25. Conversely, in models that have been preprocessed, the false negative rates are notably low, amounting to just 1.

Table 3: Performance testing results of the brain

Model	Optimizer	Performance			
		Accuracy	Precision	Recall	F1-Score
Preprocessing Using Median Blur and CLAHE					
InceptionV3	RMSProp	0.985	0.981	0.99	0.985
Without preprocessing					
InceptionV3	RMSProp	0.86	0.972	0.838	0.883

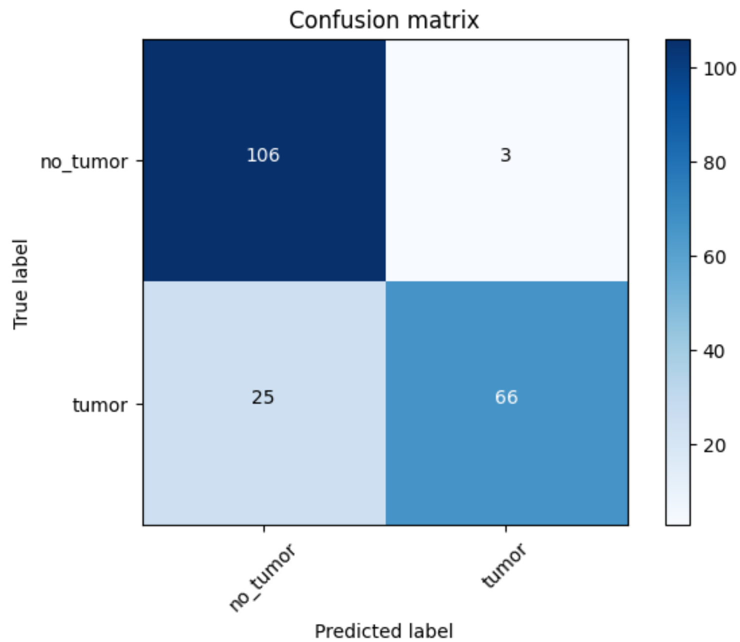
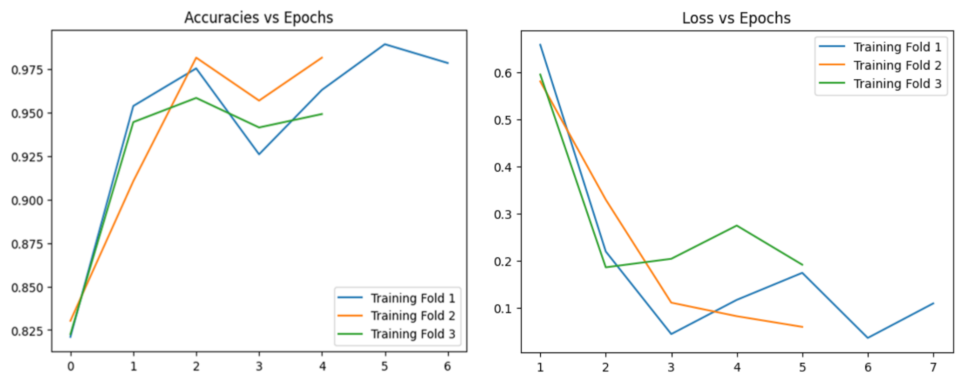


Figure 7: Confusion matrix model InceptionV3 without preprocessing.

Furthermore, the training results of the InceptionV3 model and the RMSProp optimizer can be seen in Figure 8. The accuracy value of each epoch is shown in the Line Chart Figure 8a. The accuracy value fluctuates, unlike the training process in Figure 6a, which tends to increase accuracy. The Loss value in Figure 8b also fluctuates, causing quite a lot of false negative values to be detected. This proves that models that go through the preprocessing process and have high quality will produce optimal accuracy.

After getting the most optimal Model performance, we tried to compare the Model performance values with those of the existing study. Numerous researchers have undertaken investigations into the identification of brain tumors. Most of these scholars employ CNN and transfer learning techniques to attain superior levels of accuracy. Various investigations have indicated that integrating CNN algorithms with machine learning approaches effectively categorizes brain tumors. Nevertheless, the accuracy of their findings remains inferior to the methodology applied in this study. Table 4 illustrates the comparative ac-



(a) (b)

Figure 8: Training performance graph of the Inceptionv3 model without preprocessing.

curacy of multiple brain tumor detection studies employing artificial intelligence technologies.

Table 4: Comparison of proposed method with existing approaches

Paper	Method	Dataset	Accuracy (%)
[24]	VGG-16	T1-CE MRI	77.60
[25]	RCNN	Brain Tumor MRI Dataset	95.17
[26]	ResNet-50	Brain Tumor Dataset	95.30
[27]	DenseNet121	Chandrabhaga Clinic and Nursing	97.82
[28]	Xception	Brain Tumor MRI Dataset	98.75
[29]	CNN + Six ML Techniques	T1-CE MRI	96.67
[30]	CNN-NADE	T1-CE MRI	95.00
[31]	CNN-SVM	BRATS 2015	98.49
[32]	CNN	BRATS 2015	97.50
[33]	CNN	Brain Tumor Dataset	96.08
	Proposed Method	Brain Tumor MRI Dataset	**98.5**

Based on the data from Table 4, the model accuracy is higher than that of previous research. A simple preprocessing solution that improves image quality and chooses the right optimizer is essential to high precision. Possible future developments include a method of classifying several types of brain tumors, such as pituitary, meningitis, and glioma tumors, using the method of this research.

5 Conclusion

This study successfully developed a Model for brain tumor classification using the Pre-Trained CNN model. The test results showed that the proposed Model has an accuracy of 98.5%, with precision, recall, and F1-score levels of 98.1%, 99%, and 98.5%, respectively. This result indicates that CNN can effectively capture visual feature patterns in the Brain

Tumor MRI dataset. The main contribution of this study is to prove that using CLAHE and median blur can improve Model performance. Median blur and CLAHE Enhanced Image Quality have been proven to increase Model accuracy by 14.5%. However, this study has several limitations, including the need for high computational resources and suboptimal performance on datasets with limited training data. For further study, it is recommended to explore transfer learning or data augmentation approaches to improve Model performance, especially on small-scale datasets. In addition, developing more computationally efficient models can be a focus to improve usability in real-world scenarios.

References

[1] J. R. McFaline-Figueroa and E. Q. Lee, “Brain tumors,” *Am. J. Med.*, Jan. 2018.

[2] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, “A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned,” *Magn. Reson. Imaging*, vol. 61, pp. 300–318, Sept. 2019.

[3] S. Kumar, R. Dhir, and N. Chaurasia, “Brain tumor detection analysis using CNN: A review,” in *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, IEEE, Mar. 2021.

[4] C. Srinivas, N. P. K S, M. Zakariah, Y. A. Alothaibi, K. Shaukat, B. Partibane, and H. Awal, “Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images,” *J. Healthc. Eng.*, vol. 2022, p. 3264367, Mar. 2022.

[5] S. Deepak and P. M. Ameer, “Brain tumor classification using deep CNN features via transfer learning,” *Comput. Biol. Med.*, vol. 111, p. 103345, Aug. 2019.

[6] S. Asif, M. Zhao, F. Tang, and Y. Zhu, “An enhanced deep learning method for multi-class brain tumor classification using deep transfer learning,” *Multimed. Tools Appl.*, vol. 82, pp. 31709–31736, Aug. 2023.

[7] A. Alnemer and J. Rasheed, “An efficient transfer learning-based model for classification of brain tumor,” in *2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, IEEE, Oct. 2021.

[8] R. M. Prakash, R. S. S. Kumari, K. Valarmathi, and K. Ramalakshmi, “Classification of brain tumours from MR images with an enhanced deep learning approach using densely connected convolutional network,” *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.*, pp. 1–12, May 2022.

[9] P. Bedi, N. Ningshen, S. Rani, and P. Gole, “Explainable predictions for brain tumor diagnosis using InceptionV3 CNN architecture,” in *International Conference on Innovative Computing and Communications*, Lecture notes in networks and systems, pp. 125–134, Singapore: Springer Nature Singapore, 2024.

[10] Y. S. Chowdhury, R. Dasgupta, and S. Nanda, “Analysis of various optimizer on CNN model in the application of pneumonia detection,” in *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, IEEE, May 2021.

[11] Z. Ullah, M. U. Farooq, S.-H. Lee, and D. An, "A hybrid image enhancement based brain MRI images classification technique," *Med. Hypotheses*, vol. 143, p. 109922, Oct. 2020.

[12] "Brain Tumor Classification (MRI) — kaggle.com." https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri. [Accessed 20-04-2025].

[13] G. George, R. M. Oommen, S. Shelly, S. S. Philipose, and A. M. Varghese, "A survey on various median filtering techniques for removal of impulse noise from digital image," in *2018 Conference on Emerging Devices and Smart Systems (ICEDSS)*, IEEE, Mar. 2018.

[14] K. Tenghongsakul, I. Kanjanasurat, T. Archevapanich, B. Purahong, and A. Lasakul, "Deep transfer learning for brain tumor detection based on MRI images," *J. Phys. Conf. Ser.*, vol. 2497, p. 012015, May 2023.

[15] Z. Rasheed, Y.-K. Ma, I. Ullah, Y. Y. Ghadi, M. Z. Khan, M. A. Khan, A. Abdusalomov, F. Alqahtani, and A. M. Shehata, "Brain tumor classification from MRI using image enhancement and convolutional neural network techniques," *Brain Sci.*, vol. 13, Sept. 2023.

[16] P. Musa, F. A. Rafi, and M. Lamsani, "A review: Contrast-Limited adaptive histogram equalization (CLAHE) methods to help the application of face recognition," in *2018 Third International Conference on Informatics and Computing (ICIC)*, IEEE, Oct. 2018.

[17] J. Kalyani and M. Chakraborty, "Contrast enhancement of MRI images using histogram equalization techniques," in *2020 International Conference on Computer, Electrical & Communication Engineering (ICCCECE)*, IEEE, Jan. 2020.

[18] G. Sucharitha, M. Sirisha, K. Pravalika, and K. N. Gayathri, "A study on the performance of deep learning models for leaf disease detection," *EAI Endorsed Trans. Internet Things*, vol. 10, Dec. 2023.

[19] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification," *Artificial Intelligence in Agriculture*, vol. 9, pp. 22–35, Sept. 2023.

[20] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, June 2016.

[21] G. Huang, Z. Liu, L. v. d. Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, July 2017.

[22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, June 2016.

[23] M. Yaqub, F. Jinchao, M. S. Zia, K. Arshid, K. Jia, Z. U. Rehman, and A. Mehmood, "State-of-the-art CNN optimizer for brain tumor segmentation in magnetic resonance images," *Brain Sci.*, vol. 10, p. 427, July 2020.

[24] M. Ali, J. Hussain Shah, M. Attique Khan, M. Alhaisoni, U. Tariq, T. Akram, Y. Jin Kim, and B. Chang, "Brain tumor detection and classification using PSO and convolutional neural network," *Comput. Mater. Contin.*, vol. 73, no. 3, pp. 4501–4518, 2022.

[25] R. Vankdothu and M. A. Hameed, "Brain tumor MRI images identification and classification based on the recurrent convolutional neural network," *Measur. Sens.*, vol. 24, p. 100412, Dec. 2022.

[26] M. B. Sahaai, G. R. Jothilakshmi, D. Ravikumar, R. Prasath, and S. Singh, "ResNet-50 based deep neural network using transfer learning for brain tumor classification," in *INTERNATIONAL CONFERENCE ON RECENT INNOVATIONS IN SCIENCE AND TECHNOLOGY (RIST 2021)*, AIP Publishing, 2022.

[27] S. Sal Sabila and H. Peni Agustin Tjahyaningtyas, "Multiple brain tumor with modified DenseNet121 architecture using brain MRI images," *Kursor*, vol. 12, pp. 147–158, July 2023.

[28] A. Saleh, R. Sukaik, and S. S. Abu-Naser, "Brain tumor classification using deep learning," in *2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech)*, IEEE, Aug. 2020.

[29] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," *BMC Med. Inform. Decis. Mak.*, vol. 23, p. 16, Jan. 2023.

[30] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," *Biocybern. Biomed. Eng.*, vol. 40, pp. 1225–1232, July 2020.

[31] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," *Biocybern. Biomed. Eng.*, vol. 40, pp. 1225–1232, July 2020.

[32] D. Cherifi, Z. Cherifi, and W. Belkadi, "Brain tumor classification using convolutional neural networks and transfer learning," in *Lecture Notes in Networks and Systems*, Lecture notes in networks and systems, pp. 37–48, Cham: Springer International Publishing, 2023.

[33] C. L. Choudhury, C. Mahanty, R. Kumar, and B. K. Mishra, "Brain tumor detection and classification using convolutional neural network and deep neural network," in *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, IEEE, Mar. 2020.