JURIKOM (Jurnal Riset Komputer), Vol. 13 No. 2, April 2026
e-ISSN 2715-7393 (Media Online), p-ISSN 2407-389X (Media Cetak)
DOI 10.30865/jurikom.v13i2.9610
Hal 704-711
https://ejurnal.stmik-budidarma.ac.id/index.php/jurikom

Brain Tumor Detection and Classification from MRI Images Using a Convolutional Neural Network Approach

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Submitted **18-02-2026;** Accepted **27-04-2026;** Published **30-04-2026**

Abstract

Brain tumors are a serious neurological disease that require rapid and accurate diagnosis to improve treatment success. However, conventional interpretation of brain MRI images is often time-consuming and highly dependent on radiologists' expertise, which may lead to diagnostic inconsistency. This study aims to develop a brain tumor detection and classification model from MRI images using a Convolutional Neural Network (CNN) approach. The dataset consists of four classes, namely glioma, meningioma, pituitary, and no tumor. The research stages include data collection, image preprocessing, model training, and evaluation using accuracy, loss, precision, recall, and F1-score. The results show that the CNN model achieved a training accuracy of 1.0000 at the final epoch, while the testing phase produced an accuracy of 58.75% with a loss value of 1.9600. These findings indicate that the model was able to learn important patterns from MRI images, although the gap between training and testing performance suggests overfitting. This study contributes to the development of AI-based medical image classification for brain tumor identification and shows that CNN has potential as a supportive tool for assisting medical personnel in brain tumor diagnosis. Further improvements can be achieved through data augmentation, hyperparameter tuning, and optimization of model architecture.

Keywords: Brain Tumor; MRI; Convolutional Neural Network; Deep Learning; Medical Image Classification

1. INTRODUCTION

Brain tumors are life-threatening diseases that affect millions of people worldwide[1]. They are characterized by the uncontrolled growth of abnormal cells within brain tissue, which can damage vital brain functions and may lead to severe disability or death if not detected and treated at an early stage[2]. Medical imaging, particularly magnetic resonance imaging (MRI), has become one of the most important diagnostic tools for brain tumor identification because it provides detailed and non-invasive visualization of brain structures and lesion characteristics[3][4]. However, despite the advantages of MRI, diagnosis still largely depends on manual interpretation by radiologists[5]. This process is often time-consuming and prone to human error due to the high variability of tumor appearance across patients, including differences in tumor size, shape, location, and intensity patterns[6]. These challenges indicate the need for a more efficient and consistent diagnostic support system.

In this context, artificial intelligence (AI), especially deep learning, has emerged as a promising approach for brain tumor detection and classification [7]. Deep learning models are capable of automatically learning complex image representations, enabling the identification of abnormal findings from MRI images with reduced dependence on handcrafted feature extraction[8]. Recent studies have shown that deep convolutional models such as ResNet50 can achieve strong performance in classifying brain tumors from MRI images[9] In addition, hybrid approaches that combine deep feature extraction with conventional machine learning classifiers have also demonstrated promising results in improving tumor detection performance[10]. These findings confirm that AI-based approaches have significant potential to support medical personnel in obtaining faster and more accurate diagnostic information.

From a clinical perspective, brain tumors are commonly classified into several important categories, including glioma, meningioma, and pituitary tumors, as well as normal brain conditions without tumors[11]. Accurate classification of these categories is essential because it directly influences treatment planning and medical decision-making, including surgery, radiotherapy, chemotherapy, or combined treatment strategies[12]. This becomes increasingly relevant as clinical imaging workloads continue to grow, while accurate interpretation remains essential for effective care[13]. Therefore, classification performance is not only a technical issue, but also a clinically meaningful requirement in medical image analysis.

Several studies have also emphasized the advantages of transfer learning and multimodal MRI in improving classification performance under limited data conditions [14]. Transfer learning enables pre-trained deep networks to be adapted to medical imaging tasks with fewer labeled samples, while multimodal MRI can provide complementary information from different image sequences [15]. Nevertheless, important challenges remain, including noise in MRI images, class imbalance, data scarcity, and tumor heterogeneity across patients, all of which may reduce model robustness and generalization ability [11]. These issues show that achieving high training accuracy alone is not sufficient; model performance on unseen data must also be carefully evaluated.

Although previous studies have reported promising results using advanced deep learning architectures, hybrid models, and transfer learning strategies [16]. a practical gap still remains. Many studies mainly focus on performance improvement, while fewer present a straightforward end-to-end implementation for four-class brain tumor classification using publicly available MRI data and discuss the generalization problem that may arise from limited datasets [12]. In addition, the difference between training performance and testing performance is often not sufficiently highlighted as an important practical issue in developing reliable AI-based diagnostic support systems. Therefore, further study is needed to evaluate how a CNN-based approach performs in detecting and classifying brain tumors in a practical classification setting [17].

Nevertheless, several important challenges still persist in AI-based brain tumor detection and classification. These challenges include noise in MRI images, class imbalance in datasets, limited medical image data, and tumor heterogeneity across patients, all of which may reduce model robustness and generalization ability [18]. In addition, although several studies have reported promising performance using advanced architectures, hybrid methods, and multimodal MRI inputs, many of these approaches require complex model designs, extensive computational resources, or large-scale datasets that may not always be practical in real-world implementation. Therefore, further evaluation of a CNN-based classification approach using publicly available MRI datasets remains important to understand both its potential and its limitations in practical use [19][20].

Although previous studies have reported promising results using advanced deep learning architectures, hybrid models, and transfer learning strategies [16], a practical research gap still remains. Many prior studies mainly focus on improving classification performance, whereas fewer studies present a straightforward end-to-end implementation for four-class brain tumor classification using publicly available MRI datasets and explicitly discuss the generalization issue caused by limited and heterogeneous medical image data [12], [18], [19]. In addition, the difference between training and testing performance is often not sufficiently highlighted, even though this issue is critical for assessing the reliability of AI-based diagnostic support systems in real clinical settings. Therefore, further study is needed to evaluate how a CNN-based approach performs in practical brain tumor detection and classification tasks [21].

Based on these considerations, this study aims to develop and evaluate a Convolutional Neural Network (CNN)-based model for brain tumor detection and classification from MRI images into four classes: glioma, meningioma, pituitary, and no tumor. This study contributes by presenting an end-to-end workflow consisting of data collection, preprocessing, model training, and evaluation, as well as by reporting the classification performance and identifying the model’s generalization limitations. The findings are expected to provide practical insight into the application of CNN for brain tumor classification and to support the development of more accurate and clinically relevant AI-based diagnostic systems in the future.

2. RESEARCH METHODOLOGY

2.1 Types and Sources of Data

This study uses secondary data in the form of brain MRI images obtained from the Brain Tumor dataset available on the Kaggle platform. The dataset consists of four image categories, namely glioma, meningioma, pituitary, and no tumor, which are commonly used in brain tumor classification studies. The use of MRI data is appropriate because MRI provides detailed visualization of brain tissue structures and tumor characteristics, making it suitable for image-based classification using deep learning approaches [3], [4].The class categories used in this study are summarized in Table 1.

Table 1. Brain Tumor Classification Categories

No	Class Label
1	Glioma
2	Menginioma
3	Notumor
4	Pituitary

The categories presented in Table 1 represent the target labels used in the classification process. Glioma, meningioma, and pituitary correspond to three major tumor classes, while no tumor represents normal brain MRI images without tumor indication. This four-class categorization is used to evaluate the ability of the proposed model to distinguish tumor and non-tumor conditions in a practical classification setting.

2.2 Literature Review of Applied Methods

In medical image analysis, preprocessing is an important stage to improve data quality and ensure consistency before model training. Common preprocessing techniques include image resizing, normalization, and data augmentation. Resizing is used to standardize image dimensions according to model input requirements, while normalization helps stabilize the learning process by transforming pixel values into a smaller numerical range. In addition, data augmentation such as rotation, flipping, zooming, and shifting is widely applied to increase data variation and reduce overfitting, especially when the dataset size is limited. Convolutional Neural Network (CNN) is one of the most widely used deep learning methods in medical image classification because it can automatically extract hierarchical features from image data.

CNN consists of several main layers, including convolution layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Compared with conventional machine learning methods that depend on handcrafted features, CNN offers better capability in learning complex image patterns directly from MRI scans [8],[11].

Model evaluation is also an essential part of brain tumor classification studies. Performance is commonly measured using accuracy, precision, recall, F1-score, and confusion matrix. Accuracy indicates the overall classification correctness, while precision and recall provide a more detailed view of prediction quality for each class. F1-score is used to balance precision and recall, especially in multi-class classification tasks. In addition, loss values are used to observe model optimization during training and testing [9], [10], [12].

2.3 Research Stages

The overall research procedure conducted in this study is illustrated in Figure 1.

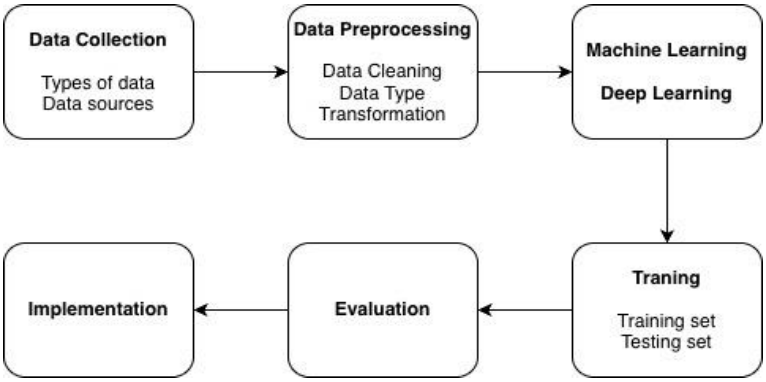


Figure 1. Research stages

Figure 1 illustrates the overall workflow of this study, which consists of five main stages: data collection, data preprocessing, model development, training, and evaluation. These stages were arranged sequentially to ensure that the MRI image data were properly prepared before being processed by the classification model. In addition, Figure 1 shows the relationship between preprocessing, model training, and evaluation in assessing the effectiveness of the proposed brain tumor classification approach.

a. Data Collection

Data collection is the first stage of this study. At this stage, brain MRI images were collected from a secondary dataset obtained from the Kaggle platform under the Brain Tumor dataset. The dataset consists of four categories, namely glioma, meningioma, pituitary, and no tumor. This dataset was selected because it provides sufficient image data, clear class variation, and relevance to the objective of brain tumor detection and classification. After the dataset was collected, an initial inspection was conducted to verify folder structure, class labels, file formats, and image quality. This stage was carried out to ensure that the data were valid and ready for preprocessing and model training.

b. Prepocessing

Preprocessing is the initial stage performed before the data are used in machine learning and deep learning model training. The purpose of this stage is to improve data quality, ensure image format consistency, and reduce noise that may affect classification performance. In this study, preprocessing was applied to the collected brain MRI images.

The preprocessing steps included data cleaning, image resizing, normalization, data augmentation, and dataset splitting. First, damaged, duplicate, or mislabeled images were identified and removed. Next, the images were resized to a standard dimension of 224 × 224 pixels to match the input requirements of the deep learning model. After that, pixel values were normalized to make the training process more stable and efficient. In addition, data augmentation techniques such as rotation, flipping, zooming, and shifting were applied to increase data variation and reduce the risk of overfitting. The dataset was then divided into training, validation, and testing sets using a proportion of 70%, 15%, and 15%, respectively. This preprocessing stage was intended to produce an optimal dataset for improving the performance of the proposed brain tumor classification model.

c. Machine Learning

The machine learning stages are carried out to build a brain tumour classification model based on features extracted from MRI images. At this stage, images that have undergone preprocessing are then feature extracted using specific methods to extract important information from the images, such as texture, shape, and intensity patterns. Feature extraction techniques that can be used include Histogram of Oriented Gradient (HOG), Gray Level Co-occurrence Matrix (GLCM), or other relevant feature engineering methods.

After the feature extraction process is complete, the data is divided into training and testing data to train the machine learning model. Several algorithms that can be used in this study include Support Vector Machine (SVM), Random Forest, K-Nearest Neighbour (KNN), and Naive Bayes. The model is trained using training data to learn brain tumour classification patterns based on available features, then evaluated using testing data to measure model performance based on evaluation metrics such as accuracy, precision, recall, and F1-score.

d. Deep Learning

Deep learning is used to automatically detect and classify brain tumours using a Convolutional Neural Network (CNN) architecture. Unlike traditional machine learning, deep learning methods are capable of automatically extracting features directly from MRI images without the need for manual feature engineering.

At this stage, the dataset that has undergone preprocessing is used to train the CNN model by performing the training process using training data and validation using validation data to monitor the model's performance during the learning process. The architectures that can be used include custom CNN models and transfer learning such as VGG16, ResNet50, MobileNet, or EfficientNet. The training process involves determining hyperparameters such as learning rate, batch size, and number of epochs to obtain optimal model performance.

After the training process was complete, the model was tested using test data to determine the model's generalisation ability in classifying brain tumour types such as glioma, meningioma, pituitary tumour, and normal. The prediction results were then evaluated using evaluation metrics such as confusion matrix, accuracy, precision, recall, and F1-score.

e. Training

The training stage is the process of training machine learning and deep learning models using a dataset that has undergone preprocessing. At this stage, the model is trained to learn the patterns and characteristics of brain MRI images so that it can recognise the differences between types of brain tumours such as glioma, meningioma, pituitary tumours, and normal brain images.

In machine learning methods, the training process is carried out using features that have been extracted beforehand. Training data is used to build classification models with specific algorithms such as Support Vector Machine (SVM), Random Forest, K-Nearest Neighbour (KNN), or Naive Bayes. The model will learn the relationship between input features and class labels to produce an optimal prediction model.

Meanwhile, in the deep learning method, the training process is carried out using a Convolutional Neural Network (CNN) architecture that can perform automatic feature extraction. During the training process, the model performs forward propagation to generate predictions, then calculates the loss value using a specific loss function, such as categorical cross-entropy. Next, the backpropagation process is carried out to update the network weights using optimisation algorithms such as the Adam optimiser or SGD. Training parameters such as learning rate, batch size, and number of epochs are adjusted to achieve the best performance and avoid overfitting.

In addition, model performance was monitored using validation data to evaluate accuracy improvements during the training process. This stage aimed to produce a model with good generalisation capabilities so that it could be used in the evaluation and testing stages of the brain tumour classification system.

f. Evaluation

The evaluation stage is a process to measure and analyse the performance of machine learning and deep learning models that have been trained in the training stage. Evaluation is carried out using testing data that was not included in the model training process, so that the evaluation results can show the model's generalisation ability in detecting and classifying types of brain tumours objectively.

At this stage, the model is tested to predict the class of brain MRI images, namely glioma, meningioma, pituitary tumor, and normal. The prediction results are then compared with the actual labels to calculate various evaluation metrics. The metrics used include accuracy to measure the overall classification accuracy, precision to determine the accuracy of predictions for each class, recall measuring the model's ability to find relevant data, and F1-score as a combination of precision and recall.

In addition, a confusion matrix is used to see the distribution of model predictions for each class in more detail, so that the types of classification errors that occur can be identified. The evaluation can also be supplemented with a ROC curve and AUC value to see the model's performance in distinguishing between classes. These evaluation results are used to compare the performance between machine learning and deep learning methods and to determine the best model that has high accuracy and stability in brain tumor classification.

3. RESULT AND DISCUSSION

3.1 Data Collection and Analysis Results

In this study, preliminary results show that the dataset has enough images for each category, namely glioma, meningioma, pituitary, and no tumor classes. Each image is a brain MRI image used as input data in the classification process using a Convolutional Neural Network (CNN)-based deep learning method. Initial data exploration was conducted to understand the dataset structure, the distribution of data in each class, and to ensure the quality of the images to be used in the model training process. Examples of MRI images from each class used in this study are presented in Figure 2.

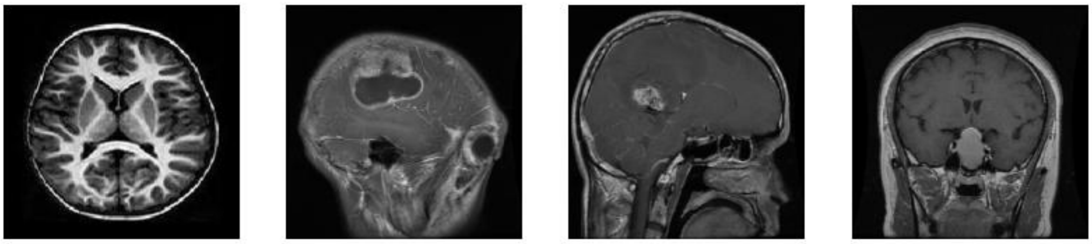


Figure 2. Representative MRI Images of Glioma, Meningioma, Pituitary, and No Tumor Classes

Figure 2 presents representative MRI images from the four classes used in this study, namely glioma, meningioma, pituitary, and no tumor. The images show visible differences in anatomical structure and tumor appearance, including variations in location, shape, and affected tissue area. These visual differences provide the basis for the CNN model to learn important features for distinguishing tumor and non-tumor classes.

Displaying examples of brain MRI images from each class in the dataset, namely glioma, meningioma, pituitary, and no tumor. Each image shows distinctive visual characteristics in brain tissue structures, such as the location and shape of the tumor area. These visual variations between classes form the basis for the classification process using the Convolutional Neural Network (CNN) method, in which the model automatically extracts important features from the images to distinguish between tumor types and normal brain conditions. The distribution of MRI images across all classes in the dataset is shown in Figure 3.

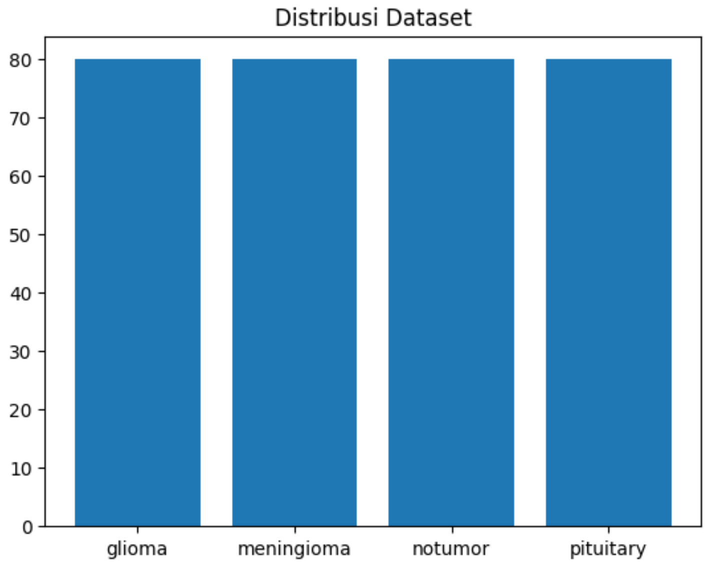
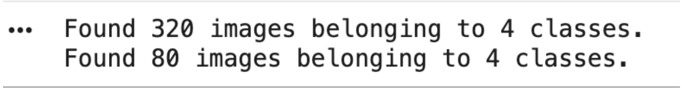


Figure 3. Class Distribution of the Brain MRI Dataset

Figure 3 shows that the dataset is evenly distributed across the four classes, namely glioma, meningioma, no tumor, and pituitary. A balanced class distribution is important because it reduces the risk of model bias toward a specific class during training and supports a fairer evaluation of model performance in multi-class brain tumor classification.

3.2 Preprocessing Data

The data preprocessing stage includes resizing images to a uniform size, normalizing pixel values, and dividing the data into training and validation data. This process aims to improve model performance and ensure that the data used has a consistent format. The exploration results show that the dataset has varying visual characteristics for each tumor class, so the deep learning method was chosen because it is capable of automatically extracting features from medical images. The result of dataset preparation after preprocessing is presented in Figure 4.



```
Found 320 images belonging to 4 classes.
Found 80 images belonging to 4 classes.
```

Figure 4. Dataset Split Results After Preprocessing

Figure 4 shows the number of images obtained after preprocessing and dataset splitting. The dataset was divided into 320 training images and 80 testing images across four classes. This division was performed to ensure that most of the data were used for model learning, while the remaining data were reserved for testing the model on previously unseen samples.

The next step is to change the labeling attributes into numerical or numerical forms using Label Encoding Techniques. Labels such as glioma, meningioma, pituitary, and notumor are converted into numerical values so that they can be processed by Machine Learning and Deep Learning models, which can only accept numerical inputs. For example, labels such as glioma, meningioma, pituitary, and notumor become 0, 1, 2, and 3, respectively, and then target labels are created to match the previous label names. The target values are divided into 4 categories: glioma, meningioma, pituitary, and notumor. These categories are divided based on the type of brain tumor. After the encoding and categorization process is complete, the dataset is divided into two parts: a training set of 320 and a testing set of 80. This division is done so that the model can be trained using most of the data and tested on data that has never been seen before, so that the results are more optimal. The Label Encoding for Brain Tumor Classes scheme used in this study is presented in Table 2.

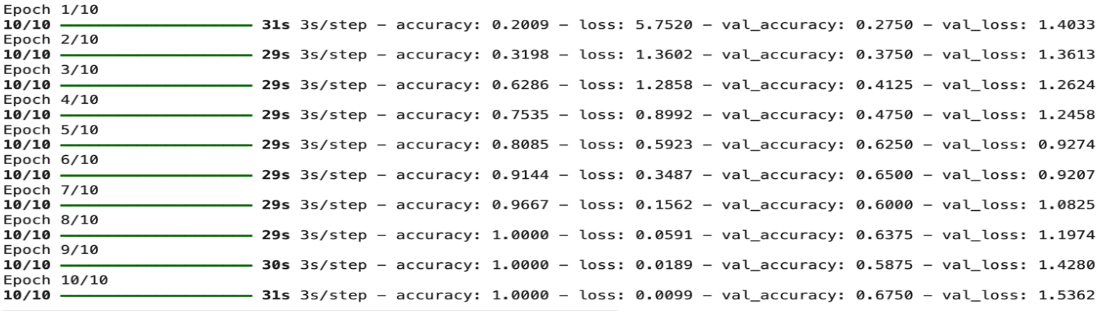
Table 2. Label Encoding for Brain Tumor Classes

Original Value	Value After Encoding
Glioma	0
Meningioma	1
Notumor	2
Pituitary	3

Table 2 shows the numerical encoding assigned to each class label before model training. This conversion is necessary because the classification model requires numerical target values rather than text labels. The encoded labels were then used as the target classes in the training and testing process.

3.3 CNN Model Training Results

After the data preprocessing stage is complete, the next stage is deep learning model training. The dataset, which has been grouped into 320 training samples and 80 testing samples, is used to create and evaluate classification models for brain tumors, gliomas, meningiomas, non-tumors, and pituitary tumors. The training performance of the CNN model over 10 epochs is presented in Figure 5.



```
Epoch 1/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 31s 3s/step - accuracy: 0.2009 - loss: 5.7520 - val_accuracy: 0.2750 - val_loss: 1.4033
Epoch 2/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.3198 - loss: 1.3602 - val_accuracy: 0.3750 - val_loss: 1.3613
Epoch 3/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.6286 - loss: 1.2858 - val_accuracy: 0.4125 - val_loss: 1.2624
Epoch 4/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.7535 - loss: 0.8992 - val_accuracy: 0.4750 - val_loss: 1.2458
Epoch 5/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.8085 - loss: 0.5923 - val_accuracy: 0.6250 - val_loss: 0.9274
Epoch 6/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.9144 - loss: 0.3487 - val_accuracy: 0.6500 - val_loss: 0.9207
Epoch 7/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 0.9667 - loss: 0.1562 - val_accuracy: 0.6000 - val_loss: 1.0825
Epoch 8/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 29s 3s/step - accuracy: 1.0000 - loss: 0.0591 - val_accuracy: 0.6375 - val_loss: 1.1974
Epoch 9/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 30s 3s/step - accuracy: 1.0000 - loss: 0.0189 - val_accuracy: 0.5875 - val_loss: 1.4280
Epoch 10/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 31s 3s/step - accuracy: 1.0000 - loss: 0.0099 - val_accuracy: 0.6750 - val_loss: 1.5362
```

Figure 5. CNN Training Results Over 10 Epochs

Figure 5 shows the progression of training and validation performance over 10 epochs. The training accuracy increased from 0.2974 in the first epoch to 1.0000 in the final epoch, while the training loss decreased substantially. However, the validation accuracy remained lower and fluctuated, indicating that the model did not generalize as well to unseen data. This pattern suggests the presence of overfitting, where the model learns the training data very well but performs less optimally on validation data.

3.4 Evaluation Results

After successfully completing the model training stage using deep learning (CNN), the next stage is to conduct an evaluation to measure the extent to which the model can classify and predict brain tumor types. The evaluation result of the trained CNN model on the testing data is presented in Figure 6.

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 491ms/step - accuracy: 0.5477 - loss: 2.2154
[1.9600048065185547, 0.5874999761581421]
```

Figure 6. CNN Model Evaluation on Testing Data

The comparison between training and validation accuracy and loss is illustrated in Figure 7.

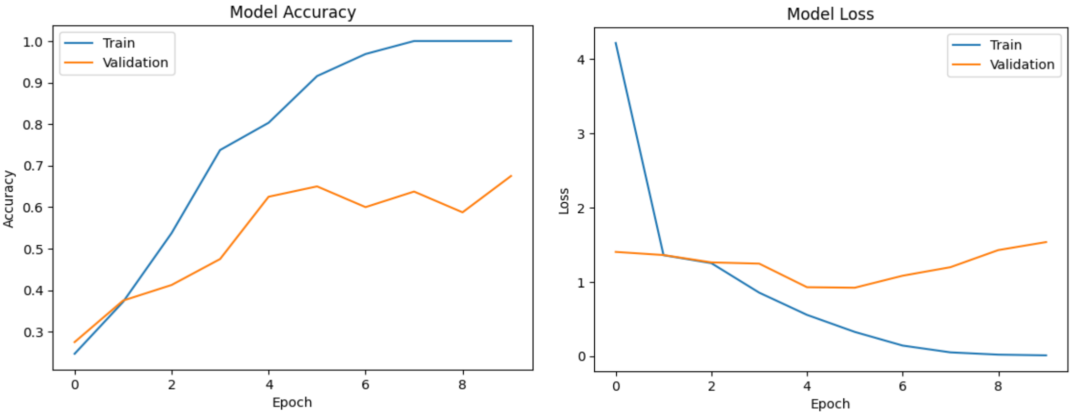


Figure 7. Accuracy Chart and Loss Chart

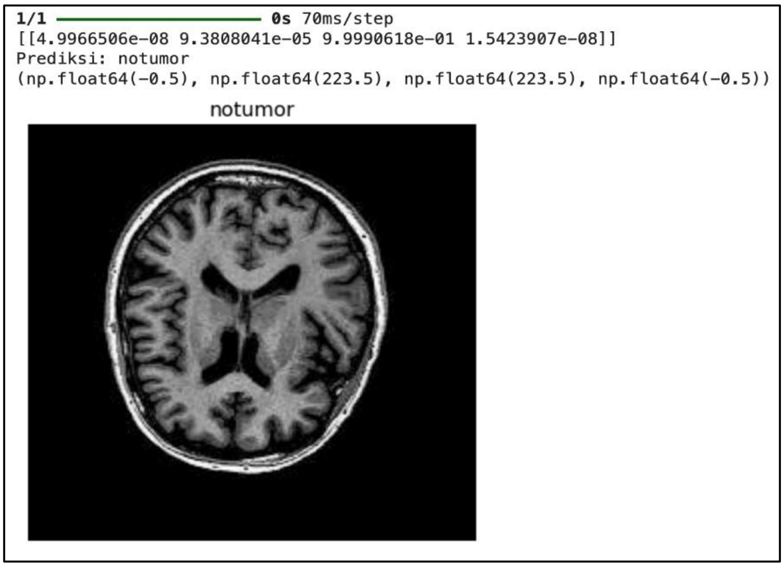
Figure 6 shows the evaluation result of the CNN model on the testing data, where the model achieved an accuracy of 0.5875 or 58.75% with a loss value of 1.9600. These results indicate that the model was able to classify brain MRI images into four classes, namely glioma, meningioma, pituitary, and no tumor, although the performance is still not optimal. The relatively high loss value suggests that prediction errors still occurred in several test samples.

The training and validation performance trends are illustrated in Figure 7. Figure 7 shows that the training accuracy increased consistently and reached 1.0000 in the final epoch, while the training loss decreased substantially. However, the validation accuracy remained lower and fluctuated, and the validation loss tended to increase again after several epochs. This pattern indicates that the model learned the training data very well but did not generalize equally well to unseen data, which suggests overfitting.

Compared with the training results, the testing accuracy of 58.75% confirms that the model performance on unseen data is still limited. This finding highlights the need for further improvement, such as increasing the number of images, applying stronger data augmentation, tuning hyperparameters, and using a more robust CNN architecture to improve generalization performance.

3.5 Prediction Results

After the evaluation stage, the trained CNN model was used to predict the class of unseen brain MRI images. This stage was carried out to observe how the model identifies one of the four target classes, namely glioma, meningioma, pituitary, and no tumor, based on the learned image features. An example of the prediction output is presented in Figure 8.



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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
[[4.9966506e-08 9.3808041e-05 9.9990618e-01 1.5423907e-08]]
Prediksi: notumor
(np.float64(-0.5), np.float64(223.5), np.float64(223.5), np.float64(-0.5))
```

Figure 8. Example of CNN Prediction Output

Figure 8 shows an example of the prediction result produced by the CNN model. The model classified the input MRI image into the no tumor category with the highest probability score. This result indicates that the model was able to extract important spatial features from the image and assign a dominant probability to one class. However, individual prediction results should still be interpreted together with overall evaluation metrics, since a single correct prediction does not fully represent the generalization ability of the model.

4. CONCLUSION

I In conclusion, the results of this study demonstrate that the Convolutional Neural Network (CNN) model has the potential to support brain tumor detection and classification from MRI images into four categories, namely glioma, meningioma, pituitary, and no tumor. The model achieved a training accuracy of 1.0000, while the testing phase resulted in an accuracy of 58.75% and a loss value of 1.9600. These findings indicate that the model was able to capture important patterns from MRI data and perform multi-class classification, but the relatively large gap between training and testing performance suggests that the model still experienced overfitting and had limited generalization ability on unseen data. This condition shows that good performance on training data alone is not sufficient to ensure reliable classification results in practical settings. Nevertheless, the study confirms that CNN remains a promising approach because it can automatically learn discriminative image features without relying on handcrafted feature extraction. Overall, this study contributes to the development of AI-based medical image classification for brain tumor analysis and emphasizes that further improvements are still required, particularly through the use of larger and more diverse datasets, more effective augmentation strategies, careful hyperparameter tuning, and the adoption of a more robust model architecture, so that the resulting system can achieve better performance and provide more dependable support for medical diagnostic applications.

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