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Medical image classification of brain tumor using convolutional neural network algorithm

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Abstract — Brain tumor is a disease that is very dangerous for humans, and this disease needs faster and more accurate treatment. This disease requires early detection because it requires fast and accurate medical treatment. Machine learning helps solve problems by leveraging deep learning technology in the branch of machine learning. Deep learning is a technology that can detect, classify, and segment various problems in machine learning. One of the methods used in deep learning is the Convolutional Neural Network. This method is most often used in performing image processing, where this method has various types of feature extraction. This study aimed to test the accuracy of using the Convolutional Neural Network method in classifying brain images. Magnetic Resonance Imaging scans the brain image used in this study. The dataset in this study was downloaded from the Kaggle website as many as 7023 data consisting of four classes of brain image data, namely glioma, notumor, meningioma, and pituitary classes. The results of this study obtained an accuracy value of 84 % so that this research can be used by medical personnel to diagnose brain tumors easily, quickly, precisely, and accurately.

Keywords – brain tumor, classification, CNN, medical image

I. Introduction

Brain tumor is a high-risk disease [1] because the brain is a vital organ in human life, and brain tumors pose a significant risk. Brain disorders can affect other organs or parts of the body. The growth of benign brain tumors is categorized as slow, while malignant brain tumors grow rapidly and affect the surrounding tissue. The survival rate of brain tumors varies according to the type of tumor and the age of the patient [2].

Some common cases of brain tumors in Indonesia include medulloblastoma, meningioma, and astrocytoma. Medulloblastoma usually occurs in children, meningioma is a benign tumor originating from the brain membrane, and astrocytoma is a brain tumor caused by gene mutations that control cell growth. These cells cause excessive development of astrocyte cells and result in tumors. The initial diagnosis of brain tumors is based on the complaints and symptoms presented by the patient during a physical examination by a doctor. More accurate advanced diagnosis is carried out using diagnostic tools such as X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI) scans [3]. Although these technologies are advanced, they still have limitations. For example, the MRI diagnosis still requires manual interpretation of the MRI scan results. MRI scans display detailed images of body organs using a magnetic field [4]. This requires using other technologies that can help analyze the image results generated from MRI [5]. One of the technologies that can help analyze these images automatically is machine learning (ML) [6].

ML is a computer program that can learn by studying a set of data provided to it. ML trains algorithms built to learn the characteristics of data based on certain algorithms, enabling them to produce an output corresponding to the purpose of the algorithm created. ML technology is designed to learn by itself without user instruction. ML is developed based on specific disciplines such as statistics, mathematics, and data mining to enable machines to learn by analyzing data without requiring reprogramming by administrators or users. ML algorithms are widely used in data processing, such as mining and image processing [7]. In healthcare, ML is extensively used in disease detection or classification [8], [9]. In recent years, machine learning has achieved remarkable advancements in various fields [10]. One ML method commonly used in image classification is the convolutional neural network (CNN) [11].

CNN is a type of artificial neural network that performs various computational tasks. The goal of CNN is to learn the spatial hierarchy structure of elements through automatic and adaptive backpropagation of several building blocks [12]. CNN is a deep learning model widely used in image object classification [7], [13]. CNN represents each neuron in two dimensions, allowing it to process image input in pictures [12]. The CNN approach takes the smallest area of an image to understand the image as a whole. Each layer in CNN has an input layer, hidden layers, and output layer. The CNN technology in ML has achieved good accuracy and can detect multiple objects simultaneously [14].

The image processing in ML using the CNN method has been introduced previously. Several studies have been conducted previously. A study titled "Brain Tumor Segmentation Using Double Density Dual Tree Complex Wavelet Transform Combined with Convolutional Neural Network and Genetic Algorithm" [15] applied several methods to optimize the MRI image segmentation process of the brain. The methods used in this study were double-density dual-tree complex wavelet transform (DDDTCWT), CNN, and genetic algorithm (GA). This study used 1397 training data and 913 testing data. The results showed that the combination of DDDTCWT, CNN, and GA can be used for MRI brain image segmentation and produce an accuracy value of 95 %.

The research entitled "Brain Tumor Classification using Convolutional Neural Networks" [16] combined several methods, such as SVM, to perform classification of brain tumor MRI images. The results of this research obtained the highest accuracy score of 97.5 %.

The research entitled "Implementation of deep learning for handwriting imagery of Sundanese script using Convolutional Neural Network algorithm (CNN)" [17] aimed to determine the accuracy of the CNN algorithm in classifying Sundanese script images. The data collection technique was carried out by distributing questionnaires to respondents. This research conducted testing using training data and obtained an accuracy score of 97.5 %, while testing using testing data obtained an accuracy score of 98 % [18].

The research titled "Convolutional Neural Network and Support Vector Machine in classification of flower images" [19] used a dataset of flower images to classify them using the CNN and Support Vector Machine (SVM) methods. The study concluded that CNN had a higher accuracy of 91.6 % compared to SVM.

Based on previous research, the CNN algorithm has been proven to be frequently utilized in classifying various types of images; thus, this study employs the CNN algorithm. The main difference between this research and previous studies is the type of images used. The medical images in this research consist of human brain MRI scan results, encompassing images of brains with or without tumors. This study examines the accuracy level of the CNN algorithm in classifying brain tumor medical images. The significance of conducting this research is underscored by its ability to facilitate the easy, fast, and accurate diagnosis of brain tumors. Higher accuracy attained from this study ensures the appropriate utilization of machine learning. Additionally, implementing this research in the medical field would alleviate the examination costs for economically disadvantaged patients.

II. Research Method

This study began with a literature review to study previous research related to this study. Fig. 1 shows the complete stages of this research.

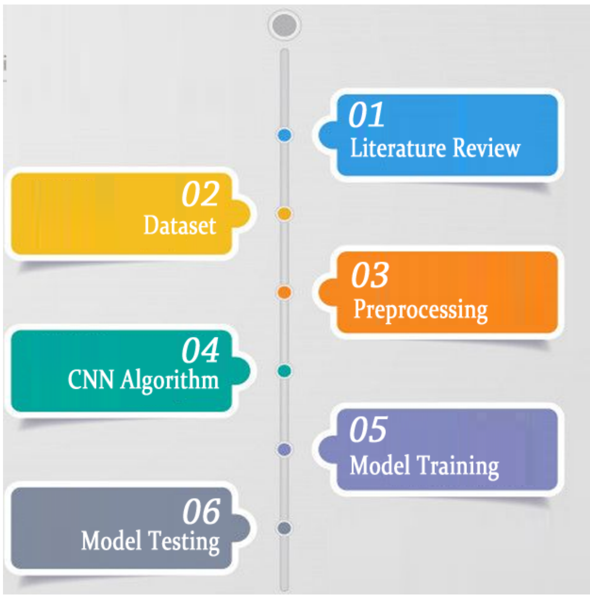


Fig. 1: Research methods.

A. Literature review

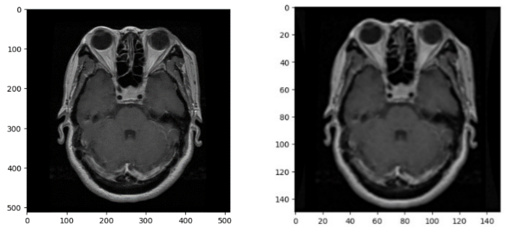
The literature review is the initial phase of this research. The purpose of a literature review is to study previous research results related to this research in terms of the research object and the methods used.

B. Dataset

The dataset for this study was downloaded from the Kaggle website. The downloaded dataset consists of brain MRI images divided into four classes: glioma, notumor, meningioma, and pituitary. The dataset obtained from the Kaggle website contains 7,032 data points.

C. Preprocessing

Preprocessing is a step to prepare the images before the model training process using the dataset. This step is done to ensure that the images classified with the CNN method have the same size, as it can affect the accuracy of the results [20]. The steps performed in preprocessing include converting the image channel from a colored (RGB) image to grayscale and resizing the image so that all image data have the same pixel size.



(a) (b)

Fig. 2: Preprocessing image of brain tumor (a) before (b) after

Fig. 2 (a) shows that the image is 500x500 pixels. This size will make the model difficult to train because of the large number of pixels that need to be extracted, thus requiring a resizing technique in the preprocessing stage. The resizing process is done by reducing the image size from 500 $\times$ 500 pixels to 150 $\times$ 150 pixels. Although this size significantly differs from the original size, it does not reduce the information in the 500 $\times$ 500 pixel image.

D. CNN Algorithm

The CNN algorithm involves designing the CNN architecture that will be used to classify brain tumor images. There are at least four stages involved in building a CNN architecture. Fig. 3 shows three architecture utilized in this study.

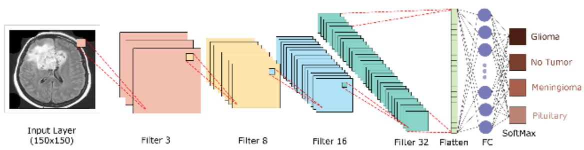


Fig. 3: Proposed CNN architecture.

1) Convolutional layer

The convolutional layer is the initial stage in the CNN architecture that functions to generate the convolutional image layer consisting of neurons arranged in such a way as to form a new image. The convolution used in this architecture consists of the first convolution with three filters size of 3 $\times$ 3 and a filter stride of one pixel [19]. The filters employed in the initial and subsequent convolutions are 3, 8, 16, 32, and 64.

2) ReLU layer

ReLU (Rectified Linear Unit) is an operation used to enhance the representation of a model. The output value of a neuron is set to 0 if its input is negative, and if the input is positive, the output value of the neuron is the input activation itself [21].

3) Polling layer

Pooling layer is a technique used to reduce the size of the matrix. There are two types of pooling: max pooling, which finds the highest value in the matrix passed by the kernel, and average pooling, which calculates the average value of the matrix passed by the kernel to be used as input for the new image. In this study, max pooling with a filter size of 2 $\times$ 2 was used.

4) Flattening

Flattening is a process of classification by comparing patterns against an image. Each image that has undergone feature extraction will be flattened to find the most similar pattern to the image output. The most similar pattern will be included as the class of the image.

E. Model Training

Training the model is training the CNN architecture built using the training data. The training data used in this study is 90 % of the total dataset. In this stage, the model is trained for 13 epochs. This stage is done so the built model can learn the training data.

F. Model Testing

Model testing is a crucial stage as it determines the performance of the built architecture. The data used for model testing consists of 10 % of the total dataset, which includes the glioma, notumor, meningioma, and pituitary classes. The results of the model testing using the testing data are presented in the form of a confusion matrix. The values in the confusion matrix provide information on TP (true positive), TN (true negative), FP (false positive), and FN (false negative) [15], [22], [23]. The values in the confusion matrix are processed using (1) [24].

$$Accuration = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

TP is expressed as true positive, TN as true negative, FP as false positive, and FN as false negative.

III. Result

This research uses the Python programming language for brain tumor classification. Before testing the model for brain tumor classification, preprocessing is needed. This step standardizes the images regarding pixel size and color mode (RGB or grayscale). The entire dataset needs to be preprocessed because the images have different sizes. All image data is resized to 150 $\times$ 150 pixels after being resized. The preprocessing output is fed into the prepared CNN model for classification according to the image class.

A. Implementation of CNN algorithm

Brain tumor images are preprocessed so that CNN can classify them accurately. After the images are preprocessed, the next step is to design the CNN model. The CNN model designed uses 2-dimensional convolution with a filter size of 3 × 3, a stride of 1, and maxpooling with a size of 2 × 2 [25]; thus, the resulting feature maps are reduced by half the size of the original image. This research used three filters for the first feature extraction, eight for the second feature extraction, 16 for the third feature extraction, and 32 for the fourth feature extraction.

After extracting the image, the next step is to flatten it for classification. This stage is called the fully connected stage. The extracted image based on the created model is then classified according to the resulting pattern's similarity level. This study uses a batch size of 32 images for each group, from the first to the last. This is done so that the classification process takes little time because the training data has been grouped into several groups according to the specified batch size. The training process on the dataset is performed for 13 iterations.

B. Model testing results

The model was tested by training on the dataset, with 13 iterations. Table 1 shows the iteration results obtained after the training process.

Table 1: Training datasets results

Epoch	Loss	Accuracy	Validation loss	Validation accuracy
1	0.81	0.66	0.67	0.74
2	0.5	0.79	0.48	0.82
3	0.4	0.84	0.4	0.84
4	0.34	0.86	0.37	0.87
5	0.27	0.89	0.34	0.87
6	0.23	0.9	0.35	0.88
7	0.22	0.91	0.3	0.89
8	0.19	0.92	0.29	0.91
9	0.16	0.94	0.32	0.89
10	0.14	0.94	0.29	0.89
11	0.06	0.97	0.29	0.91
12	0.04	0.98	0.3	0.91
13	0.03	0.99	0.32	0.91

Table 1 shows the results of each iteration during the training process on the dataset. These values were obtained after the model was trained using the dataset. Fig. 1 shows the iteration results of loss and accuracy with 13 epochs on the training data. The CNN classification process used softmax and a learning rate 0.01 in the fully connected layer.

Fig. 4 shows that the validation loss value in the first iteration is 67 %. This value is quite large, but it decreased significantly to 48 % in the second iteration and continued to decrease until 32 % in the 13th iteration. This indicates that the more frequently the built algorithm is trained, the less accuracy loss will decrease significantly from the first iteration.

Fig. 5 shows the accuracy rate graph obtained at each iteration. The first iteration achieved a value of 74 %, while the second iteration achieved a value of 82 %. This continued to increase until the 8th iteration and then decreased in the 9th iteration with an accuracy value of 89 %. In the final iteration, there was an increase with an accuracy rate of 91 %. Fig. 6 is the confusion matrix obtained in this study based on testing using 703 brain tumor images from MRI scans.

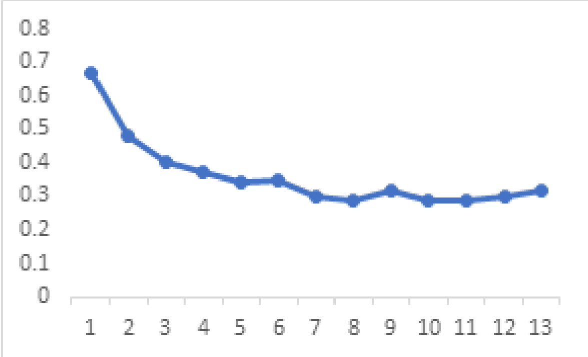


Fig. 4: Training chart loss.

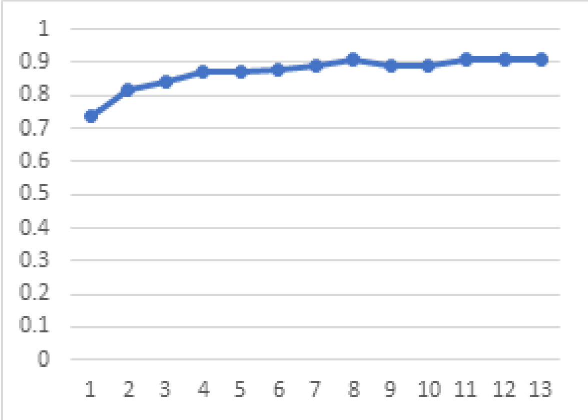


Fig. 5: Training chart accuracy.

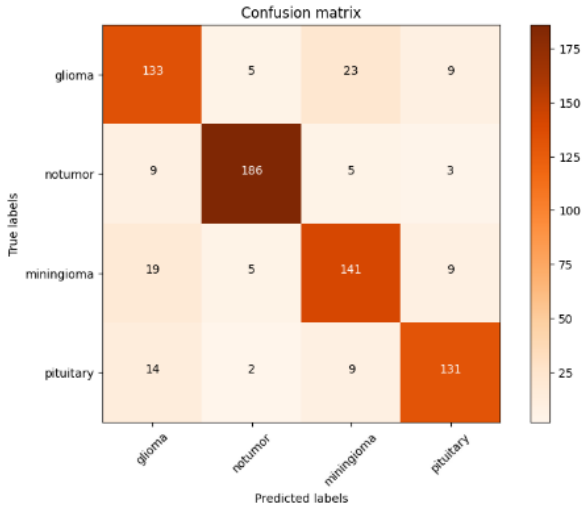


Fig. 6: Confusion matrix.

Fig. 6 displays the classification results of the model based on the class labels given to the images. In the glioma class, 133 images were successfully classified as glioma, five were classified as notumor, 23 were classified as meningioma, and nine were classified as pituitary. The images classified in the glioma class are declared as TP or images that are classified according to their labels, and images not classified as glioma are declared as TN or images that are misclassified. The same applies to the notumor, meningioma, and pituitary classes. Fig. 6 shows the test data that was successfully classified according to its class, namely 591 images and 112 images still experiencing errors in classification. Based on this, the percentage of accuracy of the CNN algorithm testing for the diagnosis of brain tumors is 84 %.

IV. Discussion

The model was tested by dividing 90 % of the dataset for model training and 10 % of the data to test the accuracy level of the CNN model in performing classification. The dataset used for testing consisted of 703 images out of 7023 images, which were divided into four classes. The classification accuracy for glioma was 78 %, notumor was 92 %, meningioma was 82 %, and pituitary was 84 %. This can be demonstrated graphically in Fig. 7.

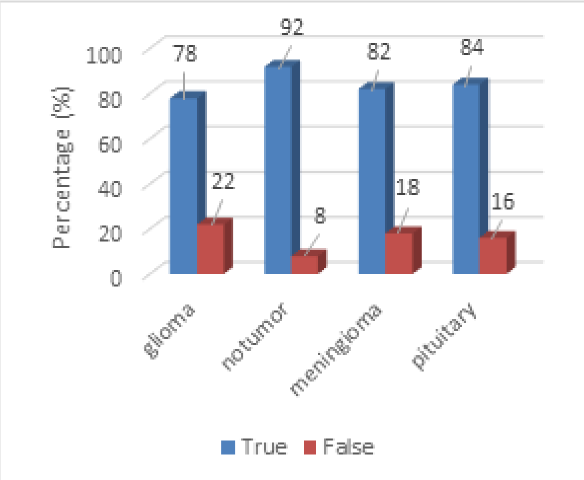


Fig. 7: Graph of confusion matrix analysis results.

Based on Fig. 7, it can be seen that the highest testing accuracy is achieved in the notumor class, which successfully classified 92 % of the dataset correctly, and 8 % of the dataset still experienced misclassification.

V. Conclusion

This research was conducted to test the performance of the CNN method in classifying brain images by utilizing a dataset obtained from the Kaggle website. The brain image classification research using the CNN method was successfully conducted with an accuracy of 84 % from the total testing data. Based on these results, the CNN model can be used to diagnose brain tumor diseases by utilizing MRI images so that the diagnosis of brain tumor disease does not take a long time, as currently done by doctors. The research on brain tumor diagnosis should continue by utilizing the latest machine learning algorithms, enhancing accuracy, and reducing errors in brain tumor diagnosis.

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