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Convolutional Neural Network for Brain Tumor Detection

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Abstract. Magnetic resonance imaging (MRI) is the imaging technique used to diagnosing brain tumor disease. Early diagnosis of brain tumors is an essential task in medical work to find out whether the tumor can potentially become cancerous. Deep learning is a handy and efficient method for image classification. Deep learning has been widely applied in various fields including medical imaging, because its application does not require the reliability of an expert in the related field, but requires the amount of data and diverse data to produce good classification results. Convolutional Neural Network (CNN) is the deep learning technique to perform image classification. In this paper, we compared two model CNN find the best model CNN to classify tumours in Brain MRI Image and at the end, we have trained CNN and obtained a prediction accuracy of up to 93%.

1. Introduction

According to the Indonesian Ministry of Health, in 2018 Indonesia became the number of 8th cancer patient in Southeast Asia and ranked 23rd in Asia[1]. Brain tumors are the second cause of death in cancer cases after breast cancer. From all cases, it is known that women are more affected by brain tumors than men. Brain tumors have continued to increase in incidence for a decade last in several countries [2]. Medical imaging is key in diagnosing brain tumors and can help prevent more virulent diseases. MRI is imaging techniques that researchers rely on to detect brain tumors[3]. MRI is one of the most widely used medical imaging techniques for brain tumors because it does not use ionizing radiation [4].

There are many studies about the detection of brain tumors, Parveen et al. [5], using a combination of Fuzzy C-Means and SVM methods. In this study, using Fuzzy C-Means to segment between parts of the brain and the parts indicated to have tumors, the use of Fuzzy C-Means in this paper shows good results. After segmentation, the Gray Level Run-Length Matrix (GLRLM) is used to feature extraction. The purpose of feature extraction is to find relevant features of an image to facilitate the classification process. The classification technique used in the method is SVM. In the method used, the accuracy achieved was 83.33%.

Avizenna et al. [6] using the fluid-attenuated inversion recovery (FLAIR) method. This study proposed to classify MRI images into two classes, normal brains and abnormal brains. BRATS database data 2017 used in this study. Process classification brain MRI images using multinomial logistic regression models with ridge estimators, and scoring using sensitivity, specificity, accuracy with cross-fold validation.

However, in unsupervised method-based segmentation, as before the extraction feature is not obtained implicitly, there is a need for human touch [7]. Then, to segment the brain image there are still many obstacles, there are problems such as the shape or location that is different from each patient.



According to Işin A et al [8], the devices used for scanning vary greatly so as to produce images that have different characteristics in the dataset.

In this paper, the CNN method is proposed to solve the problem of data complexity. CNN is able to extract features without removing the spatial information from the input data. CNN is a machine learning method to process two-dimensional data. CNN has two methods: classification using feedforward and learning using backpropagation.[7]. But apart from the advantages of CNN architecture, which is simple for users, but on the development process, CNN requires amount data for the learning process and consume a lot of learning time compared to unsupervised learning approaches. In this research, 2 CNN models were made as a comparison to find the best model for classification.

2. Literature Review

2.1. Convolutional Neural Network

CNN is a neural network that aims to process data that has a grid structure. Convolution is an operation in convolution layer that is based on a linear algebra operation that multiplies matrix of the filter in the image to be processed [9]. The convolution layer is the primary layer that is most important to use. Another type of layer that is commonly used is the pooling layer, which is a layer that is used to take the maximum value or the average value of the pixel portions of the image.

CNN has the ability to learn complicated features by forming a feature map. The convolution layer kernel is wrapped around the input sample to calculate several feature maps. Features are detected from input samples than represented by small boxes on the feature map. These maps are forwarded to the maximum collection layer, which preserves relevant features and discards the rest. The features of the max-pooling layer are converted to a one-dimensional feature vector in the fully connected layer, which is then used to calculate the output probability. The configuration of CNN is shown in Figure 1[10].

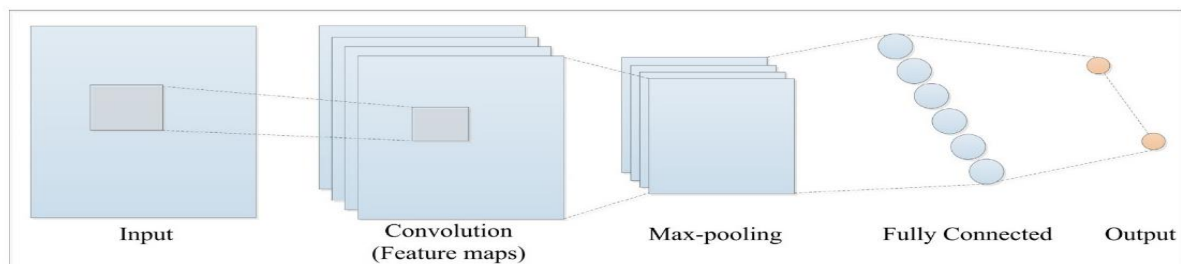


Figure 1. CNN architecture [10]

2.1.1. Convolution Layer

Convolution Layer is the core layer in the CNN method which aims to extract features from the input. Convolution performs linear transformations of input data without changing spatial information in the data. Convolution kernels are determined from the weight of the layer so that the convolution kernels can process the input data training on CNN.

2.1.2. Subsampling Layer

Subsampling aims to reduce the size of image data and to increase the invariance of feature positions. CNN uses Max Pooling as a subsampling method. The way Max Pooling works is to divide the output of the convolution layer into several smaller grids and then take the maximum value from each grid to produce a smaller image matrix. With a small image size will make it easier to process the next convolution layer.

2.1.3. Fully Connected Layer

The Fully Connected Layer changes the dimensions of the data so that it can be classified linearly. In the convolution layer, each neuron must be transformed into one-dimensional data before being inserted into another layer that is connected as a whole[11]. This process is caused by data losing its spatial information and at the end of the Fully Connected Layer network is applied.

3. Method

3.1. Dataset

The dataset used in this study is Brain MRI Images for Brain Tumor Detection obtained from kaggle.com. The dataset consists of 253 images grouped into 2 groups, 155 brain images that have tumors, and 98 brain images that do not have tumors. Figure 2 shows images in the dataset.

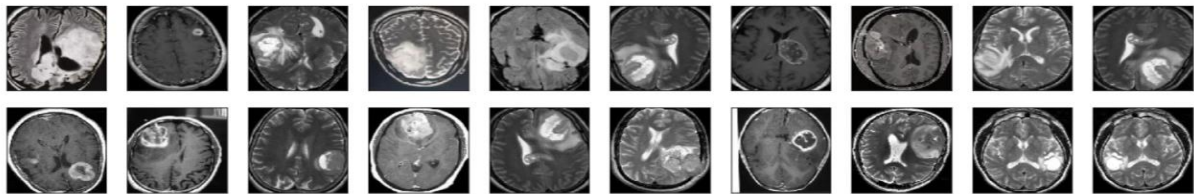


Figure 2. samples of the dataset

3.2. Proposed Method

This paper uses CNN for the automatic detection of brain tumors. This study uses input images labeled (yes/no) from the raw data and then uses these patterns to distinguish between tissues that do not contain tumors and those that contain tumors. CNN was trained to use 2065 sample images consisting of 1085 images containing tumors and 980 not containing tumors. Therefore, the proposed system is illustrated in Figure 3 method proposed in this study.

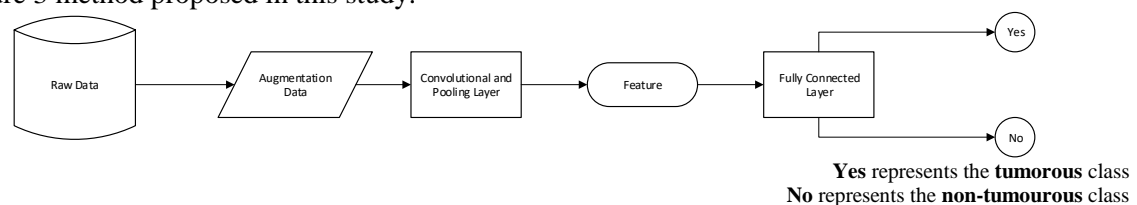


Figure 3. Method proposed

3.3. Data Augmentation

The amount of data in the dataset is not enough to be used as training data for CNN. Therefore the augmentation method is used to overcome the imbalance of issues. Augmentation is an algorithm that can utilize statistical data information and form an integrated model. This algorithm can produce a number of two-dimensional images of various poses and sizes. The application of augmentation to obtain image variants can improve the accuracy of CNN segmentation[12]. In this paper, each image with a tumor is segmented into 6 images, and an image with no tumor is segmented into 9 images. After data augmentation, the dataset consists of 1085 samples containing tumors (53%) and 980 samples not containing tumors (47%), bringing a total of 2065 images.

3.4. Image Pre-processing

Pre-processing performs to create smooth training because there are different variants of intensity, contrast, and size in images [13]. Input image will be processed into the first pre-process that is the process of wrapping and cropping. In wrapping, the input image is checked against the edge of the main object in the image. From the edge of the image, the maximum edge is determined so that when the results of cropping, the object in the image remains intact. After cropping, resize the image to shape $(240, 240, 3) = (\text{image_width}, \text{image_height}, \text{number of channels})$ because the images in the dataset have different sizes. Apply normalization: to scale pixel values to the range 0-1 to facilitate the learning process.

3.5 Model CNN

In this research, the CNN model contains several layers, namely the convolution layer, the pooling layer, the flatten layer, the dropout layer, and the dense layer. In addition to the layers used in the CNN process, there is also an activation function in this study using rule activation. In this research, 2 CNN models were made as comparison material. The CNN model design can be seen in table 1 and table 2. An image in the form of a number interweaving the first convolution, image size of 240x240 pixels. Kernels that have a size of 3x3 with a thickness of 3 in accordance with the channel of the image data and filters are

used as many as 32. After getting the results of the operation, the model will perform the activation and pooling data functions. The Pooling layer process serves to reduce the dimensions of the feature map. The result of the convolution process is a feature map that is used for the subsequent convolution process repeatedly. The next step is a flatten feature map in vector form to carry out a fully-connected layer process to produce a classification of images.

Table 1. First CNN model.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 240, 240, 32)	896
max_pooling2d (MaxPooling2D)	(None, 60, 60, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 32)	0
max_pooling2d_2 (MaxPooling2D)	(None, 15, 15, 32)	0
flatten (Flatten)	(None, 7200)	0
dense (Dense)	(None, 256)	1843456
dense_1 (Dense)	(None, 1)	257
Total params: 1,844,609		
Trainable params: 1,844,609		
Non-trainable params: 0		

Table 2. Second CNN model.

Layer (type)	Output Shape	Param #
conv0 (Conv2D)	(None, 240, 240, 32)	896
max_pooling2d (MaxPooling2D)	(None, 60, 60, 32)	0
dropout (Dropout)	(None, 60, 60, 32)	0
conv2d_1 (Conv2D)	(None, 60, 60, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 15, 15, 32)	0
dropout_1 (Dropout)	(None, 15, 15, 32)	0
flatten (Flatten)	(None, 7200)	0
dense (Dense)	(None, 256)	1843456
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 1)	257
Total params: 1,863,105		
Trainable params: 1,863,105		
Non-trainable params: 0		

4. Result and Discussion

Experiments in this article were carried out on 2065 images consisting of 1085 samples containing tumors and 980 samples containing no tumors. The data is further divided into 70% of the data as data training, 15% of the data as data validation, 15% of the data as data testing. The data is run 10 times, each using the CNN model that has been made before, each experiment using 25 epochs and 32 batches. The results are then compared using standard deviations, the mean and mean of the loss, accuracy and f1 score. In table 3 and table 4 can be seen from the results of the experiments conducted in this study. In the first CNN model, 1 convolution is used, and the average accuracy value is 94% and has an average loss value of 0.14181 on the training data, but there is a significant difference with the test data results, the average test data accuracy value is 85% and an average loss value of 0.44037. In the second CNN model using 2 convolution gets better results, the training data obtained an accuracy value of 96% and a loss value of 0.10046, then the test data obtained an accuracy value of 93% and a loss value of 0.23264. The f1 score on the second model is 92% but has a longer training time compared to the first model.

Table 3. Result of First CNN Model

No	Train			Val		Test		
	Time Training	Loss	Acc	Loss	Acc	Loss	Acc	f1
1	00:01:30	0,1895	0,9343	0,3797	0,8452	0,3938	0,8645	0,8742
2	00:01:31	0,1159	0,9592	0,3751	0,8774	0,4381	0,8483	0,8458
3	00:01:29	0,1793	0,9349	0,3908	0,8323	0,4013	0,8581	0,8682
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8	00:01:29	0,0259	0,9722	0,3674	0,8903	0,5348	0,8709	0,8802
9	00:01:26	0,1221	0,9619	0,3762	0,8581	0,4632	0,8387	0,8538
10	00:01:26	0,2707	0,9183	0,3961	0,8355	0,4405	0,8322	0,8479
Average	00:01:29	0,14181	0,9496	0,38254	0,85452	0,44037	0,85098	0,86048
Mean	00:01:29	0,14215	0,946	0,37795	0,8532	0,4293	0,8502	0,8575
STD	1,95511e-05	0,07132	0,0225	0,01134	0,02188	0,04233	0,01175	0,01119

Table 4. Result of Second CNN Model

No	Train			Val		Test		
	Time Training	Loss	Acc	Loss	Acc	Loss	Acc	f1
1	00:01:40	0,1625	0,9329	0,2765	0,9065	0,2655	0,9193	0,9158
2	00:01:39	0,0455	0,9862	0,2245	0,9258	0,2272	0,9419	0,9415
3	00:01:40	0,1105	0,9585	0,2104	0,9129	0,2258	0,9322	0,9302
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8	00:01:41	0,1123	0,9578	0,1959	0,9032	0,2532	0,9258	0,9225
9	00:01:45	0,0789	0,9744	0,1874	0,9355	0,2172	0,9354	0,9328
10	00:01:46	0,1215	0,9543	0,2156	0,9129	0,2412	0,9291	0,9256
Average	00:01:42	0,10046	0,96402	0,22538	0,91485	0,23264	0,93221	0,92996
Mean	00:01:42	0,09965	0,96435	0,2181	0,9129	0,2269	0,9338	0,9315
STD	2,7411e-05	0,03143	0,01506	0,0317	0,00988	0,01629	0,00625	0,00725

5. Conclusion

Convolutional Neural Networks are good enough to diagnose brain tumors on MRI images. This study resulted in accuracy of 93% and a loss value of 0.23264. The number of convolution layers affects the quality of classification, more convolution layers increase the accuracy results, but more number of convolution layers will require more time for training. The process of image augmentation can improve the variants of existing datasets, thereby increasing the classification results. Finally, for future suggestions, more images can be used to improve classification results. Future studies can also classify certain types of tumors.

References

- [1] "Penyakit Kanker di Indonesia Berada Pada Urutan 8 di Asia Tenggara dan Urutan 23 di Asia." [Online]. Available: <http://p2p.kemkes.go.id/penyakit-kanker-di-indonesia-berada-pada-urutan-8-di-asia-tenggara-dan-urutan-23-di-asia/>.
- [2] S. EDY, W. I, and W. A, "Clinical Characteristics and Histopathology of Brain Tumor at Two Hospitals in Bandar Lampung," *Fac. Med. Lampung Univ.*, vol. 69, pp. 48–56, 2014.
- [3] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, "Classification using deep learning neural networks for brain tumors," *Futur. Comput. Informatics J.*, vol. 3, no. 1,

- pp. 68–71, 2018.
- [4] A. Wadhwa, A. Bhardwaj, and V. Singh Verma, “A review on brain tumor segmentation of MRI images,” *Magn. Reson. Imaging*, vol. 61, no. January, pp. 247–259, 2019.
 - [5] Parveen and A. Singh, “Detection of brain tumor in MRI images, using combination of fuzzy c-means and SVM,” *2nd Int. Conf. Signal Process. Integr. Networks, SPIN 2015*, pp. 98–102, 2015.
 - [6] M. H. Avizenna, I. Soesanti, and I. Ardiyanto, “Classification of Brain Magnetic Resonance Images Based on Statistical Texture,” *Proc. - 2018 1st Int. Conf. Bioinformatics, Biotechnol. Biomed. Eng. BioMIC 2018*, vol. 1, pp. 1–5, 2019.
 - [7] S. Dabeer, M. M. Khan, and S. Islam, “Cancer diagnosis in histopathological image: CNN based approach,” *Informatics Med. Unlocked*, vol. 16, no. May, p. 100231, 2019.
 - [8] A. Işin, C. Direkoğlu, and M. Şah, “Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods,” *Procedia Comput. Sci.*, vol. 102, no. August, pp. 317–324, 2016.
 - [9] K. P. Danukusumo, Pranowo, and M. Maslim, “Indonesia ancient temple classification using convolutional neural network,” *ICCREC 2017 - 2017 Int. Conf. Control. Electron. Renew. Energy, Commun. Proc.*, vol. 2017-January, pp. 50–54, 2017.
 - [10] S. Hussain, S. M. Anwar, and M. Majid, “Segmentation of glioma tumors in brain using deep convolutional neural network,” *Neurocomputing*, vol. 282, pp. 248–261, 2018.
 - [11] R. Refianti, A. B. Mutiara, and R. P. Priyandini, “Classification of melanoma skin cancer using convolutional neural network,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 3, pp. 409–417, 2019.
 - [12] Z. Tang, K. Chen, M. Pan, M. Wang, and Z. Song, “An augmentation strategy for medical image processing based on Statistical Shape Model and 3D Thin Plate Spline for deep learning,” *IEEE Access*, vol. 7, pp. 1–1, 2019.
 - [13] T. Zhou, S. Ruan, and S. Canu, “A review: Deep learning for medical image segmentation using multi-modality fusion,” *Array*, vol. 4, no. July, p. 100004, 2019.