A good result of brain tumor classification based on simple convolutional neural network architecture

Eko Hari Rachmawanto[1], Christy Atika Sari[1], Folasade Olubusola Isinkaye[2]
[1]Department of Informatics Engineering, Faculty of Computer Science, University of Dian Nuswantoro, Semarang, Indonesia
[2]Department of Computer Science, Faculty of Science, Ekiti State University, Ado-Ekiti, Nigeria

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ABSTRACT

Brain tumor disease has become a topic of research whether it is in the case of segmentation or classification. For the case of classification, the types of brain tumors that are grouped generally consist of high-grade glioma (HGG) and low-grade glioma (LGG) tumors. In this research we are doing, we propose a method for classifying 2 types of tumors, namely HGG and LGG, using the convolutional neural network (CNN) algorithm which is trained and will be tested against the 2018 and 2019 brain tumor segmentation (BRATS) datasets which have 4 modalities, namely fluid-attenuated inversion recovery (FLAIR), T1, T1ce, and T2 totaling 2048 images. The CNN algorithm was chosen because it can directly receive input in the form of a magnetic resonance image (MRI) with the feature extraction process as well as the classification algorithm. By forming a simple CNN algorithm architecture with only 3 convolutional layers which have an input layer in the form of a full MRI image with dimensions of 240×240×3, we obtained a relatively high accuracy result of 94.14%, it can even be said to be better than similar methods but with more complicated architecture.

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Corresponding Author:

Christy Atika Sari
Department of Informatics Engineering, University of Dian Nuswantoro
Imam Bonjol 207, Semarang 50131, Indonesia
Email: christy.atika.sari@dsn.dinus.ac.id

1. INTRODUCTION

Brain tumors have become a disease that takes many victims due to the difficulty of treating patients in the early days of detecting tumors, this is also due to the difficulty of determining whether a tumor that attacks a patient is malignant or not [1], [2]. Many studies have raised the topic of brain tumors, ranging from segmenting the tumor area, calculating the survival rate of a patient with a brain tumor to classifying the type of tumor that attacks the patient, including malignant or not. The segmentation step carried out by several researchers focuses on how to accurately detect the tumor area depicted on the magnetic resonance image (MRI) or computerized tomography (CT) scan image media [3], while the classification focuses more on grouping the tumor type from several MRI image data from several patients to predict the tumor in a patient categorize as a malignant tumor or not [4]. For malignant tumors or more commonly called cancer, is a network that develops in an unorganized manner that attacks the surrounding tissue [5], [6] this can result in many negative impacts, especially if the part of the brain that is the center of nerve control is attacked. In addition to malignant/cancerous tumors, there are also non-malignant tumors or better known as benign tumors, which are different from malignant tumors, benign tumor tissue tends not to be destructive to the surrounding tissue, but continues to grow uncontrollably, thereby compressing other tissues [5]. From several studies that have been carried out over the last 5 years, many methods have been proposed to classify brain tumors, such as the K-nearest neighbors (KNN) algorithm, support vector machine (SVM) to neural network

(NN) [7]. Of the several methods that have been proposed in several previous studies, each has its advantages and disadvantages, for example, for non-NN algorithms, it has advantages in the time it takes to classify the type of brain tumor which tends to be shorter, but the disadvantage. When the classified image data is large enough to number in the thousands, the time required to process the classification will also increase significantly, and even then, it does not include feature extraction, data preprocessing, and all forms of data processing to make MRI images can be grouped into 2 tumor type. In the last 5 years, methods for classifying brain tumors have developed using the NN method which is a more modern method compared to methods such as KNN or SVM, but the principle used is still the same, namely extracting features from an MRI image and then using the extracted features to determine the type of tumor seen on the MRI image. Many types of NN have been developed to overcome problems such as MRI image classification, such as backpropagation, multi-layer perceptron, convolutional neural network (CNN), and many more. Each of the NNs has received many modifications, especially the CNN algorithm. Modifications to the CNN algorithm have grown rapidly with many research results that consider the CNN method a method that can continue to grow [8]. The advantages of the CNN method that have been proposed in recent years and why the CNN method is popular because there is no need for a preprocessing stage or feature extraction outside the classification algorithm, all processes take place in a classification algorithm commonly called layer, besides this algorithm can accept large amounts of input [9], [10]. In CNN, layer has a role in extracting features, as well as classifying MRI images in 1 architecture, so that the input needed for the CNN algorithm can be in the form of direct MRI images, and the output results are groups of MRI images based on the tumor type. The weakness of the CNN algorithm lies in the long computation time and the type of architecture applied for certain types of classification. The more layers in a CNN architecture, the longer the program will run [9], this is because each layer has its function, and the most important is the layer used to extract features from the MRI image, namely the convolution layer.

Research on the topic of brain tumor classification has used many types and combinations of algorithms, such as SVM, backpropagation, random forest, NN, and deep learning. Each of the proposed algorithms claims that their method is the most effective or most efficient in terms of the computations required, but because there is no standard to determine what the criteria for a method can be said to be accurate and efficient, any research that has been carried out can claim these 2 things by including a comparison of their research results with previous studies. The method proposed as a solution for classifying brain tumor types continues to grow every year, until now, the method proposed for classifying brain tumors has used the CNN method, where this method can utilize the entire MRI image as input and then extract the features that exist to form a model that will later be tested by providing new MRI image input and seeing the results of the classification whether it is true or false. The CNN method was proposed because it is considered to be able to cover all the features of an MRI image through the convolution process that exists in each layer of the architecture. The CNN method has been widely used as a brain tumor classification method, such as in the research of Ahmed *et al*. [9], where he proposed a CNN method that has been set in detail on each parameter, using 224×224 images with 5 convolutional layers and 2 fully connected layers to train model, the results of the prediction accuracy are 81.8%. Research conducted by Ismael and Abdel-Qader [1], adopted the backpropagation method to classify brain tumors into 3 classes, by utilizing the feature extraction method using discrete wavelet transformation (DWT) and 2D Gabor filters which will then enter the NN which contains 3 layers, namely the input layer, hidden layer, and output layer, for the number of each neuron in each layer in sequence, namely 270, 90, and 3, the results of his research obtained an average accuracy of 91.9% for the three classes. The NN method continues to be used in research on brain tumor classification, such as in the study of Mohsen *et al*. [11], proposed a brain tumor classification method using DWT feature extraction and principal component analysis (PCA) feature reduction, while forming a classification model using deep neural network (DNN), with the number of MRI image data as many as 66 images obtained from Harvard Medical School and the results obtained an accuracy of 96.97%. Classification of brain tumors using 2 types of modalities in MRI images was proposed by [12], which combines MRI images with fluid-attenuated inversion recovery (FLAIR) and T2 modalities to obtain region of interest (ROI) on MRI images, then extracts 280 features from MRI images which will later be used to build a classification model using this method. Ensemble forest which is a collection of random forests in which there is a collection of decision trees to make decisions by combining other features to produce an accurate class. The use of the CNN method as a classification method was also proposed by Seetha and Raja [13], who proposed the CNN method with a simple architecture but utilizing a smaller kernel to extract features from the MRI image, for the CNN architecture used, Seetha and Raja [13] used 6 layers to train NN, and the accuracy obtained from this study is 97.5%. The use of NNs is also applied by Choi and Sohn [14] in classifying 2 types of brain tumors, namely high-grade glioma (HGG) and low-grade glioma (LGG), for the proposed method is U-net which is one type of artificial neural network (ANN) with layer composition used in this study. are 18 convolutional layers, 8 max-pool layers, 1 input layer, and 1 output layer, and for the data used is obtained from the brain tumor segmentation (BRATS) dataset with T1ce modality, the accuracy results obtained from the proposed method for the HGG and LGG cases are 0.6315 and 0.6228. The CNN method proposed by Anaraki *et al*. [5] adopts the genetic algorithm method to form the architecture of the CNN algorithm, which is generally formed from a trial and error process, meanwhile the number of layers used in this research is 5 convolutional layers, 3 fully connected. layer, 5 types of activation function, by testing the proposed method with datasets obtained from REMBRANDT, the cancer genome atlas-glioblastomas (TCGA-GBM), and TCGA-lower grade gliomas (TCGA-LGG) with each dataset containing 2 types of tumors, namely high-grade glioma and low-grade glioma, and obtained accurate results. by 90.9% for 3 types of gliomas and 94.2% for 3 types of tumors glioma, meningioma, and pituitary. In addition to the modifications made to the CNN method used for the classification process, Sajjad *et al*. [15], proposed a brain tumor classification method using the CNN algorithm by adding an extensive augmentation process to the data in the form of rotation on the MRI image. Meanwhile, the CNN architecture used is the VGG-19 architecture that has been modified by the author so that it can maximize the classification results, while the data obtained from Radiopaedia are 121 images, and the accuracy results are 90.67 from 4 types of classified tumor classes. Sultan *et al*. [16], proposed a classification method for 3 types of gliomas, grade II, III, and IV with the data used obtained from REMBRANDT. The architecture used in Sultan *et al.* [16] has 3 convolutional layers, 3 max-pooling layers, and 1 fully connected layer, resulting in an accuracy of 96.13% from a total of 10,417 images. Thillaikkarasi and Saravanan [6] combined CNN with M-SVM to classify brain tumors into 2 types, benign and malignant tumors, but before the image enters the classification stage, the MRI image must go through a preprocessing stage in the form of contrast limited adaptive. histogram equalization (CLAHE) and noise removal. M-SVM is used to classify MRI images based on the features of the SGLDM feature extraction algorithm, then proceed with segmentation and classification using the CNN kernel algorithm, and the results obtained for the accuracy of this study are 93%. Srinivas and Rao [17] proposed a brain tumor classification method that also uses a combination of 2 CNN and KNN algorithms, the CNN architecture for its research uses 5 convolutional layers, 3 max pooling layers, and 2 fully connected layers, and the dataset used is obtained from BRATS 2015 and obtained an accuracy of 96.25%.

The CNN algorithm proposed in each study has a complex architecture that has many convolutional layers to extract features from the MRI image, but the research by Das [18], proposed a relatively simple architecture compared to similar research architectures, he proposed a tumor classification method. The brain uses the CNN algorithm with a composition of 3 convolutional layers, 2 max pool layers, and 2 fully connected layers, for accuracy of 94.39%. The development of a simpler CNN architecture for brain tumor classification was also carried out by Khan *et al*. [19], who claimed that the results of the accuracy of the CNN architecture he made with the composition of 8 convolutional layers could classify brain tumor images accurately with an accuracy obtained of 100% from 155 malignant tumor image data and 98 benign tumor image data, when compared with existing CNN architectures such as VGG-16, ResNet, and Inception-V3 which obtained lower results in terms of accuracy. The use of the CNN method continues as research conducted by Amin *et al*. [20], where the CNN method was used to classify MRI images with tumors and those without tumors, relying on a combination of 4 types of MRI images to produce precise tumor segmentation, and after that through the CNN algorithm with 5 convolutional layers and 2 fully connected layers, the features of the tumor image will be extracted to determine whether the image is a cancer tumor image or not, and the accuracy results obtained are 97% for the 2018 BRATS dataset. The classification of brain tumor types using the dataset obtained from BRATS 2018 was also carried out by Mzoughi *et al*. [21], who proposed the CNN method, which previously required the input image to go through a preprocessing process by applying the denoising and contrast enhancement processes, and obtained additional accuracy results. the preprocessing process is 96.49% and without preprocessing is 87.7%. Modifications to the CNN method were carried out by Ghassemi *et al*. [22] by developing the deep convolutional generative adversarial network, which is one of the advantages of overcoming the limitations on the input data used for the training network, while the CNN architecture used has a composition of 19 layers including an input layer, and for the dataset used are 3064 T1ce MRI images which obtained 88.01% accuracy results in the 10^{th} epoch. The ensemble-based CNN method was proposed by Lerousseau *et al*. [23] with the main focus being to improve the performance and robustness of the CNN architecture. For the type of ensemble used, Lerousseau *et al.* [23] combined several histopathological and radiological tissues to assist in classifying tumor types from a total of 3064 images with 3 tumor classes, and obtained an accuracy of 91.1%. As a reference for classification methods that use machine learning methods other than CNN, Kaplan *et al*. [24], propose a classification method using several combinations of local binary pattern (LBP) extraction features with the KNN classification algorithm. Modifications to the LBP feature extraction algorithm were carried out to obtain local features in the MRI image so that later the model to be trained could accurately classify tumor types on the MRI image. In this study, we propose a multimodality MRI image classification method, where for image input are 4 types of MRI images T1, T1ce, T2, and FLAIR which will later be grouped into 2 classes HGG and LGG, the method we propose is based on the CNN algorithm by minimizing the number of layers required so that the time required for the program to group the MRI images is shorter but still produces a relatively high accuracy.

2. RESEARCH METHOD

According to Figure 1, the data we use is obtained from the 2018 and 2019 BRATS datasets with a total number of images that we use as many as 2048 images. We also do a preprocessing process on the image before entering the CNN training stage. The next stage is to divide the data for training and testing, then the training data enters the CNN model training stage which will then produce a classification model to be tested for data testing, and the last step is to test the performance of the method we propose with the confusion matrix to determine accuracy, recall, and the error rate of our method.

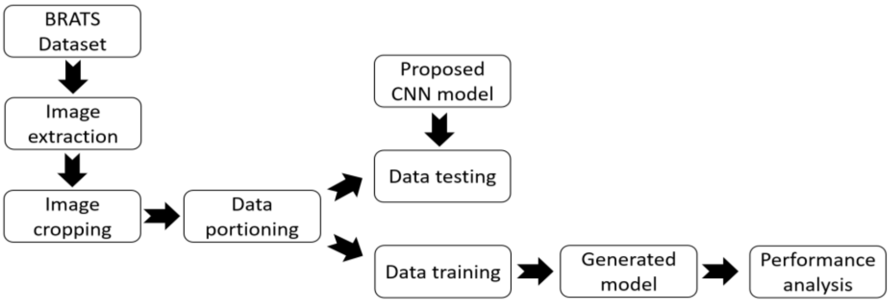


Figure 1. Proposed method based on CNN

For a more detailed explanation of the classification process flow, we explain in the section:

a. The input for the CNN algorithm is an MRI image obtained from the 2018 and 2019 BRATS datasets, with 4 types of modalities, namely FLAIR, T1, T1ce, and T2. The total number of data used in this study has a total of 2048. The data obtained from the BRATS dataset is a collection of brain tumor cases that are grouped into 2 types, namely HGG and LGG. In more detail, the 2018 BRATS dataset contains 210 MRI data of patients with definite indications of HGG type tumors and 75 MRI data of patients declared to have LGG grade tumors. For the data collection used in this study, we used medical image processing, analysis, and visualization (MIPAV) tools to extract 1 MRI image from each patient.
b. The extracted image from the BRATS dataset using the MIPAV tool has a property size of 240×240×3, which means it has a length of 240 pixels, a width of 240 pixels, and a depth of 3 colors, namely red, green, and blue. The distribution of data that will be used for the training and testing process is as follows: 0.8×the total number of training data and the rest for testing, for the number of each training and testing data is 1444 and 604 images. For training and testing data, we randomized the data collection so that it did not seem directed to the accuracy of the classification results later.
c. The CNN architecture that we created consists of 3 convolutional layers with the order for all layers as:
   – Input layer, in the form of an MRI image with dimensions of 240×240×3 without preprocessing
   – ConvoLayer (Conv1), in the form of a convolution layer with a filter size of 12×12 with 120 filters, then there is a parameter to determine the distance between the convolution 1 process and the next convolution called 'Stride', for the parameter value 'Stride' in this study is 4, with value 'Padding'=[0 0 0 0]. The function of this layer is to select specific features from the input MRI image so that several layers of the filtered MRI image are obtained [25].
   – Batch normalization is a layer whose role is to normalize values in small batches of convoluted value results, which is intended to speed up the Network training process and reduce the sensitivity level during the network initialization process. This is followed by the rectified linear unit (ReLU) layer which plays a role in correcting the convoluted layer in the previous layer by changing the value less than 0 to 0. This is done so that the feature value from the convolution process does not change the results of other features.
   – MaxPooling layer, serves to select the maximum value generated by each feature resulting from the convolution layer and ReLU layer. This layer also plays a role in reducing features that are less important which are also found in the Conv layer feature extraction results so as to increase the efficiency of the network formed [26]. In this study, we also use the 'Stride' parameter which shows how to run from the MaxPooling layer, for our research, the parameter used is 3, so when selecting

the feature value, the feature value comparison runs a distance of 3 values after the last value is compared, this is intended to save time in selecting feature values.
- ConvoLayer2 (Conv2), used to extract features from the max-pooling layer results with smaller filter size and a larger number of filters. The parameters for the convolution layer 2 are as follows: the filter size is 5×5 with the number of filters 120, and 'Stride'=2 followed by the ReLu layer.
- ConvoLayer3 (Conv3) with a smaller filter size than convoLayer2, which is 3×3 with a larger number of filters of 240 and 'Stride'=2, then followed by the ReLu layer.
- FullyCon (FC1). This is an important layer in the CNN architecture because this layer acts to combine the hidden layers that have been previously created. In this study we use the parameters for fully connected layer as follows: output class 2 (HGG and LGG), with the addition of 'WeightsInitializer'='zeros', which means to fill the initial weighting with a value of 0, this is done so that the results of the classification remain consistent and does not change with each iteration of the program.
- SoftMax layer is an activation function that is used to determine the probability class results from the previous layer. The softmax function used uses exponential equations, for example; there are 3 classes, A1, B1, and C1, to calculate the probability of class A1, then the final value on the last neuron will be divided by the total number of exponential values so that the probability value for class A1 is obtained.
- Classification layer, serves to group the results of the class probability values that have been previously calculated in the previous layer. In this layer, the loss function calculation will be carried out in each training iteration which will later be used to predict the class for the new data.

The following are the details of the layers we used for this research in Table 1 and also a graphical design of the proposed CNN at Figure 2. After the network model is obtained, the next step is to test the model with the testing data that has been prepared previously. The testing data format used in this study is an MRI image with 4 types of modalities which will be grouped into 2 classes. In addition to the parameters for forming the network as a means of training the model that will be formed, we also explain the parameters for the training process, including: MaxEpoch=50, LearnRate=0.0001, Verbose=0, VerboseFreq=50, and Shuffle='every epoch'.

Table 1. Detail layer of proposed CNN architecture

Layer	Feature Size	Stride	Activation
Input	240×240×3	-	-
Conv1	12×12×120	4	ReLu
BatchNorm (BN1)	-	-	-
MaxPool	3×3	3	
Conv2	5×5×120	2	ReLu
Conv3	3×3×240	2	ReLu
FullyCon (FC1)	2	-	SoftMax

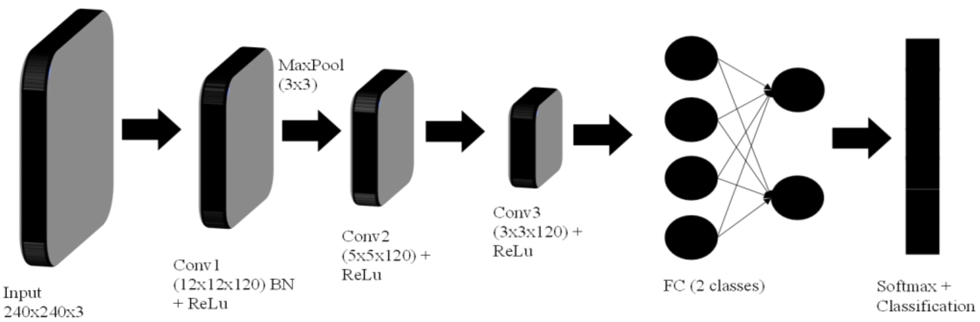


Figure 2. Proposed CNN architecture

3. RESULTS AND ANALYSIS

This study used multimodality MRI image data obtained from the 2018 and 2019 BRATS datasets, which total 2048 images, for examples of the types of images we show in the Table 2. The performance measurement for this study uses a confusion matrix calculation to obtain the accuracy, recall, precision, and F-score values from our proposed method. The confusion matrix is a table that contains 4 types of label types, true positive (TP), false positive (FP), true negative (TN), and false negative (FN). As an explanation of the confusion matrix will be explained in the Table 3. Based on the Table 3, TP is an MRI image that is included in the HGG class and TN is an MRI image that is included in the LGG class, for FP and FN it is an LGG or HGG MRI image that is incorrectly grouped in the actual class. Continuing the explanation of the performance testing that we use, the following is an explanation of each equation for accuracy, recall, precision, and F-score [14]. This research was run on a computer with specifications AMD CPU FX9830 3.00 Ghz, 16 GB RAM, GPU Radeon RX460, with MATLAB 2021a software. The results of the training network process that have been carried out have reached a training value of 100 in accuracy, in the 350th iteration, and after that, there is no visible decrease in training accuracy, which can be seen in the Figure 3. From the beginning of the experiment, the training accuracy has touched an accuracy above 50%, it takes several iterations until the training accuracy can reach the maximum value. For the level of loss from the results of the training network that we did, the results were quite satisfactory, as shown in the Figure 3 and Figure 4. Based on Figure 4, it shown the initial loss in our study also shows a relatively low value for the number of datasets that we use. Meanwhile, the results of the confusion matrix shown in the Table 4.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100\% \quad (1)$$

$$Recall = \frac{TP}{TP+FN} * 100\% \quad (2)$$

$$Precision = \frac{TP}{TP+FP} * 100\% \quad (3)$$

$$F-score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

Table 2. Dataset example from BRATS 2018 and 2019

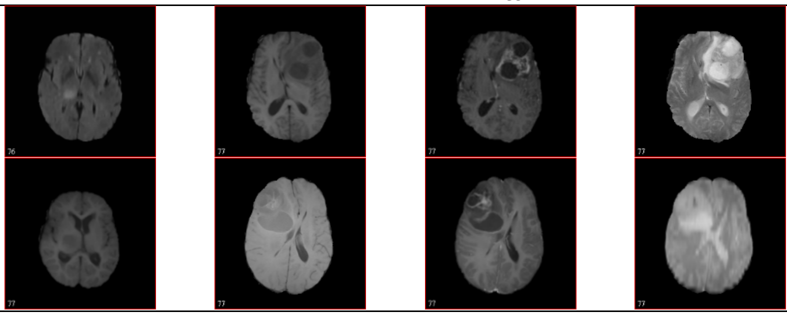
Modality				Class
FLAIR	T1	T1ce	T2	
				HGG LGG

Table 3. Confusion matrix variables

		Actual class	
		Actual positive	Actual negative
Predicted class	Predicted positive	TP	FP
	Predicted negative	FN	TN

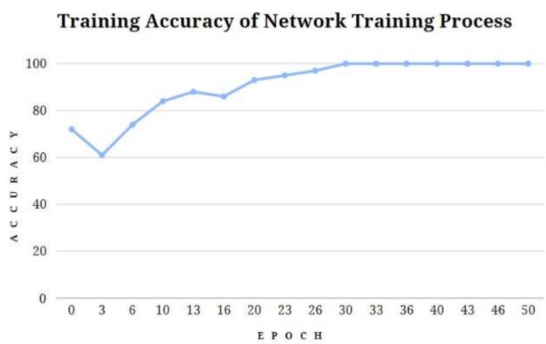


Figure 3. Training accuracy of network training process

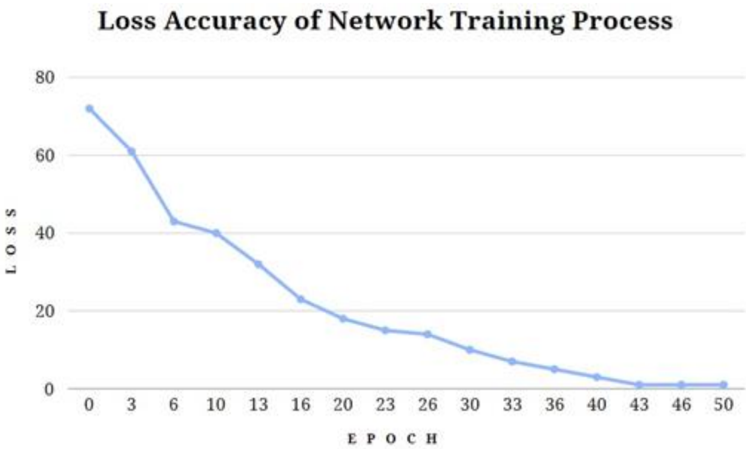


Figure 4. Loss value of network training process

Table 4. Clasification result in confusion matrix

		Actual class	
		Actual positive	Actual negative
Predicted class	Predicted positive	277	12
	Predicted negative	12	109

Based on Table 4, concluded that our research obtained results for accuracy of 94.14%, recall of 95.84%, precision of 95.84%, and F-score of 0.9584. From the results obtained, it can be said that our proposed method is proven to be accurate for classifying 2 types of brain tumors. For the data we use, it is not general data for the classification process, so not too many researchers have tested the classification method they made with the dataset we use, so maybe with the research we made, it is more encouraging for other researchers to use the BRATS dataset as data. classification test. The factor that distinguishes our dataset from other MRI image datasets is the use of multiple MRI image modalities, which can provide additional features for each class for each modality, so that a more accurate model is obtained for classifying the test MRI images. In this study, we also tested the same CNN model but with an MRI image that we previously cropped to focus only on the brain area, but the results we got were actually lower accuracy, namely 90.98%. There is no significant change to the accuracy during the training process and the loss value during the CNN model training. The CNN architecture that we form can be categorized as simple when compared to the CNN architecture that has been proposed by several researchers, this makes our CNN architecture also has advantages in terms of computing which requires less time to achieve relatively high results. From the CNN method that we propose, we extract the features of the MRI image globally with a large filter size in the Conv1 layer and then later it will be reduced in Conv2 and Conv3 to detail the features that distinguish between the 2 classes of classified tumor types. As a comparison of the results of our study with previous studies, we compared the results of the accuracy of our method with the previous method which can be seen in the Table 5.

The architectural design that differs between our research and some of the studies in Table 5 is in the number of layers and combinations with other algorithms such as the Thillaikkarasi and Saravanan [6], which uses a combination of SGDLM and M-SVM feature extraction algorithms to make it easier for CNN to classify brain tumor types. While in the research by Ghassemi *et al*. [22] using a fairly large number of layer combinations of 19 layers, but with a small kernel filter size, in contrast to our CNN method which uses a relatively large filter size at first, then shrinks in Conv2 and Conv3, this is intended to extract global features from the MRI image then extract the detailed features with a small convolution filter. Meanwhile, the Densenet-based method developed by Lerosseau *et al*. [23] uses the most layer combinations but has not been able to obtain maximum results. In addition, we also carried out experiments with a large number of layers as found in the AlexNet architecture, with the same training parameters, but the results we obtained were not much different from the CNN architectural design that we formed with fewer layers. our architecture is computationally superior because it has lower complexity. We assume that by applying convolution with a large filter size, in this case, according to our research it is 12×12, and that the number of filters that increase from Conv1 to Conv3 can provide an appropriate classification model for the MRI image dataset from BRATS 2018 and 2019.

Table 5. Comparison results with previous study

Authors	Methods	Layers count	Result (%)
Proposed method	Multimodal CNN	3	94.14
Thillaikkarasi and Saravanan [6]	M-SVM+SGDLM+CNN	4	93
Ghassemi *et al*. [22]	Deep convolutional generative adversarial network	19	88.01
Lerosseau *et al*. [23]	Ensemble CNN (based on Densenet169)	169	91.1

4. CONCLUSION

Brain tumors are a dangerous disease because it is difficult to identify the type of tumor on an MRI scan. Various studies have proposed many methods for classifying brain tumor types, ranging from simple methods such as KNN to complex methods, namely deep learning. In this study, we propose a classification method for 2 types of brain tumors, namely HGG and LGG from the 2018 and 2019 BRATS datasets, with the amount of image data used as many as 2048 images using the CNN algorithm. CNN architecture has developed far to be so complex that it requires a long computational time, the method we propose is to overcome this problem by proposing a simple but still accurate CNN architecture in classifying brain tumor images. With only 3 convolutional layers, we obtained a high accuracy result of 94.14%, besides the time needed to train the classification model can also be said to be shortened.

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BIOGRAPHIES OF AUTHORS

Eko Hari Rachmawanto received the Bachelor degree in Informatic Engineering from University of Dian Nuswantoro, Indonesia in 2010. He received the master by double degree University of Dian Nuswantoro and Universiti Teknikal Malaysia Melacca (UTeM) during 2010-2012. Since 2012, he joined as lecturer in Informatics Engineering, University of Dian Nuswantoro, Semarang, Indonesia. He awarded as best presenter and best paper in several IEEE Conferences. Now he served as Editor in Chief of Accredited Indonesian National Journal. In 2015-2016 he served as head of IT at the TV station of the University of Dian Nuswantoro. Since 2022 he supervises the Informatics Engineering Study Program in study programs outside the main campus as head of the study program in Kediri, Indonesia. Now he is member of Security Data Collaboration Research and tasked to developing a number researchers regarding data security, image processing for data security, machine learning, watermarking, and steganography. He can be contacted at email: eko.hari@dsn.dinus.ac.id.

Christy Atika Sari received the M.Sc. double degree for master in Informatic Engineering from University of Dian Nuswantoro and University Teknikal Malaysia Melaka (UTeM) in 2012. She is currently active as author in international journals and confrences scopus indexed. She also awarded as best author and best paper in national and intenational confrence in 2019 and 2020 respectively and awarded from Ministry of Research and Technology of the Republic of Indonesia (KEMENDIKBUDRISTEK) as the Indonesian top 50 best researchers in 2020. Now, she served as editor and reviewer for several international reputable journal and TPC of several IEEE Confrences. She currently as senior lecturer in intelligent systems and and continue to develop the research field image processing, machine learning, deep learning, data security, and data hiding. She can be contacted at email: christy.atika.sari@dsn.dinus.ac.id.

Folasade Olubusola Isinkaye received a Bachelor of Science degree in Computer Science from the Ondo State University, Ado-Ekiti, (now EKSU) Nigeria. Her Master of Science and Ph.D. degrees were obtained in Computer Science from the University of Ibadan, Nigeria. She is a Senior Lecturer at the Department of Computer Science, Ekiti State University, Ado Ekiti, Nigeria. She was also the Ag. Head of the Department of Computer Science, Ekiti State University from 2020-2022. She is a member of professional bodies which include the Computer Professional [Registration Council of Nigeria (CPN)] and the association for computing machinery (ACM). She was a visiting Ph.D. scholar at the Laboratory of Knowledge Management, Dipartimento di Meccanica, Matematica e Management, Politecnico di Bari, Italy. Also, a Postdoctoral research fellow at the Department of Computer Science and Information Technology, Sol Plaatje University, Kimberley, South Africa. Her research interests include recommender systems, information systems, and machine learning. She can be contacted at email: folasade.isinkaye@eksu.edu.ng.