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BRAIN TUMOR DETECTION FROM MRI IMAGES USING DISCRETE COSINE TRANSFORM FEATURES AND EXTREME LEARNING MACHINE

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Abstract

A brain tumor is an abnormal growth of brain tissue and characterized by excessive cell proliferation in certain parts of the brain. One of the current, reliable technologies that can be used to identify brain tumors is Magnetic Resonance Imaging (MRI) scans. The scanned MRI images are then conventionally monitored and examined by a specialist for the presence of tumors. As the number of people suffering from brain tumors is significantly increasing and their corresponding mortality rate has reached 18,600 by 2021, research on designing more effective and efficient tools to assist medical specialists in identifying brain tumors is considered of great importance. In a previous study, a machine learning-based model demonstrated its ability to detect brain tumors with a classification accuracy of 92%. Several hyperparameters were computationally tested using public MRI datasets to obtain the most reliable detection/binary classification accuracy on MRI brain images. Sophisticated model accuracy was achieved by testing various neuronal units and ELM activation functions, followed by inserting a feature map extracted from the Discrete Cosine Transform (DCT). The model obtained the highest testing accuracy of 95% with several 20 ELM neuron units with a tanh activation function

Keywords: *Brain Tumor Detection, MRI, DCT, ELM*

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1. INTRODUCTION

Tumors are cells that grow abnormally (excessive cell proliferation) in certain parts of the body. Tumors are abnormal tissues that may be solid or can also be liquid [1]

According to SEER (2021), there are an estimated 24,530 new cases of cancer and brain tumors in 2021, while the death rate for people with brain tumors will reach 18,600 deaths. In addition, the life expectancy of people affected by this disease is up to 5 years is 32.6% [2]. Tend to lead to mental illness or mental illnesses such as anxiety and depression [3].

Identifying the presence of a brain tumor is not easy because the symptoms experienced by sufferers of brain tumors tend to lead to mental illnesses such as anxiety and depression. Therefore, at an early stage, they will usually be diagnosed as having a disorder when the patient should have had a brain tumor. Before the diagnosis step, using one of the most reliable technologies available today, sections of the brain tumor are first captured with the help of a magnetic resonance imaging (MRI) scan. Radiologists and other medical specialists then monitor and examine the scanned MRI images to check for tumors. Therefore, making a decision whether a patient is indicated for a brain tumor or not, may take a long time because it requires in-depth analysis from a team of medical experts who can read and identify tumors from a collection of MRI images. In addition, because of the complexity of the MRI images, detection of the presence of a brain tumor can sometimes lead to a false adverse decision. Therefore, to overcome this critical weakness, high-speed computers with machine learning paradigms may be required by medical teams not only to speed up the entire process of assistance but also to make more informed decisions about brain tumor detection and localization.

In this new research, a method of recognizing or detecting brain tumors using pattern recognition on digital images has been widely carried out. A number of journals that have been collected based on several inclusion criteria in the form of discussing machine learning or deep learning used in tumor detection using MRI (Magnetic Resonance Imaging) images of the brain and the period of journals from 2018 to 2022, quite divmixedsults were obtained.

Previous research in [4] used image binary processing techniques and morphology. Tumor classification is applied after the Shape Feature Extraction process carries out segmentation. The results of the tumor classification obtained were 89.5 percent, which can provide more precise and more specific information regarding tumor detection. These results were obtained using the K-Nearest Neighbor classification. In another study [5] on the classification process, the statistical properties of the input images were analyzed, and the data was systematically divided into various categories, then compared three classification algorithms, namely KNN, Random Forest, and SVM. We obtained the highest accuracy of 90% by using SVM.

Other studies classify MRI brain images as consisting of 3 tumors: glioma, meningioma and pituitary. Their algorithm that extracts high-level feature maps from the VGG16 base model uses Fast R-CNN as a classifier. This study achieved an average precision of 77.6% for all classes [6].

Meanwhile, in the experiment [7], he compared two types of algorithms for the segmentation stage: U-net and CNN-based. Meanwhile, at the stage of tumor grading, compare the VGG-16 and CNN algorithms. Based on the experiments to get the best results using U-Net segmentation, the tumor detection algorithm using the random forest classifier and tumor grading stages using the VGG-16 algorithm. This experiment used MR Spectroscopy and FLAIR data for the highest experimental accuracy of 92 percent.

The purpose of this study is to design a brain tumor diagnostic tool (as algorithm and model weights) using an MRI image base using feature extraction in the form of Discrete Cosine Transform (DCT), which is an algorithm in signal compression and uses Extreme Learning Machine (ELM) as a classification model builder. The final result of this study is to obtain the confusion matrix and the accuracy of testing the proportions of the configurations built.

2. RESEARCH METHOD

The research stages used in this study are presented in Figure 1.

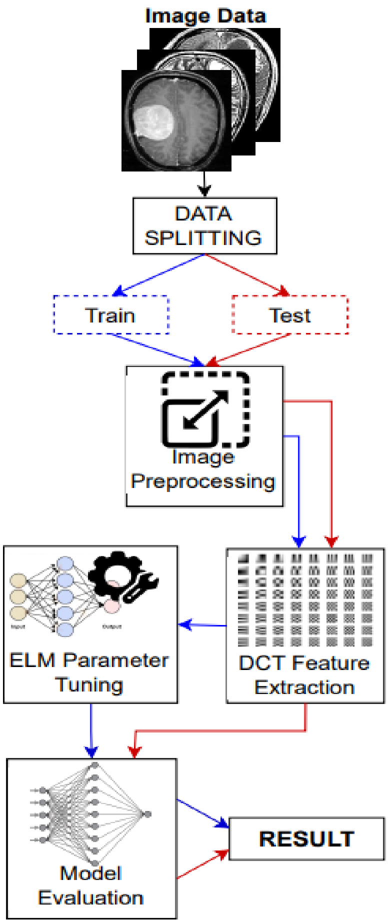


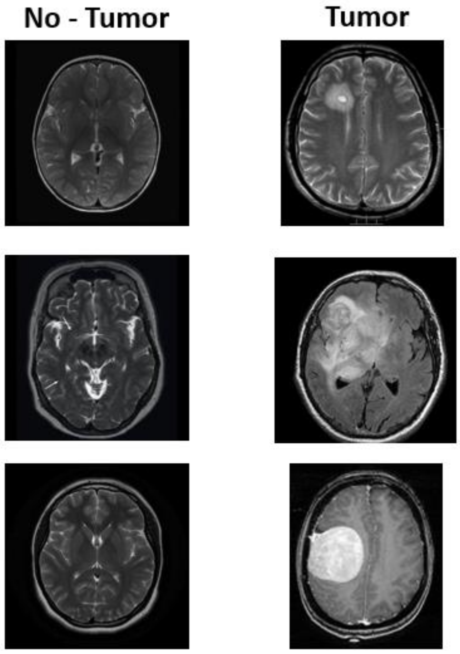
Figure 1. Research Stages

Explanation of the Research Stages process from Figure 1 namely:

a. Data collection

At this stage, a search for data sets that are following this research is carried out. The dataset collected must be MRI image data for brain tumors with a label in the form of a tumor or no tumor.

At this stage, a brain tumor MRI image dataset can be accessed via the Kaggle site [8] with a dataset called BraTS 2019. This dataset contains a total of 3,000 brain MRI images, of which 1,500 images have tumors and the other 1,500 images do not have tumors. Some examples of pictures from the 2019 BraTS dataset can be seen in Figure 2.



Gambar 2. Example of the 2019 BraTS Dataset

b. Data Splitting

The data was divided into 2 parts in a stratified manner, namely 2800 data for training (1400 tumors, 1400 healthy) and 200 data for testing (100 tumors, 100 healthy).

c. Data Preprocessing

At this stage, the image is changed to a gray level so that the image that initially has 3 color channels only has 1 color channel. Apart from that, at this stage also changes the image which initially had a different size to a size of 150x150 pixels.

d. Ekstraksi Fitur DCT

Image classification requires feature extraction processing to change an image that originally has many features that may have insignificant values (low correlation) into simpler but meaningful features. In this study, DCT was used as feature extraction from existing MRI images.

The DCT (Discrete Cosine Transform) algorithm is commonly used in image or signal compression [9]. This algorithm converts spatial data into frequency form, processes frequency data, and converts it back into spatial form by inverting the method. Where, the frequency domain is a signal in the form of amplitude with respect to time (spectrum at one-time signal), the frequency domain refers to the analysis of mathematical functions or movements related to frequency in time. Meanwhile, the spatial domain refers to the basis of direct pixel manipulation in images [10], [11] .

Discrete cosine transform is formulated as in equation (1).

$$v(k) = \alpha(k) \sum_{n=0}^{N-1} U(n).Cos\left[\frac{\pi(2n+1)k}{2N}\right] \qquad (1)$$

$$for\ 0 \le k \le N-1$$

$$\alpha(k) \begin{cases} \sqrt{\frac{1}{N}} & if\ w = 0 \\ \sqrt{\frac{2}{N}} & otherwise \end{cases}$$

where v(k) is the result of DCT feature extraction, with k denoting the extracted row or column index. N is the size of the row or column of the image block for which DCT feature extraction is to be carried out. Whereas U(n) represents an image block with a gray level.

In DCT feature extraction, it can usually be done in a number of stages. The first stage is to obtain an image or image as an image color matrix (usually, matrix calculations on one color component, either red or green or blue or a gray image [red+green+blue] / 3). Next, the image is divided into blocks measuring 8 x 8 pixels, sequentially from left to right, and from top to bottom.

e. Formation of the ELM Model

ELM (Extreme Learning Machine) is an algorithm of an artificial neural network (ANN) which has only one hidden layer and learning takes place in a feedforward manner [12], [13] .

Basically, ANN is a mathematical model function that defines y = f (x * w)[14]–[16] Where y is an output element, f is an activation function, x is an input signal (sensory) and w is a synaptic weight. The term network refers to the interconnection of neurons at a number of different layers. The layers in ANN are divided into three parts:

1) Input Layer
2) Hidden Layer
3) Output Layer

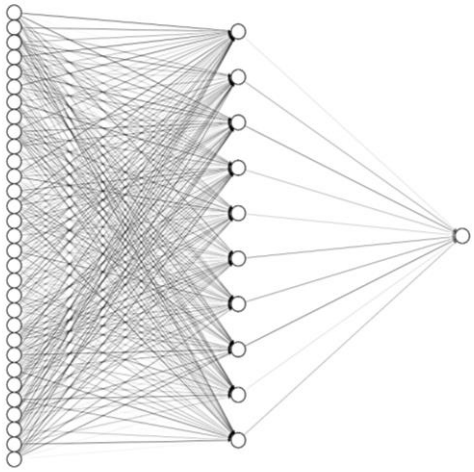


Figure 3. ELM Visualization

In this study, the number of neurons used in the hidden layer will be tested which is the best out of a number of 5, 10, 15 and 20 neurons with the activation functions tested being tanh and relu. The ELM architecture with 10 neurons in the hidden layer when visualized will be like in Figure 3.

Mathematically, a neuron is a function that receives input from the previous layer gi (layer i). This function generally processes a vector and then converts it to a scalar value by calculating a nonlinear weighted sum

$$f = K(\sum_i w_i g_i) \quad (2)$$

where K is a special function which is often called the activation function and wi is the weight.

f. Model Evaluation

The evaluation used in this study is the Confusion Matrix, Accuracy, Precision, Recall and F1 Score. The confusion matrix in binary classification cases presents true positive (TP), true negative (TN), false positive (FP) and false negative (FN) cases.

Accuracy is defined as the percentage of all data that is correctly classified either in the positive or negative class. So that means all prediction data that is true is divided by all available data. If it is formulated, it will become equation (3).

$$Accuracy = \frac{(\mathrm{TP+TN})}{(\mathrm{TP+TN+FN+FP})} \quad (3)$$

All values in the equation can be seen from the confusion matrix to get each part of the value [17].

Precision or also known as confidence is a metric that discusses how precise/accurate a model is. This can be measured from the prediction results which are positive (how many are actually positive) [18]. So that precision can be formulated in equation (4).

$$Precision = \frac{(\mathrm{TP})}{(\mathrm{TP+FP})} \quad (4)$$

Recall or what is called sensitivity is a metric that calculates how many Actual Positives are captured by the model through labeling it as Positive (Really Positive)[19]. So that recall can be formulated like equation (5).

$$Recall = \frac{(\mathrm{TP})}{(\mathrm{TP+FN})} \quad (5)$$

The F1 score is a metric for measuring by considering the balance between precision and recall so that the f1-score ignores the value of the actual negative (true negative)) [17]. Then the f1 score can be formulated into equation (6).

$$F1 - Score = \frac{(2 \text{ x Precision x Recall})}{(\text{Precision+ Recall})} \quad (6)$$

3. Result and Discussion

In this study the performance evaluation of the model was tested in a Google Colab Pro Python environment accelerated by a Graphics Processing Unit (GPU) and 25 GB of RAM. Using DCT feature extraction followed by classification using ELM showed good results, even beating the accuracy of previous studies using a deep learning approach.

This experiment was carried out with the lbfgs optimizers, the learning rate was 0.001 and the number of iterations was 500. The experimental results of detecting or binary classification of brain tumors with DCT and ELM with the hyperparameters tested in the form of the number of neurons and the activation function can be seen in table 1.

Table 1. DCT + ELM Experiment Results

Number of Neuron	Activation Function	Metrics		
		Name	**Value**	**Average**
5	Relu	Accuracy	0.90	0.8975
		Precision	1.00	
		Recall	0.80	
		F1-Score	0.89	
	Tanh	Accuracy	0.885	0.88125
		Precision	1.00	
		Recall	0.77	
		F1-Score	0.87	
10	Relu	Accuracy	0.90	0.8975
		Precision	0.99	
		Recall	0.81	
		F1-Score	0.89	
	Tanh	Accuracy	0.93	0.9275
		Precision	1.00	
		Recall	0.86	
		F1-Score	0.92	
15	Relu	Accuracy	0.935	0.9375
		Precision	1.00	
		Recall	0.87	
		F1-Score	0.93	
	Tanh	Accuracy	0.92	0.9175
		Precision	0.98	
		Recall	0.86	
		F1-Score	0.91	
20	Relu	Accuracy	0.90	0.8975
		Precision	1.00	
		Recall	0.80	
		F1-Score	0.89	
	Tanh	**Accuracy**	**0.95**	**0.95**
		Precision	**0.99**	
		Recall	**0.91**	
		F1-Score	**0.95**	

Based on the results in the table above it is known that the best ELM configuration model can be obtained with the number of neurons in the hidden layer of 20 with the tanh activation function (Hyperbolic Tan). This configuration managed to get a training accuracy of 100% and a testing accuracy of 95%, with an average of accuracy, precision, recall and F1-Score worth 95% as well.

Based on the configuration of the best model formed (with the number of neurons 20 and activation tanh) get the confusion matrix presented in Figure 4. Figure 5 also presents the learning curve of this model configuration.

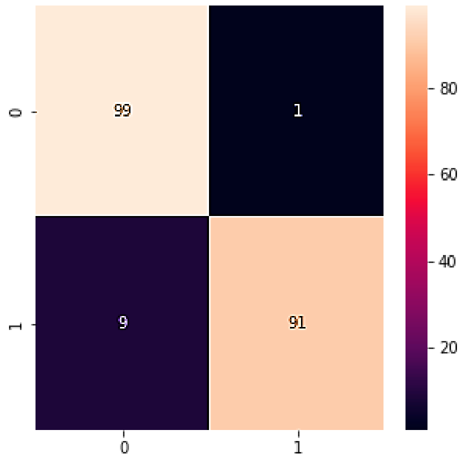


Figure 4. Confusion Matrix

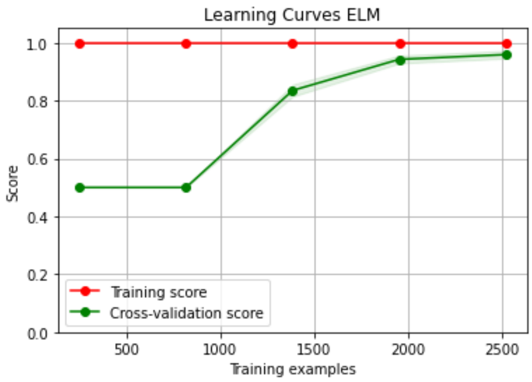


Figure 4. Learning Curve

The confusion matrix shown in Figure 4, the upper left is a True Negative (TN) of 99, the upper right is a False Positive (FP) of 1, the lower left is a False Negative (FN) of 9, and the lower right is True Positive (TP) is 91. Where on the X and Y axes there are zeros and one, zero is the no-tumor class and one is the tumor class.

The Learning Curve shown explains that using less data results in lower validation values and shows that if the data used is less than 1000 it shows overfitting results (this is shown in high training accuracy but low validation). Meanwhile, after reaching 2000 the data model produces a good classification and no overfitting occurs because the difference between the values in the training coincides (no significant difference) with the validation.

4. CONCLUSION

It has been shown that the application of feature extraction using the Discrete Cosine Transform (DCT) to obtain a feature map using the Extreme Learning Machine (ELM) classification model is capable of achieving high classification test accuracy scores on binary detection or classification tasks. A training accuracy score of 100% and a testing accuracy of 95.0% are obtained by applying the number of neurons in the hidden layer to a total of 20 units and using the Tan Hyperbolic (Tanh) activation function.

As a suggestion for improving the model, optimization can be carried out in the future by finding the best hyperparameters from the model such as the number of neuron units in the hidden layer, type of activation function, learning rate, and type of optimizer used.

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