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COMPARISON OF SUPPORT VECTOR MACHINE, NAIVE BAYES, AND ARTIFICIAL NEURAL NETWORK BACK PROPAGATION IN DETECTING BRAIN TUMOR

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ABSTRACT

Background: Brain tumors are abnormal tissue that grow uncontrolled and affect a patient's neurological function. Brain tumors come in different shapes and characteristics. Moreover, its location also differs for each patient. Brain tumors can be detected using machine learning algorithms using magnetic resonance imaging (MRI) images. However, a different machine-learning comparison is limited and needs further investigation. This study aims to compare three machine-learning methods, i.e., Support Vector Machine (SVM), Naive Bayes (NB), and Artificial Neural Network Back Propagation (ANN-BP) algorithms for detecting brain tumors. Before the comparison started, MRI image quality was enhanced by performing denoising, histogram equalization, and thresholding. After that, Gray Level Co-occurrence Matrix feature extraction was performed. MRI brain images in JPEG format were acquired from an open-access database. One thousand brain tumor and 1000 normal tumor images are used as the training data, while 100 brain tumor and 100 normal tumor images are used as testing data. Each algorithm's accuracy, precision, sensitivity, and Matthews Correlation Coefficient (MCC) are evaluated and reported. The study showed that the SVM algorithm acquired the highest performance in detecting brain tumors, followed by ANN-BP and NB. The highest accuracy, precision, sensitivity, and MCC values for testing in SVM were 98,75%, 98,22%, 99,30%, and 0,9751, respectively. Meanwhile, in testing, the highest accuracy, precision, sensitivity, and MCC values were 90.50%, 98.80%, 82.00%, and 0.8220, respectively. In conclusion, this study showed the superiority of the SVM algorithm in detecting brain tumor compared to ANN-BP and NB by performing image enhancement steps and GLCM feature extraction before its detection.
Keywords: *Artificial Neural Network, Gray Level Co-occurrence Matrix, Support Vector Machine, Naive Bayes.*

BACKGROUND

Brain tumors are the uncontrolled development of abnormal tissue without physiological function in the brain. This tumor causes swelling and also neurological disorders that can interfere with brain function. In adults, brain tumors cause decreased quality of life and can pose a risk of death. Meanwhile, in children, brain tumors have a higher incidence of cancer than leukemia[1-3]. This life quality reduction is caused by weak identification of tumors in the early stage. In addition, tumors are identified in various sizes, textures, and locations, making comprehensive identification difficult[1-2,4].

Compared to computed tomography, magnetic resonance imaging (MRI) is the primary modality in detecting brain tumors[1-8]. The selection is based on MRI's ability to differentiate soft tissue contrast using various imaging protocols, primarily the T2 weighted, T2 fluid-attenuated inversion recovery (FLAIR), T1 weighted protocols[1-2,4]. Furthermore, MRI can determine the size and location of the tumor and evaluate the tumor mass to help diagnose the patient's condition[2,4].

Various computer algorithms have been developed to identify tumors when diagnosing brain tumors using MRI images. Nowadays, experts use machine learning and deep learning algorithms to extract tumors identification information using several image datasets[5-7]. In its practice, deep learning is more favorable than machine learning. However, its application needs a large dataset. Therefore, its application is not recommended for evaluating a center with a limited image dataset. Limited image dataset problem to identify brain tumors is the primary problem in most hospitals or research centers. Therefore, the implementation of machine learning is superior in this condition. Machine learning algorithms carry out three extensive diagnoses: tumor identification, segmentation, and classification[8]. Support Vector Machine (SVM)[9-10], Naive Bayes (NB)[9-10], and Artificial Neural Network (ANN)[11] algorithms are types of algorithms used to detect tumors and are included in the traditional machine learning group[8]. These algorithms are known for their good detection ability even with using small image datasets[5-6,12]. In implementing a machine learning algorithm, feature

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extraction, such as the Gray Level Co-occurrence Matrix (GLCM), is needed to weigh the value of the information contained in the MRI image[13-14]. Even though it has been widely used in tumor identification, comparisons between different machine-learning algorithms are still needed to determine the ability of each algorithm to detect tumors, especially brain tumors. Therefore, this study aims to compare the capabilities of three machine learning algorithms, SVM, NB, and ANN, in detecting brain tumors using GLCM feature extraction.

METHODS

This study was conducted retrospectively using MRI images in JPEG from the open-access database https://doi.org/10.34740/kaggle/dsv/2645886 accessed in March 2024. This study used limited brain images which is not adequate for deep learning algorithms but suitable for machine learning. In total, 1000 brain images with meningioma tumors and 1000 normal brain images are used as training data, and 100 brain images with tumors and 100 normal brain images as testing data. The image data is comprehended in three different anatomical planes, i.e. axial, sagittal, and coronal as shown in Figure 1. The image data tabulation in different anatomical planes for normal brain and tumor is displayed in Table 1.

After performing image feature extraction, tumor detection is performed by SVM, NB, and ANN algorithms. The SVM algorithm aims to determine data classification based on two regions indicated by the hyperplane. Hyperplane is created by using feature information from the image as input information. Meanwhile, NB classifies or predicts data more simply by using Bayes' theorem, this algorithm will classify images based on their probabilistic aspects. The last method, the ANN algorithm, works by using a large number of neurons (nodes) that are connected to learn the information provided and make predictions based on this information in a linear and non-linear manner. Generally, ANN consists of three parts, namely, the input layer, the hidden layer, and the output layer. The ANN back propagation (ANN-BP) method is used in this study.

In predicting brain tumors on training and testing data, the confusion matrix is used to show the True Negative (T.N.), True Positive (T.P.), False Negative (F.N.), and False Positive (F.P.) values. T.N. shows the number of normal brain images correctly predicted as normal. The T.P. value indicates the number of tumor brain images correctly predicted as a tumor. F.P. is the number of normal brain images predicted as a tumor, while F.N. indicates the number of tumor brain images predicted as normal. The performance of the three machine learning algorithms is assessed using the parameters accuracy, precision, sensitivity[12], and Matthews Correlation Coefficient (MCC)[20] according to the following equations:

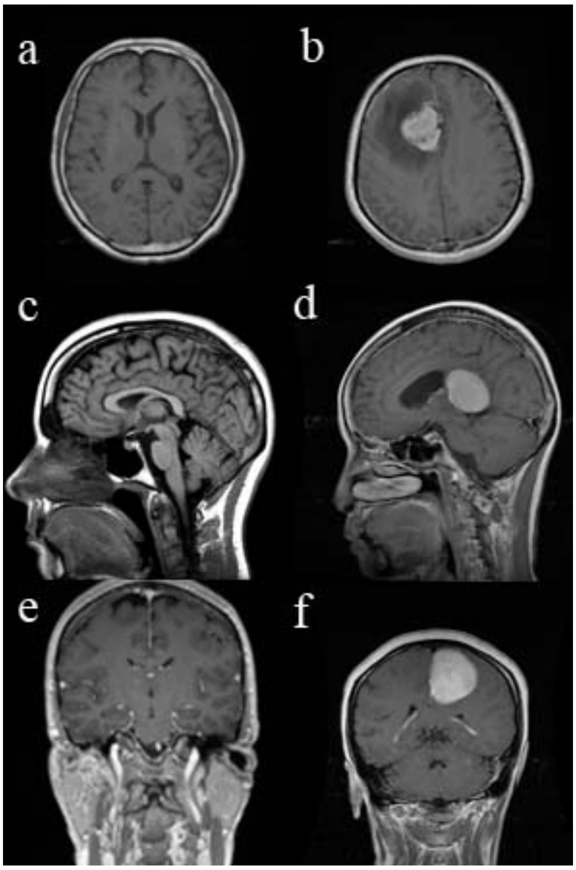

Figure 1. Anatomical planes of MRI image dataset in axial (a,b), sagittal (c,d), and coronal (e,f) planes for the normal brain (a,c,e) and tumor (b,d,f).

Table 1. Image tabulation of normal brain and tumor in different anatomical planes

	Total image	Axial plane	Sagittal plane	Coronal plane
Normal	1100	985	90	25
Tumors	1100	375	278	447

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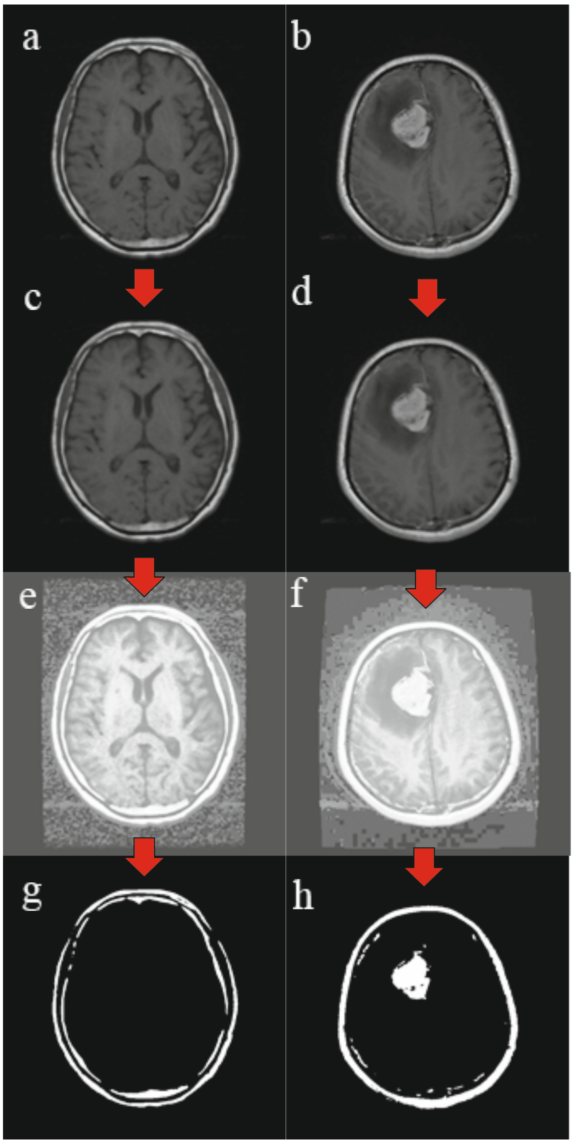

Figure 2. A sample of normal brain (a) and tumor image (b) and its image enhancement process: denoising (c,d), histogram equalization (e,f), and thresholding (g,h).

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

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$MCC = \frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (4)$$

Where T.P., TN, F.P., F.N. is previously defined. In analyzing the parameter value, a score of 100% for Accuracy, Precision, Sensitivity, and a score of 1 for MCC is considered perfect detection.

RESULTS

With performing image enhancement before tumor detection, the SVM algorithm training results from 2000 images show a prediction score of T.P. = 993, TN = 982, F.P. = 18, and F.N. = 7. Meanwhile, in SVM training, the prediction results from 200 images show a prediction score of T.P. = 82, TN = 99, F.P. = 1, and F.N. = 18. In the NB algorithm training, the prediction score of T.P. = 959, TN = 699, F.P. = 301, and F.N. = 41. Meanwhile, in the NB testing, the prediction score of T.P. = 76, TN = 67, F.P. = 33, and F.N. = 24. Furthermore, in training the ANN-BP algorithm, the prediction scores were T.P. = 974, TN = 921, F.P. = 79, and F.N. = 26. Meanwhile, testing ANN-BP gave prediction scores TP = 85, TN = 91, FP = 9, and FN = 15.

The performance of the three algorithms in detecting brain tumors is summarized in Table 2. The SVM algorithm generally has the best parameter values when performing image enhancement, followed by ANN-BP and NB In SVM algorithms, the training data accuracy value of 98.75% was obtained with a precision of 98.22%, sensitivity of 99.30%, and MCC value of 0.9751. Meanwhile, in the testing data, an accuracy value of 90.50% was obtained with a precision value of 98.80%, a sensitivity value of 82.00%, and an MCC value of 0.8220.

Table 2 also shows the performance of the three algorithms when using image enhancement before conducting GLCM. In general, higher accuracy, precision, sensitivity, and MCC scores when using image enhancement compared to none in the SVM and NB algorithm. However, no different results are acquired when using the ANN-BP algorithm even though the outcome is still inferior compared to the performance score of the SVM algorithm.

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Table 2. Three Machine Learning algorithm performances in detecting brain tumor using GLCM feature extraction with and without image enhancement.

Algorithm	Parameter	With image enhancement		Without image enhancement	
		Training	Testing	Training	Testing
SVM	Accuracy	98,75%	90,50%	86,90%	74,50%
	Precision	98,22%	98,80%	81,92%	76,34%
	Sensitivity	99,30%	82,00%	94,70%	71,00%
	MCC	0,9751	0,8220	0,7471	0,4912
NB	Accuracy	82,90%	71,50%	85,05%	75,00%
	Precision	76,11%	69,72%	79,38%	77,17%
	Sensitivity	95,90%	76,00%	94,70%	71,00%
	MCC	0,6814	0,4318	0,7144	0,5016
ANN-BP	Accuracy	94,75%	88,00%	97,00%	89,00%
	Precision	92,50%	90,43%	97,86%	100,00%
	Sensitivity	97,40%	85,00%	96,10%	78,00%
	MCC	0,8963	0,7614	0,9402	0,7996

DISCUSSION

The results in Table 1 show the best performance of SVM in detecting brain tumors. The performance is based on SVM's ability to optimally determine a hyperplane to separate two data groups[21]. Several studies have also reported the ability of SVM to provide high accuracy values in tumor detection [12,22-24]. Furthermore, the NB algorithm shows the weakest performance in detecting brain tumors because this algorithm "naively" assumes no feature dependence on the data class. Besides that, NB uses a Bayesian probabilistic model to classify data whose category is unknown[10-11].

When using feature extraction such as GLCM, image enhancement helps increase the clear contrast boundaries of the detected object. The necessity is based on the possibility of low image quality obtained using standard MRI sequences in tumor detection[15-17]. In the denoising process, noise in the image is reduced through a filtering process using the ADF method to soften the signal intensity of the noise pixels while still maintaining essential details in the object image[15]. Furthermore, the overall image contrast is increased using histogram equalization[16]. In the thresholding step, a clear difference between the object to be identified and the background is defined by determining the appropriate cutoff value[17]. These three image enhancement steps determine the increase in feature extraction used by GLCM. Other studies have shown a significant increase in tumor detection capabilities when images are enhanced before feature extraction processing[25]. Our results also support other study findings where image enhancement before performing image extraction can significantly improve the detection performance of brain tumors.

Even though SVM shows better brain tumor detection performance than ANN-BP and NB, this performance is still aimed at detecting brain tumors without knowing its classification of tumor type and stage due to the limited database information used in this study. Further research is recommended to be carried out to determine the reliability of SVM in detecting tumors in groups of different types and stages.

Moreover, the performance score of different machine learning algorithms in this study is conducted with small image datasets and different anatomical planes. It is still unsure what is the best estimate number dataset required to optimally perform the machine learning method. Therefore, to further elaborate on the influence of these factors in affecting brain tumor detection, further studies are encouraged.

CONCLUSION

In conclusion, the SVM machine-learning algorithm performs better in detecting brain tumor

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than the ANN-BP and the NB algorithms. The best performance in testing data is acquired with an accuracy value of 90.50%, a precision value of 98.80%, a sensitivity value of 82.00%, and an MCC value of 0.8220. This conclusion is acquired using image enhancement steps before performing GLCM feature extraction.

ETHICAL APPROVAL

There is no ethical approval.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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AUTHOR CONTRIBUTIONS

conceptualization, PT; methodology, PT, HZA, IM; software, HZA; validation, PT, HZA, IM; formal analysis, PT; investigation, PT; resources, HZA; data curation, PT HZA,; writing—original draft preparation, PT, HZA, IM; writing—review and editing, PT, HZA, IM; visualization, PT; supervision, PT; project administration, PT.

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