Indonesian Journal of Data and Science

Volume 4 Issue 2
ISSN 2715-9930
https://doi.org/10.56705/ijodas.v4i2.73

Research Article

Comparison Analysis of Random Forest Classifier, Support Vector Machine, and Artificial Neural Network Performance in Multiclass Brain Tumor Classification

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Received 10 June 2023; Accepted 18 June 2023; Published 31 July 2023

Abstract:

This study aims to analyze and compare the performance of three main classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network, in classifying Multiclass brain tumors based on MRI images. The research method includes exploratory data analysis (EDA), dataset preprocessing with image segmentation using the Canny method, and feature extraction using the Humoment method. The performance of the classification models is evaluated based on accuracy, precision, recall, and F1 score. The analysis results show variations in the performance of the three classification models, with Random Forest Classifier having an accuracy of 0.7, weighted precision of 0.55, weighted recall of 0.7, and weighted F1 score of 0.59; Support Vector Machine having an accuracy of 0.71, weighted precision of 0.5, weighted recall of 0.71, and weighted F1 score of 0.59; and Artificial Neural Network having an accuracy of 0.62, weighted precision of 0.6, weighted recall of 0.62, and weighted F1 score of 0.61. Visualization using box plots also reveals outliers in the performance of the three models. These findings indicate variations and outliers in the performance of the classification models for Multiclass brain tumor classification. Further analysis is needed to understand the factors that influence performance differences and identify ways to improve the classification model performance for brain tumor diagnosis based on MRI images.

Keywords: tumor otak, klasifikasi *Multiclass, Random Forest Classifier*, SVM, ANN, Perbandingan Perofrma
Dataset link: brain-tumor-classification-mri

1. Introduction

Brain tumor disease is a serious health problem that affects many people worldwide [1]. The classification of brain tumors is an important task in accurate diagnosis and effective management. In recent years, the use of machine learning techniques has shown great potential in classifying brain tumors based on MRI images [1], [2]. In this study, we aim to analyze and compare the performance of three main classification models: Random Forest Classifier, Support Vector Machine, and Artificial Neural Network in Multiclass brain tumor classification.

The problem addressed in this study is to develop an accurate classification model to classify Multiclass brain tumors based on features extracted from MRI images. With an effective classification model, it is expected to improve accuracy and efficiency in brain tumor diagnosis.

The objectives of this study are to analyze and compare the performance of three main classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network in Multiclass brain tumor classification. Additionally, this study aims to develop an accurate and reliable classification model for brain tumor classification based on MRI images. Furthermore, this study also aims to enhance understanding of the capabilities and advantages of each classification model in the context of brain tumor classification.

The research questions to be answered in this study are whether there are differences in the performance of the three main classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network, in Multiclass brain tumor classification. Additionally, this study aims to identify the classification model that provides the best results in classifying brain tumors based on MRI images. By addressing these questions, this study will provide a better understanding of the strengths and weaknesses of each classification model in the context of Multiclass brain tumor classification [3]–[5].

This study will focus on Multiclass brain tumor classification using the "brain-tumor-classification-mri" dataset. The feature extraction method used is Humoment. However, this study has some limitations, such as not considering other factors besides MRI image features in brain tumor classification.

The main contribution of this study is to provide a better understanding of the performance of three main classification models in Multiclass brain tumor classification. The results of this study are expected to assist medical professionals in selecting the most suitable classification model for brain tumor diagnosis. Additionally, this study contributes to the development of more effective diagnostic methods in the field of medical pattern recognition.

2. Method

Our research design consists of 5 well-structured main stages with the aspects illustrated in **Figure 1**.

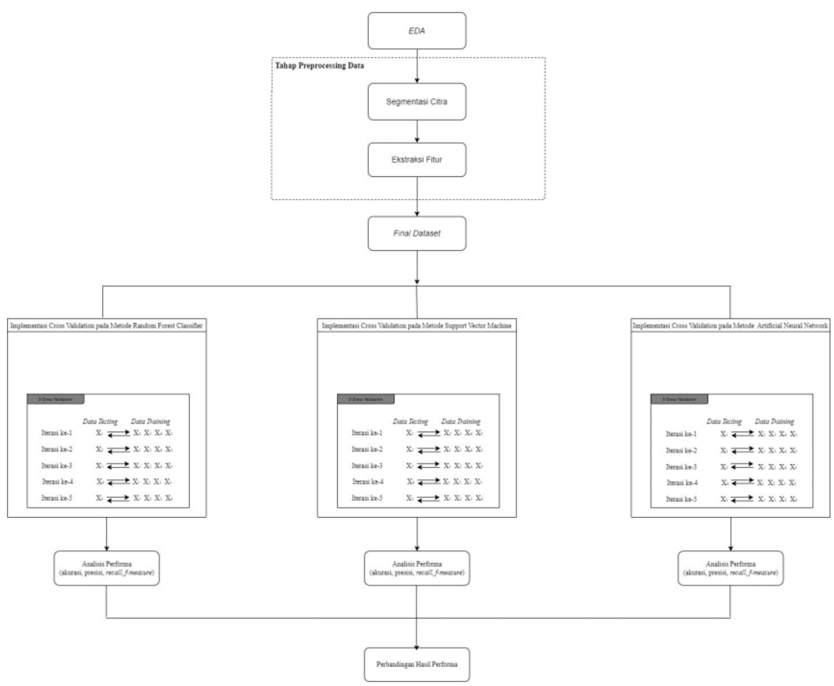

Figure 1. General Research Design Stages

Exploratory Data Analysis

The first step in this study is to perform initial exploratory data analysis (EDA) to understand the characteristics of the Multiclass brain tumor dataset used [6], [7]. EDA involves data visualization, statistical analysis, and understanding the tumor class distribution. **Table 1** shows general information about the dataset used in this study.

Table 1. Dataset Information

Dataset	***Number of cases***	***Number of classes***	***Attribute characteristics***	***Missing values***
brain-tumor-classification-mri	3264	4	*Object*	*No*

Canny Image Segmentation

Next, the brain MRI images will be preprocessed using the Canny image segmentation method. This method helps separate object edges in the images and remove unnecessary noise. **Figure 2** shows the results of Canny image segmentation [8].

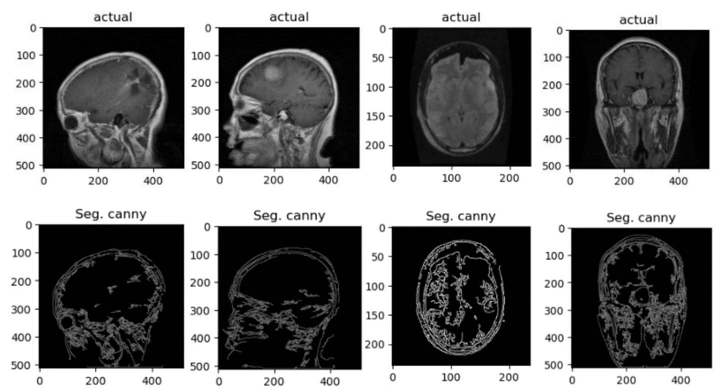

Figure 2. Canny Image Segmentation Results

Hu Moments Feature Extraction

Hu Moments features will be extracted from the segmented brain MRI images. This method captures shape and texture information from the images to be used as features in the classification process. **Figure 3** shows the visualization of the Hu Moments feature extraction using Scatter Plot and Heatmap.

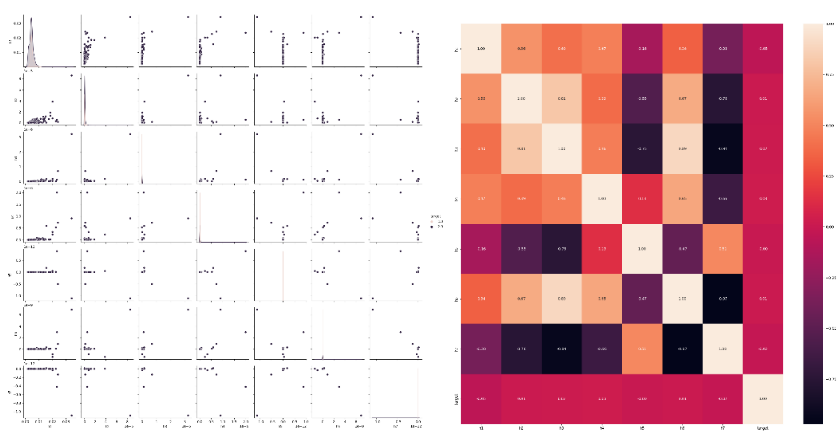

Figure 3. Visualization of Scatter Plot and Heatmap for Feature Extraction: Humoment

Algorithm Implementation

The final dataset will consist of the extracted Hu Moments features and corresponding brain tumor class labels. This dataset will be used to train and test three classification models: Random Forest Classifier, Support Vector Machine, and Artificial Neural Network.

Random Forest Classifier

Random Forest is an ensemble learning method that uses multiple Decision Trees built randomly and independently, and their predictions are combined through majority voting (classification) or averaging (regression) for the final prediction [9]-[11]. The Random Forest Classifier is illustrated in **Figure 4**.

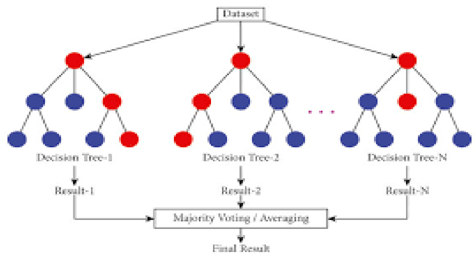

Figure 4. Random Forest Classifier Algorithm

The Random Forest algorithm consists of several steps. First, the algorithm selects random subsets of training data from the available data, as shown in Equation 1 [12], [13]. Next, in the second step, it builds Decision Trees using these subsets of data, as shown in Equation 2 [14]. Decision Trees are tree-like structures that partition data based on relevant features. Steps 1 and 2 are repeated several times to create multiple independent Decision Trees, as shown in Equation 3 [15]. Finally, in the fourth step, the algorithm performs majority voting by taking predictions from each Decision Tree and choosing the class that appears most frequently as the final prediction, as shown in Equation 4 [16]. Thus, the Random Forest algorithm is a powerful and widely used algorithm for classification and regression problems with complex data [17].

$$D = \{(x1, y1), (x2, y2), \ldots., (xn, yn)\} \tag{1}$$

$$T_i = BuildTree(D_i) \tag{2}$$

$$T = \{T_1, T_2, \ldots, T_n\} \tag{3}$$

$$y_pred = MajorityVote(T_1, T_2, \ldots, T_n) \tag{4}$$

Support Vector Machine

Support Vector Machine (SVM) is a machine learning algorithm used for data modeling and classification. SVM can be used for both binary and Multiclass classification problems, as seen in **Figure 5** [18].

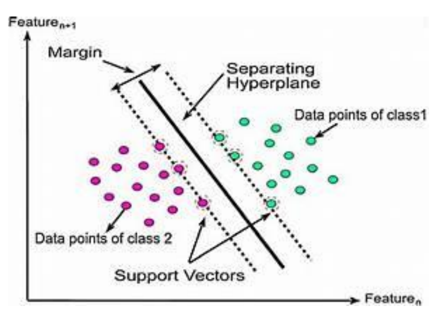

Figure 5. Support Vector Machine (SVM) Algorithm

The SVM algorithm consists of several main steps. First, the training data is preprocessed, such as normalization and noise removal [19]. Next, a kernel is chosen to map the data into a higher feature space, which helps better separate the data. Then, the training data is used to train SVM by finding the optimal hyperplane that maximizes the margin. The margin is the distance between the hyperplane and the nearest support vectors, and the parameter C controls the trade-off between margin and classification errors. After training, SVM can be used to classify new data based on its position relative to the hyperplane determined during training. Data on one side of the hyperplane is considered as a member of that class, while data on the other side is considered as a member of a different class [20].

$$Dataset = (x_I, y_i)$$

$$y_i(w \cdot x_i + b) \geq 1 \quad (5)$$

Artificial Neural Network

Artificial Neural Network (ANN) is a machine learning algorithm inspired by the structure and function of biological neural networks [21]. ANN is used to model the complex relationship between input and output in a given dataset, as seen in **Figure 6**.

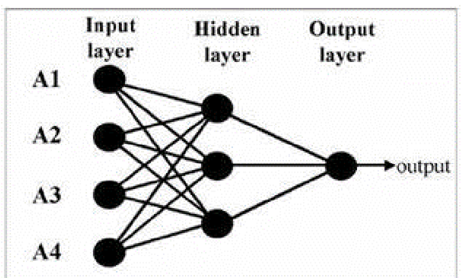

Figure 6. Artificial Neural Network (ANN) Algorithm

The ANN algorithm is a model consisting of interconnected layers of neurons. During the training process, the input flows forward through the network in a forward propagation stage, where each neuron computes its output using weights and activation functions [13], [22]. Then, the backpropagation stage is used to adjust the weights based on the comparison of the predicted output with the expected output. This allows the network to learn and optimize its performance by reducing errors as seen in Equations 6 and 7.

$$\begin{aligned} &Formula\ untuk\ feedforward\ pada\ neuron: \\ &Z = \sum input * bobot) \\ &Output = FungsiAktivasi(Z) \end{aligned} \quad (6)$$

$$\begin{aligned} &Formula\ menghitung\ gradien\ pada\ bobot: \\ &GradienBobot = LearningRate * Delta * Input \end{aligned} \quad (7)$$

Performance Comparison Analysis

The performance of the three classification models will be evaluated using metrics obtained from the Random Forest Classifier, Support Vector Machine, and Artificial Neural Network models, such as accuracy, precision, recall, and f-measure [20]. These metrics will provide information about how well the models can classify brain tumors into the correct classes. The results of the performance analysis will be compared among the three classification models [23]. This comparison will provide an understanding of the strengths and weaknesses of each model in the Multiclass brain tumor classification.

Accuracy measures how well the model classifies data correctly overall, as shown in Equation 9.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{9}$$

Precision measures how well the model correctly identifies positive cases compared to all its positive predictions, as shown in Equation 10.

$$Pericision = \frac{TP}{(TP + FP)} \tag{10}$$

Recall (Sensitivity or True Positive Rate) measures how well the model can correctly classify true positive cases, as shown in Equation 11.

$$Recall = \frac{TP}{(TP + FN)} \tag{11}$$

F-Measure is the harmonic mean of precision and recall. It is used to combine precision and recall into a single comprehensive value, as shown in Equation 12.

$$F - measure \ = \frac{2(presisi \times recall)}{(presisi + recall)} \tag{12}$$

The formulas above explain:
TP (True Positive) is the number of correctly predicted positive cases.
TN (True Negative) is the number of correctly predicted negative cases.
FP (False Positive) is the number of wrongly predicted positive cases.
FN (False Negative) is the number of wrongly predicted negative cases.

Decision Making

Based on the performance analysis and comparison among the three classification models, conclusions will be drawn to determine the most effective model for Multiclass brain tumor classification based on MRI image features.

3. Results and Discussion

This study evaluates the performance of three classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network, using several evaluation metrics, including accuracy, precision weighted, recall weighted, and F1 weighted. **Table 2** shows the comparison of performance results on the used dataset

Table 2. Performance Comparison Results

∑ Rata-rata	***Random Forest Classifier***	***Support Vector Machine***	***Artificial Neural Network***
Accuracy	0.7	0.71	0.62
Precision weighted	0.55	0.5	0.6
Recall weighted	0.7	0.71	0.62
F1 weighted	0.59	0.59	0.61

Based on the performance analysis of the three classification models for Multiclass brain tumor classification, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network, the average accuracy values obtained were 0.7, 0.71, and 0.62, respectively. The Support Vector Machine (SVM) model achieved the highest accuracy with a value of 0.71, followed by Random Forest Classifier with a value of 0.7, and Artificial Neural Network (ANN) with a value of 0.62. This indicates that SVM performs better in classifying Multiclass brain tumors based on MRI image features.

However, when considering precision weighted, recall weighted, and F1 weighted values, variations in the performance of these models were found. The Random Forest Classifier model has a precision weighted value of 0.55, recall weighted value of 0.7, and F1 weighted value of 0.59. The Support Vector Machine model has a precision weighted value of 0.5, recall weighted value of 0.71, and F1 weighted value of 0.59. Meanwhile, the Artificial Neural Network model has a precision weighted value of 0.6, recall weighted value of 0.62, and F1 weighted value of 0.61. This indicates that although SVM has higher accuracy, the ANN model performs better in terms of precision and F1 score.

In the context of Multiclass brain tumor classification, accuracy is an important metric that represents how well the model can classify correctly. However, it is also important to consider precision, recall, and F1 score, especially in cases where there is an imbalance in the number of samples between brain tumor classes. Precision describes how well the model identifies brain tumors from a particular class, while recall describes how well the model finds all brain tumors in a particular class. The F1 score is a metric that combines both precision and recall.

Further discussions are needed to understand the factors that may influence the performance of these classification models. One possible factor that may affect the results is the parameter selection and tuning performed for each model. Additionally, the characteristics of the dataset and the features used in the analysis also play a crucial role in the model's performance. Therefore, further exploration is necessary to identify factors that can improve the performance and accuracy of these models in Multiclass brain tumor classification.

The visualization results using a box plot show the presence of outliers in the performance of the three classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network. Random Forest Classifier has 3 outliers, Support Vector Machine has 4 outliers, and Artificial Neural Network has 7 outliers. The existence of these outliers indicates variations in the performance of these models in classifying Multiclass brain tumors. Outliers can serve as indicators that these models may not be effective in handling some difficult or complex cases. Further analysis is required to identify the factors causing these outliers, such as model suitability with the dataset, optimal parameter settings, or unique characteristics of brain tumors in the dataset. Through a deeper analysis of these outliers, a better understanding of the weaknesses or limitations of each classification model in dealing with complex cases can be obtained. The visualization results can be seen in **Figure 7**.

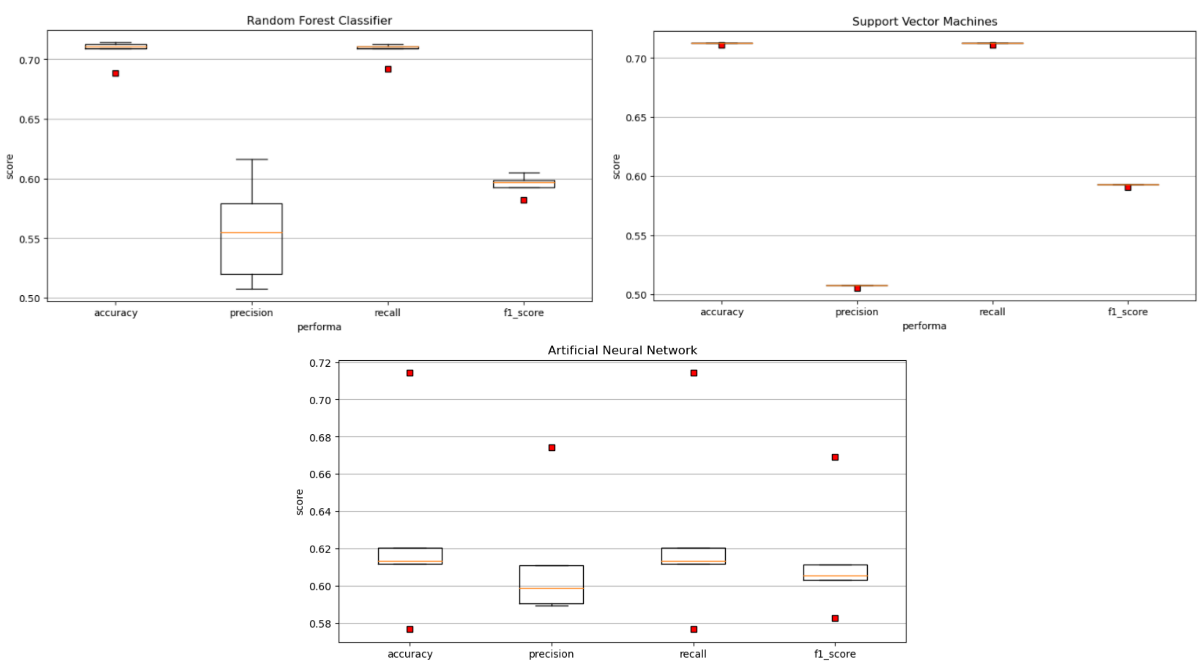

Figure 7. Box Plot Visualization Results

4. Conclusion

Based on the performance analysis of the three classification models, namely Random Forest Classifier, Support Vector Machine, and Artificial Neural Network, in Multiclass brain tumor classification, variations in their performance were found. Although Support Vector Machine (SVM) has the highest accuracy, the Artificial Neural Network (ANN) model shows better performance in terms of precision and F1 score. Visualization using box plots also reveals the presence of outliers in the performance of these three models. These outliers suggest that these models may not be effective in handling some more difficult or complex cases. Further analysis is needed to understand the factors influencing the performance and identify ways to improve the performance in Multiclass brain tumor classification. With this understanding, better and reliable classification methods can be developed for brain tumor diagnosis based on MRI images.

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