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Classification of Glioma and Meningioma Brain Tumour Disease Using MRI Image Based on Texture Feature with Random Forest Method

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ABSTRACT

This research aims to develop an automatic classification system that distinguishes between glioma and meningioma brain tumours using texture-based MRI images and the Random Forest method. Gliomas, which originate from glial cells, and meningiomas, which originate from the meninges, are the two most common types of brain tumours and have different characteristics. The accuracy of diagnosis is crucial for determining suitable treatment options. MRI image analysis has become a significant method in brain tumour diagnosis, although visual interpretation is often subjective and prone to errors. Therefore, the Random Forest algorithm is applied to overcome these limitations by identifying complex patterns from image data. This study used 300 glioma and 306 meningioma images from the Kaggle database, with texture features extracted using histograms, the Gray Level Co-occurrence Matrix (GLCM), and the Gray Level Run Length Matrix (GLRLM). The Random Forest algorithm in this research achieved an accuracy of 78.88%, a precision of 77.39%, and a recall of 81.00%. These findings demonstrate the potential of Random Forest as an effective tool in brain tumour diagnosis.

Keywords:
Brain tumour; Glioma; Meningioma; MRI image; Texture feature; Random Forest.

Introduction

Brain tumours in neurology are one of the most complex diseases. Among the various types of brain tumours, gliomas and meningiomas are the most common. Gliomas grow from glial cells that support neurons in the brain, while meningiomas originate from the meninges, the protective lining of the brain and spinal cord. Both have different characteristics, making accurate diagnosis crucial. Errors in determining the type of tumour can lead to inappropriate treatment options, which can ultimately endanger the patient's life (Louis et al., 2016). Due to their different characteristics, the treatment and clinical approach to these two tumours are also other, so proper classification is crucial in determining the appropriate therapeutic steps.

MRI image analysis has become an integral part of diagnosing and monitoring brain tumour progression. Its ability to visualize brain structures in detail without exposure to ionizing radiation makes MRI the imaging modality of choice. However, visual interpretation of MRI images is often subjective and very easy to get distracted. To alleviate this deficiency, the Random Forest method based on texture features of MRI images is used to automatically classify brain tumours. This algorithm overcomes the limitations of subjective visual interpretation by identifying complex patterns that are invisible to the human eye. Moreover, random forest possesses the capacity to manage high-dimensional data and non-linearity, which are common characteristics of medical image data (Breiman, 2001).

Previous research has discussed brain tumour classification using various machine-learning methods. Research by Febrianti et al. (2020) who applied the Support Vector Machine (SVM) method, discussed the performance of different SVM models, including C-SVM and Nu-SVM, which showed their effectiveness in achieving a high level of accuracy in tumour classification. One of the gap analyses identified in his research was the limited diversity of the dataset used to train the SVM. The dataset consists of images from two sources, with a total of 100 images, which may not adequately represent

the variety of brain tumours encountered in clinical practice. A broader and more diverse dataset may improve the generalisability of the model.

Research by Sofian and Laluma (2019), which uses the k-nearest Neighbor (k-NN) method, uses thresholding techniques to separate tumours from other objects in MRI images. This technique helps improve tumour visibility by creating a binary image that distinguishes between tumour and non-tumour areas. This research highlighted the ongoing challenge of discriminating between tumour and non-tumour tissue, as the visual characteristics of these tissues can be highly similar. This indicates a gap analysis in the methodology of this study, which can be addressed by developing a more robust deep-learning model to achieve higher classification accuracy.

Therefore, Random Forest is a superior choice as it can process large datasets efficiently while maintaining high accuracy (Breiman, 2001). This research uses the Random Forest method based on texture features, where extracting texture features in MRI images is an efficient technique for automatically classifying tumour types. Texture feature is information that represents the pattern of pixel intensity distribution, thus providing in-depth microstructural information of the tumour. Compared to manual visual analysis methods, texture feature-based approaches can detect fine details that may escape the radiologist's visual observation (Haralick et al., 1973). Therefore, this approach of combining texture feature analysis with the Random Forest method for the classification of two types of brain tumours needs to be further developed.

Glioma is a tumour that originates from brain glial cells or spinal cord glial cells. Basically, nerve tissue has neuron cells and their supporting cells; these supporting cells are called glia cells commonly referred to as neuroglia. Neuroglia in the central nervous system is divided into four cell types: oligodendrocytes, astrocytes, ependymal, and microglia. Glioblastoma Multiforme is one of the most common classifications of glioma (about 45% of all glioma cases); based on 2014 data, it is estimated that only about 5% of the Spanish population has less than 5 years left to live (Ostrom et al., 2014). Patients with glioma have a relatively low life expectancy due to high recurrence factors and can be resistant to therapy. It can be concluded that the clinical manifestations of glioma patients depend on the location of the tumour.

A study conducted by IJzerman-Korevaar et al. (2018) which stated that 27% of patients complained of headaches and 27% of patients complained of decreased consciousness. In terms of international data, in the United States, from 1978 to 2014, there was an increase in the incidence of glioma cases (APC 1978-1992 = 2.7%, 1992-2014 = 0.3%) (Li et al., 2018). The average incidence of glioma in the United States from 2010 to 2014 through The Central Brain Tumour Registry of the United States (CBTRUS) Statistical Report was estimated to be approximately 6 per 100,000 people with a percentage of survival (Ostrom et al., 2021). The increase in cases is also found in the Netherlands, where a study said that there was an increase in glioma incidence in adults from 4.9 per 100,000 population in 1989 to 5.9 per 100,000 population in 2010 (Ho et al., 2014).

Gliomas constitute the most frequent type of primary brain tumour in Indonesia. In a study conducted by Parastuta et al. (2020) in 2014-2018 at Sanglah General Hospital Denpasar Bali, the most common cause was Astrocytoma as many as 70 patients (83.4%) and 45 of them were Glioblastoma Multiforme (64%). Then, out of 84 patients, the most tumour location was in the Cerebrum as many as 61 patients (72.6%).

In research conducted by Ardhini and Tugasworo (2019), from the range of 2015-2018 at Dr Kariadi Semarang General Hospital, the most common glioma case was Astrocytoma as many as 47 patients (85.4%) and 18 of them were Glioblastoma Multiforme (38.2%). It was found that 15 patients (53.6%) with Astrocytoma grade I-III complained of headache. When compared with research by Bell et al. (2004) in the UK, it was found that 90% of Low-Grade Astrocytoma patients complained of headache as the main complaint. In the majority of schwannoma patients, as many as four patients (57%) complained of limb weakness. Compared to the study of Harimaya et al. (2022) in Japan, 57.9% of schwannoma patients complained of pain and limb weakness.

Meningioma is the most common tumour of the central nervous system (CNS), originating from meningothelial cells of the arachnoid layer (Kleinschmidt-DeMasters et al., 2016). In America and Korea, the incidence of meningioma is the most frequent brain tumour at around 36% and 37.3%, respectively (Dho et al., 2017). In accordance with data from the Global Cancer Observatory (GLOBOCAN) of the International Agency for Research on Cancer (IARC) in 2012, 34% of meningiomas can occur at any age, more often in adults, with a peak decade of 5 years of life. The ratio

of meningioma incidence between women and men is 2:1 (Janah et al., 2020). The location of meningiomas is most commonly found in the intracranial, intraspinal, and orbital, while intraventricular and epidural are rare. 98% of cases were CNS meningiomas. The most common locations are cerebral convexities (most commonly parasagittal), sphenoid ridges, para-/suprasellar, olfactory groove, optic nerve sheath, petrous ridges, tentorium, and posterior fossa (Alalade & Kitchen, 2018).

According to the WHO (2016) Classification of Tumours of the Central Nervous System by Komori (2017), meningiomas are classified as divided into three grades, namely grades I, II, and III. The most common cytogenetic abnormality of meningioma is a monosomal chromosome 22 change where allelic loss of 22q12 in the neurofibromatosis-2 (NF-2) gene encoding merlin protein, usually found in sporadic meningiomas around 40%-80%. Other cytogenetic changes are deletion of chromosome 1p, 6q, 9, 10q, 14q, and 18q (Bi et al., 2016).

This research aims to develop an automatic classification system that can distinguish glioma and meningioma brain tumours using MRI images based on texture characteristics with the Random Forest method. Hopefully, this method can provide accurate results with more efficient computation time than other methods. In addition, this research is expected to contribute to the development of medical image- based diagnostic technology, which in turn can improve the quality of care for patients with brain tumours.

Methods

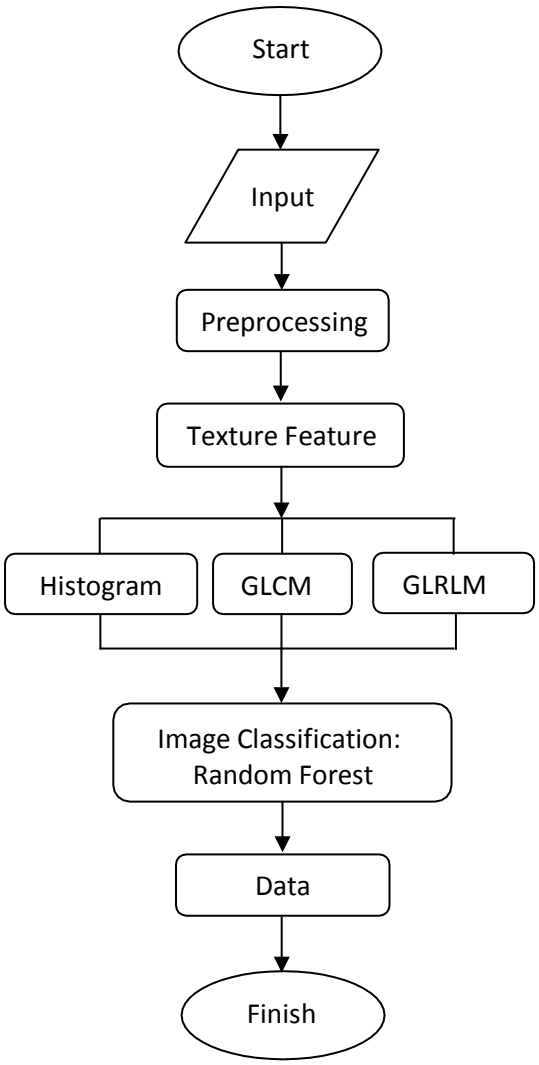


Figure 1. Research Flowchart

Dataset

This research focuses on the comparative analysis of glioma and meningioma through MRI image processing obtained from the Kaggle.com public dataset. This dataset consists of 300 images with glioma characteristics and 306 images with meningioma characteristics. The entire data processing process, from feature extraction using the OpenCV library in the Google Colab computing environment to classification using the Random Forest algorithm on the Weka platform, was integrated. The research stages include image pre- processing to improve data quality and consistency, extraction of texture features that are sensitive to differences in tumour morphology, binary classification using the Random Forest method to distinguish glioma and meningioma, and evaluation of model performance using accuracy, precision, and recall metrics (Figure 1). The main objective of this research is to develop a reliable and efficient classification model to support early diagnosis of brain tumours.

There are several processes, namely taking pictures on kaggle.com software, then collecting images, and converting images that were originally rgb into grayscale. The result of this extraction process produces data that can be used to obtain important information. Three important concepts in texture feature extraction are the histogram, the Gray Level Co-occurrence Matrix (GLCM), and the Gray Level Run Length Matrix (GLRLM).

Texture Feature Extraction

Texture is a spatial arrangement of intensity variations in an image. Texture features are commonly used in image classification, including in the diagnosis of brain tumours through MRI images. Statistical features can be extracted from an image using a variety of methods. This study used histogram, Gray Level Co-occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRLM) to identify texture features on MRI images. GLCM is a method of extracting second-order statistical features that analyse the spatial frequency of different pairs of intensities (Maula, 2021). GLRLM is a run-length matrix that measures the number of homogeneous areas (runs) of a certain length that occur along a certain direction at a particular intensity (Aohana et al., 2024).

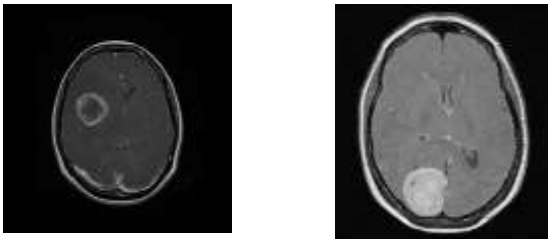
Random Forest

Random Forest is a classification technique that combines several decision trees to improve the accuracy of overall predictions. This algorithm works by constructing a set of decision trees from different samples taken from the training data using bootstrap sampling techniques. Each decision tree is trained on different data subsets, and the classification results are determined based on the majority vote of all trees generated. This method is highly effective in addressing overfitting and can efficiently process high-dimensional data without requiring significant feature reduction (Hafizd et al., 2020). Random Forest's strength lies in its ability to identify complex patterns and produce stable results even on datasets with variation and outliers (Dash et al., 2021).

The classification was performed using the application software Weka 3.8.6. The training and test data were combined with an 80:20 split, which means 80% for training data (485 images) and 20% for test data (121 images). In the training process, ten folded cross-validations are used to get a more general model (Liaw & Wiener, 2002). This method divides the training data into ten groups, where each group is used as a validation once, and the other nine groups are used for training. This process is repeated ten times so that each group will be used for validation once. Cross-validation is crucial because it provides a more reliable estimate of model performance and reduces the risk of overfitting (Romadloni et al., 2022).

Results and Discussion

This study successfully classified glioma and meningioma brain tumours using texture features from MRI images with the Random Forest method. The Random Forest model was applied to a dataset of 606 MRI images, consisting of 300 glioma and 306 meningioma images (Figure 2), which were split into 80% training data and 20% test data.



(a) (b)

Figure 2. MRI of brain tumour patient (a) Glioma (b) Meningioma

Based on Table 1, the confusion matrix shows that out of 100 glioma cases, 81 were correctly classified as glioma (true positive), while 19 were misclassified as meningioma (false negative). For meningioma, out of 21 cases, 13 were correctly classified as meningioma (true negative), and 8 were misclassified as glioma (false positive).

Table 1. Confusion Matrix of Classification

Classified as	Glioma	Meningioma
Glioma	81	19
Meningioma	8	13

From Table 2, the Random Forest algorithm achieved an accuracy of 78.88%, indicating that the model correctly classified approximately 79 out of 100 images. Precision of 77.39% shows that when the model predicts an image as glioma, it is correct about 77% of the time. The recall value of 81.00% indicates that the model can identify 81% of actual glioma cases. The F1-score of 79.15% represents a balanced measure between precision and recall, demonstrating the model's overall effectiveness.

Table 2. Performance Metrics of Random Forest Classification

Metric	Value (%)
Accuracy	78.88
Precision	77.39
Recall	81.00
F1-Score	79.15

The results of this study are comparable to previous research in brain tumour classification. Andre et al. (2022) used Convolutional Neural Network (CNN) with EfficientNet-B3 architecture and achieved an accuracy of 98%, which is higher than this study. However, CNN requires more complex computational resources and longer training time compared to Random Forest. Baranwal et al. (2020) compared CNN and SVM methods, obtaining accuracies of 90.67% and 85.33% respectively. Prasetyo and Nabiilah (2023) compared several machine learning models including Random Forest, achieving accuracy values ranging from 75% to 95% depending on the features used.

The Random Forest method offers several advantages in this context. First, it is relatively fast in training and prediction compared to deep learning methods. Second, it can handle high-dimensional data without requiring extensive preprocessing. Third, it provides feature importance rankings, which can help identify which texture features are most discriminative for distinguishing between glioma and meningioma (Mehrotra et al., 2020).

However, this study also has limitations. The dataset size of 606 images may not fully represent the variability of brain tumours in clinical practice. Additionally, the model's performance might be affected by image quality variations and differences in MRI acquisition protocols. The misclassification of 27 images (19 false negatives and 8 false positives) indicates that some texture features may overlap between glioma and meningioma, making differentiation challenging (Winnarto et al., 2022).

The texture features extracted using histogram, GLCM, and GLRLM proved effective in capturing the structural differences between glioma and meningioma. GLCM features such as contrast, correlation, energy, and homogeneity provide information about the spatial relationship between pixels,

while GLRLM features describe the run-length patterns that are characteristic of different tumour types. The combination of these features with Random Forest's ensemble learning approach creates a robust classification system.

Conclusion

This study successfully demonstrated the effectiveness of the Random Forest method in classifying glioma and meningioma brain tumours using texture features from MRI images. The model achieved an accuracy of 78.88%, precision of 77.39%, and recall of 81.00%, indicating its potential as a diagnostic support tool in clinical settings. The research highlights the importance of texture feature extraction using histogram, GLCM, and GLRLM methods in capturing the distinctive characteristics of different brain tumour types. While the results are promising, future research should focus on expanding the dataset, incorporating additional feature extraction techniques, and validating the model across different imaging protocols and patient populations to improve generalizability and clinical applicability.

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