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RESEARCH PAPER

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Classification of brain tumor based on shape and texture features and machine learning

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ABSTRACT

Information from brain tumour visualisation using MRI can be used for brain tumour classification. The information can be extracted using different feature extraction techniques. This study compares shape-based feature extraction such as Zernike Moment (ZM), and Pyramid Histogram of Oriented Gradients (PHOG) with texture-based feature extraction such as Local Binary Patterns (LBP), Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG) in brain tumour classification. This research aims to find out which feature extraction is better for handling brain tumour images through the accuracy and f1-score produced. This research proposes to combine each feature based on its approach, i.e. ZM+PHOG for shape-based feature extraction and LBP+GLCM+HOG for texture-based feature extraction with default parameters from the library and modified parameters configured based on previous research. The dataset used comes from Kaggle and has three classes: meningioma, glioma, and pituitary. The machine learning classification models used are Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB) and K-Nearest Neighbours (KNN) with default parameters from the library. The models were evaluated using 10-fold stratified cross-validation. This research resulted in an accuracy and f1-score of 84% for texture-based feature extraction with modified parameters in RF classification. In comparison, shape-based feature extraction resulted in accuracy and f1-score of 70% and 68% with modified parameters in RF classification. From the results, it can be concluded that texture-based feature extraction is better in handling brain tumour images compared to shape-based feature extraction. This study suggests that focusing on texture details in feature extraction can significantly improve classification performance in medical imaging such as brain tumours.

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1. INTRODUCTION

Brain tumours are cells that grow abnormally in the brain tissue, and there are two main types: malignant and benign. Malignant brain tumours are cancerous and can spread to other organs, such as gliomas. Benign brain tumours are benign ones that do not spread to other organs, such as pituitary and meningiomas. One way to diagnose brain tumours is usingagnetic resonance imaging (MRI) [1].

Magnetic resonance imaging (MRI) is one of the technologies used to image the inside of the human body. Compared to other imaging techniques such as computed tomography (CT), ultrasound (US) and X-rays, MRI is more commonly used because it provides clearer and more detailed images, making it easier to detect disease. MRI is often used to classify brain tumours because it can see through the thin tissue of organs and soft tissues such as muscles, which are difficult to see on X-rays [2].

Prior to the classification process, the MRI image must undergo processing to extract pertinent information, including its appearance, texture, and shape. This data is then transformed into statistical features that encapsulate the image's intrinsic characteristics. The shape and texture of the image, in particular, offer insights that can be leveraged to differentiate between various brain tumour types [3].

This concept has been used in the classification of brain tumours in several previous studies, such as the previous research by [4] studied brain tumour classification using three different brain tumour MRI datasets named BT-small-2c, BT-large-2c and BT-large-4c. The feature extraction algorithms used are CNNs such as ResNet, DenseNet, VGG, AleNet, InceptionV3, ResNeXt, ShuffleNetV2, MobileNetV2 and MnasNest. with machine learning classification methods. KNN with InceptionV3 feature extraction produced an accuracy of 82.35% on the BT-small-2c dataset. However, this

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research does not include validation models such as cross-validation, so this research is prone to bias or high variance, and the results may not reflect the model's performance on different data. In [5], brain tumour classification using shape-based feature extraction on brain tumour MRI image dataset from TCIA (The Cancer Imaging Archive). Using the KNN classification method with the number of neighbours of 5 and the validation of the Stratified Random Sampling model resulted in an accuracy of 73.8%. However, in this research, shape-based feature extraction still uses simple methods such as filled area and centroid, where features are extracted from objects that have been separated from the background. While these methods offer simplicity and computational efficiency, the resulting features are highly dependent on the quality of the segmentation stages that potentially provide informative features. In contrast, more general shape-based feature extraction methods such as Zernike Moments (ZM) and Pyramid Histogram of Oriented Gradients (PHOG) do not require a segmentation stage. These methods can work directly on the image, with the ability to adjust parameters according to image characteristics, thus capturing more complex details and producing more informative features. In research [6], brain tumour classification was performed using combined feature extraction from Discrete Wavelet Transformation (DWT), PHOG and Tamura's. Using the SVM classification method and the leave-one-out cross-validation model, this research achieved an accuracy of 91.11%. Due to the combination of shape-based feature extraction, such as PHOG, with texture-based feature extraction, such as DWT and Tamura, it is not possible to provide an evaluation between shape-based feature extraction and texture-based feature extraction individually.

Although many feature extraction methods have been used in brain tumour classification, there is no clear evidence as to which methods are most effective individually or in combination based on the approach used. By comparing different shape-based and texture-based feature extraction methods separately, this study aims to fill this gap and provide information on the effectiveness of each method in handling brain tumour classification.

Based on the previous description, this research aims to determine the effectiveness of different feature extraction techniques in brain tumour classification, specifically comparing shape-based methods such as shape-based feature extraction, i.e. Pyramid Histogram of Oriented Gradient (PHOG) and Zernike Moments (ZM) and texture-based feature extraction, i.e. Local Binary Pattern (LBP), Gray Level Co-Occurrence Matrix (GLCM) and Histogram of Oriented Gradient (HOG) to compare which type of feature extraction is more effective in handling the classification of brain tumours. This research will use a dataset from Kaggle containing three brain tumour classes. As the dataset used is unbalanced, stratified cross-validation is used to determine the performance of the classification model. Classification is performed using machine learning methods such as Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB) and K-Nearest Neighbour (KNN). The contributions of this study are 1) This research provides a comparative analysis of texture-based and shape-based feature extraction methods in the context of brain tumour classification, 2) the research highlights the importance of parameter optimisation in improving classification accuracy, 3) this research provides insight into the performance of different machine learning algorithms when combined with specific feature extraction techniques, contributing to the development of more effective brain tumour diagnostic tools.

This study is structured as follows: section II discusses the dataset used, proposed methods and proposed training and testing schemes. Section III displays the results. Section IV discusses the interpretation and comparison of results with other studies and limitations. Section V contains conclusions that rewrite the objectives, primary findings, and future works.

2. MATERIALS AND METHOD

A. Dataset

The dataset used in this study is an image dataset from Kaggle, i.e. the Brain Tumour Dataset, which contains three classes of brain tumours: meningioma, glioma and pituitary [7]. Table 1 shows the dataset used in this research.

Table 1. Dataset used in this research

Class	Number of Samples	Percentage
Meningioma	708	23%
Glioma	1426	47%
Pituitary	930	30
Total	3064	100%

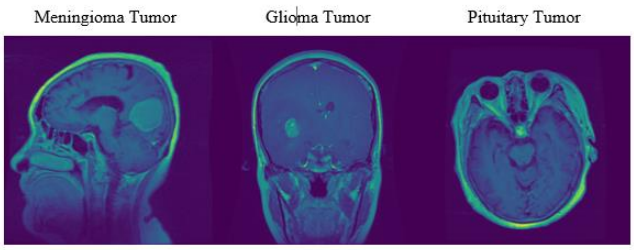

Fig. 1. Image of each class in the dataset

The dataset is available for download at the following link: https://www.kaggle.com/datasets/denizkavi1/brain-tumor. The research from [8] also used the same dataset, which used deep learning models to classify brain tumours. Fig. 1 displays the image of each class in the dataset.

B. Preprocessing

The images in the dataset have inconsistent sizes, with the majority at 512x512 and some images at 256x256. Therefore, all images will be resized to a consistent size

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of 256x256 at this stage. This dimensional change will affect the number of features formed and the processing time in classification mode. The image in the dataset is in RGB format, so it needs to be converted to greyscale, as the feature extraction used generally processes images in greyscale format.

C. Feature Extraction

In the context of image processing, whether dealing with binary images, grayscale images, or colour images, the feature extraction process is essential for deriving pertinent information from the image for subsequent analysis. The insights acquired through feature extraction can be effectively utilized in various processes, including classification, detection, and diagnostic procedures. The range of features that may be extracted from an image is extensive, encompassing various types, including but not limited to texture features and shape features present within the image [9].

The information extracted from texture-based feature extraction lies in the homogeneity of the set of pixels in the image. Examples of texture-based feature extraction algorithms are LBP, HOG and GLCM. Information obtained from shape-based feature extraction is taken from the entire image object or just the object's outline. Examples of shape-based feature extraction algorithms are Zernike Moments and Pyramid Histogram of Oriented Gradient (PHOG) [10]. All feature extraction algorithms used in this study were selected for their performance in brain tumour classification [11] [12].

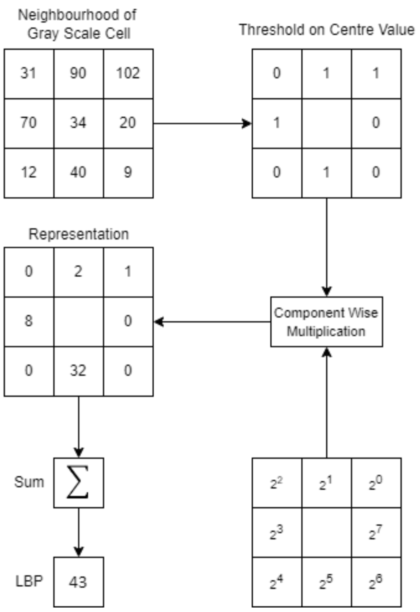

Fig. 2. Visualisation of the LBP operation with parameters P = 8 and R = 1 [14]

1. Local Binary Pattern (LBP)

One of the simple texture-based feature extraction algorithms. The resulting feature is each pixel processed with its neighbouring pixels, resulting in a feature vector matching the dimensions of the processed greyscale image [13]. Parameters such as P determine the number of neighbouring pixels processed, and R determines the distance between the neighbouring pixels and the centre pixel. These two parameters affect the features produced by LBP. Fig. 2 shows a visualisation of the LBP operation with parameters P = 8 and R = 1.

2. Histogram Of Oriented Gradient (HOG)

This feature extraction generates features using orientations derived from the size and angle of a pixel. The image is then divided into cells, each consisting of a number of pixels, and each cell is combined into blocks. The number of features generated in an image depends on the orientation value, the number of pixels in a cell, the number of cells in a block, and the image dimension [13]. Fig. 3 shows a visualisation of the HOG operation with parameters pixels_per_cell = 8x8 and orientations = 8.

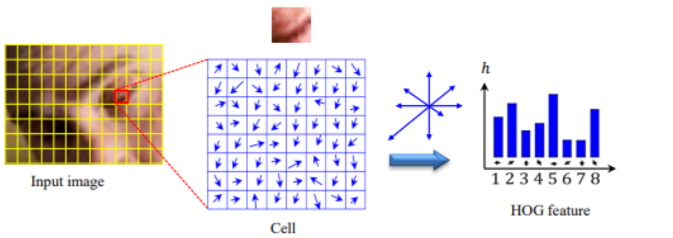

Fig. 3. Visualisation of the HOG operation with parameters pixels_per_cell = 8x8 and orientations = 8 [15]

3. Gray Level Co-Occurrence Matrix (GLCM)

The features generated by GLCM do not come from neighbouring pixels but from the similarity of a pixel's greyscale intensity value based on the angle used, which is then stored in the co-occurrence matrix. The resulting features are contrast, correlation, energy and homogeneity of an image [10]. Equations (1) to (5) show some of the features that GLCM can produce [13] [16].

$$Contrast = \sum_{i,j=0}^{n-1} P(i-j)^2 \tag{1}$$

$$Correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{2}$$

$$Entropy = \sum_{i,j=0}^{n-1} -\ln(P_{ij})P_{ij} \tag{3}$$

$$Energy = \sum_{i,j=0}^{n-1} (P_{ij})^2 \tag{4}$$

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$$Homogeneity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \quad (5)$$

where P_{ij} is (i,j)th elements of normalized GLCM matrix,

μ is mean of GLCM matrix calculted using the Eq. (6), and

$$\mu = \sum_{i,j=0}^{n-1} i\, P_{i,j} \quad (6)$$

$$\sigma^2 = \sum_{i,j=0}^{n-1} P_{i,j}\,(i-\mu)^2 \quad (7)$$

where σ = the variance of intensities of all pixels calculated using Eq. (7) and N is number of gray levels in the image.

4. Zernike Moments (ZM)

The features generated by ZM are derived from moments, which are the number of pixels contained within the radius of the object. Each moment generates 1 feature, and each order has a different number of moments. ZM generates features depending on how many orders are applied to an image [15]. Table 2 shows the number of moments generated at each order in ZM.

Table 2. The number of moments generated at each order in ZM [16]

Order	Moments	No. of Moments
0	A_{00}	1
1	A_{11}	1
2	A_{20}; A_{22}	2
3	A_{31}; A_{33}	2
4	A_{40}; A_{42}; A_{44}	3
5	A_{51}; A_{53}; A_{55}	3
6	A_{60}; A_{62}; A_{64}; A_{66}	4
7	A_{71}; A_{73}; A_{75}; A_{77}	4
8	A_{80}; A_{82}; A_{84}; A_{86}; A_{88}	5

5. Pyramid Histogram Of Oriented Gradient (PHOG)

This feature extraction is an extension of HOG. In this feature extraction, the image is divided into several levels, each containing HOG with different parameter values, such as cell, block, or orientation, to create a stack like a pyramid. The number of features generated from PHOG is the sum of the number of features of each HOG [10]. Fig. 4 shows the cell differences of each level in PHOG.

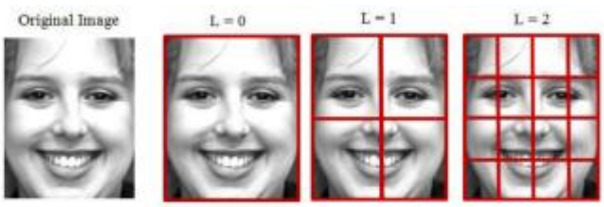

Fig. 4. The cell differences of each level in PHOG [17]

In this study, the parameters of each feature extraction used are divided into parameters derived from the Scikit-Image library for each feature extraction (default) and new parameters adapted from previous research (modified). Table 3 shows the parameters of each feature extraction.

Table 3. The parameters of each feature extraction

Feature Extraction	Parameter Default	Parameter Modified
LBP	*R* = 3 *P* = 8*radius method = default	*R* = 1 *P* = 8*radius method = default
HOG	orientations = 8 pixels_per_cell = (16, 16) cells_per_block = (1, 1)	orientations = 9 pixels_per_cell = (8, 8) cells_per_block = (2, 2)
GLCM	distances = 5 angles = 0 levels = 256 symmetric = True normed = True props = dissimilarity, correlation	distances = 5 angles = 0 levels = 256 symmetric = True normed = True props = contrast, energy, honogeneity, correlation
ZM	degree = 8 radius = 10	degree = 8 radius = 128
PHOG	Lvl 1: orientations = 8 pixels_per_cell = (256, 256) cells_per_block = (1, 1) Lvl 2: orientations = 8 pixels_per_cell = (128, 128) cells_per_block = (1, 1) Lvl 3: orientations = 8 pixels_per_cell = (64, 64) cells_per_block = (1, 1)	Lvl 1: orientations = 9 pixels_per_cell = (256, 256) cells_per_block = (1, 1) Lvl 2: orientations = 9 pixels_per_cell = (128, 128) cells_per_block = (1, 1) Lvl 3: orientations = 9 pixels_per_cell = (64, 64) cells_per_block = (1, 1)

D. Stratified Cross Validation

The 10-fold stratified cross-validation is used in this research because of the imbalance of each class in the dataset. In Stratified Cross Validation, the dataset is divided into several folds, with each fold having a number of classes similar to the number of classes in the original dataset. In this study, the dataset used is 3064 images, with each class having a class proportion of approximately 23% for the meningioma class, 47% for the glioma class and 30% for the pituitary tumour class. Therefore, each

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fold will have approximately 23% meningioma class, 47% glioma class, and 30% pituitary tumour class. This ensures that each fold has a balanced number of classes [18]. By maintaining class balance across all folds, stratified cross-validation mitigates the risk of bias that could arise from uneven class representation, thereby reducing the likelihood of overfitting and ensuring that model performance is evaluated in a fair and consistent manner. This approach improves the validity of the results by providing a more accurate measure of the model's generalisation ability [19].

E. Classification

Classification is one of the key concepts in machine learning approaches used to categorise unlabelled data into separate classes [20]. Machine learning aims to enable computers to perform actions based on experience without being specifically programmed, for example in the case of classification [21]. The machine learning classification models used in this research are Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB) and K-Nearest Neighbour (KNN). All classification methods used in this study were selected for their performance in brain tumour classification [11].

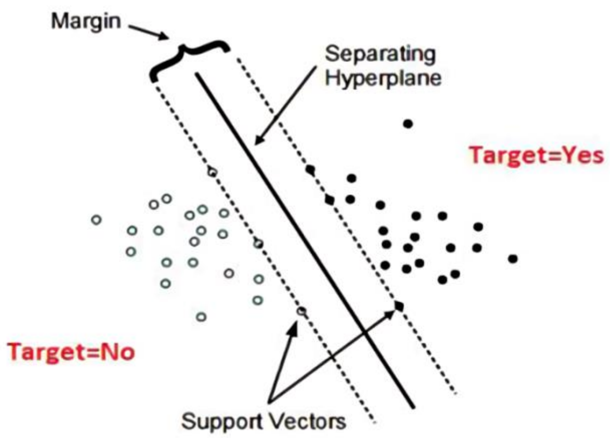

Fig. 5. An overview of the hyperplane in SVM [23]

1. Support Vector Machine (SVM)
The SVM performs classification by dividing each feature into its class. These divisions are called hyperplanes. SVM can fit the hyperplanes to the data set using a kernel function. The disadvantage of SVM is that it cannot process large datasets and datasets with a lot of noise [22]. SVM classification is divided into linear and non-linear classification, which the kernel controls. If a straight line or hyperplane can separate the features of the dataset, then a linear kernel is appropriate. If a straight line cannot clearly separate the features, non-linear kernels such as Radial Basis Function (RBF) and Quadratic Kernel are more appropriate. Fig. 5 shows an overview of the hyperplane in SVM [23].

2. Random Forest (RF)
Random Forest (RF) classification consists of a series of independent Decision Tree (DT) classifiers. The features are processed by each DT and produce different class votes. The class of the feature will be selected based on the most votes from each DT. In order to have different votes, each DT model trained with different parts of the dataset [24]. Because of the way RF makes decisions based on the majority of predictions, RF classification models have a low possibility of model variance. The prediction accuracy obtained is also better than using only one decision tree or DT [25].

3. Naive Bayes (NB)
Naïve Bayes classification works on the rule that each feature is categorised as an individual. This means that each feature is processed individually and classified with the most likely class. Due to the computations that occur on each feature, the classification process with NB takes quite a long time, depending on the feature vector being processed [22]. The Bayes theorem is the basis of this classification model. This theorem is used to calculate the probability of class y in a set of x features. Bayes' theorem can be seen in equation (8) [26].

$$P(y|x_i, \ldots, x_n) = \frac{P(y)P(x_i, \ldots, x_n|y)}{P(x_i, \ldots, x_n)} \quad (8)$$

4. K-Nearest Neighbour (KNN)
KNN performs classification by finding information from the nearest features of the processed data. By calculating the distance and taking the 'K' closest features and then selecting the class with the highest frequency of the closest features. KNN also has difficulties in processing large datasets and datasets with a lot of noise [22]. The main advantage of KNN classification is its ability to classify data without making assumptions about the data distribution because it does not require parameters that define how the data is distributed, so it does not go through a complicated training phase. Therefore, KNN classification is referred to as a non-parametric classification model and a lazy algorithm [27].

The classification models used in this study, such as SVM, RF, NB, and KNN, are called from the scikit-learn library without changing the parameters provided in each model. Table 4 shows the parameters of each classification model.

F. Evaluation

Confusion Matrix is a method that presents the results of mode evaluation in a matrix table. In the Confusion Matrix, there are values that can be used to calculate model

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scores, such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

Table 4. Parameters of each classification model

Classification Model	Parameter
Support Vector Machine	C=1.0, kernel='rbf', degree=3, gamma='scale', coef0=0.0, shrinking=True, probability=False, tol=0.001, cache_size=200, class_weight=None, verbose=False, max_iter=-1, decision_function_shape='ovr', break_ties=False, random_state=None
Random Forest	n_estimators=100, *, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='sqrt', max_leaf_nodes=None, min_impurity_decrease=0.0, bootstrap=True, oob_score=False, n_jobs=None, random_state=None, verbose=0, warm_start=False, class_weight=None, ccp_alpha=0.0, max_samples=None, monotonic_cst=None
Naïve Bayes	priors=None, var_smoothing=1e-09
K- Nearest Neighbors	n_neighbors=5, *, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None

TP occurs when the model successfully predicts positive value data, TN occurs when the model successfully predicts negative value data, while FP occurs when the model predicts negative value data as positive value data and FN occurs when the model predicts positive value data as negative value data [24]. The results of this study were evaluated using the precision and f1 score of the confusion matrix. Precision is the proportion of correctly predicted positive cases (TP) out of all cases predicted as positive by the model (TP + FP). It represents the ability of the model to avoid false positives. Recall (also known as sensitivity) is the proportion of correctly predicted positive cases (TP) out of all actual positive cases in the dataset (TP + FN). It indicates the ability of the model to detect actual positives. The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the accuracy of the model, especially in cases where the class distribution is unbalanced. Accuracy is the total proportion of correct predictions (both TP and TN) out of all predictions made by the model [25]. Accuracy, precision, recall and f1-score can be seen in equations (9) to (12) [14].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100 \tag{9}$$

$$Precision = \frac{TP}{TP+FP} * 100 \tag{10}$$

$$Recall = \frac{TP}{TP+FN} * 100 \tag{11}$$

$$f1 - Score = \frac{Recall * Precision}{Recal + Precision} * 100 \tag{12}$$

where TP (True Positive) is the number of correctly predicted positive cases, TN (True Negative) is the number of correctly predicted negative cases, FP (False Negative) is the number of wrongly predicted positive cases, and FN (False Negative) is the number of wrongly predicted negative cases [32].

3. RESULT

From the results of the confusion matrix evaluation, it is clear that texture-based feature extraction outperforms shape-based feature extraction. The highest accuracy and F1 scores, both at 95%, were achieved by the standard and modified HOG using the KNN classification models. In contrast, the best performance among the shape-based feature extractions was an accuracy of 78% using the RF classification model and an F1 score of 84% using the modified ZM using the KNN classification model. Table 5 shows the performance metrics for each feature extraction method across different classification models.

Table 5. Results of each feature extraction on each model

Feature Extraction	Number of Features	Classification Model	Accuracy	Precision	Recall	F1-score
Default LBP	65536	SVM	88	87	88	87
		RF	87	88	87	87
		NB	58	62	58	52
		KNN	92	92	92	92

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Default HOG	2048	SVM	92	92	92	92
		RF	89	89	89	89
		NB	71	72	71	71
		KNN	95	95	95	95
Default GLCM	2	SVM	66	51	66	57
		RF	61	59	61	60
		NB	61	47	61	53
		KNN	62	59	62	60
Default ZM	25	SVM	51	38	51	42
		RF	52	48	52	47
		NB	49	45	49	45
		KNN	47	43	47	43
Default PHOG	HOG LVL 1 = 8, HOG LVL 2 = 32, HOG LVL 3 = 128. PHOG = 8+32+128 = 168	SVM	61	68	61	56
		RF	66	69	66	63
		NB	50	48	50	45
		KNN	62	69	62	64
Default *Texture*	65536 + 2048 + 2 = 67586	SVM	60	71	60	55
		RF	79	79	79	79
		NB	36	34	36	31
		KNN	83	83	83	83
Default *Shape*	25+ 168 = 193	SVM	58	66	58	51
		RF	62	64	62	59
		NB	48	45	48	40
		KNN	58	62	58	59
Modified LBP	65536	SVM	86	86	86	86
		RF	86	87	86	86
		NB	58	60	58	52
		KNN	86	87	86	86
Modified HOG	34596	SVM	92	92	92	92
		RF	89	89	89	89
		NB	70	71	70	70
		KNN	95	95	95	95
Modified GLCM	4	SVM	58	44	58	50
		RF	78	78	78	78
		NB	64	63	64	62
		KNN	52	50	52	50
Modified ZM	25	SVM	71	71	71	64
		RF	82	81	82	80
		NB	64	64	64	63
		KNN	84	84	84	84
Modified PHOG	HOG LVL 1 = 9, HOG LVL 2 = 36, HOG LVL 3 = 144. PHOG = 9 + 36 + 144 = 189	SVM	62	67	62	57
		RF	67	71	67	64
		NB	48	46	48	45
		KNN	61	70	61	63

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Modified Texture	65536 + 34596 + 4 + 100136	SVM	60	70	60	54
		RF	84	84	84	84
		NB	36	35	36	31
		KNN	78	78	78	78
Modified Shape	25 + 189 + 214	SVM	63	68	63	58
		RF	70	73	70	68
		NB	46	44	46	41
		KNN	67	73	67	69

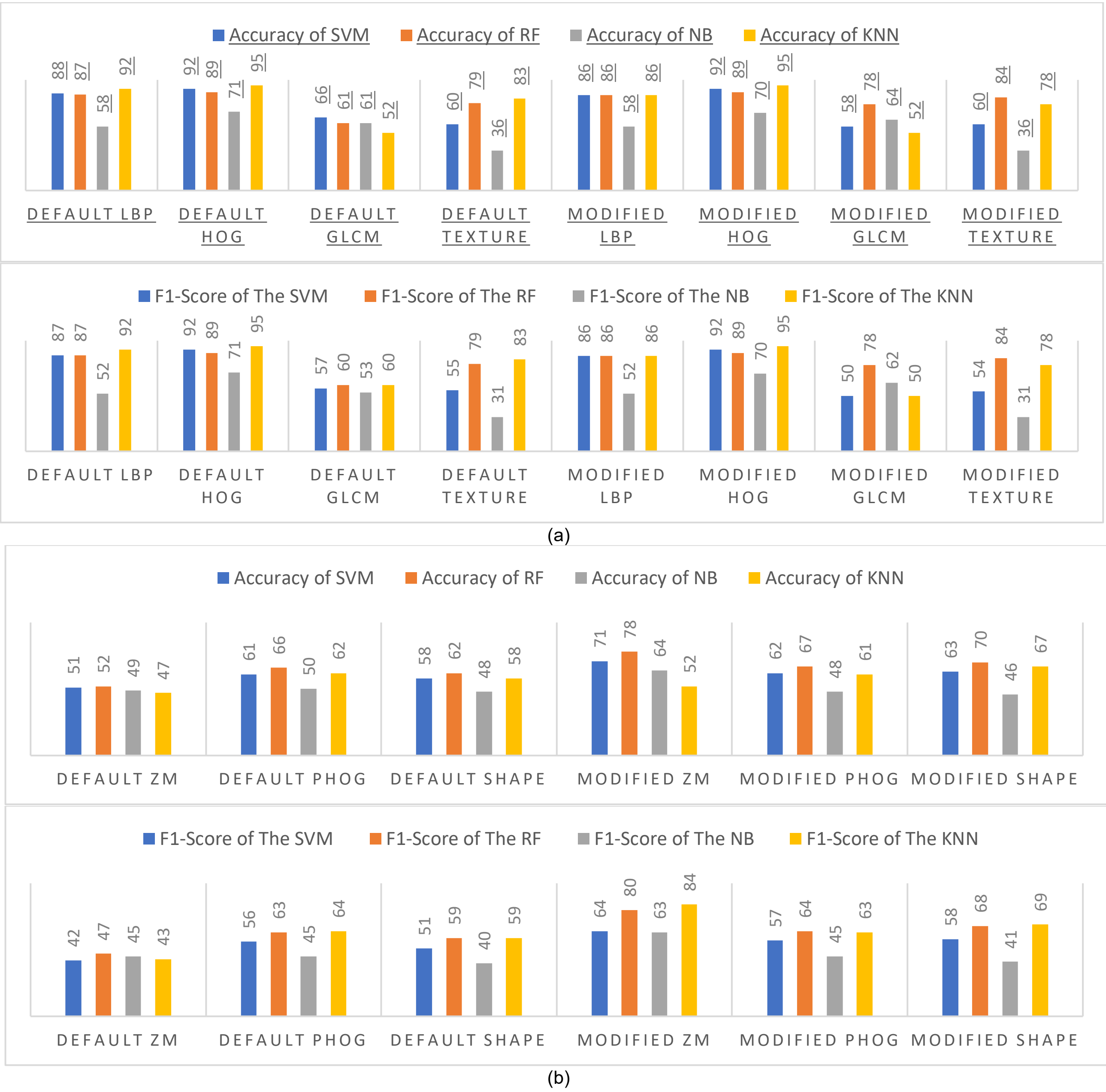

Fig. 6. The comparison of accuracy and f1-score of texture-based feature extraction (a) and shape-based feature extraction (b)

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The comparison of accuracy and f1-score of texture-based feature extraction and shape-based feature extraction is shown in Fig. 6. Fig. 6 shows that the combination of texture feature extraction, i.e. LBP, GLCM and HOG, produces superior accuracy and f1-score, reaching 84% with the modified parameters in RF classification. Compared to the combined shape feature extraction, i.e. ZM and PHOG, which produced an accuracy of 70% and f1 score of 68% with the modified parameters in RF classification. Although the results of the combined texture-based feature extraction show better performance compared to the combined shape-based feature extraction, the individual performance of some texture feature extraction methods is higher. For example, HOG individually achieves 95% accuracy and f1-score with default and modified parameters in KNN classification, while LBP achieves 92% accuracy and f1-score with default parameters and 95% with modified parameters in KNN classification. However, combined texture feature extraction remains superior to individual feature extraction such as GLCM, which achieves the highest accuracy and f1-score of 78% with modified parameters in RF classification. This shows that texture-based feature extraction is superior to shape-based feature extraction in brain tumour image classification. By combining an appropriate texture feature extraction method and optimally tuning the parameters, as well as selecting an appropriate classification method, the results obtained show a significant increase in accuracy. This confirms that texture-based approaches, when applied with the right strategy, have greater potential to improve the accuracy and reliability of brain tumour classification.

The results of this study show that the combination of texture feature extraction with the highest accuracy and f1-score reaching 84% using modified parameters on KNN classification is superior to the research [4] using InceptionV3 and KNN which only achieved an accuracy of 82.35%. In addition, individual shape-based feature extraction such as Zernike Moments (ZM) with modified parameters resulted in an accuracy of 78%, which is higher than that of [5] which used simple shape feature extraction methods such as filled area and centroid with an accuracy of 73.8%. Although [6] showed a high accuracy of 91.1% using a combination of shape and texture features in SVM classification, individual texture-based features such as Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) performed better. The HOG achieved an accuracy of 92% with the modified parameters in the SVM classification, while the LBP achieved an accuracy of 88% with the default parameters in the SVM classification.

Although the results of this study show that texture-based feature extraction methods tend to be superior in brain tumour image classification, some results were not significant. For example, certain combinations of feature extraction and parameters resulted in lower accuracy than expected. These results show that while texture-based approaches are generally effective, there are conditions where certain features do not contribute significantly to improving model performance.

4. DISCUSSION

This study aims to determine which feature extraction is better in handling brain tumor images between texture-based feature extraction such as LBP, HOG and GLCM with shape-based feature extraction such as ZM and PHOG based on the Confusion Matrix results from classifications such as accuracy and f1-score. Table 6 shows the best results for each feature extraction. The best results are obtained by texture-based feature extraction i.e. HOG and LBP with accuracy and f1-score of 95% and 92% respectively using default parameters for LBP and default & modified for HOG in the KNN classification model. While the combination of texture-based feature extraction has a superior accuracy and f1-score of 84% from the combined shape-based feature extraction of 70% and 68% using modified parameters for both combined features in the RF classification model.

Table 6. The best results for each feature extraction

Feature Extraction	Number of Features	Parameter	Classification Model	Accuracy	F1-Score
LBP	65536	Default	KNN	92	92
HOG	2048 & 34596	Default & Modified	KNN	95	95
GLCM	16	Modified	RF	78	78
ZM	25	Modified	KNN	84	84
PHOG	189	Modified	RF	67	64
Texture	100148	Modified	RF	84	84
Shape	214	Modified	RF	70	68

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Table 7. Comparison of the research conducted with previous studies

Researcher	Feature Extraction	Dataset	Classification Model	Model Validation	Result
[4]	ResNet, DenseNet, VGG, AleNet, InceptionV3, ResNeXt, ShuffleNetV2, MobileNetV2, and MnasNest	BT-small-2c, BT-large-2c, and BT-large-4c	Fully Connected Layer, NB, AdaBoost, KNN, RF, SVM, and Extreme Learning Machine.	-	KNN with InceptionV3 feature extraction produces an accuracy of 82.35% on the BT-small-2c dataset. .
[5]	Shape's features	TCIA (The Cancer Imaging Archive)	KNN	Stratified Random Sampling	73,8%
[6]	DWT+ PHOG+ Tamura's features	Data from Shenjing Hospital of China Medical University	SVM	Leave One Out Cross Validation	91,1%
This Research	LBP+ HOG+ GLCM	*Kaggle*-Brain Tumor Dataset	SVM, RF, NB, KNN	10-fold Stratified Cross Validation	84% with RF
	ZM+ PHOG				70% with RF

This shows that texture-based feature extraction is superior to shape-based feature extraction in handling brain tumour classification, and can speed up the diagnosis process and improve detection accuracy. This may have implications for the development of image-based decision support systems for brain tumour diagnosis.

Although the results show that texture-based features excel in brain tumour classification, some limitations should be noted. One of them is the use of parameters for each feature extraction that had not been maximised, it can be seen that some feature extractions with default parameters produce better results than feature extractions with modified parameters. The combination of feature extraction methods also needs to be considered, since the research results show that the accuracy and f1 score produced by individual feature extraction is better when compared to combined feature extraction for each approach. This shows that combining feature extraction requires appropriate parameters and mutually compatible combinations to achieve significant results.

Researchers in previous studies used various methods to achieve optimal results, such as parameter configuration, model merging, and model combination are used to achieve the best results. Table 7 shows a comparison of the research conducted with previous studies.

Table 7 shows a comparison of the methods used. Compared to previous research, this study did not produce significant results. This may be due to the lack of parameter configuration in the classification model, which makes the results not optimal compared to previous studies that used parameter configuration in the classification model. This shows that it is important to pay attention to more precise parameter settings and methods used in the classification process to achieve more optimal results. Further research using more detailed parameter configurations and configuration methods is expected to provide better insights and more significant results.

5. CONCLUSION

From the research results, it can be concluded that texture-based feature extraction is superior in handling brain tumor image datasets. This can be seen from the

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accuracy and f1-score results of texture-based feature extraction, such as LBP and HOG, which are 92% and 95%, respectively. The accuracy and f1-score of texture-based feature extraction, such as ZM, is 84%, using the KNN classification model. The accuracy and f1-score results of combined texture features are also superior to 84% of combined shape features, which are 70% and 68% using the RF classification model. This study did not produce significant results compared to previous studies. This is due to the lack of parameter configuration in the classification model used in previous studies. The parameters used are the default parameters of the Scikit-Learn library, so it allows the mismatch of the classification model with the features of the dataset. Future research can combine shape- and texture-based features with parameter configuration to achieve optimal results for feature extraction and classification models.

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