JMSCR Vol||11||Issue||12||Page 118-128||December 2023

http://jmscr.igmpublication.org/home/
ISSN (e)-2347-176x ISSN (p) 2455-0450
crossref DOI: https://dx.doi.org/10.18535/jmscr/v11i12.21

Journal Of Medical Science And Clinical Research
IGM Publication
An Official Publication Of IGM Publication

Feature extraction of brain tumor MR Image by Local gradient pattern- and Local Binary pattern

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Abstract
Automatic classification of brain tumor types is very important for accelerating the treatment process, planning and increasing the patient's survival rate. MR images are used to determine the type of brain tumor. Manual diagnosis of brain tumor type depends on the experience and sensitivity of radiologists. Therefore, researchers have developed many brain tumor classification models to minimize the human factor. In this study, two different feature extraction LGP and LBP approaches were used to classify the most common brain tumor types; Glioma and meningioma, Detection of a brain tumor is an essential process because of the difficulty in distinguishing between abnormal and normal tissues. With the right diagnosis, the patient can get excellent treatment, extending their lifespan. Despite all the research, there are still significant limitations in detecting tumor areas because of abnormal lesion distribution. It may be challenging to locate an area with very few tumor cells because areas with such small areas frequently appear healthy. Studies are becoming more common in which automated classification of early-stage brain tumors is performed using deep learning or machine learning approaches. This study proposes a hybrid deep learning model for the detection and early diagnosis of brain tumors via magnetic resonance imaging. The dataset images were subjected to a Local Binary Pattern (LBP).
Keywords: *LBP, Brain tumor, Local feature Descriptor, Recognition of pixel, Feature extraction.*

1. Introduction

Evaluating brain tumor images is generally a time-consuming task for radiologists. Therefore, it prolongs the treatment planning process and endangers patient health. Nowadays, computer-aided automatic diagnostic methods have become very popular. It is important to identify this lethal cancer type and its classification according to its specific grades for the effective treatment of brain tumors. The image densities of brain tumors detected in studies performed with imaging processes are different. Magnetic resonance imaging (MRI) is one of the most accurate methods for classifying and identifying brain tumors. MRI contributes to obtaining very high-quality images of human body organs in 3D and 2D formats. The MRI imaging system is a non-invasive, painless medical imaging procedure [1]. The feature extraction of the image is to first segment the image, and then extract the texture features in the image after segmentation. There are a lot of textures on trees, The associate editor coordinating the review of this manuscript and approving it for publication was Victor Hugo Albuquerque. cloths, and clothes. These things that can be seen visually are taken from their textures. Of course, medically, for tumors, it is not as intuitive as trees or clothes. It can only be sliced into tumors, relying on imaging equipment to make its texture features into medical images such as MRI.

In the concept of typing, the texture in the image has rotation, translation, and scale invariance, which means that regardless of the state of the image, the position, orientation and size of the texture are constant. For texture feature extraction, the commonly used methods are statistical analysis, model analysis, structural analysis and spectrum analysis. As with the classification of images, the correct selection of features and classifiers is vital to achieve the highest performance in brain tumor classification[2].

LBP-local binary pattern[10], which is adopted by many researchers also has disadvantages, for example: (a) it produces long histograms, which slows down the recognition speed, and (b) Under some certain circumstances, it misses the local feature, as it does not consider the effect of the center pixel. To overcome all the above problems, this paper proposed a novel appearance-based local feature descriptor LGP - Local Gradient Pattern, which has a tiny feature vector length of 8. Appearance based methods are less dependent on initialization and can encode patterns from either local or full facial area. However, appearance features do not generalize across individuals, as they encode specific appearance information.

2. Literature Survey

The first successful application of image feature extraction texture features was in 1972, when Sutton and Hall identified normal and abnormal lungs[3]. Taleb Ahmed uses the theory of typing to extract the CT image of the bone, and obtains the image difference between the osteoporosis patient and the normal human bone. Further, the osteoporosis patient can be discriminated according to the image[4]. Ganeshan et al. analyzed the MRI image of the liver and achieved the detection of patients with cirrhosis[3]. In 2014, Sun et al.[4] developed a face recognition system through the feature extraction of the figure, with an error rate of only 3.55%, reaching the world's top effect. Similarly, Chen et al.[5] also studied face recognition. For the local binary mode and the convolutional neural network to solve the problem of image feature extraction, Liu et al. established a three-level scale space pyramid, and used the canny detector to detect the edge and tested on 326 images, achieving an accuracy of 0.93. Good results[6]. Sidibé et al.[7] solved the image problem based on the semisupervised learning Gaussian mixture model, reaching 93% and 80% of SE and SP. Lee et al.[8] first trained the CNN model and then performed image segmentation, but because of the small amount of data samples, the final segmentation accuracy and generalization ability of the model were limited. Kermany et al.[9] used the CNN model to classify and identify bacterial pneumonia and viral pneumonia with a final resolution of 96.6%. However, there are still some shortcomings in the process of processing images: the source of the training image samples is different, which may cause the image scale to change too much. The mark made during the image cutting process will affect the image feature extraction, and then the data sample size is thin. Not enough to train the CNN model.

3. Feature extraction Methods.

This paper proposes to use the local binary mode on MR image translation rotation invariance to cut and classify the image, and then extract the feature to achieve the purpose of brain tumor classification. In this study, a large number of labeled tumor MR images are used to train the Fractional Prey Optimization (FHPO) model, and then the trained model is used to extract the features of brain tumor medical images, and the features are identified and classified according to these texture features. The lesion image was prescreened and later assisted. Feature extraction is a critical phase in image processing applications, and efficient techniques can significantly enhance the performance of a model. In this context, segmented outputs serve as input for the feature extraction process. The features considered in this phase include Local Gradient Patterns (LGP), Line Operator of Orientation Pattern (LOOP), Local Binary Patterns (LBP), and various statistical features.

3.1 Local Binary Pattern Feature

Local binary pattern is the most commonly used method for image recognition. Obtaining LBP values of the image is as shown in figure(1). Rotation invariance is an improved local binary model which can accurately describe the shallow texture features of medical images. The local binary pattern feature extraction is to compare the gradation difference values of the pixel points in the center portion, the quarter portion and the edge portion of the image to represent the local texture feature information of each portion. If the image features of the central part of the study are studied, then the quarter and the edge are the neighborhoods of the central part. The local gray matter of the central pixel and the neighborhood can be used to obtain the local texture features of the central pixel, which is:

$$\mathrm{LBP}(i,j) = \sum_{p=1}^{P} 2^{p-1} * f(g_c - g_p) \qquad (1)$$

$$f(x) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases}$$

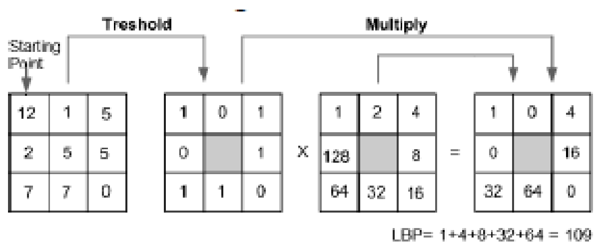


Figure 1. Example of obtaining LBP value.

3.2 Complete Local Binary Pattern Feature:

When applying Local Binary Pattern (LBP) features to the analysis of brain tumor images, the process follows the general LBP principles but is tailored to the characteristics of medical imaging data. Here's an adaptation of the Local Binary Pattern feature for brain tumor analysis:

$$CLBP\_S_{N,R} = \sum_{i=0}^{N-1} 2^i s(g_i - g_c);\ s(x) = \begin{cases} 1 & |x| \geq T_{LBP} \\ 0 & |x| < T_{LBP} \end{cases} \tag{2.2}$$

$$CLBP\_M_{N,R} = \sum_{i=0}^{N-1} 2^i t(m_N - c);\ t(m_N - c) = \begin{cases} 1 & m_N \geq c \\ 0 & m_N < c \end{cases} \tag{2.3}$$

$$CLBP\_C_{N,R} = t(g_c, c_I);\ t(x, c) = \begin{cases} 1 & x \geq c \\ 0 & x < c \end{cases} \tag{2.4}$$

1. **Image Preprocessing:**
   - Medical images, such as MRI scans, are typically used for brain tumor analysis.
   - Preprocess the images to enhance contrast, remove noise, and normalize intensity levels.
2. **Region of Interest (ROI) Extraction:**
   - Identify and extract the region of interest containing the brain tumor from the preprocessed image.
3. **LBP Computation:**
   - For each pixel in the tumor region, compute the LBP code based on the intensity values of its neighboring pixels.
   - Choose an appropriate neighborhood size and radius, considering the scale of structures in medical images.
   - Use a suitable LBP variant, such as uniform LBP, depending on the specific requirements of the analysis.
4. **Feature Vector Extraction:**
   - Generate an LBP histogram by counting the occurrences of different LBP codes within the tumor region.
   - This histogram serves as the LBP feature vector for the brain tumor image.
5. **Texture Analysis:**
   - Analyze the texture patterns encoded in the LBP feature vector.
   - Different textures may correspond to various tumor characteristics, such as necrotic regions, edema, or solid tumor areas.
6. **Feature Normalization:**
   - Normalize the LBP feature vector to account for variations in image acquisition parameters and ensure that the features are comparable across different images.
7. **Classification or Segmentation:**
   - Utilize machine learning algorithms for tasks such as tumor classification or segmentation based on the LBP features.
   - Train a classifier using labeled data to differentiate between different tumor types or to identify tumor regions within an image.
8. **Incorporate Additional Features:**
   - Combine LBP features with other relevant features, such as shape descriptors or intensity-based features, to improve the overall analysis performance.
9. **Validation and Evaluation:**
   - Validate the performance of the LBP-based analysis using independent datasets.
   - Evaluate the accuracy, sensitivity, specificity, and other relevant metrics to assess the model's effectiveness in brain tumor characterization.
10. **Consideration of 3D Data:**
   - For volumetric medical imaging data (e.g., 3D MRI), extend the LBP analysis to three dimensions, considering spatial relationships across slices.

The Local Binary Pattern feature extraction for brain tumor analysis involves adapting the general LBP principles to the specifics of medical imaging, incorporating preprocessing steps, and considering the unique characteristics of brain tumor images. This approach provides a texture-based representation that can contribute to the understanding and diagnosis of brain tumors.

3.3 Local Binary Pattern Feature Extraction Based On Image Rotation Invariance:

Local Binary Pattern (LBP) is a texture descriptor used in computer vision for various applications, such as image classification, face recognition, and texture analysis. LBP is known for its simplicity, efficiency, and robustness to monotonic gray-scale changes. However, it lacks rotation invariance, meaning the same texture pattern may be represented differently if the image is rotated.

To address this limitation, researchers have proposed methods to make LBP more robust to rotation. One common approach is to extend the LBP operator to incorporate rotation invariance. Here's a general outline of how you might perform Local Binary Pattern feature extraction with rotation invariance:

1. **Original LBP Operator:** The traditional LBP operator works by thresholding the pixel values in a local neighborhood around each pixel in an image. It then encodes the binary pattern of the threshold values into a decimal value. This process is repeated for each pixel, resulting in an LBP map.
2. **Rotation-Invariant LBP:** To make LBP rotation invariant, you can modify the operator to consider the patterns that are invariant to rotation. One way to achieve this is to compare the pixel intensity values in a circular neighborhood around a central pixel with the central pixel's intensity. Instead of considering the binary pattern directly, you compare the intensity values in a circular manner.
3. **Rotation of the Circular Neighborhood:** To handle rotation invariance, you can rotate the circular neighborhood for each pixel and consider the minimum binary pattern among all rotations. This ensures that the LBP representation is invariant to rotation.
4. **Histogram Calculation:** Once you have the rotation-invariant LBP values for each pixel, you can calculate a histogram of these values for the entire image. This histogram can then be used as a feature vector for further analysis, such as in machine learning algorithms for classification.
5. **Parameter Tuning:** Depending on your application, you may need to experiment with the radius of the circular neighborhood, the number of points in the neighborhood, and other parameters to optimize the performance of the rotation-invariant LBP.

Implementing rotation-invariant LBP involves additional computational steps, but it enhances the robustness of the descriptor, especially in scenarios where rotation variations are present. Figure(2) shows Flow chart of LBP algorithm based on image rotation invariance and figure(3) shows LBP algorithm analysis and block diagram generic-process-flow-of-brain-tumor-detection-system shown in figure(4)

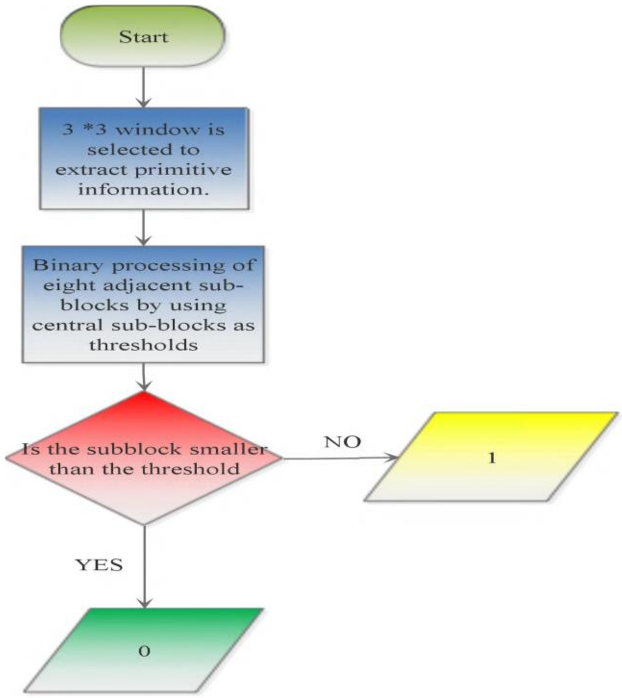


Figure 2. Flow chart of LBP algorithm based on image rotation invariance

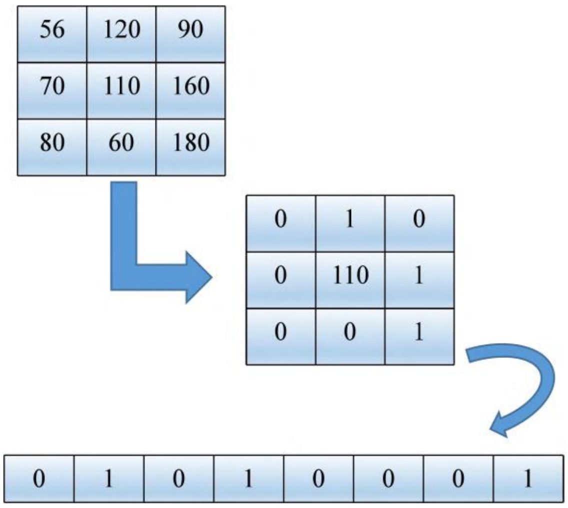
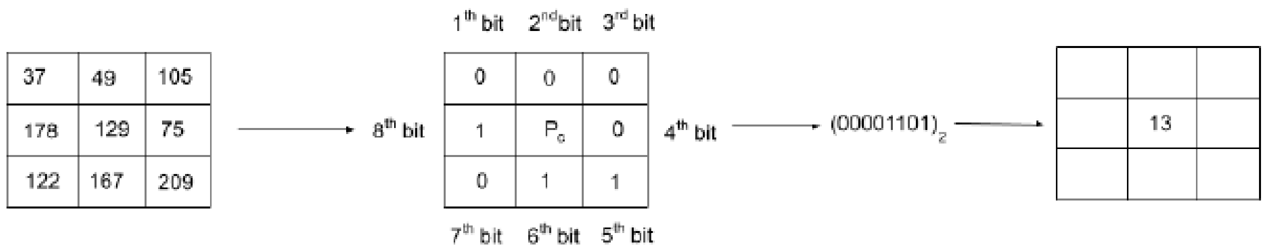


Figure 3. LBP algorithm analysis



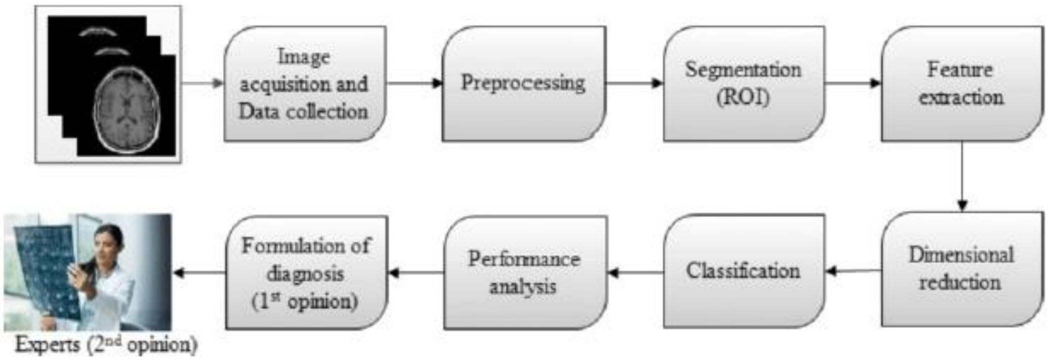


Figure (4) Generic-process-flow-of-brain-tumor-detection-system

4. Results and Discussion

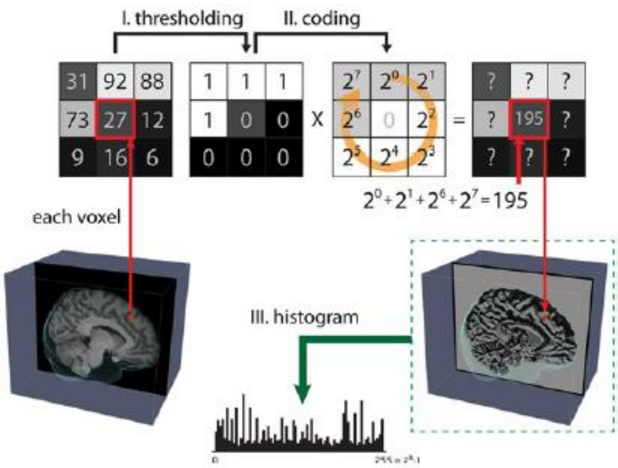


Figure (5) Steps-for-computing-the-local-binary-pattern-LBP-operator-The-LBP-of-2D-images

The main objective of this study is to propose a medical diagnostic support system for brain tumour classification as shown in figure(5), i.e. to set up an automated system that can accurately classify the types of brain tumour from MRI using machine learning, and to show that with feature engineering, we can find comparable accuracy to deep learning. The primary benefit of utilizing machine learning models is that they allow for a better interpretability of the classification model because they are based on feature engineering. Feature extraction is a particular kind of dimensionality modification. The chief purpose of this technique is to capture the important characteristics of the raw data and interpret this character in a less dimensionality space[11]. In this work, we used 3 methods for feature extraction, which involved local binary pattern, the histogram of oriented gradient, and grey level co-occurrence matrix. Local binary patterns (LBP) are an effective descriptor in tasks of recognition and computer vision[12]. The local binary patterns coding the grey levels of an image by comparing the central pixel with its neighbours and the result counted as a binary number converted to decimal number substitutes the central pixel value. A histogram of oriented gradients (HOG) is an introduced object descriptor, focalizing on the structure or appearance of an object in an image. The histogram of oriented gradients provides distinguishing features when lighting variation and background noise, so of specific grey levels about other grey levels. The grey level co-occurrence matrix measures the frequency of various sequences of grey level values that appear in a region of interest[12]. This technique examines the association among adjacent pixels; the original pixel is identified as a reference, and the other is a neighbor pixel. Furthermore, we have taken the most prominent discriminatory features of each extraction technique. Deep learning models, on the other hand, are black box networks whose workings are extremely difficult to understand due to the complex design of the network. As a matter of fact, feature engineering is an essential part of the medical and diagnostic field for doctors because it gives them the ability to know the importance and impact of each feature on the classification and identification of cancer types, in contrast to deep learning models, which are black box networks. The main aim of this research was to find the optimal performance in brain tumour classification using multiclass data with numerous training models by means of machine learning with its paradigms. Again, comparative analysis can be done within the machine learning models with their paradigms for brain tumour classification.

The major contributions of this work are as follows:

- For the first time, the concept of feature engineering is applied to the 4-class brain tumour classification problem;
- Three set of features such as GLCM, LBP, and HOG are extracted from brain MRIs, and then these features are used in various classifiers, namely support vector machine, K-nearest neighbor (KNN), naive Bayes, tree, and ensemble classifier;
- All the classification methods are evaluated in single set feature and combined set of features;
- The combined set of features, i.e. GLCM + LBP + HOG, contributed 91.1% accuracy and 0.95 area under the curve (AUC) in fine KNN;
- The proposed method gives very good performance even with a small dataset, and it is comparable to the deep learning approach.

4.1 About the dataset

The brain dataset investigated in this study is collected from the Figshare repository[3]. The dataset comprises TI-weighted MRI of no tumour and 3 different types of tumours: meningioma, glioma, and pituitary. Image resolution of 512 × 512 with different views such as axial (transverse plane), coronal (frontal plane), or sagittal (lateral plane) planes was used in this dataset. The sample distribution based on the number of classes consisted of 826, 822, 827, and 395 sample instances of glioma, meningioma, pituitary, and no tumours, respectively. The sample of 3 types of brain tumour is shown in Figure (6).

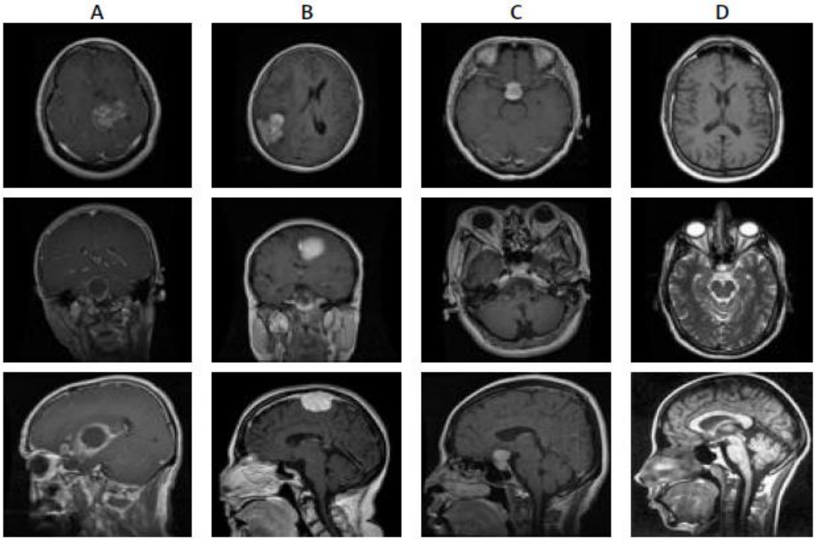


Figure (6) Samples of brain magnetic resonance imaging. 1st line: axial, 2nd line: coronal, 3rd line: ssagittal, glioma (A), meningioma (B), pituitary (C), no tumour (D).

4.2 Methodology

Figure (7) provides an overview of the methodology used to classify brain tumours. A total of 2870 T1-weighted MRIs were utilised throughout all phases of this study. The features of the images were extracted before the machine learning system classified the images according to their class. 20% of the dataset was utilised as test data, and 80% was used for training data (randomly chosen). The machine learning algorithm was trained using the training set's visual features. Finally, image attributes of the testing set were utilised to evaluate the model's performance. For a predictive analysis for classification. The features contained in MRI are vital for disease diagnosis, and efficient feature extraction is crucial for improving diagnostic accuracy and cancer classification.

The extracted image characteristics were fed into machine learning algorithms. Support vector machine, KNN, tree, naive Bayes, and ensemble classifier were the machine learning techniques employed. These machine learning algorithms were trained with the training set's visual characteristics. In this paper we extracted 13 GLCM, 36 HOG, and 59 LBP features. Here, to enhance the performance of classification models, the feature fusion technique was introduced. The combination of GLCM + LBP, GLCM + HOG, HOG + LBP and GLCM + HOG + LBP were fed into the classifiers and the performance was shown in Table 1.

The features extracted from MRI are combined, such as GLCM + HOG + LBP. The performance of different combinations of feature sets are recorded in Table 1. It was observed from Table 1 that the fine KNN performed well for the classification of 4 types of brain MRI. In fine KNN the accuracy achieved was 88.7%, 80.3%, 88.9%, and 91.1% by the combination of feature sets like GLCM + HOG, GLCM + LBP, HOG + LBP, and GLCM + HOG + LBP, respectively. Furthermore, the AUC achieved by fine KNN using GLCM + HOG, GLCM + LBP, HOG + LBP, and GLCM + HOG + LBP is 0.94, 0.85, 0.94, and 0.96, respectively. Overall, the highest performance recorded in the feature engineering approach (single-set feature and combined-set feature) is 91.1% accuracy and 0.96 AUC in the case of fine KNN.

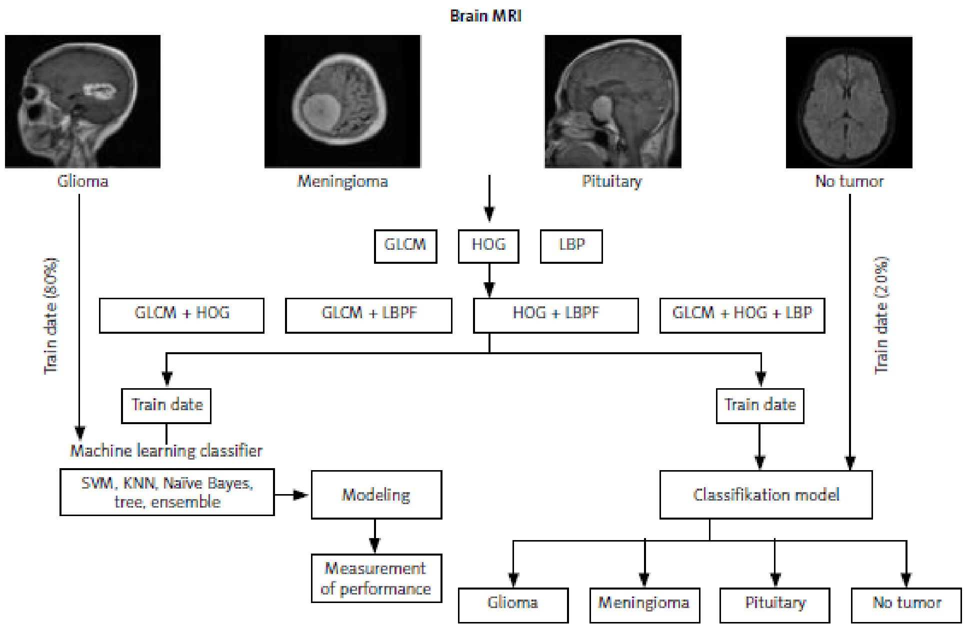


Figure (7) Overall work flow of methodology for classification brain tumour magnetic resonance imaging

Table 1. Brain tumour classification using magnetic resonance imaging based on a combination of feature sets

Classifiers		Accuracy				AUC			
		GLCM + HOG (%)	GLCM + LBP (%)	HOG + LBP (%)	GLCM + HOG + LBP (%)	GLCM + HOG	GLCM + LBP	HOG + LBP	GLCM + HOG +LBP
SVM	Linear	72.8	77.4	73.3	79.1	0.91	0.92	0.92	0.93
	Quadratic	80.7	82.8	82.6	87.5	0.96	0.94	0.96	0.97
	Cubic	85.0	81.0	85.4	87.8	0.97	0.94	0.97	0.97
	Fine gaussian	77.7	64.1	69.3	73.0	0.96	0.93	0.96	0.96
	Medium gaussian	83.4	81.2	80.8	85.2	0.96	0.94	0.96	0.96
	Coarse gaussian	69.7	68.5	68.3	71.4	0.90	0.88	0.90	0.89
KNN	Fine KNN	88.7	80.3	88.9	91.1	0.94	0.85	0.94	0.96
	Medium KNN	76.5	80.0	79.8	81.4	0.95	0.94	0.95	0.96
	Coarse KNN	67.6	68.5	66.2	67.6	0.91	0.88	0.89	0.88
	Cosine KNN	76.0	75.8	75.4	79.4	0.94	0.92	0.93	0.94
	Cubic KNN	76.3	78.6	77.5	80.3	0.95	0.94	0.95	0.95
	Weighted KNN	82.8	82.2	83.4	86.4	0.97	0.95	0.97	0.97
	Naive Bayes	66.7	56.1	57.5	56.8	0.86	0.77	0.78	0.77
Tree	Fine tree	65.9	69.0	67.4	74.9	0.82	0.83	0.81	0.83
	Medium tree	62.2	64.6	63.4	67.9	0.84	0.82	0.82	0.82
	Coarse tree	60.1	65.7	62.2	64.6	0.79	0.81	0.77	0.79
Ensemble	Boosted trees	68.8	72.3	70.2	72.8	0.87	0.86	0.90	0.88
	Bagged trees	79.3	75.6	75.6	81.9	0.92	0.91	0.90	0.94
	Subspace Discriminant	69.5	73.7	71.1	76.0	0.89	0.90	0.90	0.90
	Subspace KNN	63.4	62.0	85.5	65.5	0.84	0.82	0.98	0.84
	Rus boosted trees	66.9	70.7	71.3	69.0	0.86	0.87	0.90	0.86

Conclusion

The brain tumour classification is an exploring research for machine learning people and medical practitioners because the deep learning approach is a black box method and medical practitioners are unable to analyse the exact features of brain MRI for classification. The approach proposed in this article is challenging enough to the deep learning approach. The proposed method, i.e. fine KNN, achieved 91.1%

accuracy and 0.96 of AUC. Furthermore, this model has the possibility to integrate in low-end devices unlike deep learning, which requires a complex system. Again, the performance of the classification models may improve by the introduction of optimization techniques.

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