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Classification of intracranial hemorrhage CT images based on texture analysis using ensemble-based machine learning algorithms: A comparative study

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ABSTRACT

Blood vessels in the brain tissue can leak or burst, causing an intracranial hemorrhage, a potentially fatal disorder. One of the critical steps in brain stroke imaging is the categorization of intracranial hemorrhages. This article aims to perform texture-based intracranial hemorrhage computed tomography image classification with ensemble and machine learning classifiers using local binary pattern, local ternary pattern, and Weber local descriptor approach. The most common texture feature extraction method is a local binary pattern; however, other methods such as local ternary pattern, Weber local descriptor, and local binary pattern are also utilized for texture feature extraction. For all the extracted texture codes, histograms are applied, and finally, single feature vector texture codes by performing the concatenation of the bin. The efficacy of feature descriptors for classifying images into abnormal and normal classes was assessed using ten distinct classifiers. The result shows that Weber's local descriptor shows promising results in texture code classification for ensemble-based classification. For all texture-based methods, classification accuracy was better than standard machine learning. According to the findings of the experiment, the Random Forest classifier outperformed all other classifiers in terms of classification accuracy (86.55%), recall (86.31%), precision (87.23%), sensitivity (86.31%), specificity (86.81%), and F1-score (86.77%) for the Weber local descriptor.

1. Introduction

Intracranial hemorrhage is a life-threatening medical emergency that can only be treated with medication as early as possible. Early detection and classification of cerebral bleeding are critical in the medical field. Intracranial bleeding is identified by using diagnostic modalities such as positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT) [1]. CT is the most widely used imaging modality because of its accuracy, speed, and lack of invasiveness [2]. Because of the disease's high mortality rate, non-contrast computed tomography of cerebral bleeding is required to ensure a good prognosis and prevent neurological damage [3].

In recent years, machine learning (ML) has progressed and has been significantly used in brain stroke imaging. ML is a cutting-edge technology with the potential to help in classification, diagnosis, anomaly detection, prognosis, and therapy response prediction [4]. In general, one of the essential goals of a ML algorithm is classification, which tries to categorize each input value into one of a set of classes. Recently the ensemble-based machine learning classification approach has been gaining more attention due to its high accuracy. Ensemble-based models are powerful because they combine several models, some of which are based on a random feature (and sample) selection, to reduce the error. The performance of machine learning-based techniques mainly depends on the number of features and quality extracted from the image.

In brain stroke image classification, the extraction of informative features is crucial. Various types of essential features can be identified for further analysis. Texture-based feature extraction is one of the essential techniques. It is an efficient discriminator in computation, resistant to variations in image intensity and ease of use. Researchers also experimented with rotation-invariant patterns, uniform patterns, and uniform rotation-invariant patterns. Algorithms for extracting texture-based features have been proposed in a variety of approaches. The texture-based feature extraction methods used are local binary patterns and their variations. The feature extraction approach was

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developed by Ojala et al. [5] and assesses the relationship between center and neighbor pixels by thresholding neighbor pixel values with the center pixel value. In addition to medical applications, local binary pattern (LBP) has been used in visual identification, texture classification, human identity, etc.

This paper compares the performance of ensemble-based classifiers with machine learning for classifying CT images of cerebral hemorrhage. The idea is to identify which methodology is the best for CT images of cerebral hemorrhage. For texture-based feature extraction, local ternary pattern (LTP), Weber local descriptor (WLD), and LBP are considered. The feature descriptor code is treated using the feature vector histogram-based methodology. The machine learning classifiers are trained using these feature vectors. The evaluation of ten classification algorithms and three feature extraction methods yields classification accuracy, precision, specificity, recall, sensitivity, and F1-score for training and testing data.

The article is organized as follows: Section 2 discusses related work. Section 3 discusses the dataset used for experimentation. Section 4 presents the methodology and explains the feature extraction and classification techniques. The results and discussion are presented in Section 5, and the conclusions are included in Section 6.

2. Related work

Most of the intracranial hemorrhage image classification research has been done using machine learning approaches. There has been less research found on classifying hemorrhage based on textural features. This work mainly targets intracranial hemorrhage image classification using a texture-based feature extraction approach, as textural characteristics have played an essential role in medical imaging classification.

Many types of feature extraction methods are used in medical image classification applications. The most often used for feature extraction is the local binary pattern (LBP). LBP is a texture image classification method proposed in [6]. LBP mainly works by assigning a label to the pixel of an image. While setting the label to the pixel, it thresholds the pixels near the center pixel and gives them a binary value of 0 or 1. The histogram of different intensity labels is used to form the feature vector and to perform the classification. An LBP variation for medical image classification based on texture features was proposed in [7]. Different LBP variants are obtained using different shapes like circles, parabolas, hyperbolas, and ellipses to generate the neighborhoods. Elongated quinary patterns based on ellipse shapes show improved performance compared to other variations. Many researchers also worked on modified LBP for medical image classification, like block-based LBP, and average LBP for classifying abnormal breast tissue [8]. To improve the performance of the LBP method, block-based LBP and average LBP encoding were proposed. It was observed that block-based and average LBP enhances texture structure by investigating intensity differences in certain blocks of pixels and neighboring pixels in a local neighborhood.

A modified version of LBP uses the distance relation between neighbors (nLBP), and the angle relation between neighbors (αLBP) approach has been introduced to classify the brain tumor images along with the LBP [9]. Based on each pixel's relationship with its neighbor, nLBP was formed. The αLBP technique primarily calculates each pixel's value based on an angle value. LBP shows improved classification accuracy for the K-nearest neighbors (KNN) model.

The related literature also includes the discriminative feature extraction method based on the local wavelet pattern (LWP) proposed in [10]. Here the histogram is found as a feature vector using LWP, built for each image pixel. From the experimental results, the LWP feature descriptor is more efficient, discriminative, and may be utilized to diagnose medical CT images successfully. Local mesh patterns (LMeP) were proposed for biological-image indexing and retrieval, and their performance was improved when paired with the Gabor transform [11]. A new content-based image retrieval (CBIR) method for lung nodule categorization was proposed in [12]. For feature extraction, they employed Gabor, LBP, and their combinations.

Considering LBP as a traditional approach, a modified version of LBP, local ternary patterns also pave the attention in the area of medical imaging for texture feature extraction; local ternary co-occurrence patterns (LTCoP) are proposed in [13]. Based on the gray values of the central pixel and its neighbors for medical image retrieval, LTCoP produced comparable ternary edges. A new midline detection method was proposed in [14] to detect bleeding from CT images. The intracranial area was divided into left and right hemispheres. Here the LBO is applied to obtain the texture feature. Finally, histogram features were extracted from both hemispheres, and a support vector machine learning classifier was used to detect the presence of hemorrhage. The directional local ternary quantized extrema approach for image retrieval in medical imaging is presented in [15]. To encode spatial structure information, ternary patterns of vertical-horizontal-antidiagonal-diagonal patterns are used. Synchronized rotation local ternary pattern approach presented in [16] to perform image classification. An invariant and uniform pattern histogram is encoded for the lower and upper patterns.

The local mesh ternary pattern is proposed in [17] for CT and MRI image retrieval and indexing. In this method, three selected orientations of mesh patterns built from 2D images express the grayscale relationship among neighbors for a given center pixel. Ternary patterns are extracted from mesh patterns to obtain more spatial structure information. Weber's local descriptor was introduced in [18] for texture classification; it is a function of orientation and differential excitation, characterized by the ratio of relative intensity differences and current pixel intensities. Weber Local Descriptor is proposed for image texture classification [19]. The histogram was calculated from the small spatial region of the image. Because of small spatial regions, the image's texture at the cell level is effectively defined. Classification has been performed by applying a support vector machine classifier. The CLBP and neutrosophic set-based methods were proposed to obtain effective texture features in [20]. Neutrosophic sets provide an efficient way to handle the degree of uncertainty. The authors of this article achieved improved performance for the proposed method. A new adaptive weight joint multi-scale local binary pattern method is proposed to perform image classification in [21]. To obtain adaptive weight, the square of variance was considered as the cumulative weight of histogram value.

Considering the information presented above, this article is developed to mainly target the extraction of texture features from intracranial hemorrhage CT images using a local binary pattern, Weber local descriptor method, and local ternary pattern. The images are classified it into normal and abnormal class using various machine learning classification algorithms.

3. Dataset

The dataset used for experimentation was collected from the Kaggle repository. More specifically, the dataset includes intracranial hemorrhage CT images. It is compiled from publicly available sources [22]. The dataset consists of a total of 2501 CT images. There are 825 hemorrhages CT images in the train folder and 125 images in the test folder. A total of 31 patients with hemorrhage CT images and 39 patients have normal CT image datasets are available in the dataset.

Similarly, 1426 normal CT images in the train and 125 images in the test folder are available. The dataset provides nearly 25 to 40 CT images for each patient. For experimentation, 31 normal and 31 abnormal patients' image data were considered for the experiment. Images belonging to the normal category are labeled as one, and hemorrhage images are labeled as 0. The collected images are 640x640 in size. Images are resized to 256x256 dimensions to reduce the computation. The sample hemorrhage image and the normal image are shown in Fig. 1.

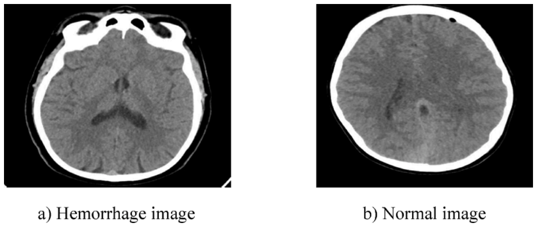

Fig. 1. Sample normal and hemorrhage images from the dataset.

4. Methodology

This work has been performed to classify the hemorrhage and normal CT images. The dataset was divided into 30 percent testing and 70 percent training sets. Handcrafted features are extracted using Weber's local descriptor (WLD), local ternary pattern (LTP), and local binary pattern (LBP) texture analysis methods. Finally, the histogram is applied to these handcrafted features to generate feature vectors [26]. Classification has been done using Gaussian Naive Bayes, Decision tree, logistic regression, K- nearest neighbor, and Support vector machine learning classifiers. This work was further extended and evaluated for Random forest, Bagging, AdaBoost, and Gradient boosting ensemble-based classifiers. This section explains the basic concepts of the proposed methodology.

4.1. Feature extraction

A significant role has been played by using textural features in classification in medical imaging. Image classification based on texture holds important image characteristics. Analyzing the brain stroke images with their texture helps for accurate images. This work includes feature extraction using the histogram-based texture feature analysis. Texture features are extracted using a Weber local descriptor, local binary pattern, and local ternary pattern method. Fig. 2 shows the system architecture for texture-based analysis using LBP, LTP, and WLD approaches.

4.1.1. Local binary pattern

The local binary pattern (LBP) method was proposed to classify image textures [5,31]. It is frequently used to process images. The LBP value of a given center pixel in a picture is derived by comparing its grey value to its neighbors. Based on 33-pixel blocks, LBP uses the center pixel as a threshold for nearby pixels, whereas the LBP code threshold value is converted to a decimal value to produce the center pixel. The mathematical representation of LBP uniformity measurement is given in Eq. (1).

$$LBP = \sum_{i=0}^{M-1} T(S_i - S_c)2^i,\ T(x) = \begin{cases} 1 & if\ \ x > 0 \\ 0 & Otherwise \end{cases} \tag{1}$$

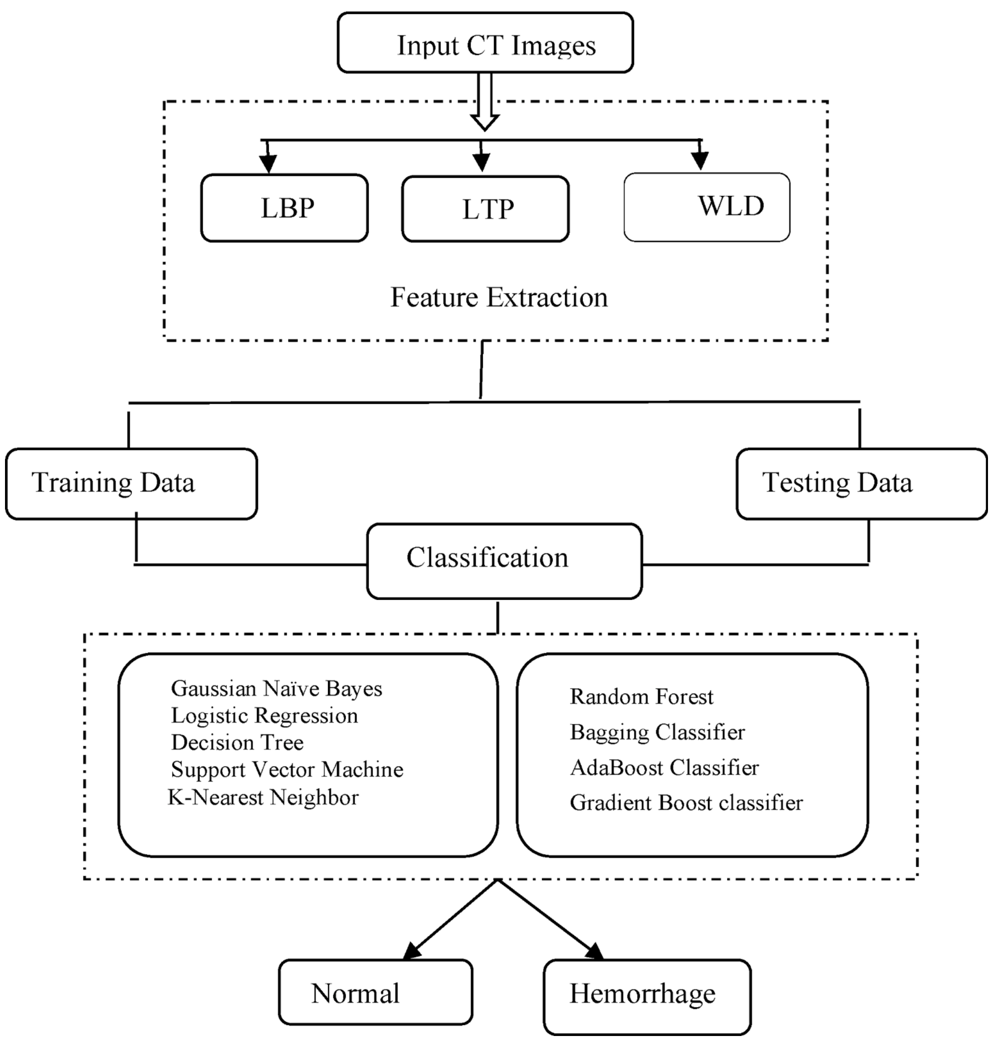

Fig. 2. System architecture for texture-based analysis using Local Binary Pattern (LBP), Weber local descriptor (WLD) approach, and Local ternary pattern (LTP) approach.

where M = Number of neighborhood pixels, $S_i = i$ -th neighboring pixel and c = Center pixel.

From the LBP code, histogram features of 2^M were extracted to yield a 256-length feature vector for eight neighboring pixels [23,27]. Local Binary pattern operation with$P_c = 15$ and neighbor = 8 is represented in Fig. 3. The mathematical representation of the local binary pattern code calculations is given in Eq. (2).

$$\text{LBP Code} = 0*2^0 + 0*2^1 + 0*2^2 + 0*2^3 + 0*2^4 + 1*2^5 + 1*2^6 + 0*2^7 = 96 \tag{2}$$

4.1.2. Local ternary pattern

Local ternary patterns (WLP) are a more detailed form of local binary patterns. It does not use a threshold constant to divide pixels into 0 and 1 as LBP does; instead, it divides pixels into three values based on a threshold constant. Local Ternary pattern operation is defined in Eq. (3).

$$LTP = \sum_{i=0}^{M-1} \mathrm{T}(S_i - P_c),\ T_x = \begin{cases} 1 & x \geq k \\ 0 & -k < x < k \\ -1 & x < -k \end{cases} \tag{3}$$

As a result of the threshold step, the upper and lower patterns are derived; the LTP operator is constructed by concatenating the upper and lower pattern [24,25]. Histogram features are then extracted from the upper pattern, and the lower pattern results in a feature vector size of 512 [28].

4.1.3. Weber local descriptor

Weber Local Descriptor (WLD) can be derived from two main principles: (a) differential excitation (ψ) and (b) orientation. The micro-variation can be derived from intensity differences between neighboring pixels, and orientation determines the directional property of the pixels. It is represented in mathematical form in Eq. (4).

$$\delta S = \sum_{i=0}^{M-1} (T_i - T_c) \tag{4}$$

where i = the total number of neighbors and c = the intensity of the current pixel, δS is the intensity difference current pixel with its neighbor. A column represents dominant orientation, and a row represents differential excitation in the 2D histogram. [19].

4.2. Classification framework

This section describes the process for the classification of brain CT images using ensemble-based models and conventional machine learning methods. Classification accuracy for training data and testing is analyzed. Machine learning classification algorithms [28,29] are considered for classifying the images into normal and hemorrhage: Naive Bayes, decision tree (entropy, Gini), logistic regression, support vector machine, and k-nearest neighbor classifier [32]. Further, this work is further evaluated using ensemble-based classification models. The proposed methodology of the texture-based CT image classification model is represented in Algorithm 1.

***Algorithm 1:** Proposed methodology of texture-based CT image classification* [17]

Input: CT images

(continued on next column)

11	8	6
7	15	2
19	45	4

⇒

0	0	0
0		0
1	1	0

Fig. 3. Local Binary pattern operation.

(*continued*)

***Algorithm 1:** Proposed methodology of texture-based CT image classification* [17]

Output: Accuracy of the classification model for training and testing data.
Steps:
1. Input intracranial hemorrhage CT images.
2. Apply texture-based feature extraction methods.
3. Apply histograms to the pattern codes. Form a feature vector.
4. The classification model is trained.
5. Classification accuracy for training and testing sets has been evaluated for different machine learning classifiers along with precision and recall scores.

5. Results and discussion

In brain stroke imaging, intracranial hemorrhage identification and classification is one of the critical research areas. Due to intracranial hemorrhage, bleeding happens inside the brain and its surrounding parts, leading to the formation of abnormal regions in the brain. Early identification of abnormal areas is critical at clinical ends to prevent future patients' vital conditions. Accurate classification of intracranial hemorrhage can fasten the diagnostic process and helps to provide the correct and effective treatment to the patients. Intracranial hemorrhage classification based on the image's texture requires growing research in medical imaging. The local binary pattern is one of the most popular texture-based methods because of its simplicity and low-cost computation. This work mainly targeted classifying intracranial hemorrhage from CT images based on image texture. Texture features from images were obtained for the feature extraction using three different texture feature methods like LBP, LTP, and WLD. Extracted features are used to form a feature vector. Finally performance of a classifier's precision, recall, sensitivity, specificity, F1-score, and accuracy score have been obtained.

Intracranial hemorrhage CT image classification is implemented and tested on an Intel® CoreTM i7, 2.5 GHz processor with 4 GB RAM using a Jupyter notebook. To perform the comparative analysis of classification algorithms, different performance measures are precision, classification accuracy, recall, specificity, sensitivity, and F1-score. Section 5.1 discusses the evaluation metrics used in the result analysis. Experimentation is carried out in three parts, presenting results in subsections. Local binary pattern-based image classification results are discussed in section 5.2. In subsection 5.3, the extended form of LBP, the local ternary pattern method, is applied to extract the texture code. Further experimentation has been extended for Weber's local descriptor. Section 5.4 discusses the WLD results for all classifiers.

5.1. Evaluation metrics

To train and evaluate the classification model, various experiments were performed. The model's performance was accessed using the following metrics [30]. The proportion of accurate predictions to the total number of occurrences evaluated serves as a gauge of categorization accuracy. The accuracy is calculated by using Eq. (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

From Eq. (5), false negatives, true negatives, false positives, and true positive are all abbreviated as FN, TN, FP, and TP, respectively.

A precision metric is the percentage of positive patterns adequately predicted from the total projected patterns in a class. The precision is calculated by using Eq. (6).

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

The recall metric measures the fraction of correctly classified patterns from positive ones. The mathematical formula to calculate recall is given in Eq. (7).

$$Recall = \frac{TP}{TP + TN} \tag{7}$$

The sensitivity metric measures the fraction of correctly classified patterns from positive ones. The mathematical formula to calculate sensitivity is given in Eq. (8).

$$Sensitivity = \frac{TP}{TP + TN} \tag{8}$$

Specificity metric displays the percentage of negative patterns correctly classified. The mathematical representation of specificity is given in Eq. (9).

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

The F1-score metric represents the harmonic mean of recall and precision values. F1-score is calculated by using Eq.10.

$$F1 - score = \frac{2^*(Precision^*Recall)}{Precision + Recall} \tag{10}$$

5.2. Local binary pattern

The local binary pattern (LBP) mainly uses local micropattern variation to build the statistics from images. It extracts more local structure information from the image. In this experiment, LBP code is obtained from images, and the histogram is applied to the LBP code for generating the feature vector.

In LBP, applying LBP texture analysis methods on images, texture code is obtained, and classification accuracy is evaluated. This experimentation aims to extract histogram-based LBP code and perform the image classification into abnormal and normal classes. Classification has been achieved by using standard machine learning classifiers. Further experimentation has been extended for the random forest, bagging, AdaBoost, and gradient boost ensemble-based algorithms. Classification accuracy is analyzed for training and testing sets along with precision, recall, sensitivity, specificity, and F1 scores. In all classification algorithms, an ensemble-based algorithm shows better performance. The bagging classifier shows maximum testing accuracy is 78.49 percent. After the bagging algorithm, the Gradient boost shows better classification accuracy is 74.73 percent. Table 1 shows the LBP method's analysis of machine learning and ensemble-based classifiers.

5.3. Local ternary pattern

This experimentation includes histogram-based local ternary pattern (LTP) feature extraction from intracranial hemorrhage CT images. LTP is a more detailed form of the LBP method, which involves extracting texture code's upper and local parts from images. Standard machine learning classifiers have performed classification. Experimentation has been extended for the random forest, bagging, AdaBoost, and gradient boost ensemble-based algorithms.

Classification accuracy is calculated for training and testing sets along with precision, recall, sensitivity, specificity, and F1-score. In all classification algorithms, ensemble-based algorithms show better performance. The bagging classifier shows maximum testing accuracy of 79.03 percent, followed by the gradient boost algorithm of 78.49 percent. Table 2 shows the LTP method's analysis of machine learning and ensemble-based classifiers.

5.4. Weber local descriptor

Weber local descriptor (WLD) extracts the images' most powerful discriminating texture features. In WLD, it mainly computes the micropattern (differential excitement) and then builds the statistics from that pattern along with the gradient current pixel gradient orientation. In this experimentation, feature extraction is performed using histogram Weber local descriptor, and classification has been achieved using standard machine learning classifiers. Further experimentation has been extended for the random forest, bagging, AdaBoost, and gradient boost ensemble-based algorithms. Classification accuracy is analyzed for training and testing sets and precision, recall, sensitivity, F1-score, and specificity. Table 3 shows the result analysis of machine learning and ensemble-based classifiers for the WLD method. In all classification algorithms, ensemble-based algorithms show better performance. According to the Random forest classifier, the maximum testing accuracy is 86.55 percent. After the random forest technique, the bagging classifier's superior classification accuracy is 84.94 percent.

5.5. Discussion

The main objective of this experimentation is to evaluate the discriminating features of LBP, LTP, and WLD methods. The experiment mainly involves two components, texture code extraction and image classification. An associated similarity measurement criterion is used within the classifiers. For classification tasks, machine learning classifiers, along with ensemble-based classifiers, are used. Different machine learning classifiers have been evaluated. Classification algorithms considered are Naive Bayes, decision tree (entropy, Gini), logistic regression, support vector machine, K-nearest neighbor classifier, random forest, bagging, AdaBoost, and gradient boost classifier.

A total of 10 classification algorithms are evaluated for three feature extraction methods, and 30 experimental results are obtained. For the K-nearest neighbor classifier algorithm, k = 1, 3, 5, 7 neighbors are considered. In all, k = 1 shows better performance. In the case of the decision tree classifier, the entropy-based and Gini-based approaches have experimented. In all classification models, the ensemble-based approach shows better performance. Especially, Random forest, bagging, and gradient boost showed good classification accuracy. In the Texture extraction approach, WLD performs well compared to other methods. Fig. 4 compares all classifiers for testing set classification

Table 1
Result Analysis of Classifiers for LBP method.

Sr. No.	Classification Models	Accuracy score of training data	Accuracy score of test data	Recall score	Precision Score	Sensitivity score	Specificity score	F1-Score
1	Logistic Regression	77.367	68.817	67.777	67.777	67.777	69.791	67.777
2	Naive Bayes	82.448	62.903	60.000	62.068	60.000	65.625	61.016
3	K-Nearest Neighbor	100.000	71.505	73.333	69.473	73.333	69.791	71.350
4	Support vector machine	98.614	60.752	61.111	59.139	61.111	60.416	60.108
5	Decision Tree - Entropy	100.000	61.827	65.555	59.595	65.555	58.333	62.433
6	Decision Tree- Gini	100.000	66.129	66.666	64.516	66.666	65.625	65.573
7	Random Forest	100.000	70.967	76.666	67.647	76.666	65.625	71.875
8	Bagging	100.000	78.494	81.111	76.0416	81.111	76.041	78.494
9	AdaBoost	75.288	64.516	62.222	63.636	62.222	66.666	62.921
10	Gradient Boost	99.769	74.731	78.888	71.717	78.888	70.833	75.132

Table 2
Result analysis of classifiers for the LTP method.

Sr. No.	Classification Models	Accuracy score of training data	Accuracy score of test data	Recall score	Precision Score	Sensitivity score	Specificity score	F1-Score
1	Logistic Regression	85.219	76.344	79.5454	72.91	79.545	73.469	76.0833
2	Naive Bayes	70.669	55.913	62.500	52.886	62.500	50.000	57.292
3	K-Nearest Neighbor	100	69.35	67.045	67.816	67.045	71.428	67.428
4	Support vector machine	100	73.118	69.318	72.619	69.318	76.530	70.930
5	Decision Tree - Entropy	100	61.82	57.954	60.000	57.954	65.306	58.959
6	Decision Tree- Gini	100	69.35	65.909	68.23	65.909	72.448	67.049
7	Random Forest	100	68.81	65.909	67.44	65.909	71.428	66.665
8	Bagging	100	79.03	72.727	81.01	72.727	84.693	76.645
9	AdaBoost	77.82	71.50	67.045	71.03	67.045	75.510	68.979
10	Gradient Boost	99.76	78.49	84.090	74.00	84.090	73.469	78.723

Table 3
Result analysis of classifiers for the WLD method.

Sr. No.	Classification Models	Accuracy score of training data	Accuracy score of test data	Recall score	Precision Score	Sensitivity score	Specificity score	F1-Score
1	Logistic Regression	72.979	62.365	60.000	64.044	60.000	64.836	61.956
2	Naive Bayes	54.272	55.913	63.157	56.074	63.157	48.351	59.405
3	K-Nearest Neighbor	100.000	76.344	81.052	74.757	81.052	71.428	77.777
4	Support vector machine	79.676	70.430	67.368	72.727	67.368	61.467	69.945
5	Decision Tree- Entropy	100.000	77.956	76.842	79.347	76.842	79.120	78.074
6	Decision Tree- Gini	100.000	77.956	74.736	80.681	74.736	81.318	77.594
7	Random Forest	100.000	**86.559**	86.315	87.234	86.315	86.813	86.772
8	Bagging	100.000	84.946	84.210	86.0215	84.210	85.714	85.106
9	AdaBoost	72.517	67.741	83.157	64.227	83.157	51.648	72.476
10	Gradient Boost	97.690	83.333	85.263	82.653	85.263	81.318	83.937

14

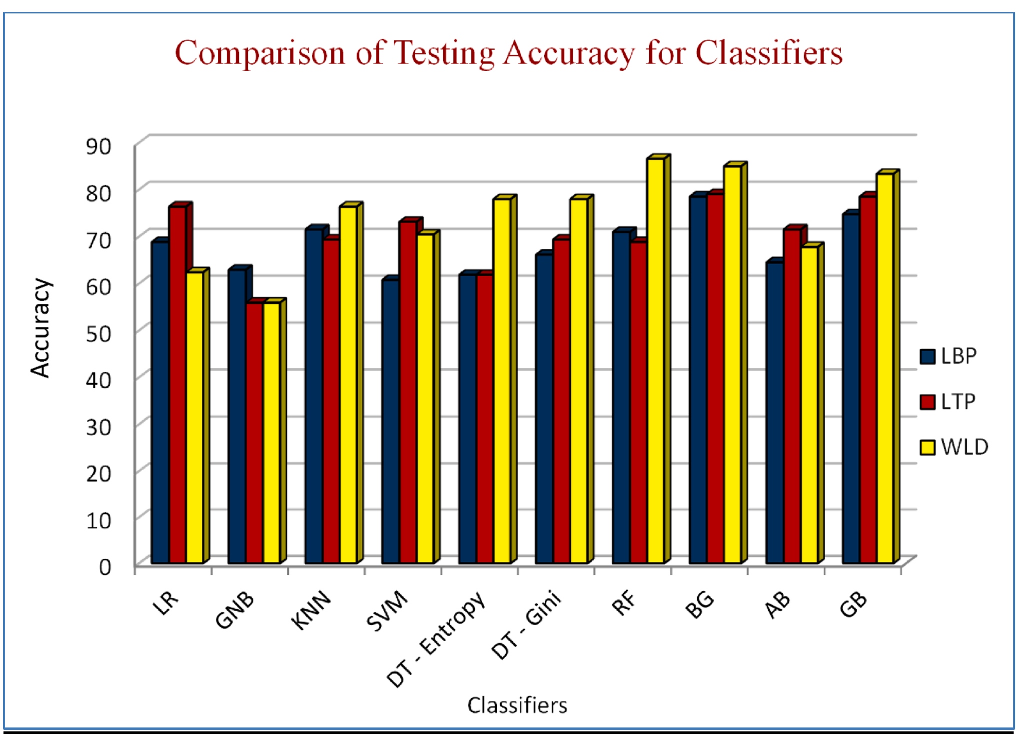

Fig. 4. Comparisons of classifiers for testing classification accuracy for Logistic Regression(LR), Gaussian Naïve Bayes(GNB), K- nearest neighbor(KNN), Support vector machine(SVM), Decision Tree (DT)- Entropy & Gini, Random Forest (RF), Bagging (BG), AdaBoost(AB.) and Gradient Boosting (GB) classifiers with the local binary pattern, local ternary pattern, and Weber local descriptor method.

accuracy with the local binary pattern, Weber local descriptor methods, local ternary pattern, and all machine learning classifiers and Ensemble-based classifiers.

A comparison of all algorithms has been made in order to choose the best classifier for the proposed work. The algorithm with the highest percentage of correctly identified images or the lowest percentage of wrongly classified images is considered the best classifier. Table 4 shows the comparative analysis of all algorithms with LBP, LTP and WLD methods for correctly classified images and non-classified images based on true positive + true negative and false negative + false positive, respectively. From the result analysis, bagging classifiers can correctly categorize images with a minimum accuracy of 21.50% and a maximum accuracy of 78.49% for local binary patterns across all classification algorithms. Similar to this, the best classifier for the local ternary pattern has an accuracy rate of 79.032 for correctly classified images and a low error rate of 20.968 for non-classified images. In the instance of the Weber local descriptor technique, Random forest has the largest percentage of correctly identified photos and the lowest percentage of incorrectly categorized images, which are 86.55% and 13.44%, respectively. In order to accurately categorize the images from the test dataset, random forest surpasses all other classifiers in all texture-based techniques.

Table 4
Comparative analysis of all algorithms with LBP, LTP and WLD methods for correctly classified image and non-classified images.

Methods/ Classifiers		Correctly Classified Image (%)	Non-classified images (%)
LBP	Logistic Regression	68.817	31.183
	Naive Bayes	62.903	37.097
	K-Nearest Neighbor	71.505	28.495
	Support vector machine	60.753	39.247
	Decision Tree-Entropy	61.828	38.172
	Decision Tree- Gini	66.129	33.871
	Random Forest	70.968	29.032
	Bagging	78.495	21.505
	AdaBoost	64.516	35.484
	Gradient Boost	74.731	25.269
LTP	Logistic Regression	76.344	23.656
	Naive Bayes	55.914	44.086
	K-Nearest Neighbor	69.355	30.645
	Support vector machine	73.118	26.882
	Decision Tree-Entropy	61.828	38.172
	Decision Tree- Gini	69.355	30.645
	Random Forest	68.817	31.183
	Bagging	79.032	20.968
	AdaBoost	71.505	28.495
	Gradient Boost	78.495	21.505
WLD	Logistic Regression	62.366	37.634
	Naive Bayes	55.914	44.086
	K-Nearest Neighbor	76.344	23.656
	Support vector machine	70.430	29.570
	Decision Tree-Entropy	77.957	22.043
	Decision Tree- Gini	77.957	22.043
	Random Forest	86.559	13.441
	Bagging	84.946	15.054
	AdaBoost	67.742	32.258
	Gradient Boost	83.333	16.667

6. Conclusion

Texture-based image analysis is a required field of study in medical imaging. Identification of the aberrant regions from images is made possible by classifying images based on texture. This study used machine learning and an ensemble-based classifier to do texture-based intracranial hemorrhage CT image categorization. The texture features of an image are extracted using texture-based techniques such as local binary pattern, local ternary pattern, and Weber local descriptor. The feature vector is created when histograms are applied to the texture feature. Finally, ten different classifiers have been used to examine the classification accuracy for training and testing datasets. The following are the findings: Without sacrificing the local information, the Weber local descriptor extracts strong and potent prominent micro-discriminating pattern characteristics. Compared to local binary pattern and ternary pattern texture-based techniques, Weber's local descriptor performs the best. When it comes to classification, the ensemble-based classification method outperforms traditional machine learning classifiers in terms of classification accuracy. With a classification accuracy of 86.55 percent, the Random Forest ensemble-based classification algorithm performs best for the Weber local descriptor. When evaluating the best classifier, the Random Forest algorithm outperforms all others with a minimum accuracy of 13.44% for unclassified images with WLD approach. The small size of the image dataset is a drawback of this effort. Future evaluation of the presented work will require a sizable dataset. Advanced weber based approach can be the next target to improve classification accuracy. By eliminating the skull area from the images and performing validation at the clinical end, additional future research work can be directed to improve the classification accuracy.

7. Dataset

The data collection can be accessed for free through the Kaggle Repository at https://www.kaggle.com/datasets/afridirahman/intracranial-brain-hemorrhage-ct-images.

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CRediT authorship contribution statement

Santwana S. Gudadhe: Software, Methodology, Conceptualization, Data curation, Formal analysis, Writing – review & editing. **Anuradha D. Thakare:** Software, Resources, Writing – original draft, Writing – review & editing. **Diego Oliva:** Writing – original draft, Writing – review & editing, Conceptualization, Supervision, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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