ENSEMBLE MACHINE LEARNING MODEL FOR TEXTURE FEATURE EXTRACTION AND CLASSIFICATION

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ABSTRACT

Ensemble methods are learning algorithms that build a group of classifiers and then categorize fresh data by voting on their predictions in a (weighted) manner. In this study, an ensemble technique is suggested for enhancing textural classification performance. It is difficult to find informative patterns in image textures, which is a crucial problem for image categorization. This paper suggests a useful technique for categorizing textures using machine learning techniques. Proposed work focus is building custom dataset in the form of a CSV file using Haralick features that are taken from the Brodatz texture dataset. To categorize the textures of the Brodatz dataset, various ML techniques are utilized, that include: Decision Tree classifier, Random Forest classifier, and Ada Boost classifier. Finally, the effectiveness of the proposed model is evaluated in comparison to the various machine learning techniques. According to the comparison analysis, In comparison to individual machine learning techniques, the ensemble machine learning model performs better. And state-of-the-art method with improved classification results of 100%.

Keywords: Texture Analysis, Brodatz, Classification, Decision Tree, Random Forest, Ada Boost Classifier, ensemble classifier, Voting Classifier

[1] INTRODUCTION

Ensemble techniques are growing models that combine the opinions of various learners to produce excellent performance. The benefit of ensembles is that they have the potential to significantly enhance the performance of new data. Hybrid approaches are frequently used in machine learning. These techniques integrate various predictions to get better and more precise answers when solving problems [1]. These techniques are employed to address classification issues and have been applied to a variety of classification issues in order to make a variety of predictions. [2]

In author's previous work [3], they have proposed the texture feature extraction using the ML algorithms (machine learning) like: K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest Tree (RFT) etc. Based on the authors' previous work [3].

The present research suggests an ensemble method based on the voting classifier for enhancing the textural classification performance in order to overcome the limiting classification performance of machine learning algorithms. The ensemble technique is examined to get better the categorization performance more significant as compare to the individual machine learning methods.

Since practically every image contains texture and high-resolution images are now more widely available thanks to ongoing advancements in image collecting technologies, the success of texture analysis is understandable. Numerous machine learning challenges, such as surface inspection, medical image analysis, and a variety of image detection and classification issues, all benefit from texture analysis. The literature is full of methods for describing image textures as a result of intensive study on texture analysis during the past 30 years.

The most popular techniques for describing local texture are those based on the grey level co- occurrence matrix (GLCM), which measures the joint probability of the grey levels at two pixels at a fixed relative position, such as Haralick features (Haralick et al., 1973), where a set of features is computed using GLCMs constructed in different orientations, and (ii) neighborhood-based techniques, which are computed directly on the image using a shifting neighborhood (sq Since the 1990s), there has been a lot of research on neighborhood-based texture descriptors. A variety of different approaches have been proposed, including the Rank Transformations (Zabihand Woodfil, 1994), which considers neighborhood pixels with lower intensity than the central neighborhood pixel, and the Texture Transformations (Zabih and Woodfil, 1994)[26].

No algorithm is perfect in every circumstance. Every learning algorithm has a model bound to it. In reality, errors will happen if data assumptions are false [4]. If the model's parameters are specified for a training dataset, The model may not be suitable for all types of data available, in that case a different model would be more effective [5]. One type of multi component classifier designed to outperform a single-component classifier is the ensemble classifier [6]. Ensemble classifiers are utilized in these classifications to produce better results. Other ensemble approaches use different classifiers and aggregate different basic classifiers using different weights [7]. Dependent (serial) and independent (parallel) ensemble frameworks are available. In a dependent framework, the output of one classifier is used by the next classifier. As a result, learning in subsequent rounds can be guided by knowledge from past iterations. An example of one of these frameworks is boosting. Every classifier produces result individually in the second framework, which is referred to as independent. These results are added to those from voting processes.

Novelty of the proposed method lies in:

1) Provides a novel hybrid method-based model to enhance and lower the error rate of multi-class image classification.
2) In comparison to earlier methods, the combination of these ones yields increased stability.
3) Creating the CSV files from the Brodatz texture images.
4) Strengthen and improve poor classifiers using the ensemble model, which makes an effort to improve its modeling and learning.

[2] LITRATURE REVIEW

Hasan et al. [9] proposed a mix of deep learning (DL) techniques and related fusion techniques to categorize the images. This technique is supposedly capable of lowering the mistake rate in image classification. The hybrid Ada-Boosting and bi-layer convolutional learning methods make up the suggested algorithm.

Srisupang and Keiichi [10] proposed a model based on a sophisticated network model; the local spatial pattern mapping method has been suggested for classifying textures. The method's goal was to use multi-radial distance analysis to change the spatial distribution of an image texture. Use of a single support vector machine (SVM) as a classifier has limitations, despite improvements in classification performance in order to get around this restriction and demonstrate improved textural classification performance.

M. Kavitha et al. [11] have proposed a technique to predict cardiac disease and unique machine learning approach. In the proposed study, the Cleveland heart disease dataset was used, and data mining methods like regression and classification were used. Machine learning techniques Random Forest and Decision Tree were employed.

Reddy et al. [12] worked on dataset of diabetic retinopathy, an ensemble-based machine learning (ML) model made up of the Machine Learning (ML) algorithms Random Forest classifier, Decision Tree classifier, Ada boost classifier, K-Nearest Neighbor classifier, and Logistic Regression classifier were tested.

Songetal. [13] Described a novel classification technique that combines the textural characteristics of images that have been filtered using Gaussian derivative models with an extreme learning machine. To locate texture information in images, linear filters based on the difference of Gaussian and difference of offset Gaussian derivative models were used. Along with that, it is advised to use an ensemble extreme learning machine to reduce the randomness of the original ELM. Machine learning methods were utilized.

Khatri et al. [14] to classify wheat seeds. Seven physical characteristics are used to classify seeds. During the test, for classification in the first stage, the techniques employed were Gaussian Naive Bayes, classification and regression trees, and K-nearest neighbor. Compared the outputs of various algorithms using the ensemble technique of machine learning. According to the findings, KNN, decision, and Naive Bayes classifier accuracy were assessed to be 92%, 94%, and 92%, respectively. The ensemble classifier reaches the highest accuracy of 95% and bases its conclusions on hard voting. Abdul Basit et al. [21] proposes a cutting-edge ensemble approach to find phishing attempts on the website. Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Decision Tree (C4.5) are the three machine learning classifiers are choosen to use in an ensemble method with Random Forest Classifier (RFC). This ensemble method effectively and more accurately than previous studies detects website phishing attacks. According to experimental findings, the combination of KNN and RFC successfully detects phishing assaults 97.33% of the time.

Yaman et al. [22] In order to enhance the performance of biometric systems, Author built an intelligent face recognition framework that recognizes faces through effective ensemble learning techniques, namely Random Subspace and Voting. Additionally, a number of techniques are discussed, including the identification of skin color, feature extraction from histograms, and ensemble learner-based face recognition. The symmetrical structure of the suggested frame work is found to have a high potential for biometrics. Therefore, when compared to state-of-the-art face recognition, the proposed framework using histogram feature extraction with Random Sub space and voting ensemble learners has demonstrated its superiority over two separate databases. On the FERET face database, authors proposed technique achieved an accuracy of 99.25% using random forest and both ensemble learners.

Dietterich [23] has explained the techniques and explains why ensembles frequently outperform single classifiers. To understand why Adaboost does not over fit quickly, some past studies comparing ensemble algorithms are reviewed, and some fresh experiments are presented. Roy et al.

[25] worked on combining the final representation layer of widely used AlexNet and VGG16, fused CNN (TexFusionNet) is proposed for texture categorization. The class score is produced using a completely linked layer on top of the fused layer. The additional layer that comes after the fusion layer is trained using the categorical cross-entropy loss, which is utilized to produce the error during training. The outcomes are calculated using many well-known texture data sets, including Brodatz, CUReT, and KTH-TIPS, and they are contrasted with cutting-edge texture classification techniques. The experimental results validate the proposed TexFusionNet architecture's superior performance in classifying textures.

Kasinathan et al. [26] employed a variety of feature descriptors, such as texture, color, form, histogram of oriented gradients (HOG), and global image descriptor (GIST), to classify crop Insects using machine learning and knowledge-based methodologies. The classification of insects made use of a mixture of all these characteristics. Three different insect datasets were used in this study, and a variety of machine learning techniques, including basic classifiers and ensemble classifiers, were employed. The performances of the classification results were assessed by majority voting. Base classifiers included Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Multi-Layer Perceptron (MLP). To improve the classification and identification of insects, ensemble classifiers such as random forest (RF), bagging, and XGBoost were used. A 10-fold cross-validation test was also carried out. From the literature review it is observed that the ensemble model works more efficiently in comparison to the individual machine learning models.

[3] CLASSIFICATION ALGORITHMS

The following subsections detail the algorithms in corporate into the proposed model.

[3.1] DECISION TREE ALGORITHM (DT)

A hierarchical model called a decision tree (DT) [15] has branches, leaves, and nodes. In this model, each node represents a feature test. Class label is represented as a leaf, while groups of features pointing to that class are represented by branches. The path that emerges from root to leaf represents classification rules. The logic that determines how to partition the datasets based on different scenarios is used to build the decision trees. Every stage of the process of

Creating trees, the choice of which characteristic to divide is made using information gained. When the datasets contain both category and numerical data, the decision tree method is more suited. The decision tree's key advantage is its resistance to outliers.

Decision trees have a "if then, then else" structure that makes them adaptable for use in programming logic. They can also be utilized in situations involving difficulties with categorization.

[3.2] RANDOM FOREST ALGORITHM (RF)

Several separate decision trees that function as an ensemble make up random forest [16]. The class with the most votes is divided into two groups by each of these trees in the random forest, and its prediction is used as the basis for the model. The main idea behind random forest is to collaboration of different independent trees working mutually during the process of prediction.

[3.3] ADA BOOST ALGORITHM (ABC)

To create powerful classifiers from less powerful ones, the Ada Boost [17] method is developed into the Adaptive Boosting algorithm and utilized with a variety of machine learning approaches. The goal is to increase or boost how well the ML algorithms perform. Constructing a model using training data, followed by the addition of a second model to address the drawbacks of the first model. The classifier is enhanced. Up until the maximum number of models is introduced and the Forecasts are 100% correct, these model additions continue. AdaBoost is generally used to improve decision trees' performance while categorizing binary problems. The single level DT is a well-liked Ada Boost algorithm contender [17].

[3.4] ENSEMBLE LEARNING

When many machine learning models are trained together, ensemble learning [18] produces improvised predictions that enhance the effectiveness of specific machine learning models. The predictors that are trained to calculate predictions are essentially what the phrase "ensemble" alludes to. The majority of ensemble learning implementations use decision trees, which are useful for solving quantitative problems. Using the collective findings from the ensemble, ensemble learning computes the final categorization. Produced by decision trees, rather than relying on the predictive analysis and outcome of a single decision tree. In one such use of ensemble learning, different ML models, includes Random Forest Classifier, SVM Classifier, Logistic Regression, and others, are used to train and then display the combined results of these models in order to reach definitive conclusions...Soft voting classifiers and hard voting classifiers are the two types of voting classifiers used to produce the results. [18].

[4] PROPOSED ENSEMBLE MACHINE LEARNING MODEL

Figure 1depicts the suggested model architecture. Ensemble model is mixer of three classifiers. Using the voting classifier the final results are calculated.

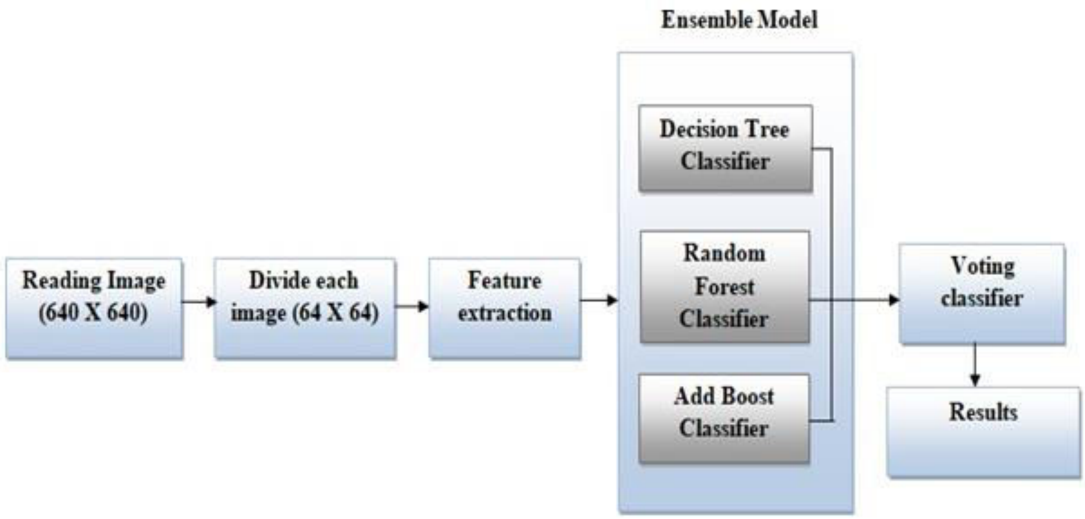

Figure: 1. Experimented ensemble machine learning model

[4.1] METHODOLOGY

Proposed approach for image classification follows the following steps:

Step 1: Read the Brodatz texture image (640 X 640) from the dataset.

Step 2: Divide each texture image into sub image of size 64 X 64.

Step3: Extract Haralick features (contrast, dissimilarity, Homogeneity, energy and correlation) from each sub image.

Step 4: Create the CSV file from the features extracted in the Step 3. **Step5:** Create training and testing sets from the dataset in an 80:20 ratio. **Step 6:** Train the ML classifiers using training set.

Step7: Test the ML classifiers using the testing set.

Step8: Train the ensemble model.

Step9: Using a voting mechanism, the ensemble model's predictions are taken into account for making predictions about the test dataset.

[4.2] FEATURE EXTRACTION

The image's textures quality is identified using features [10]. The following aspects are employed during the proposed task.

[4.2.1] HARALICK FEATURES

The gray level co-occurrence matrix (GLCM) is used to obtain Haralick characteristics. This GLCM describes the frequency with which two neighboring gray-level pixels appear in an image [19]. For the proposed work, the 5 various Haralick features are retrieved and are described below.

Contrast: To distinguish between the amount of gray scale or color present in the photographs, contrast is used.

Dissimilarity: It demonstrates how distinct data samples are from one another.

Homogeneity: is a specific kind of image that display shows a region's intensity changes over time.

Energy: Explain how the image's quality has changed.

Correlation: is the action of dragging the mask across the image to calculate the product of each area's sum.

[5] DATACOLLECTION

[5.1] DATASET PREPARATION

The suggested approach is tested on two texture image datasets from Brodatz. The first dataset, known as Brodatz-1, is made up of 1600 sub images drawn from 16 texture images in the Brodatz texture dataset [20]. The second dataset, known as Brodatz-2, consists of 11100 sub images drawn from 111 pictures in the original Brodatz texture collection [20]. The images are in grayscale, .gif format, and are not rotated. Each of the 111 texture images in the original Brodatz texture dataset has a size of 640×640 pixels. For both datasets, sub images are re sampled into 100 separate, 64x64 pixel patches that do not overlap. The sample

Images from the Brodatz texture dataset are displayed in The Fig.2. Table1 provides an explanation of the both datasets which are taken for the experiment.

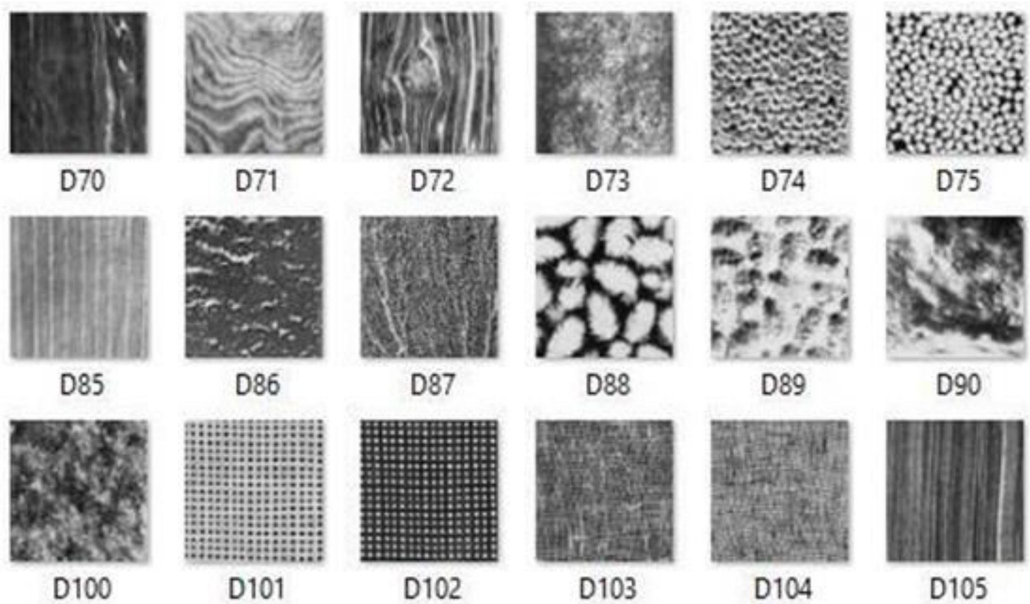

Figure: 2. Sample images of the Brodatz Texture dataset [20] Table: 1. Overview of the dataset used for the experiment

Dataset Used	***Brodatz-I***	***Brodatz-II***
Total no. of images experimented	16	111
Original image size	640 X 640	640 X 640
Patchified sub image size	64 X 64	64 X 64
Total no. of images after pacifying	1600	11100
Features extracted	**Features: Contrast, Dissimilarity, Homogeneity, Energy, Correlation**	

Brodatz texture datasets used for the proposed study are described in detail in the Table1.

[5.2] RANDOMIZATIONS AND SPLITTING THE DATA

The dataset's training and testing sets stated in the Section 5.1 are divided in the ratio 80:20, respectively.

[6] RESULTS AND DISCUSSION

The proposed work is experimented on Intel core i3 processor running at 2.40 GHz speed using 4GB RAM, Windows 10 Operating System.

The proposed work focused on ML classifiers which are discussed in the Section 3, are experimented. The results so obtained are shown in the following Figures 3, 4, and 5 represents the results of Brodatz-I (1600texture images) dataset in the form of confusion matrix for Ada Boost Classifier, Random Forest Classifier (RFC), and Decision Tree Classifier (DTC) respectively. Fig 6 represents the ensemble model of all three classifiers. Below figures shows the confusion matrix for the Brodatz- I dataset

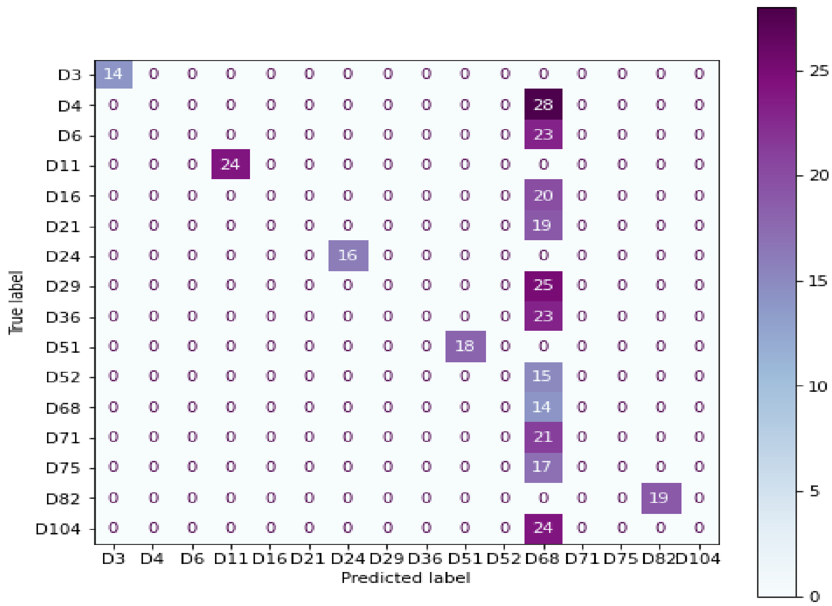

Figure: 3. Ada Boost Classifier

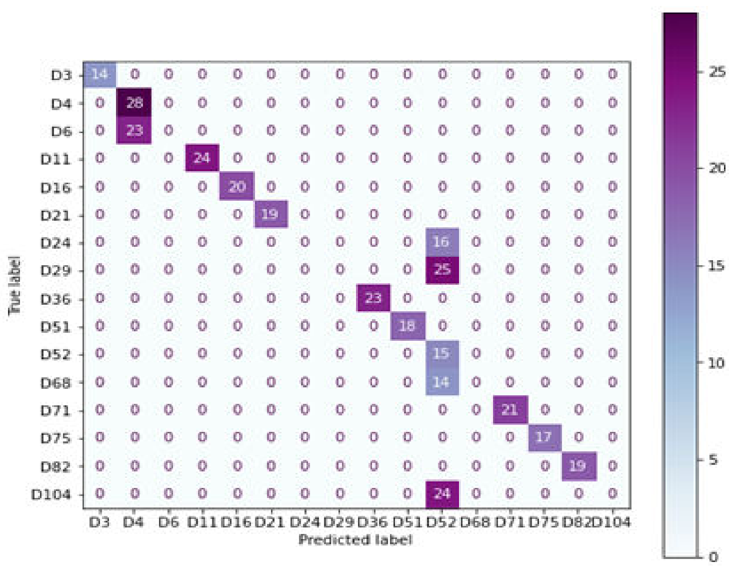

Figure: 4. Random Forest Classifier

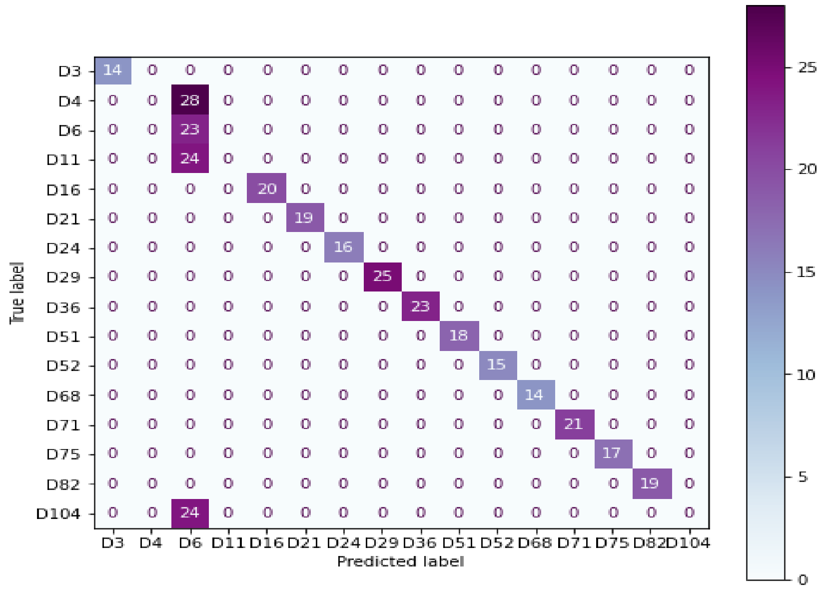

Figure: 5. Decision Tree Classifier

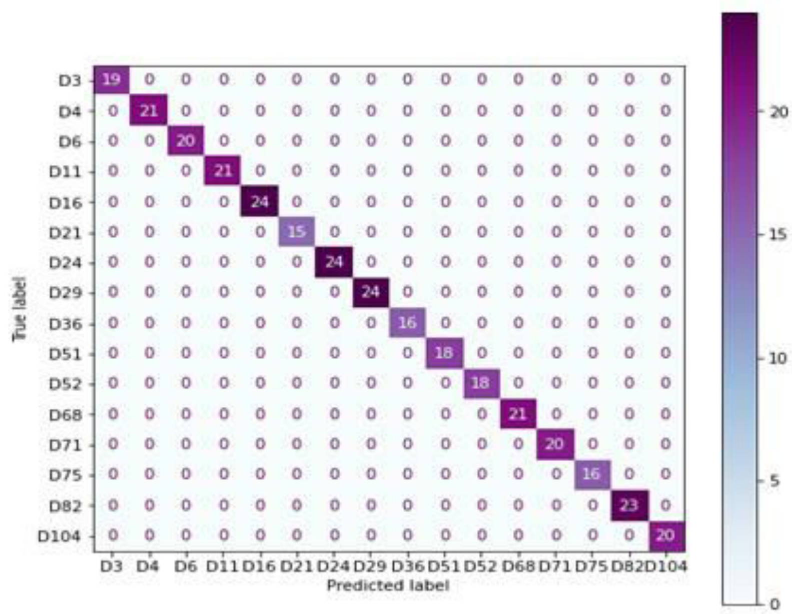

Figure: 6 . Ensemble model

The information regarding each classifier's prediction is shown in the figures above. We may infer from the findings that the ensemble model, which had a 100% accuracy rate and has the best match for the feature derived from the Brodatz image texture dataset, produced the better results.

Table 2 provides information regarding the precision, recall, and F1 scores of each classifier as well as the classification accuracy for the Brodatz-I dataset. For each classifier, the train time and test time are likewise noted.

Table: 2. Accuracy and classification report of Brodatz-I (1600 texture images) texture dataset

Classifiers	*Accuracy of 10 folds validation (%)*	*Precision*	*Re- call*	*F1-score*	*Train time (sec)*	*Test time (sec)*
ABC [1]	50	32	33	33	1.71	0.030
RFC [1]	64	81	76	76	0.11	0.03
DTC [1]	65	68	63	63	0.09	0.009
Proposed Ensemble model	**100**	**100**	**100**	**100**	**3.84**	**0.065**

From the Table 2 it is observed that the Ada Boost classifier has 50% of accuracy Random Forest classifier of 64% of accuracy and Decision Tree classifier has 65% of accuracy. The results are well exhibited with proposed Ensemble model with 100% accuracy with comparable computation time. This exhibits the effectiveness of the suggested approach. The Table 3 shows the results of Brodatz-2 (11100 texture images) texture dataset. From the Table 3 it is observed that the Ada Boost classifier has 12 % of accuracy, Random Forest classifier has 64 % of accuracy and Decision Tree classifier has 26% of accuracy. The results are well exhibited with Ensemble model with 100% accuracy. The classification accuracy of 10-fold cross validation is considered for comparison purpose in the discussion.

Table: 3. Accuracy and classification report of Brodatz-II (11100 texture images) texture dataset

Classifiers	*Accuracy of 10 folds validation (%)*	*Precision*	*Re-call*	*F1- score*	*Train time (sec)*	*Test time (sec)*
ABC [1]	12	11	11	11	7.85	0.90
RFC [1]	64	57	64	62	0.31	0.09
DTC [1]	26	22	18	18	0.08	0.008
Proposed Ensemble model	**100**	**100**	**100**	**100**	**37.8**	**1.311**

The Figure 7 depicts the results of the dataset Brodatz-I

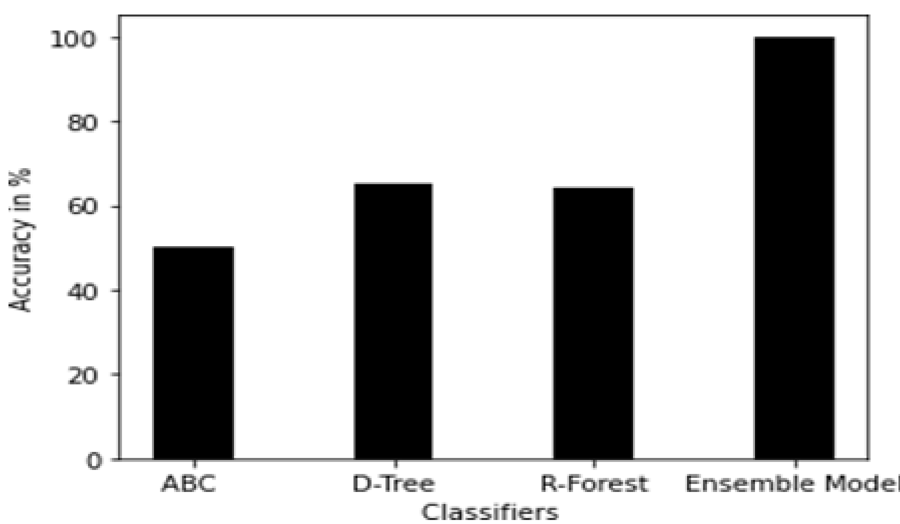

Figure: 7. Bar chart view of Brodatz-I

The Figure 8 depicts the results of the dataset Brodatz-II

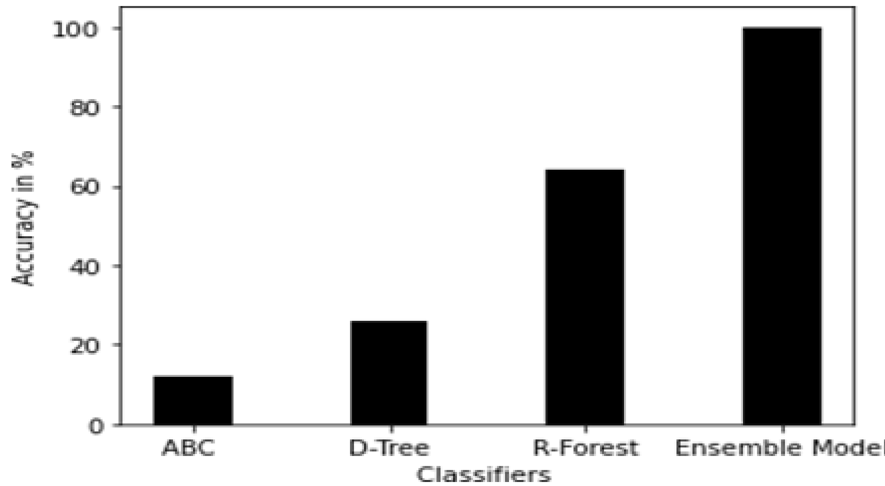

Figure: 8. Bar chart view of Brodatz-II

It is observed from the Figure 7and 8 that ensemble model performs better for both the datasets

Table: 4. Comparison of the acquired classification accuracy with the proposed method and state-of-the-art method using Brodatz image texture dataset.

Sl. No.	*Author*	*Features*	*Classifier*	*Classification result (%)*
01	Alharan et al. [15]	GLCM and LBP	KNN	**99**
02	Dhingra et al. [8]	LBP	KNN	**98**
03	Proposed Method	GLCM	Ensemble Model	**100**

Table 4 shows the comparisons of the acquired accuracy with the proposed methods and state of art method using the Brodatz image texture dataset.

The correctness of the performance is assessed using the Brodatz dataset. In comparison to several state-of-the-art procedures, an experimental finding of the proposed experimentation shows a higher categorization rate.

[7] CONCLUSIONAND FUTURE WORK

The proposed study mainly focuses on creation of ensemble model for the machine learning techniques. It mainly contributes the creation of own feature dataset in the form of CSV file using Brodatz texture dataset through Haralick feature extraction. Experiment is carried out on two datasets, one with 16 Bordatz texture image dataset and other with 111 Brodatz image texture dataset. Different machine learning classifiers, namely, Ada Boost classifier, Random Forest classifier and Decision Tree classifier are experimented on the both datasets to classify the Brodatz textures. Further, authors have designed the ensemble model of all three classifiers using the voting classifier. The proposed approach has performed better on created feature dataset with 100% classification accuracy. The future work can be extended with deep learning techniques and can work with the different features to analyze the dataset compatibility.

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