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Selective Harvesting of Tobacco Leaves: An Approach Based on Texture Features

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Abstract

A texture-based model for classification of tobacco leaves for the purpose of selective harvesting is proposed in this paper. It relies on texture features which are extracted by various texture models to represent the roughness of leaves. Extracted texture features are fused using concatenation rule. Discriminative texture features are then selected by employing wrapper feature selection methods. Finally, *K-NN* classifier is adapted for the purpose of classification. An extensive experimentation has been conducted on our own dataset to evaluate the performance of the proposed model. The experimental results reveal that the proposed model has achieved the best classification accuracy.

Key words: Tobacco leaves; Harvesting; Texture features; Feature selection; Classification.

1. Introduction

Precision agriculture is an integrated crop management system that attempts to match the type and quantity of inputs with the actual crop requirements for small areas within a farm field (Srinivasan, 2001). The potential of precision agriculture in terms of economic and environmental benefits could be visualized through reduced use of water, fertilizers, herbicides and pesticides in addition to the cost farm equipments. Instead of managing an entire field based upon some hypothetical average conditions, a precision agriculture approach recognizes site-specific differences within the field and adjusts accordingly the actions of management (Goovaerts, 2000). The objectives of the precision agriculture are profit maximization, rationalization of agriculture input and environmental damage reduction, by restricting the agriculture practices to the site demands. These objective could be achieved by adapting some site specific practices such as application of agrochemicals, right time harvesting, and grading of crops. Human intervention in these practices raises many disadvantages such as wrong diagnosis of diseases in crops, wrong quality analysis of crops, man power, labor cost and time consuming. Therefore, we need to automate these practices to increase efficiency and speed using computer vision (*CV*) algorithmic models.

Requirement of Precision agriculture at different stages of plant growth is shown in Figure 1.

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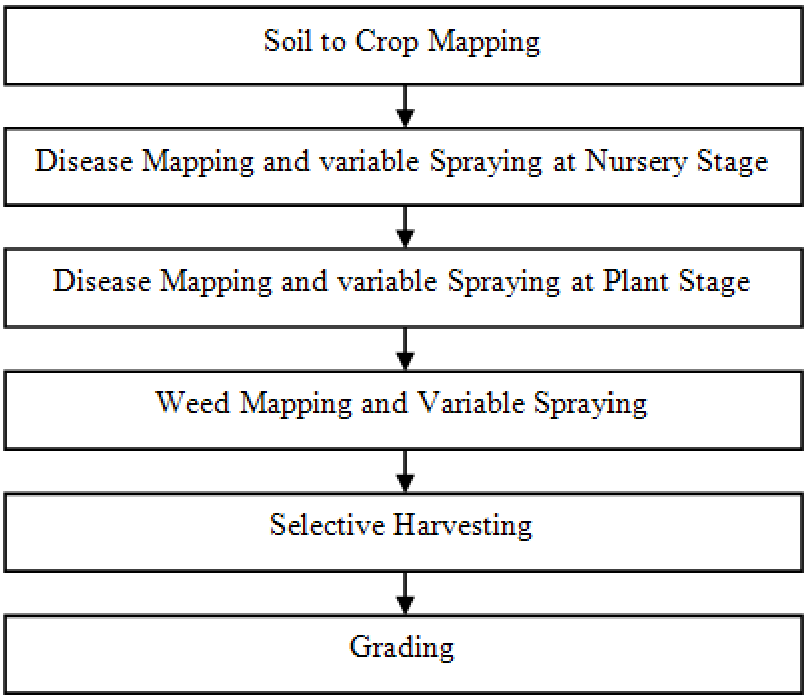


Figure 1: Requirement of precision agriculture at different stages of plant growth

Tobacco is a commercial crop in many countries like China, India, Brazil, United States, European Union, Zimbabwe, Indonesia, Malawi and Russia because of its high economic value. Especially in Karnataka state in India, that too around Mysore district, many farmers are depending on tobacco crop because of suitable climate conditions and soil. It created a gainful employment to several lakhs of people in India. Roughly 80 percent of the flue cured variety (*FCV*) of tobacco grown in Karnataka is being exported abroad to meet the demand of multinational industries for various purposes.

Harvesting is an important stage in tobacco crop. Tobacco crop is grown for production of quality leaves. The quality of a leaf depends upon the ripeness of the leaf while it is harvested. Therefore, while harvesting, farmers should look into factors such as unripe or ripe or over-ripe properties of leaves based on degree of ripeness of leaves. Ripeness of leaf begins after 50 days of plantation of tobacco seedlings. Harvesting usually begins after 60 days of plantation of tobacco seedlings. Leaves are removed at intervals as they ripened. Manual classification of unripe, ripe and over-ripe leaves is laborious, time consuming, inefficient and costly process. Automation of this process helps the tobacco farmers to gain more profit. Computer vision and image processing techniques can be exploited for classification of tobacco leaves supporting automatic harvesting, which increases the speed and accuracy of harvesting in addition to, reducing the number of human labors and cost.

With this backdrop, this work is to propose a model to automatically classifying tobacco leaves using computer vision technologies. Following are the overall contributions of this work.

- Development of a model which fuses the different texture features and selects the best discriminating features for classification of tobacco leaves on a plant for the purpose of harvesting ripen leaves.
- Segmentation of tobacco leaves from the background using *CIELAB* color model.

- Creation of a relatively large dataset of harvesting tobacco leaves due to non-availability of a benchmarking dataset.
- Conduction of experimentations on the created large tobacco dataset for demonstrating the effectiveness of the proposed model.

2. Related Work

Few attempts could be traced on ripeness evaluation of different crops for automatic harvesting. Medjool date fruits were taken as a case study to demonstrate the performance of a novel color quantization and color analysis technique for fruit maturity evaluation and surface defect detection (Lee *et al.*, 2008). Direct color mapping method (Lee *et al.*, 2011) was proposed for maturity evaluation of tomato and date fruits. This color mapping method maps the RGB values of colors of interest into 1-D color space using polynomial equations. It uses a single index value to represent each color in the specified range for the purpose of maturity evaluation of tomato and date fruits. A robotic system for harvesting ripe tomatoes in greenhouse (Yin *et al.*, 2009) was designed. In this work, L*a*b color space was used to segment tomatoes from complex background and K-means clustering method was applied on segmented tomatoes to recognize ripe tomatoes. Recently L*a*b color features and their combination along with texture features have been applied for the purpose of grading of mangoes using hierarchical classification approach (Anitha *et al.*, 2020). A novel and robust color space conversion and color index distribution analysis technique for automated date maturity evaluation (Lee *et al.*, 2008) was proposed. Computer vision technology for detecting fruit size, color, bruise, surface defects and evaluation of fruit overall quality (Gao *et al.*, 2010) were discussed. A genetic algorithm based neural network detecting system (Xu, 2009) was developed for evaluating maturity of strawberry fruits. In this paper, H frequency of HIS color model was used to distinguish maturity levels of strawberry fruits in a variable illumination conditions. An intelligent and robust algorithm (Furfaro *et al.*, 2007) was proposed to estimate absolute percentages of under-ripe (green), ripe (yellow), and over-ripe (brown) coffee cherries displayed on the canopy surface. The proposed algorithm was tested on the multispectral images. It was based on a coupled leaf/canopy radiative transfer model (*LCM2*). Feasibility of monitoring coffee field ripeness with airborne multispectral imagery (Johnson *et al.*, 2004) was proposed. In this work, reflectance spectrum was recorded from four major components of coffee field *viz.*, green leaf, under-ripe fruit, ripe fruit and over-ripe fruit. Based on reflectance spectrum, ripeness evaluation of coffee field was performed. A Bayesian classifier considering a multivariate, three-class problem (Baltazar *et al.*, 2008) was incorporated for data fusion to classify fresh intact tomatoes based on their ripening stages. In this work, data extracted from multiple sensors were fused. Further, fused data was used for the purpose of classification.

In our recent publication (Guru *et al.*, 2012), a model for classification of tobacco leaves for automatic harvesting of tobacco leaves using texture models was proposed. Apart from this, no attempts have been made on classification of tobacco leaves for automatic harvesting. In the proposed work, the classification accuracy has been improved by applying feature level fusion and feature selection methods.

3. Proposed Model

The proposed model consists of five stages – segmentation, feature extraction, feature level fusion, feature selection and classification. The color space model *CIELAB* is used to segment tobacco leaf area from the background. Features are extracted from segmented tobacco leaf using various texture models such as *LBP* (Local Binary Pattern), *LBPV* (Local Binary Pattern Variance), *GLTP* (Gray Level Local Texture Pattern), *GFR* (Gabor Filter Response) and *WD* (Wavelets Decomposition). These features are fused on different combination of texture models. The obtained fused feature vector is normalized. Features are selected from fused feature vector using wrapper feature selection methods such as *SFS* (Sequential forward selection), *SFFS* (Sequential floating forward selection), *SBS* (Sequential backward selection) and *SFBS* (Sequential floating backward selection). Then, *K-NN* classifier is used for classification of tobacco leaves in to three classes – unripe, ripe and over-ripe.

3.1. Segmentation

We have selected *CIELAB* (Viscarra *et al*., 2006) color model to segment a leaf area from their background (soil, stones and noise). Since the color of a leaf varies from green to yellow, the chromacity coordinate is used to segment the leaf from its background. For an illustration, we have shown three different samples (Figures 2, 3 and 4) of tobacco leaves and also the results of the segmentation.

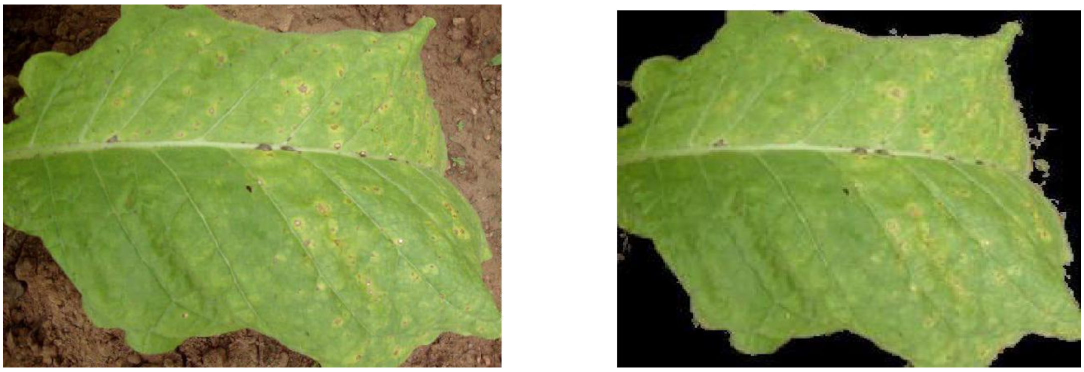
3.2. Feature extraction

Top surface of a leaf with rare maturity spots (see Figure 2) is smoother and its roughness increases as number of maturity spots increases (see Figures 3 and 4). This roughness is reflected by transitions in intensity levels on the surface of a leaf in the form of uniform and non-uniform patterns. To exploit this, we recommend to extract texture features from gray scale images of segmented tobacco leaves using the various texture based models *viz*., *LBP* (Ojala *et al*., 2002), *LBPV* (Guo *et al*., 2010), *GLTP* (He and Wang, 1990) (Surliandi and Kumar, 2008), *GFR* and *WD*.

3.3. Feature level fusion

Feature level fusion refers to combining different feature vectors that are obtained by employing multiple feature extraction algorithms. When the feature vectors are homogeneous, a single resultant feature vector can be obtained as a weighted average of the individual feature vectors. When the feature vectors are non-homogeneous, we can concatenate them to form a single feature vector (Jain *et al*., 2005).

The extracted feature vectors of *LBP*, *LBPV*, *GLTP*, *GFR* and *WD* are fused in all possible combinations by concatenating the feature vectors. The fused feature vectors are normalized using min-max method.



(a) (b)

Figure 2: (a) A sample tobacco leaf with rare maturity spots (b) Segmented image

(a) (b)

Figure 3: (a) A sample tobacco leaf with moderate maturity spots (b) Segmented image

(a) (b)

Figure 4: (a) A sample tobacco leaf with rich maturity spots (b) Segmented image

3.4. Feature selection

Feature selection is the process of selecting a subset of relevant features for building robust learning models. Feature selection is broadly classified into two categories such as filter model and wrapper model. The filter model relies on general characteristics of the training data to select some features without involving any learning algorithm. The wrapper model requires one predetermined learning algorithm in feature selection and uses its performance to evaluate and determine best features for selection.

A well-known filter method Relief (Kira and Rendel, 1992) relies on relevance evaluation. Time Complexity of Relief for a dataset with M instances and N features is O(MN). However, the Relief method does not help to eliminate redundant features. Empirical evidence from feature selection literature shows that, along with irrelevant features, redundant features also affect the speed and accuracy of learning algorithms and thus should be eliminated as well (Hall, 2000). Therefore, we have exploited feature selection methods based on wrapper model such as sequential forward selection (*SFS*), sequential floating forward selection (*SFFS*), sequential backward selection (*SBS*) and sequential floating backward selection (*SFBS*) (Ververidis and Kotropoulos, 2005, 2008). The criterion employed in these methods is the correct classification rate of the Bayes classifier assuming that the features obey the multivariate Gaussian distribution. These methods eliminate irrelevant features as well as redundant features but they are computationally slightly expensive than any filter method.

3.5. Classification

In the proposed model, the *K-NN* classifier based on G-statistic, Chi-square and Euclidean distance measure has been used to classify tobacco leaves into unripe, ripe and over-ripe for the purpose of harvesting.

3.5.1. Performance measures

To evaluate the correctness of classification algorithms, one should look into confusion matrix. A confusion matrix is a matrix plot of predicted versus actual classes of the samples.

Let k be the number of classes. Let r_i be the total number of samples of i^{th} class. Let c_i be the number of samples classified (labeled) as i^{th} class. Let T_i be the number of samples correctly labeled as i^{th} class. Then precision, recall, F-measure and classification accuracy (Espindola and Ebecken, 2005) are defined as follows.

Precision (P): Precision of the classifier model with respect to i^{th} class is the ratio of the number of samples correctly labeled as i^{th} class to the total number of samples labeled as i^{th} class. The precision of the classifier model with respect to i^{th} class is given by

$$\boldsymbol{P_i = \frac{T_i}{c_i}} \tag{1}$$

Recall (R): Recall of the classifier model with respect to i^{th} class is the ratio of the number of samples correctly labeled as i^{th} class to the total number of samples of i^{th} class. The recall of the classifier model with respect to i^{th} class is given by

$$R_i = \frac{T_i}{r_i} \tag{2}$$

F-measure (F): F-measure is the harmonic mean of precision and recall and it is given by

$$F = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{3}$$

Classification Accuracy (CA): It is the ratio of correctly classified samples to the total number of samples classified.

$$CA = \frac{\sum_{i=1}^{k} T_i}{\sum_{i=1}^{k} r_i} \tag{4}$$

4. Experimental Result

4.1. Dataset

Color images of tobacco leaves in real tobacco field are acquired using a Sony digital color camera. The leaves used for imaging are randomly selected from the tobacco field at Central Tobacco Research Institute (*CTRI*), Hunsur, Karnataka, India. Images are acquired at variable illumination conditions (sunny and cloudy). A total of 1300 sample images of size 250×250 are used for evaluating the proposed texture-based model.

Table 1: Number of samples of individual classes of tobacco leaves

Tobacco leaf Class	Number of samples	Total samples
Unripe leaf	323	1300
Ripe leaf	667	
Over-ripe leaf	310	

4.2. Experimentation

In the first set of experimentation, we conducted experiments for the proposed model based on individual texture models. During experimentation, we conducted four different sets of experiments. In the first set of experiment, we used 30% of the samples of each class of a harvesting dataset to create class representative vectors (training) and the remaining 70% of the samples for testing purpose. In the second set, third set and fourth set of experiments, the numbers of training and testing samples are in the ratio of 40:60, 50:50 and 60:40 respectively. In each set of experiment, experiments are repeated 20 times by choosing the training samples randomly. As measures of goodness of the proposed model based on individual texture model, we computed minimum, maximum, average and standard deviation of classification accuracy of all the 20 trails using the *K-NN* classifier. Classification accuracy of the proposed model based on individual texture models (*LBP*, *LBPV*, *GLTP*, *GFR* and *WD*) for 30% training, 40% training, 50% training and 60% training are depicted in Figures 5-8 respectively. It is observed from Figures 5-8 that the *GLTP* texture model has achieved a better average classification accuracy in experiment 4 (60% training samples) when compared to the other texture models. It is also observed that the proposed model has achieved a good classification accuracy for all the individual texture models in experiment 4 (60% training samples) when compared to that of experiment 1 (30% training samples), experiment 2 (40% training samples) and experiment 3 (50% training samples).

Therefore, we present experimental results obtained for 60% training only for fusion of texture features and application of feature selection method. In the second set of experimentation, we conducted experiments for the proposed model based on fusion of texture features. That is, the extracted feature vectors of *LBP*, *LBPV*, *GLTP*, *GFR* and *WD* are fused in all possible combinations by concatenating the feature vectors. During experimentation, experiments are repeated 20 times by choosing the training samples randomly. As measures of goodness, we computed minimum, maximum, average and standard deviation of classification accuracy of all the 20 trails using *K-NN* classifier. Classification accuracy of the proposed model based on fusion of 2 texture models at a time, 3 texture models at a time, 4 texture models at a time and all 5 texture models are depicted respectively in Figures 9-12. It is observed from Figures 9-12 that overall fusion of *GLTP* and *WD* features has achieved the best average classification accuracy when compared to the other fusion of texture models in any combination. Fusion of *GLTP* and *WD* features has achieved an improvement in classification accuracy when compared to that of an individual texture model. It is also observed that for all combinations of fusion of texture features, good classification accuracy is achieved for G-statistic distance measure when compared to the Chi-square and the Euclidean distance measures. Also, Confusion matrix for fusion of *GLTP* and *WD* features is tabulated in Table 2 and performance measures such as Precision, Recall and F-measure of individual classes are tabulated in Table 3.

In third set of experimentation, we conducted experiments based on fusion of texture features and the application of feature selection method. That is, we applied the wrapper feature selection method (*SFS*, *SBS*, *SFFS* and *SFBS*) on fused texture feature vector to reduce the dimension of feature matrix and to obtain discriminative texture features. During experimentation, experiments are repeated 20 times by choosing the training samples randomly. Classification accuracy of the proposed model based on fusion of texture features and feature selection method for 2 texture models at a time, 3 texture models at a time, 4 texture models at a time and all 5 features are depicted respectively in Figures 13- 16. Here we presented results of G-statistic for 60% training as it was observed to have good results for the G-statistic based *K-NN* classifier. It is observed from Figures 13-16 that the fusion of *GLTP* and *WD* features with *SBS* feature selection method has achieved best average classification accuracy when compared to other combinations. Also, Confusion matrix for fusion of *GLTP* and *WD* features with *SBS* feature selection method is tabulated in Table 4 and performance measures such as Precision, Recall and F-measure of individual classes are tabulated in Table 5.

5. Discussion

From the experimental results, it is observed that the *GLTP* texture model has dominant features when compared to *LBP*, *LBPV*, *GFR* and *WD*. Since the *GLTP* is built by the advantages of TS and *LBP*, it reveals more local texture information when compared to texture models such as Gabor response and Wavelet decomposition. The *GLTP* assigns a label (uniform label or non-uniform label) for each pixel in an image based on the uniformity or non-uniformity of neighborhood, where as the *GFR* is based on frequency and orientation of edge information. Though, the *GFR* is rotation invariant local texture information, fusion of Gabor response with the other texture models such as *LBP*, *LBPV*, *GLTP* and Wavelet decomposition has deteriorated the performance because the Gabor response will not represent edge information in the form of uniform patterns and non-uniform patterns. Fusion of *LBPV* with other texture models such as *LBP*, *GLTP*, Gabor response and Wavelet decomposition has also deteriorated the performance because global information such as variance is embedded with local information in the *LBPV*. Therefore, the *LBPV* will deteriorate the classification accuracy.

Feature selection after fusion has improved the classification results for all combination of fusion of texture models. In all feature selection methods, the dominant features are selected. When analyzed we observed that, the *SBS* method on fusion of *GLTP* and Wavelets has selected only 15 features out of 55 features (*GLTP* – 46 features and Wavelets – 9 features). Out of 15 features, 10 features are from the *GLTP* and 5 features are from the *WD*. Therefore, the *GLTP* has more number of discriminating features with *WD* features and improve the classification accuracy. Similarly, the *SFS* on fusion of *GLTP* and *LBP* has selected only 6 features out of 56 features (*GLTP* – 46 features and *LBP* – 10 features). All 6 features are from the *GLTP* alone. This indicates that the *LBP* has no discriminating dominant features when it is with the *GLTP* features. Further, the *SFBS* on fusion of *GLTP*, *LBP* and *WD* has selected only 8 features. Out of 8 features, 4 features are from the *GLTP* and 4 features are from the *WD*. No discriminating features of *LBP* are selected when they are with *GLTP* and *WD* features.

The above observations appraise that *GLTP* and *WD* features have more discriminating and dominating features when compared to the other texture models such as *LBP*, *LBPV* and *GFR*.

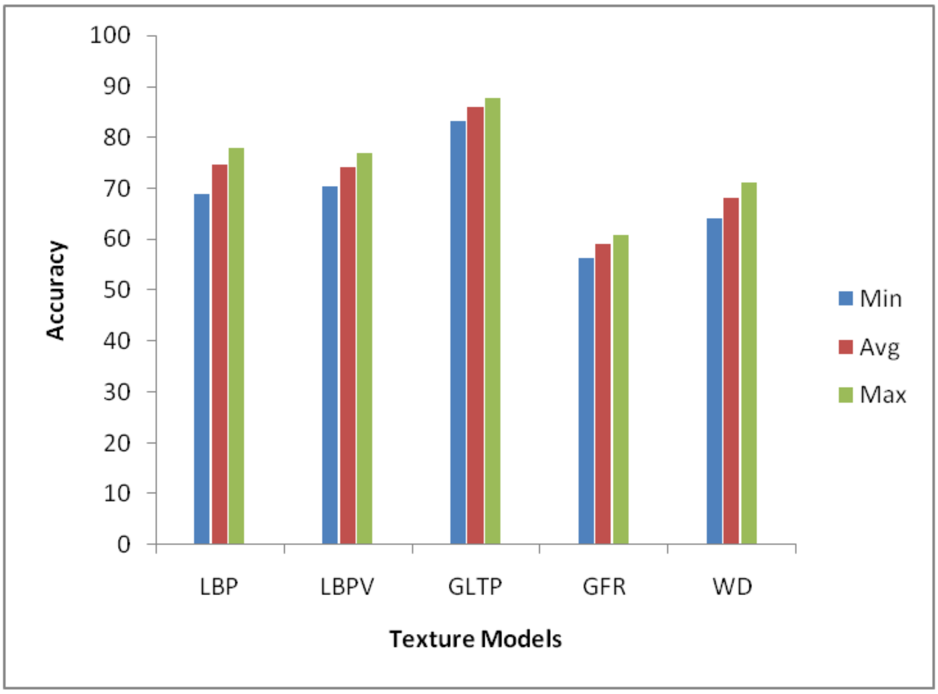


Figure 5: Classification accuracy of the proposed model based on individual texture models for 30% training

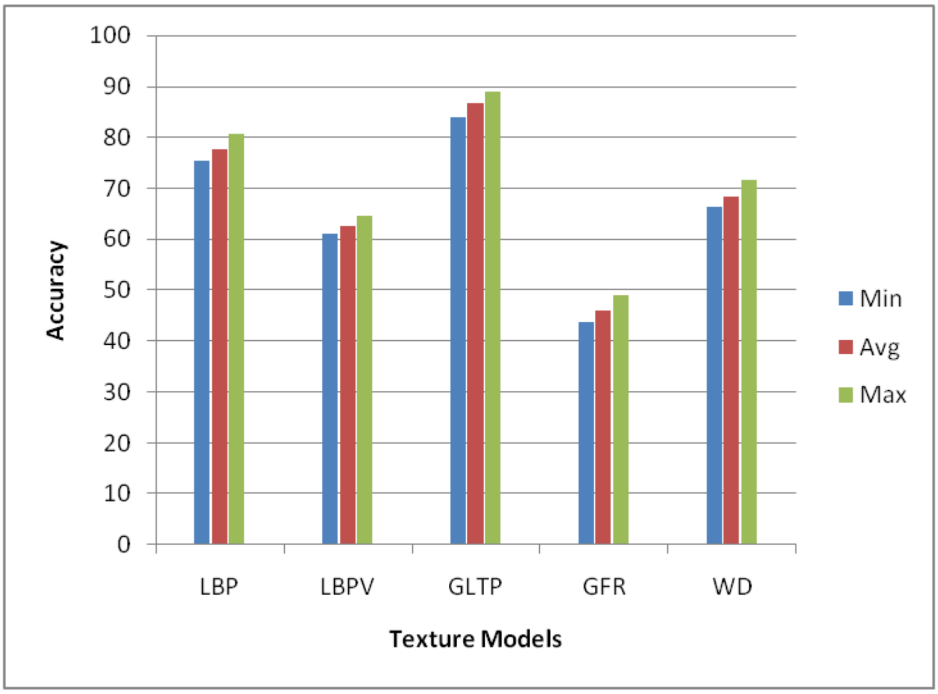


Figure 6: Classification accuracy of the proposed model based on individual texture models for 40% training

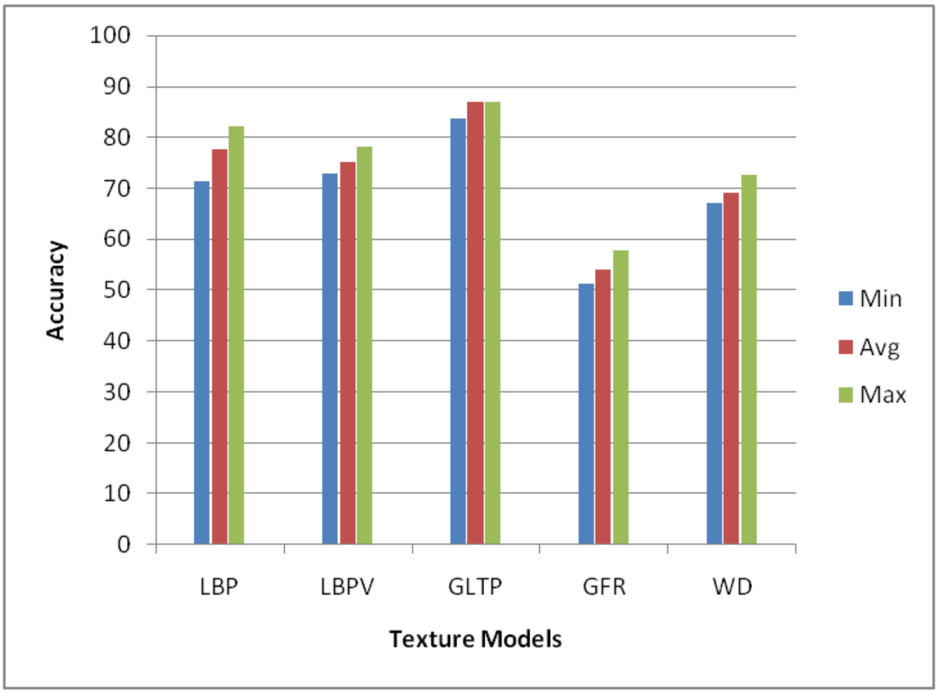


Figure 7: Classification accuracy of the proposed model based on individual texture models for 50% training

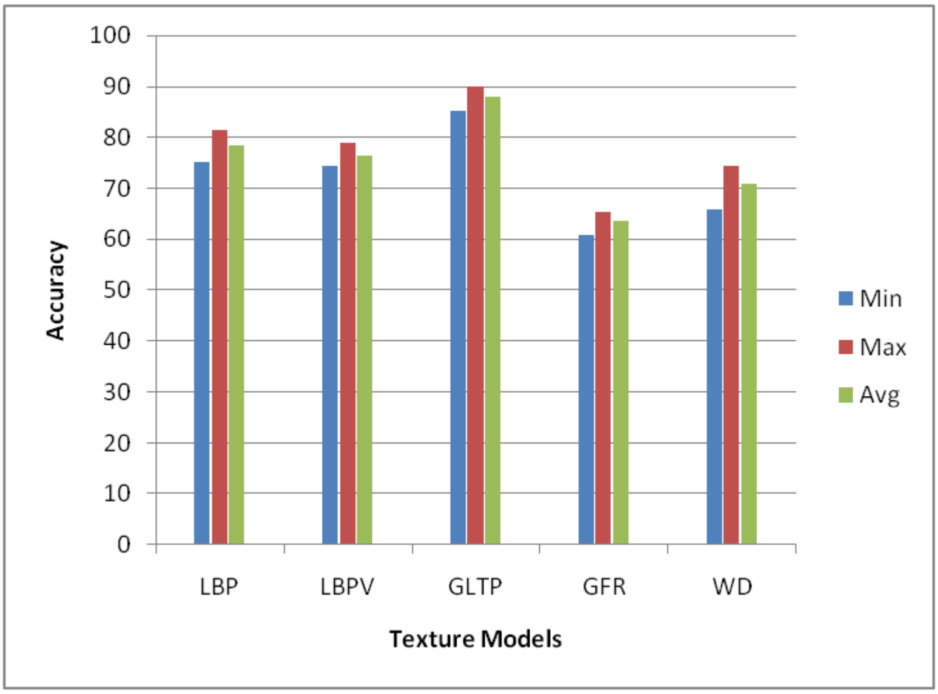


Figure 8: Classification accuracy of the proposed model based on individual texture models for 60% training

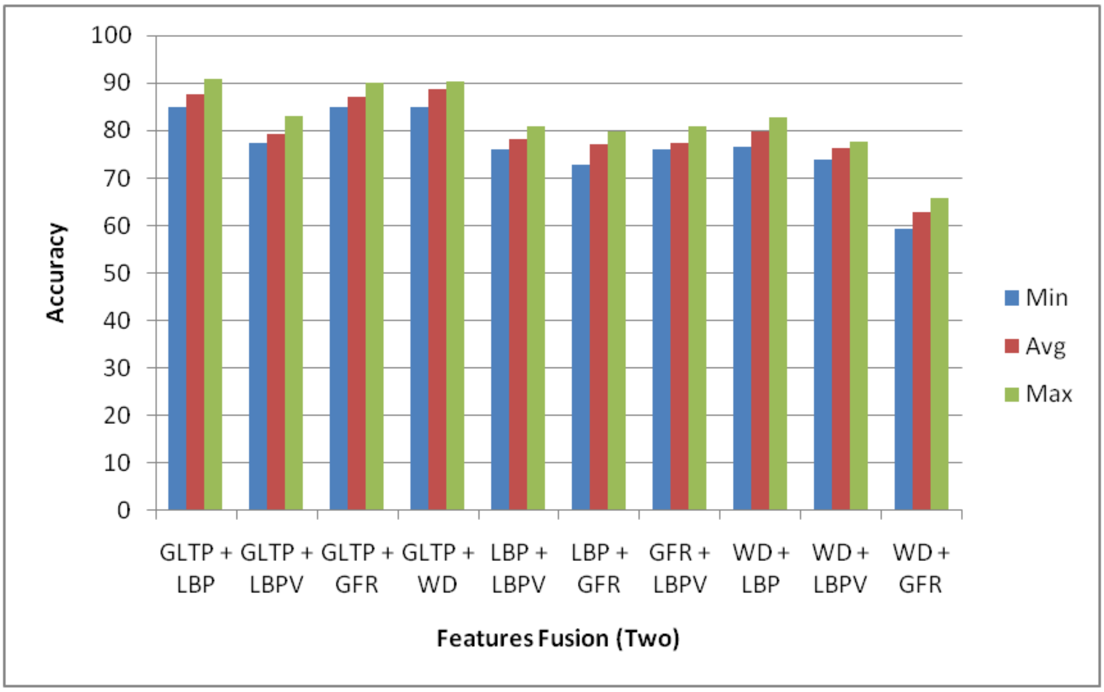


Figure 9: Classification accuracy of the proposed model based on fusion of 2 texture models at a time

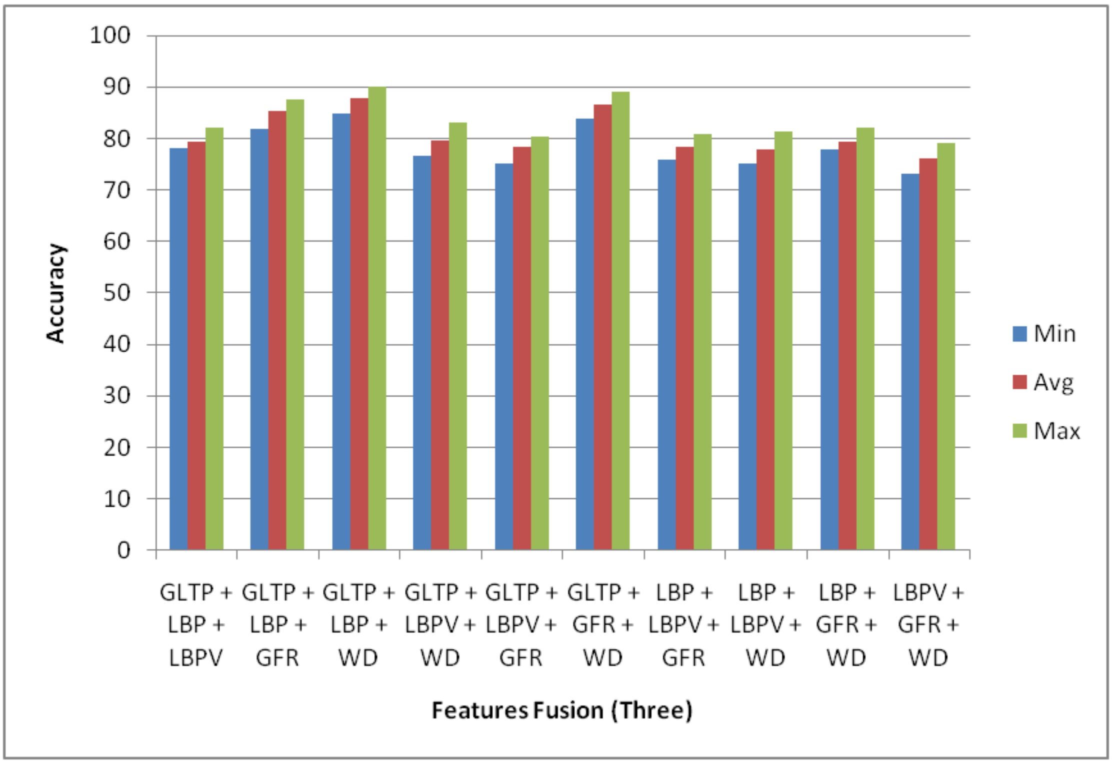


Figure 10: Classification accuracy of the proposed model based on fusion of 3 texture models at a time

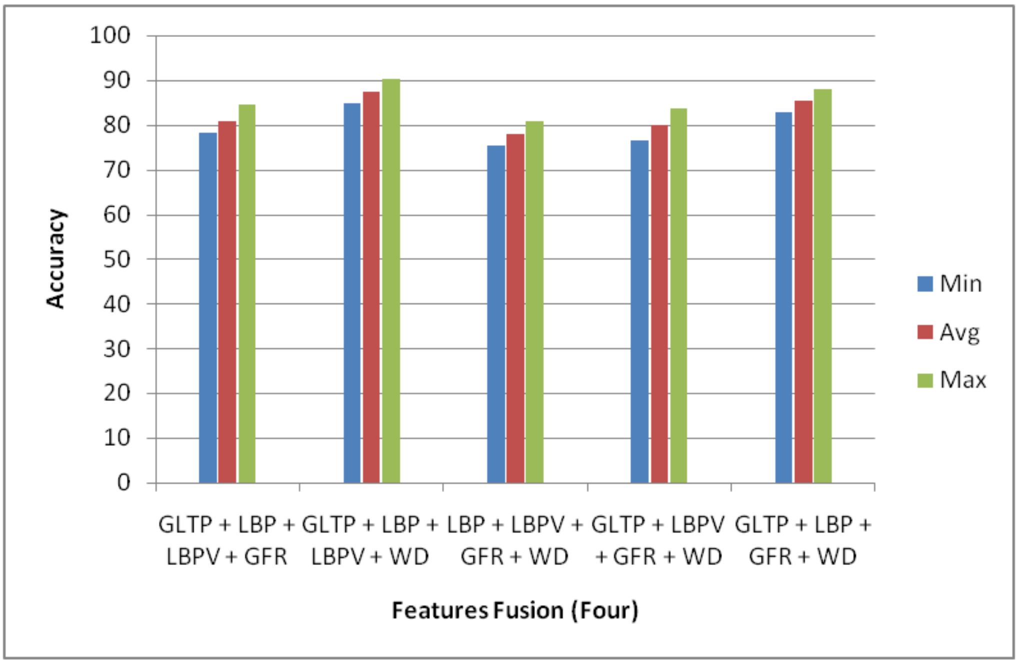


Figure 11: Classification accuracy of the proposed model based on fusion of 4 texture models at a time

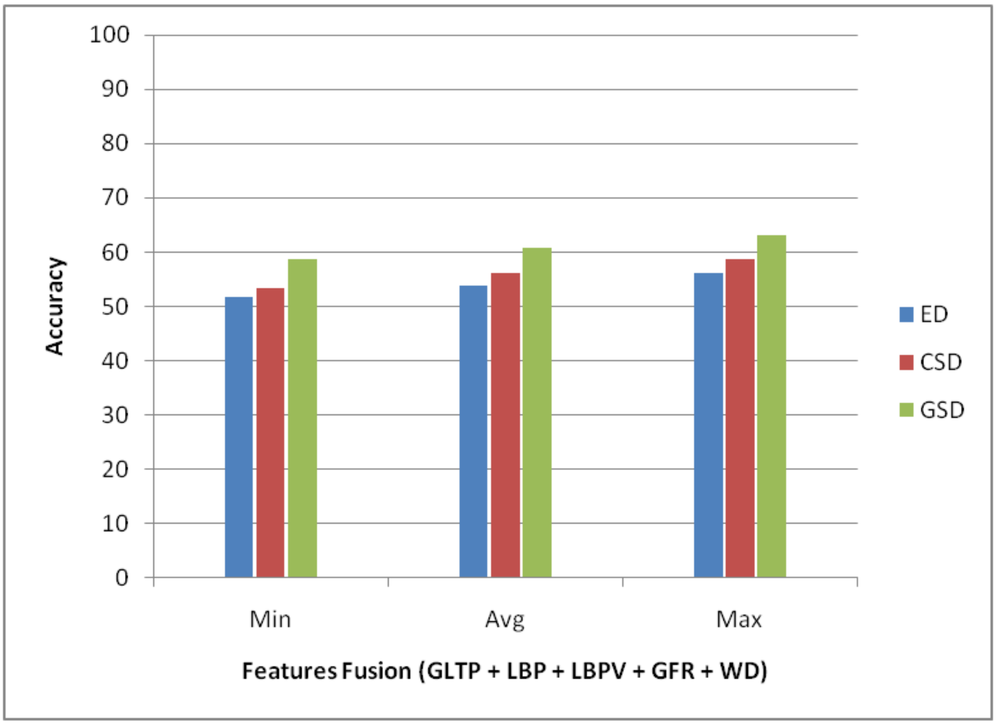


Figure 12: Classification accuracy of the proposed model based on fusion of 5 texture models at a time

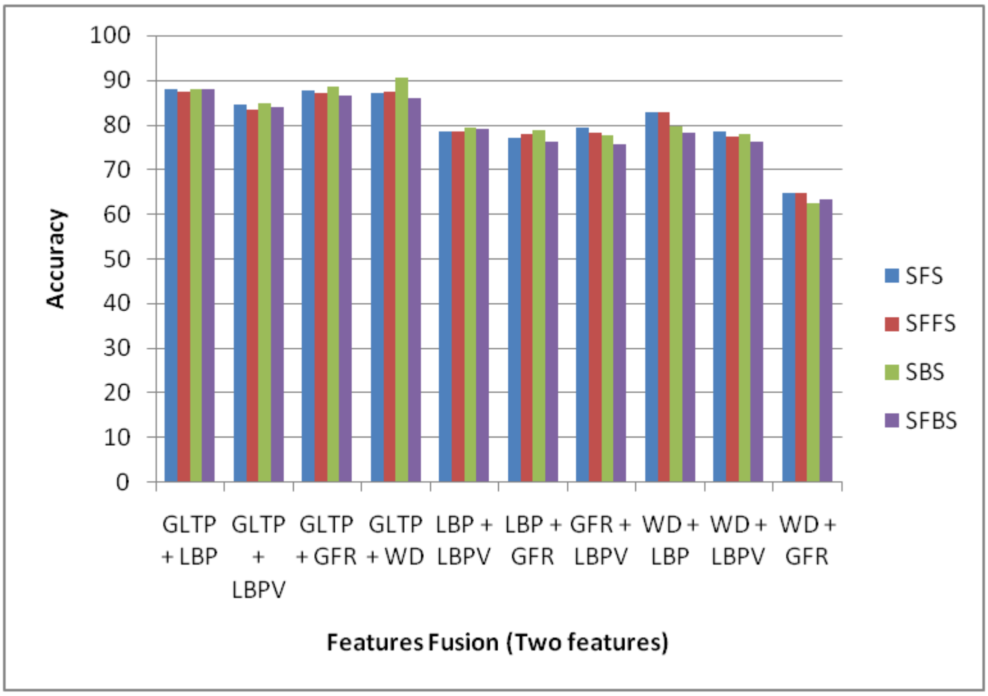


Figure 13: Classification accuracy of the proposed model based on fusion of 2 texture models at a time and feature selection methods

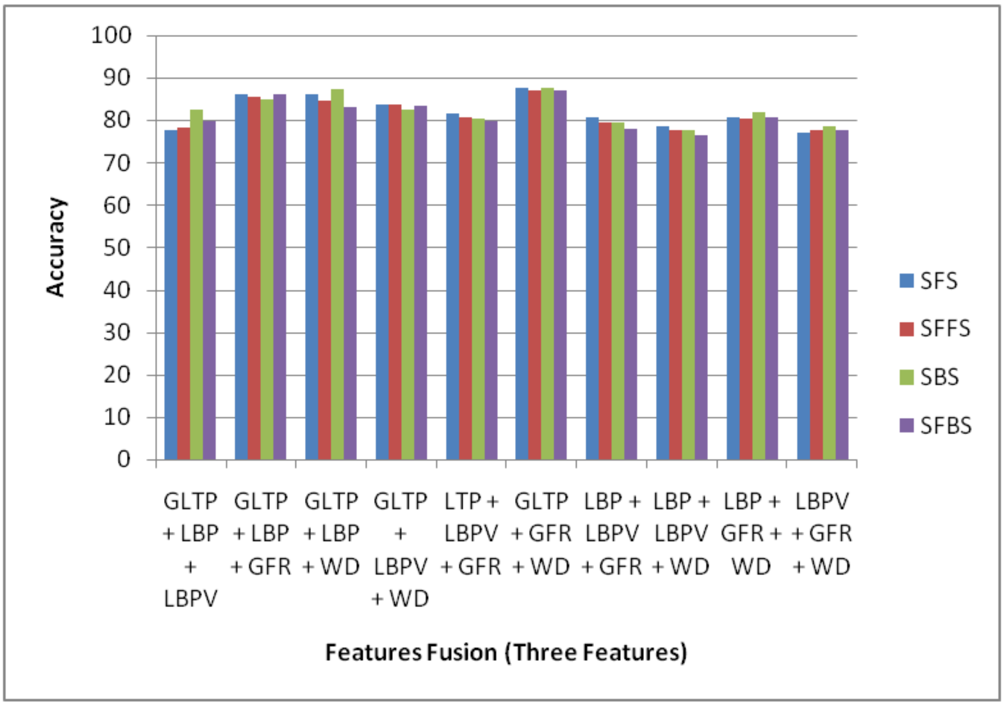


Figure 14: Classification accuracy of the proposed model based on fusion of 3 texture models at a time and feature selection methods

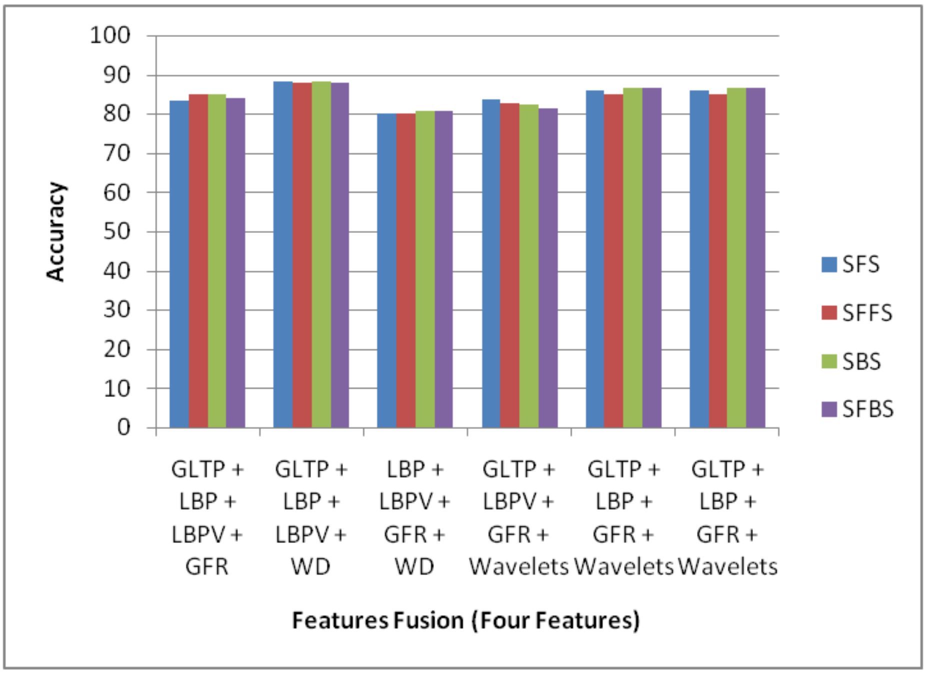


Figure 15: Classification accuracy of the proposed model based on fusion of 4 texture models at a time and feature selection methods

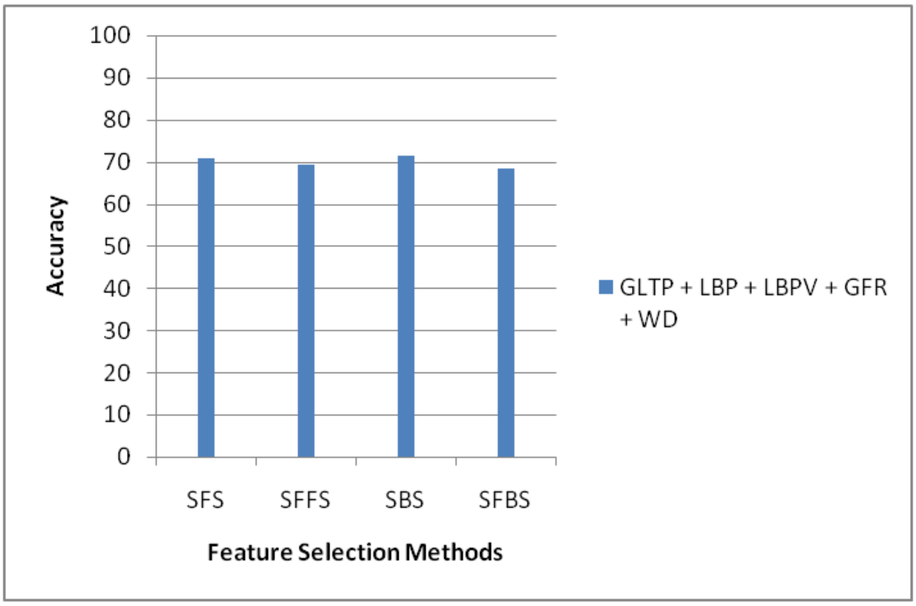


Figure 16: Classification accuracy of the proposed model based on fusion of 5 texture models at a time and feature selection methods

Table 2: Confusion matrix across leaf types using the proposed model based on fusion of 2 texture models (*GLTP* and *WD*) at a time

		Predicted Class		
		Unripe	Ripe	Over-ripe
Actual Class	Unripe	109	20	00
	Ripe	10	240	16
	Over-ripe	00	18	106

Table 3: Performance of the proposed model based on fusion of 2 texture models (*GLTP* and *WD*) at a time

Leaf Class	Precision	Recall	F-measure
Unripe	0.91	0.84	0.87
Ripe	0.86	0.90	0.87
Over-ripe	0.86	0.85	0.85

Table 4: Confusion matrix across leaf types using the proposed model based on fusion of 2 texture models (*GLTP* and *WD*) and *SBS* feature selection method

		Predicted Class		
		Unripe	Ripe	Over-ripe
Actual Class	Unripe	112	17	00
	Ripe	07	250	09
	Over-ripe	00	16	108

Table 5: Performance of the proposed model based on fusion of 2 texture models (*GLTP* and *WD*) and *SBS* feature selection method

Leaf Class	Precision	Recall	F-measure
Unripe	0.94	0.86	0.89
Ripe	0.88	0.93	0.90
Over-ripe	0.92	0.87	0.89

6. Conclusion

In this paper, a model based on texture features for classification of tobacco leaves for the purpose of harvesting is presented. A successful attempt is made to explore the applicability of texture features and wrapper feature selection methods for effective classification of tobacco leaves for the purpose of selective harvesting. The future work is expanding this for video data and developing in a real time environment.

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