Ventral side of a Leaf Image: Another Alternative for Leaf Image Classification

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Abstract

The plants have been used by human beings since ages for satisfying his general needs for food, shelter and medicinal values. Many of the plant species are on the verge of extinction, therefore, in order to preserve them for future, naming convention has a role to play. Many of the plant species are yet unknown and due to climatic changes and human factors, the plant species are dying out. Therefore, it is a dire necessity to know these unknown species in a better and a faster way. Leaf is an ornament of the plant and has a crucial role in classifying the plant on its own basis. The objective of this study is to find an alternative for the dorsal leaf image classification. As of now, only the dorsal side of the leaf image is considered for this purpose. This study proposes to utilize the texture features available on the ventral side of the leaf image for classification purpose using Gabor based texture features. The discrimination of the leaf images have been performed through classification algorithms: K-nearest neighbor, J48, Classification and Regression Tree and Random Forest. The results show better classification accuracy rates for ventral side of the leaf image over the dorsal side.

Keywords: *Classification, Leaf Images, Dorsal Side, Ventral Side, Gabor Filter, Texture Features.*

1. Introduction

The plants have been used by human beings since ages for satisfying his general needs for food, shelter and medicinal values. The plants have been studied for improving food production, varieties of fruits and flowers and for finding remedies for plant diseases. The different parts of the plant like flower, stem, roots & shoots and leaves have been under constant scientific observations, in order to study taxonomy, to make them disease free and independent of environmental effects on production. There are millions of plant species on this planet with regional variations within the subcontinent. Many of the plant species are on the verge of extinction, therefore, in order to preserve them for future, naming convention has a role to play. Though, the taxonomic classification of plants is more than a century old activity and computer vision scientists have played their own role in automatization of the plant identification process by considering the visual leaf attributes, the shape, size and color of the leaves, still plants have often been the major area of research in botanical science, and in computer science as well.

Texture is a basic characteristic visual feature, which helps the human visual system in segmentation and recognition based processes, performed by human brain. Texture based features in computer vision science have been playing its role for the last couple of years. Textures can be divided into two categories, namely, *tactile* and *visual* textures. Tactile textures refer to the immediate tangible feel of a surface. Visual textures refer to the visual impression that textures produce to human observer, which are related to local spatial variations of simple stimuli like color, orientation and intensity in an image [1] as shown in Fig. 1.

The objective of this study is to find an alternative for the leaf image classification as of now, only the dorsal side of the leaf image is considered for this purpose. This study proposes to utilize the texture features available on the ventral side of the leaf image for classification purpose. The texture features have been extracted using Gabor filter and the classification has been performed using K-nearest neighbor (KNN), J48, Classification and Regression Tree (CART) and Random Forest (RF) algorithms for both dorsal and ventral sides of the leaf images. Section 2 explains the methodology adopted for achieving the objective of the study. In section 3, the results obtained from the proposed study have been discussed as well as compared with the present research and in section 4, conclusion has been drawn.

Fig. 1. A sample of visual texture images

2. Methodology Adopted

2.1 Creation of leaf image dataset

There are several dorsal leaf image datasets available [2], [3], [4], but for the proposed study, there was a need to create a dataset having dorsal as well as ventral sides of the leaf images. For the proposed study the dorsal as well as the ventral side of the 10 different leaf species have been captured as shown in Fig. 2. The captured images include 25 dorsal side and 25 ventral side images for each leaf species, totaling a sample size of 500 images with a pixel size of 1080 X 920.

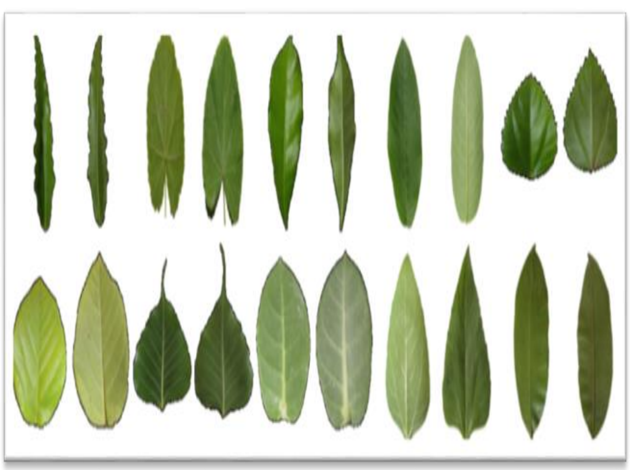

Fig. 2. A partial leaf image dataset

2.2 Preprocessing and enhancement of images

All the colored images were converted into 8-bit gray scale and their size was reduced to 256 X 256 which reduced the size of the dataset and a stack was created using [5]. The 8-bit gray scale images are normalized which involves stretching the image pixel values to cover the entire pixel value range (0-255). The normalization process [6] transforms the gray scale image I with intensity values in the range of $\{Min, ..., Max\}$ as shown in Eq. (1)

$$I : \{X \subseteq \mathbb{R}^n\} \to \{Min, ..., Max\} \tag{1}$$

to a new image I_N with intensity values in the range of $\{newMin, ..., newMax\}$ as shown in Eq. (2)

$$I_N : \{X \subseteq \mathbb{R}^n\} \to \{newMin, ..., newMax\} \tag{2}$$

The linear normalization process is represented with Eq. (3)

$$I_N = (I - Min)\left(\frac{(newMax - newMin)}{(Max - Min)}\right) + newMin \tag{3}$$

Now, this I_N image undergoes histogram equalization [7] process which is a technique for adjusting image intensities to enhance contrast of the images and this gives image g (a histogram equalized image) which is represented through the Eq. (4)

$$g_{i,j} = floor\left((Max - 1)\sum_{n=0}^{I_{i,j}} I_N\right) \tag{4}$$

Now, this $g_{i,j}$ is utilized for processing with the Gabor filter.

One of the dorsal leaf images Slice-1 and its enhanced image Slice-1E is shown in Fig. 3 with corresponding normal and enhanced histograms respectively. Similarly, one of the ventral leaf images Slice-265 and its enhanced image Slice-265E is shown in Fig. 4 with corresponding normal and enhanced histograms respectively. It can be clearly seen that after enhancement, both the dorsal and ventral images show proper distribution of gray level pixels as shown in Fig. 3 and 4. This process has been adopted for all the dorsal and ventral images of the dataset. The enhanced images have been collected separately and further processed with the Gabor filter technique as mentioned in the subsection 2.3.

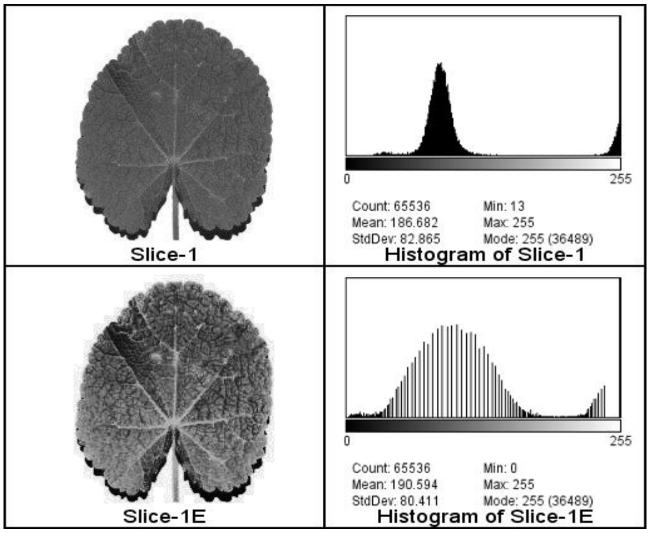

Fig. 3. Histogram representation for Slice-1 and Slice-1E(Dorsal side of the leaf image)

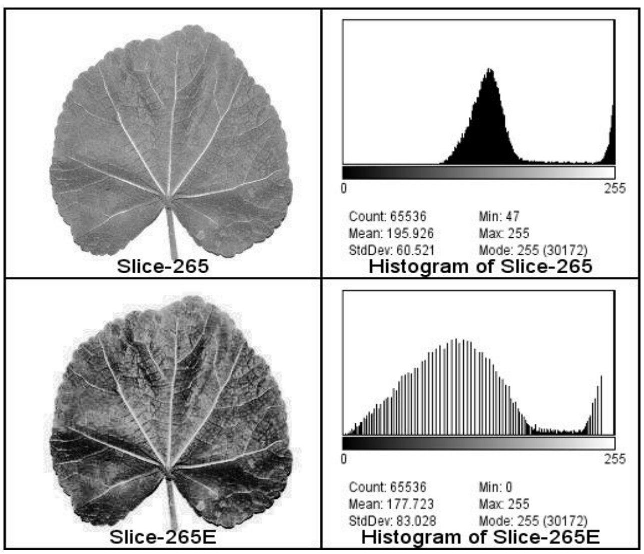

Fig. 4. Histogram representation for Slice-265 and Slice-265E(Ventral side of the leaf image)

2.3 Extraction of texture features using Gabor filter

The term Gabor filter has been coined after the name of Dennis Gabor who in the year 1946 experimented and subsequently proposed the representation of the signals. In image processing tasks, Gabor filters have been extensively been used for feature extraction for the digital leaf images. The frequency and orientation representation as used in Gabor filters, are useful for texture representation and discrimination and the same concept is used in human visual system.

The most important properties are related to invariance to illumination, rotation, scale, and translation. The Gabor filters have several advantages in feature extraction process over other techniques used for the similar purpose. The Gabor feature vectors can be used directly as input to a classification or segmentation operator or they can first be transformed into feature vectors, which are then used as input for another stage. The Gabor features have created a niche for themselves in the areas of face recognition, character recognition, browsing and retrieving of image data. The concept of Gabor theory [8] has been represented in Eq. (5), (6) and (7).

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(\frac{-x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (5)$$

The Eq. (5) represents the complex form of the Gabor representation.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(\frac{-x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (6)$$

The Eq. (6) represents the real part of the Gabor representation.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(\frac{-x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (7)$$

The Eq. (7) represents the imaginary part of the Gabor representation, where $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$.

In Eq. (5), (6) and (7), λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the standard deviation of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

The contrast enhanced image with the help of histogram equalization process undergo Gabor transform as mentioned in Eq. (6). The Gabor transform of an image $I(x, y)$ is defined as the convolution of a Gabor filter $g(x, y)$ as shown in Eq. (8) and (9).

$$R(x,y) = g(x,y) * I(x,y) \quad (8)$$

Therefore,

$$R(x,y)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} g\left(m,n\right).I\left(x-m,y-n\right) \tag{9}$$

The operator $*$ in Eq. (8), denotes the two dimensional linear convolution, M and N are the sizes of the Gabor filter space.

The Gabor filters extract characteristics in specific orientation and frequency bands called Gabor coefficients [9], [10] and denoted by Eq. (10).

$$G\left(s,\theta\right)_{(x,y)}=\sqrt{E^2{}_{(s,\theta)(x,y)}+O^2{}_{(s,\theta)(x,y)}} \tag{10}$$

Where, $E_{(s,\theta)}=I*g_{e(s,\theta)}$ and $O_{(s,\theta)}=I*g_{o(s,\theta)}$

Here, scale s and orientation θ are odd symmetric and even symmetric filters for the image I and in Eq. (10) $*$ denotes the convolution operation.

A single Gabor filter will detect patterns in the leaf images with a certain fixed frequency and an orientation value. To capture the entire texture feature available in a digital image, the Gabor filter bank is tuned at different frequency and orientation values.

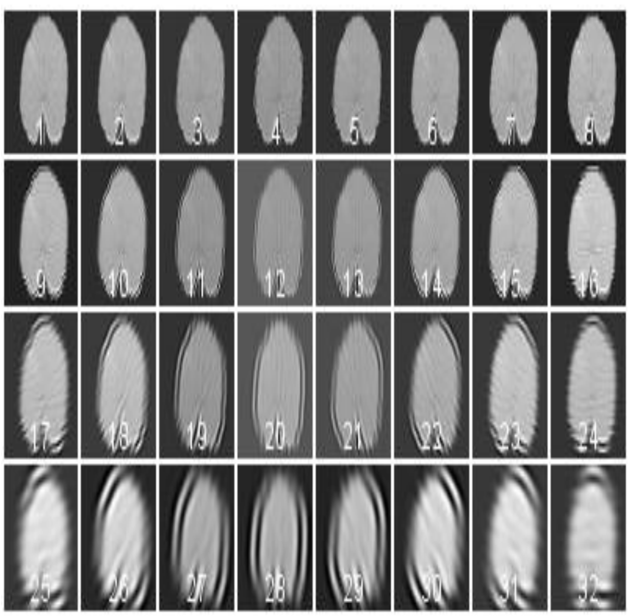

Fig. 5. Slice-1 convolved with Gabor Filter, generates 32 images at different scale and orientation values.

The 32 real images generated by Gabor filter for leaf image Slice-1 of the dorsal side leaf image dataset is shown in Fig. 5 for 4 different scale values(2,4,8,16) and 8 different orientation values(22^0,44^0,66^0,88^0,110^0, 132^0,154^0,176^0). Similar process is followed for all the leaf images of dorsal and ventral sides of the dataset mentioned in subsection 2.1. For each image in the dataset, a group of wavelets is generated by dilation and rotation of the Gabor function. The image details of Slice-1 of the dorsal leaf image dataset at specific scale and orientation are captured and is shown in Fig. 6 and these details are the same as that of the ones present at the visual cortex of the human beings. Similar procedure has been adopted for generating the image details of the complete dataset mentioned in subsection 2.1.

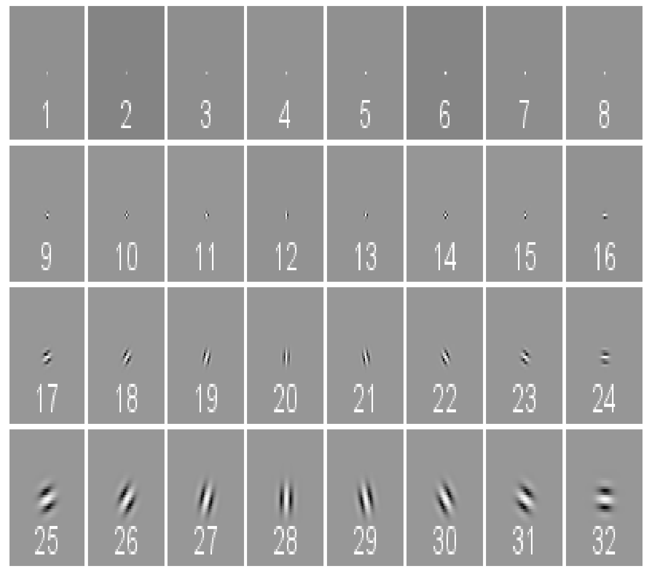

Fig. 6. Image details for Slice-1 convolved with Gabor Filter, generates 32 images at different scale and orientation values.

After the images have undergone enhancement and convolution with Gabor transform, the Gabor texture features[11], [12] like Mean, Energy, Standard deviation, contrast, skewness and kurtosis have been extracted from the complete set of preprocessed slices in the dataset as mentioned in Eq. (11), (12), (13), (14) and (15).

The Gabor features extracted are mentioned below.

Mean(TF_1): The mean is denoted as mentioned in Eq. (11).

$$\mu_{(s,\theta)}=\frac{1}{NM}\sum_{x=1}^{N}\sum_{y=1}^{M} G_{(s,\theta)(x,y)} \tag{11}$$

Mean has been calculated at specific values of scale s and orientation θ.

Energy(TF_2): The texture energy is expressed as $E\left(x,y\right)$ and is mentioned in the Eq. (12).

$$E(x,y) = \frac{1}{M} \sum_{(a,b \in w)} \left| R(a,b) - \mu \right| \quad (12)$$

Standard Deviation(TF_3): The standard deviation has been calculated as mentioned in Eq. (13).

$$\sigma_{(s,\theta)} = \sqrt{\frac{1}{NM} \sum_{x=1}^{N} \sum_{y=1}^{M} \left(G_{(s,\theta)(x,y)} - \mu_{(s,\theta)} \right)^2} \quad (13)$$

Skewness(TF_4): Skewness is the measure of asymmetry and is denoted by γ**,** it can be positive which means that the distribution tends towards right, and if it is negative then the distribution tends towards left and is represented by Eq. (14).

$$\gamma_{(s,\theta)} = \frac{\mu^3_{(s,\theta)}}{\sigma^3_{(s,\theta)}} \quad (14)$$

Where, μ is the mean value and σ is the standard deviation at specific values of scale s and orientation θ.

Kurtosis (TF_5) and Contrast (TF_6): Contrast is expressed as $\psi_{(s,\theta)}$ and has been calculated using Eq. (15).

$$\psi_{(s,\theta)} = \frac{\mu_{(s,\theta)}}{k^{0.25}_{(s,\theta)}} \quad (15)$$

Where, $k_{(s,\theta)} = \frac{\mu^4_{(s,\theta)}}{\sigma^4_{(s,\theta)}}$ is the kurtosis or the degree of peakedness in a dataset.

The texture feature dataset (TFD) which accumulates all the six Gabor texture features extracted earlier and has been shown in Eq. (16).

$$TFD = \left(TF_1, TF_2, TF_3, TF_4, TF_5, TF_6 \right) \quad (16)$$

Where $TF_1, TF_2, ..., TF_6$ indicate all the 6 different values of texture features namely Mean, Energy, Standard Deviation, Skewness, Contrast and Kurtosis.

In this work, the magnitudes for three different Gabor texture feature dataset have been prepared separately for the following sides of the leaf images: dorsal, ventral and dorsal-ventral combined as mentioned in Eq. (17), (18) and (19) respectively.

$$TFDD = \left(TF_1, TF_2, TF_3, TF_4, TF_5, TF_6 \right)_{Dorsal} \quad (17)$$

$$TFDV = \left(TF_1, TF_2, TF_3, TF_4, TF_5, TF_6 \right)_{Ventral} \quad (18)$$

$$TFDDV = \left(TF_1, TF_2, TF_3, TF_4, TF_5, TF_6 \right)_{Dorsal-Ventral} \quad (19)$$

These three datasets, Texture Feature Dataset for Dorsal side (TFDD), Texture Feature Dataset for Ventral side (TFDV), Texture Feature Dataset for Dorsal-Ventral combined(TFDDV) have been prepared by concatenating features as mentioned in Eq. (17), (18) and (19) respectively and which have been further used for classification purpose in subsection 2.4.

2.4 Analysis of the Dataset

The three datasets (TFDD, TFDV, and TFDDV) prepared in subsection 2.3 need to be analyzed in detail as the Gabor texture features that have been accumulated to form these datasets greatly influenced, the degree of classification of these digital leaf images. The Box-plot in the Fig. 7, 8 and 9 show the distribution of the texture feature data in the dorsal, ventral and combined dorsal-ventral sides of the leaf images respectively.

Mean (TF_1) is the texture feature that tells about the brightness of the image, by measuring the average intensity values. If the value of the mean is high, it is an indication for the image being bright and low value is an indication for dark images. Since, both the dorsal and ventral images have been captured with a high resolution camera, both are bright but ventral images having prominent veins at the ventral side have slightly higher values for mean as shown in Fig. 8.

The energy (TF_2) feature measure the uniformity of the pixel intensity level distribution in the entire digital image. In other words, it tells about the local homogeneity in the image. If the value of energy texture feature is on the higher side, it indicates the higher homogeneity of the image and its range is [0, 1].The value of 1 for energy indicates constant image. The energy feature values are better on the ventral side as shown in Fig. 8.

The smoothness of the texture is calculated by using the standard deviation (TF_3) as the texture feature. A low value of standard deviation indicates low contrast and a high value indicates a high contrast in the image. Since the ventral sides of the leaf images have perturbed venation pattern, higher values have been observed in the TFDV dataset as shown in Fig. 8.

The skewness (TF_4) indicates the pixel intensity level distribution about the mean in a gray digital image. If the value is zero or near around zero, then it is an indication for equal distribution of pixel intensity on both sides of the mean of the pixel intensity values. A negative value indicates that there is a large deviation of the pixel intensity data towards the right side of the mean of the pixel intensity values. A positive value indicates a large tilt of the pixel intensity value towards the left side of the mean pixel intensity distribution. The skewness value shows the asymmetric nature of the data in the three data sets, tilted in either of the directions. The skewness value is more in the case of TFDD(as shown in Fig. 7) as compared to the TFDV(as shown in Fig. 8) dataset. In this study, the dorsal and ventral both the leaf images have positive skewness value.

The kurtosis (TF_5) texture feature indicates the peak of the distribution of pixel intensity values around the mean. A high peak in the case of kurtosis indicates that the pixel intensity value distribution is sharp and a low value indicates the flat distribution. It has been observed that the kurtosis is lower in the dorsal images as compared to ventral images as shown in Fig. 7 and 8. As more prominent venation pattern has been observed on the ventral sides, therefore, more peakedness has been observed in the ventral leaf image dataset as shown in Fig. 8.

The high value of contrast (TF_6) texture feature indicates presence of edges. If the neighboring pixels are similar to each other or nearly similar, then the contrast value is low. If the neighboring pixels are distinct and prominent then the contrast value is high. A high contrast value indicates presence of prominent texture features and a low value of contrast indicates smooth textures. If the contrast is zero or nearly zero then the image is constant [13].

2.5 Classification of leaf images

The classification of the leaf image datasets obtained in Eq. (17), (18) and (19) has been done using KNN, J48, CART, RF classification algorithms [14]. The dataset has been divided into the ratio of 75:25 where training dataset consists of 75% and the test dataset consists of the 25% of the total dataset.

In the classification process 10-fold cross validation technique has been adopted for the resampling process. The term accuracy refers to the number of times a correct match has been found for a particular image in the leaf image dataset.

3. Results and Discussion

In this study, six dorsal and ventral features have been extracted from each side of the leaf image. From the results obtained in this study as shown in Fig. 10, it is found that the RF algorithm with TFDV dataset gives the best accuracy value of 92.08%, where as in the case of TFDD, it gives the predictive accuracy value equal to 89.72%

The results shown in Fig. 10 reflect the best predictive accuracy performance of the RF algorithm over other classification algorithms (KNN, J48, and CART) taken up for this study. The RF algorithm is an ensemble learning technique and unlike single decision trees. It tries to balance the problems of high variance and bias property, which is very prominent in single decision trees. As it is based on boot strapping model, the jungle of trees is built every time with a new training dataset which leads to the construction of highly de-correlated trees which provide better accuracy results and such properties are not exhibited by other algorithms.

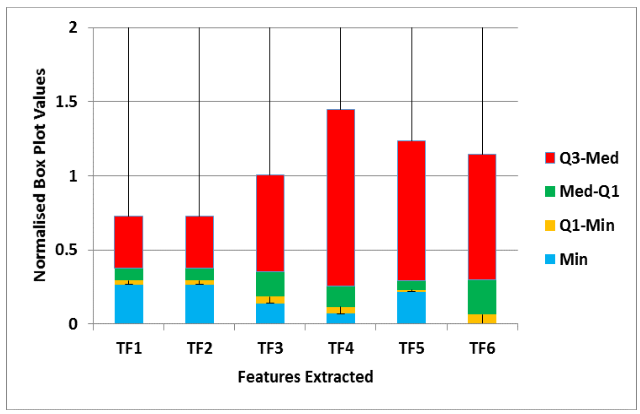

Fig. 7. Adjusted Box Plot for TFDD

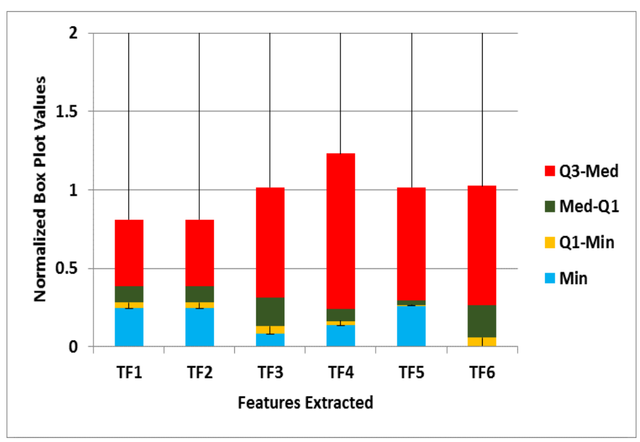

Fig. 8. Adjusted Box Plot for TFDV

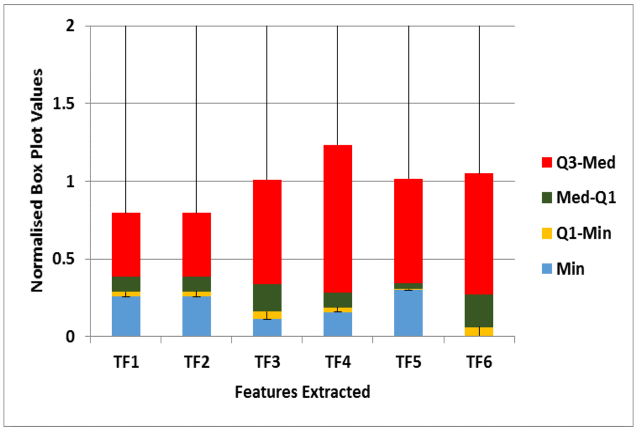

Fig. 9. Adjusted Box Plot for TFDDV

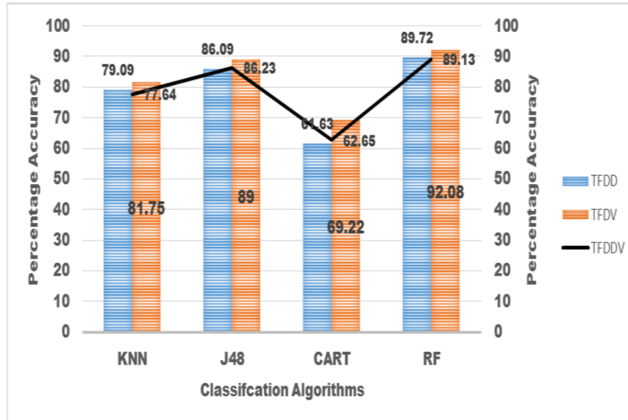

Fig. 10. Predictive classification accuracy results

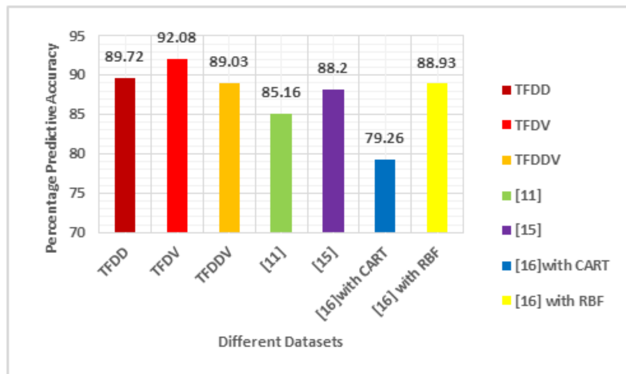

Fig. 11. Comparative results

The results obtained in this study are not directly comparable with other works, due to the differences in the leaf image datasets used, but are still comparable on the basis of the Gabor texture features extracted from the dorsal side of the leaf images. Therefore, the results of this study have been comparatively presented with that of the studies carried out in [11], [15] and [16].

The Fig.11 shows the comparison of the predictive accuracy results of this study with [11], [15], and [16].
It is observed that the value of predictive accuracy for [11] is 85.16%., for [15], it is 88.2% and the value obtained by [16] are 79.26% and 88.93% using CART and RBF algorithms respectively.

It can be clearly stated from the results obtained in this study that the ventral side of leaf image provides better predictive accuracy for Gabor based texture features as compared to dorsal image set as shown in the Fig. 11.

4. Conclusion

In this study, the texture features have been extracted from both dorsal and ventral leaf images as discussed in section 2. The dorsal side of the leaf image has fairly good texture content, but the ventral side of the leaves have prominent veins and they form a network of patterns. This makes the ventral side more suitable for extracting texture features and show better classification accuracy for the ventral texture feature set as shown in Fig. 10 and 11.

The objective of this study has been proved with better performance of ventral leaf image dataset as compared to dorsal leaf image dataset as discussed in section 3, therefore, the ventral side of the leaf image can be an alternative for the leaf image classification.

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