CHAPTER 6

EFFECT OF FUSION OF STATISTICAL AND DIRECTIONALITY FEATURES ON CLASSIFICATION RESULTS

6.1 Introduction

The nature has given innumerable objects to view and to use them according to our requirements, but before starting to use them, our eyes must discern one object from the other. Once our brain has seen the characteristic features of the object of concern, we name it, and keep a copy of the object for future use. This copy of the image helps a person in segregating one object from the other. In computer based automatic classification of the images, several methods have been proposed in machine vision studies, which try to imitate the human visualization system. In a natural image, one portion of the scene has a boundary clearly demarcated from the other by its edges and ridges. The digital images are full of patterns inclined at angular positions. Therefore, getting appropriate information about the feature pattern helps in proper classification of digital images.

In the case of leaves, nature provides two faces to the leaves i.e. dorsal or the front side and the ventral or the back side which is not the case for other types of objects. The classification on the basis of the dorsal side of the objects including leaves has been done by many researchers [Kalyoncu et al. and Chaki et al. (2015); Perez et al. (2000)]. The role of ventral side of a leaf image in classification of data set remained untouched, therefore, there is a drastic need to study the role of ventral or the back side of the leaf in discriminating the leaf images because of the presence of prominent venation patterns and protruding hairy structures.

The leaf image classification can be done by using leaf's geometrical features, texture and shape based features and color features as described by many researchers [Kalyoncu et al. and Chaki et al. (2015); Perez et al. (2000)]. A digital image is composed of pixels of different intensity values, the change in intensity values around the images leads to a scene with visible objects, if there is no change in the intensity, there is no image formation and this change in intensity values occur in a particular direction in the image. The concept of directionality histogram has been used for the characterization of brain micro-device interface using the device capture histology as described by Woolley et al. (2011) and for 3D microstructure modeling of long fiber reinforced thermoplastics as described by Fliegener et al. (2014). The concept of directionality also finds its use for finding texture features using the method of directionality histogram on geometric property of images as described by Islam et al. (2015).

In statistical jargon, a sample is a subset of values taken out from a digital image for understanding its characteristic properties through which detailed statistical analysis can be performed by utilizing first order statistics like mean, mode, median and standard deviation etc. for discriminating the images into various classes.

This present work has tried to extract the various statistical features and directional features from the digital images and observing their effects in automated classification of digital images based on the dorsal side, ventral side and combined dorsal-ventral sides. The statistical features like Mean Gray, Median, Integrated density, Skewness, Kurtosis, Standard Deviation, First order spatial moments(XM, YM)and Minimum Gray value have been computed for the dorsal, ventral and combined dorsal-ventral sides. In the present work, directional features like direction, dispersion and fitness etc. have been computed on the dorsal, ventral and combined dorsal-ventral sides of the leaf images. These directionality feature sets have been combined with the statistical feature sets for different sides. The classification algorithms like K-Nearest Neighbor (KNN), J48, Classification and Regression Tree (CART) and Random Forest (RF) have been used for classification of statistical features as well as combined statistical-directionality feature sets. The objective of this work is to find out whether the ventral side of the leaf image can be considered for leaf image classification or not and can the classification accuracy results be improved by adding directionality features with the statistical features. This chapter has been divided into different sections, where section 6.2 describes the methodology adopted, section 6.3 highlights the results and analysis and section 6.4 states the conclusion. This chapter has been adapted from Kumar et al. (2015).

6.2 Methodology Adopted

6.2.1 Database requirement and its preprocessing

The database created in section 4.2.1 of Chapter 4 has been used for achieving the present objective. As the database created in chapter 4 has both the dorsal and ventral sides of leaves and has been processed too. The same datasets have been utilized for extracting the statistical as well as directionality features in this present chapter. The colored sample of the dorsal and ventral sides of the leaf image datasets have been shown in Figures 6.1 and 6.2 respectively. The Figure 6.3 shows the preprocessed dorsal side of Slice-1 and ventral side of Slice-265. The process of preprocessing of both the dorsal as well as ventral leaf image datasets is same as has been described in section 4.2.2 of Chapter 4.

6.2.2 Preparation of statistical feature dataset

Since, there are a variety of images available like X-ray images of the body parts, traffic scene etc., and all the images are different from one another but there are certain features which can be captured so that the images can be represented with minimum number of bits. In an image, a pixel can take any value randomly from a set of values that appear in the same grid. Therefore, a pixel becomes a random variable and the image becomes a random field.

The statistical features that have been extracted from the leaf image dataset for dorsal, ventral and combined dorsal-ventral sides using ImageJ [A I.2] are Mean Gray value (Mean), Integrated Density (IntDen), Skewness (Skew), Kurtosis (Kurt), Standard Deviation (StdDev), First order spatial moments XM and YM for the ten different classes of leaf images named as $P_1, P_2, ..., P_{10}$. The detailed explanation of these statistical features and their mathematical representation has been discussed in Section 5.2.3 of Chapter 5.

The box and whisker's plot is called a box plot that is used to represent a five point graph and contains the following values computed for each of the dataset variable: minimum value, maximum value, median, lower quartile and upper quartile. The five point graph is helpful in understanding the individual variable of the dataset, presence of outliers if any, the middle value of the entire variable set, minimum and maximum value of the variable set. The Figures 6.4, 6.5 and 6.6 show the boxplot values plotted for different plant classes (x-axis) and their corresponding statistical feature values (y-axis) for each of the variables extracted for the dorsal, ventral and dorsal-ventral combined leaf image datasets.

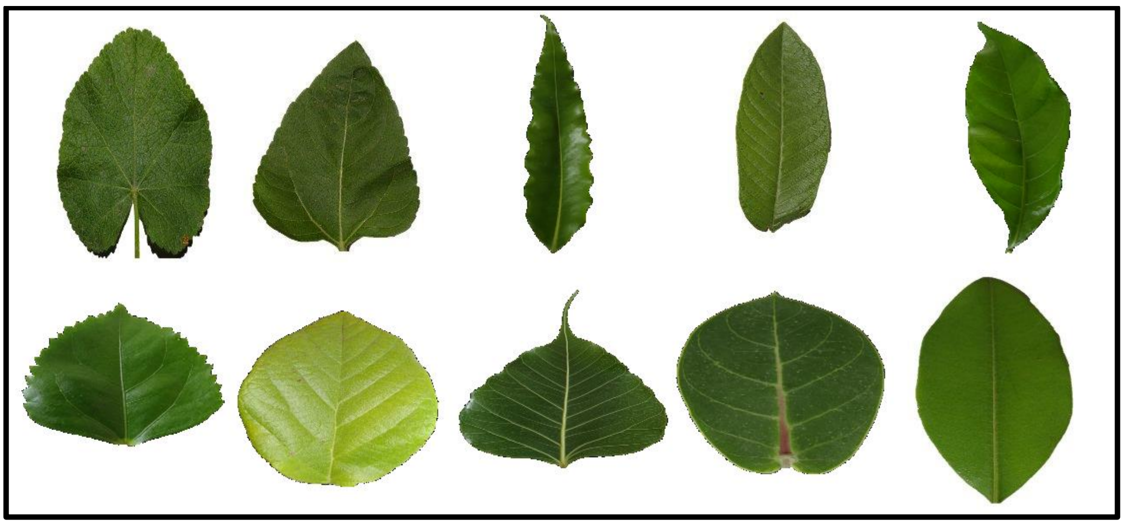

Figure 6.1 Colored sample of dorsal side of the leaf images

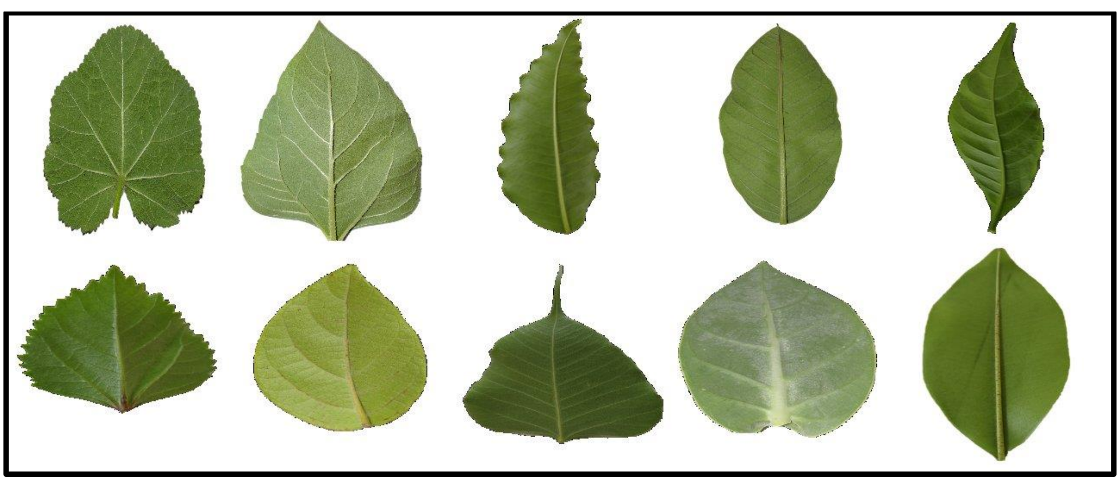

Figure 6.2 Colored sample of ventral side of the leaf images

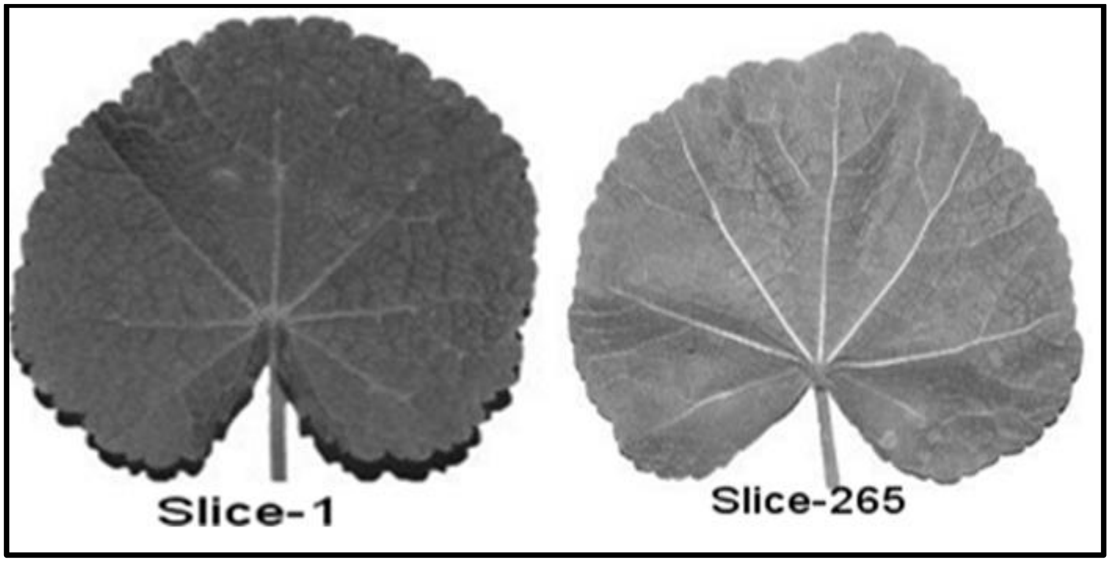

Figure 6.3 Dorsal side of the leaf image Slice-1 and ventral side of the leaf image Slice-265 after preprocessing

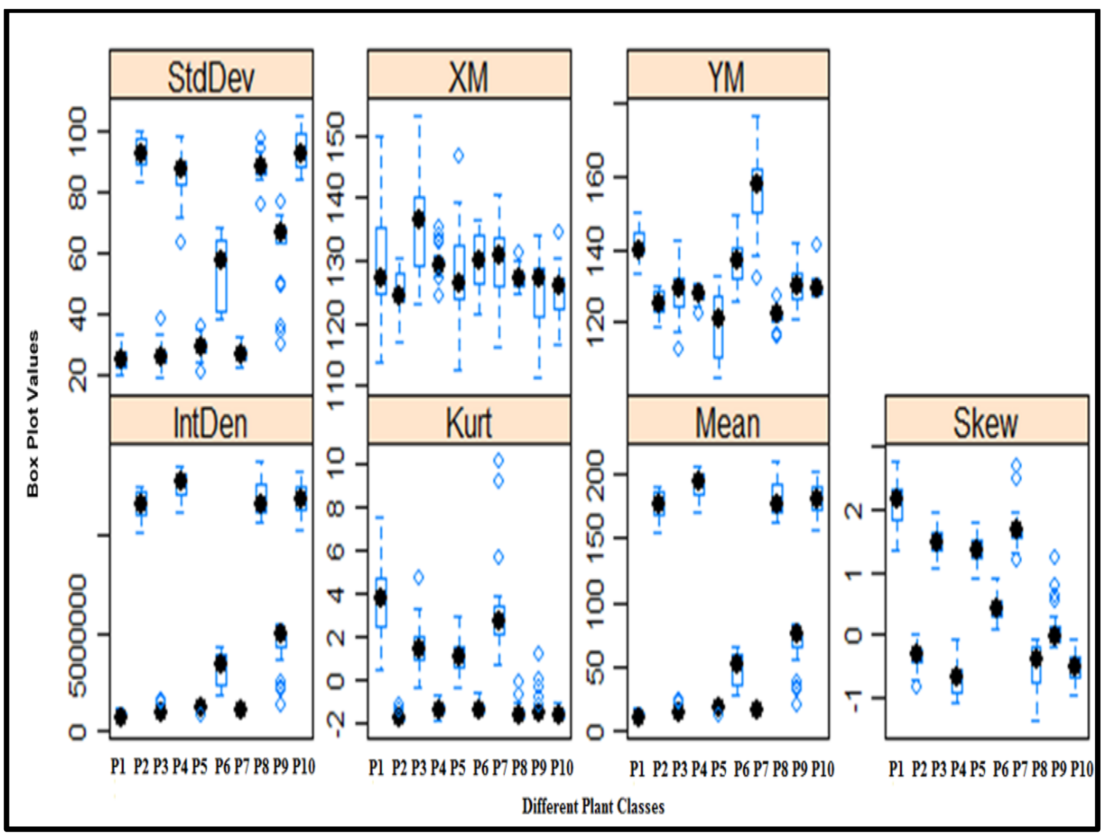

Figure 6.4 Boxplot values for different plant classes for different statistical features for dorsal leaf image dataset

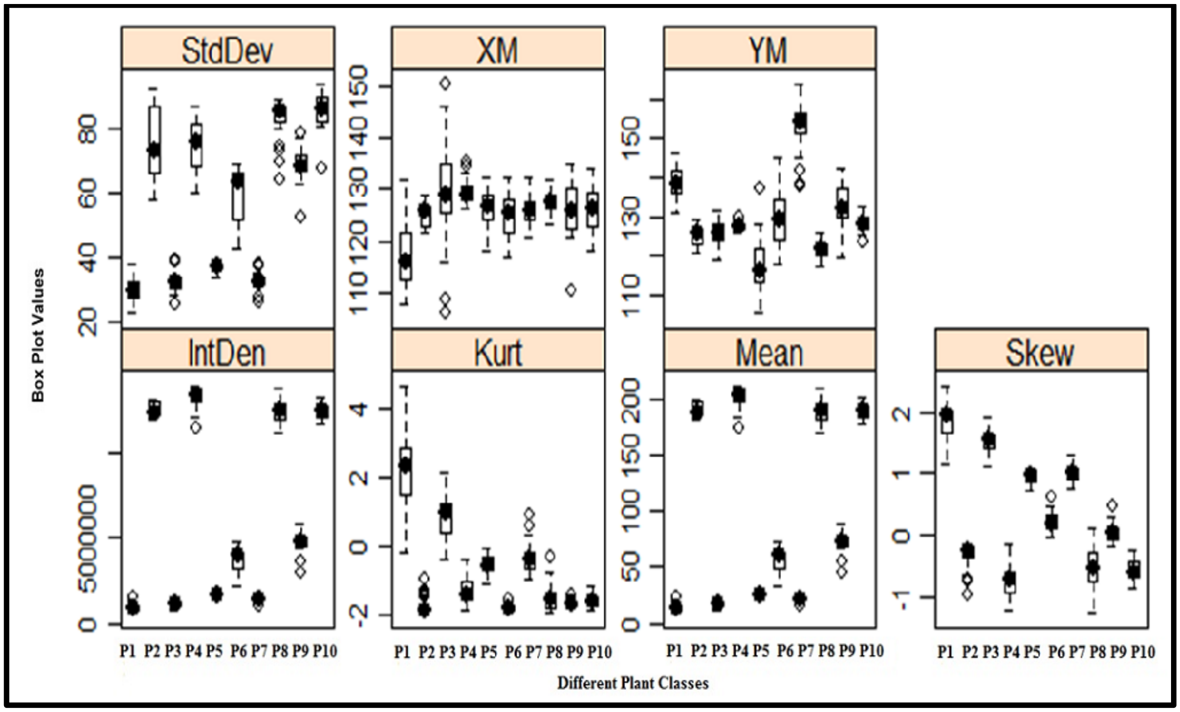

Figure 6.5 Boxplot values for different plant classes for different statistical features for ventral leaf image dataset

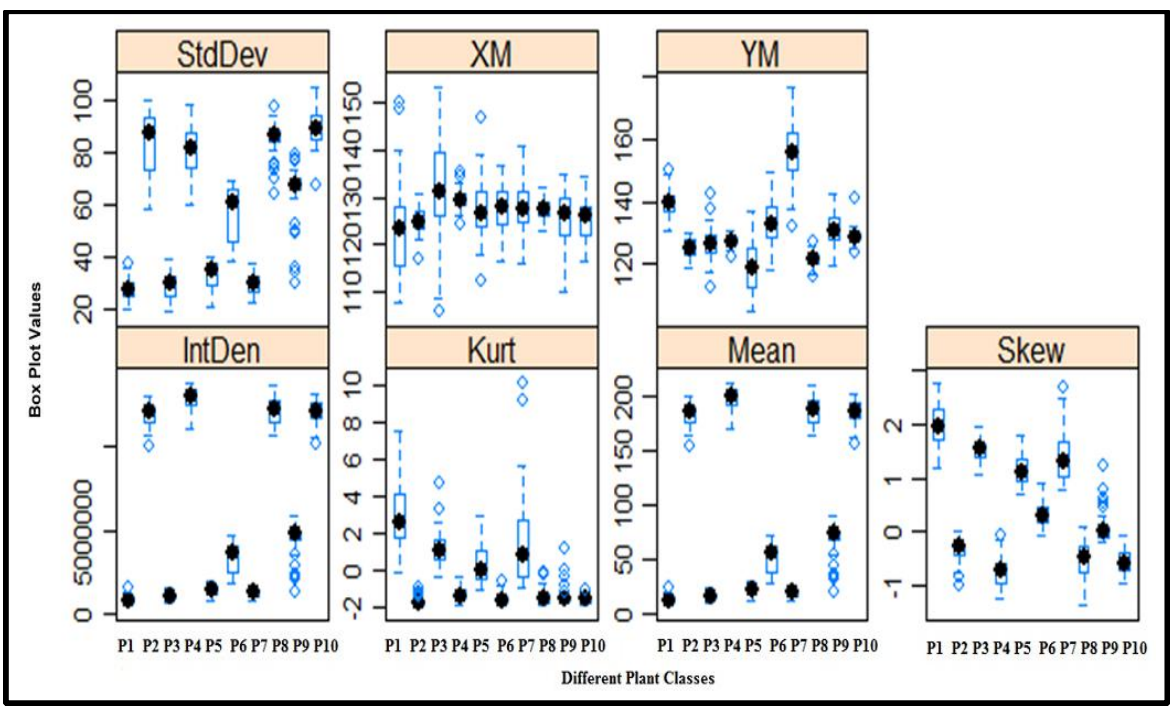

Figure 6.6 Boxplot values for different plant classes for different statistical features for dorsal-ventral leaf image dataset

6.2.3 Preparation of directionality feature dataset

A digital image is made up of pixels of various intensity values which may vary over the entire region of the image space. This leads to the formation of texture structures in the images which can be studied with the help of directionality. The basic concept of directionality in the digital images was given by Liu (1991). According to Liu (1991), when Gaussian filter as represented by Eq. (6.1) is applied to the image coordinates (x,y), with different scale (σ), it generates sets of images with different levels of smoothness. The next step is to find the edges in the images which can be obtained by finding the Laplacian of Gaussian (LOG) as mentioned in Eqs. (6.2) and (6.3).

$$g(x,y,\sigma)=\frac{1}{2\pi\sigma^2}\exp\left[\frac{1}{2}\left(\frac{r}{\sigma}\right)^2\right] \tag{6.1}$$

Here, $r^2=\left(x^2+y^2\right)$ and $\left(x,y\right)$ represents the image coordinate values.

At the edges, the intensity of the pixels changes rapidly i.e. the zero-crossing detector looks for the places in the image where the Laplacian passes through zero. This results in the generation of binary image with single pixels thickness lines showing the position of zero crossing pixels, which is represented through Eq. (6.3). The Laplacian highlights the regions of rapid change which is used in edge detection.

$$L\left(x,y\right)=\frac{\partial^2 I}{\partial x^2}+\frac{\partial^2 I}{\partial y^2} \tag{6.2}$$

$$LOG\left(x,y\right)=\frac{-1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{\left(\frac{-\left(x^2+y^2\right)}{2\sigma^2}\right)} \tag{6.3}$$

According to Witkin et al. (1988), a concept of scale space can be applied to find information in images and it can be expressed as Eq. (6.4)

$$\psi(x,y;\sigma)=\left\{(x,y;\sigma)\mid z(x,y;\sigma)=0;\left(\left(\frac{\partial z^2}{\partial x}\right)+\left(\frac{\partial z}{\partial y}\right)^2\neq 0,\sigma>0\right)\right\} \tag{6.4}$$

Where $z(x,y;\sigma)=LOG(x,y)*I(x,y)$ and * here represents convolution operation, $I(x,y)$ is the image and Eq. (6.4) shows the scale space as applied to images to find the directional information.

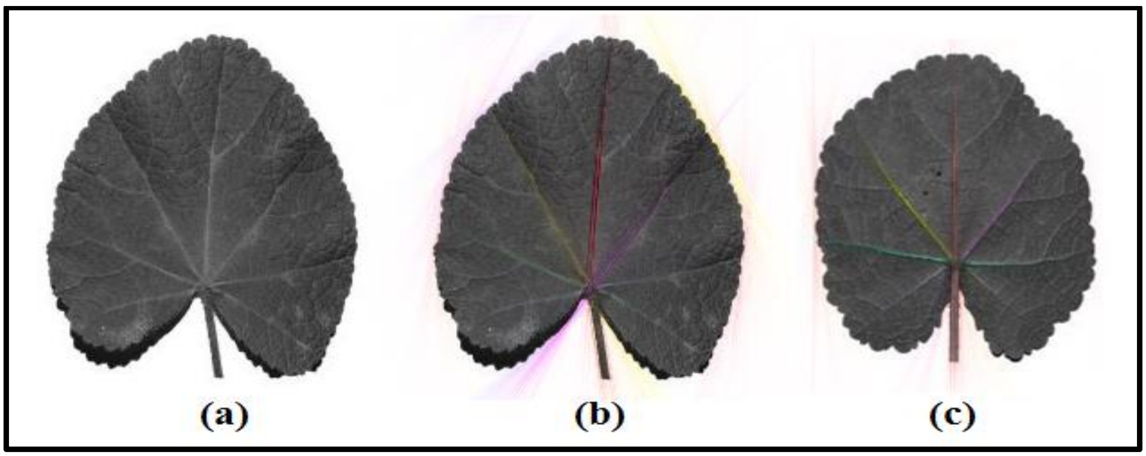

Figure 6.7 (a) Original Slice-2 and its orientation map for (b) dorsal side (c) ventral side

The directionality plugin [A I.2] offers the possibility to generate an orientation map, where the image is colored according to its local directionality, or location orientation. The image is filtered using the Fourier filters and transformed back using inverse Fourier transform. For each pixel, the direction retained is the one that has the strongest intensity when filtered in this orientation. Figure 6.7 shows the a single slice-2 with its orientation map for dorsal and ventral side. Figure 6.8 shows the directionality histogram for Slice-2 shown in Figure 6.7 with its analysis value table using Fourier component analysis with 90 bins.

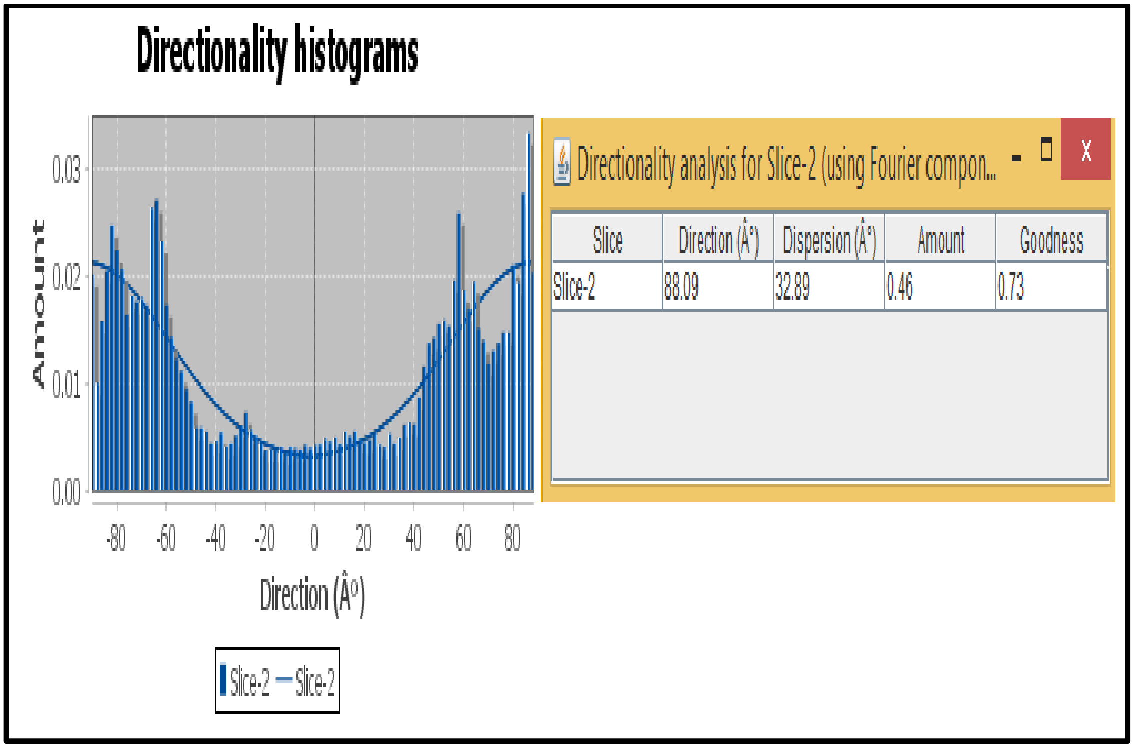

Figure 6.8 Directionality histogram for Slice-2 with its analysis values

The directionality plugin [A I.2] has been used to produce a histogram for the dorsal and ventral leaf image as shown in the Figure 6.9. There are 90 bins for a total orientation of 180^0 that have been used for generating the histogram for the images. The plugin generates a comma separated values file (CSV) with direction column that reports the center of the Gaussian, the dispersion column that gives the standard deviation of the Gaussian calculated above. The amount column gives the sum of the histogram from the center minus standard deviation to the center plus standard deviation divided by the sum of the histogram. The goodness column reports the goodness of the fit and its value is 1 for good and 0 for bad. A normalized directional histogram has been constructed which shows the angles in the horizontal axis and vertical axis shows the percentage of pixels with different gradient angles as shown in Figure 6.9. The major role of directionality is to find the amount of structure in a given direction in the digital image.

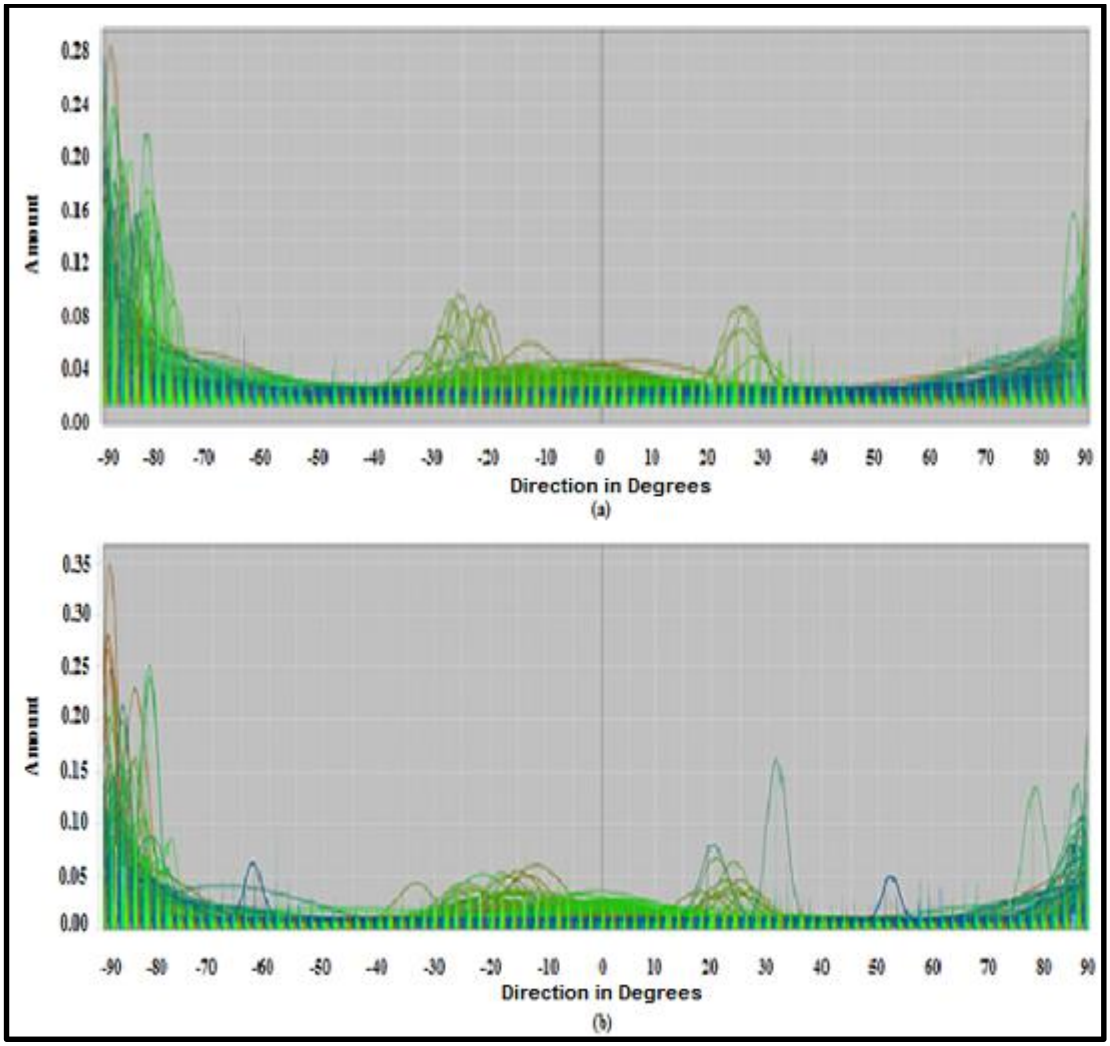

Figure 6.9 Directionality Histogram for (a) Dorsal (b) Ventral sides of the leaf images

6.2.4 Application of classification algorithms

To find the classification accuracy, the KNN, J48, CART and RF classification algorithms have been used on the data sets obtained in section 6.2.2 and 6.2.3 using "Caret" package under RStudio [Appendix I]. The datasets obtained from section 6.2.2 and 6.2.3 are combined to find the effect of directionality on the statistical feature sets on the classification accuracy for the dorsal, ventral and combined dorsal-ventral sides of the leaf images using ImageJ plugin [A I.2]. Each data set was split into two groups (Training and Testing sets) in the ratio 70:30. To obtain an accurate estimate to the accuracy of a classifier, k-fold cross validation is run several times, each with a different random arrangement of data sets. This work has used 10 fold cross validation for the resampling process.

The accuracy for the analysis purpose have been calculated where the term accuracy refers to the number of times a correct match has been found for a particular leaf image in the dataset. The predictive accuracy and kappa values have been adopted as a measurable parameter for the classification process. The Table 6.1 shows the predictive accuracy and kappa values obtained after applying the four classification algorithms i.e. KNN, J48, CART and RF for Statistical feature set for dorsal image dataset. Similarly Table 6.2 and 6.3 show the predictive accuracy and kappa values obtained for Statistical feature set for ventral and dorsal-ventral combined image datasets respectively. The Tables 6.4, 6.5 and 6.6 represent the predictive accuracy and kappa values obtained for Statistical-Directionality feature set for dorsal, ventral and dorsal-ventral combined image datasets respectively.

Table 6.1 Predictive accuracy and kappa values for Statistical feature set for dorsal image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	72.93	69.87
J48	72.40	69.28
CART	70.00	66.55
RF	78.87	76.44

Table 6.2 Predictive accuracy and kappa values for Statistical feature set for ventral image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	79.56	77.22
J48	81.76	79.67
CART	77.68	75.15
RF	83.92	82.08

Table 6.3 Predictive accuracy and kappa values for Statistical feature set for dorsal-ventral combined image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	76.06	73.38
J48	76.39	73.76
CART	75.77	73.07
RF	81.81	79.78

Table 6.4 Predictive accuracy and Kappa values for Statistical-Directionality feature set for dorsal image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	73.11	70.11
J48	72.93	69.85
CART	70.34	66.99
RF	84.05	82.23

Table 6.5 Predictive accuracy and Kappa values for Statistical-Directionality feature set for ventral image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	78.29	75.83
J48	84.37	82.57
CART	84.89	83.18
RF	88.54	87.23

Table 6.6 Predictive accuracy and Kappa values for Statistical-Directionality feature set for dorsal-ventral combined image dataset

Classification Algorithm	**Predictive Accuracy Values (%)**	**Kappa Values**
KNN	73.08	70.08
J48	77.52	75.01
CART	77.04	74.49
RF	86.18	84.63

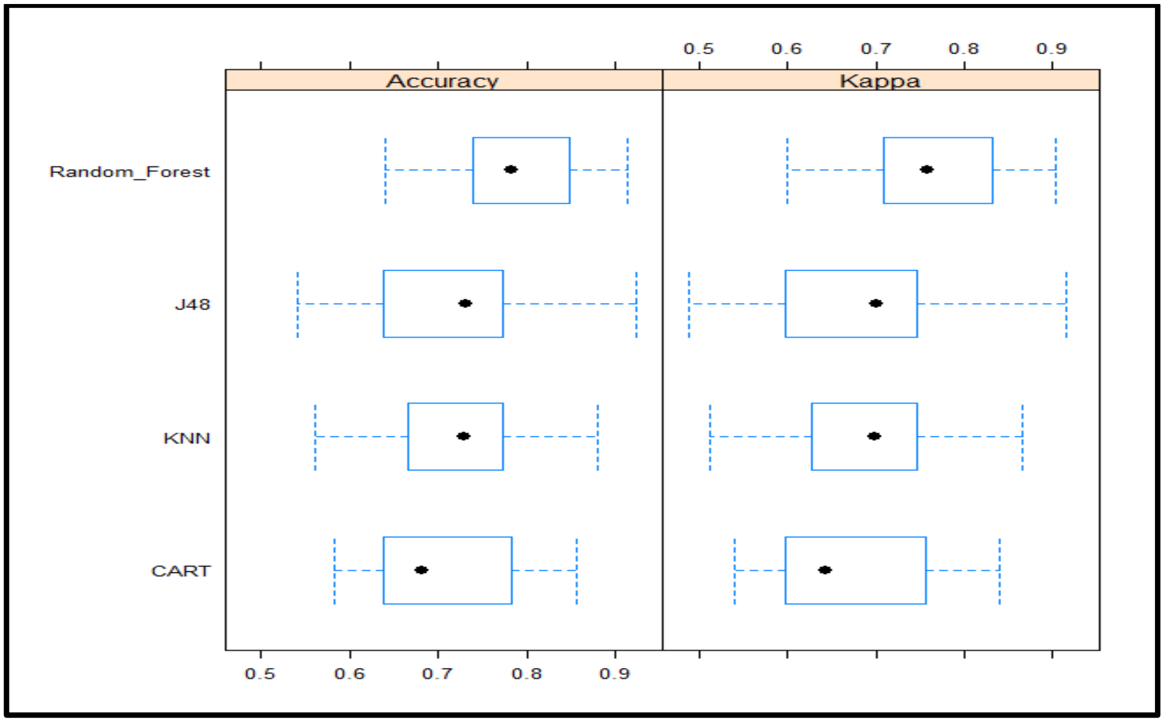

Figure 6.10 Box plot of Predictive accuracy and Kappa results for Statistical feature set for dorsal side of the leaf image dataset

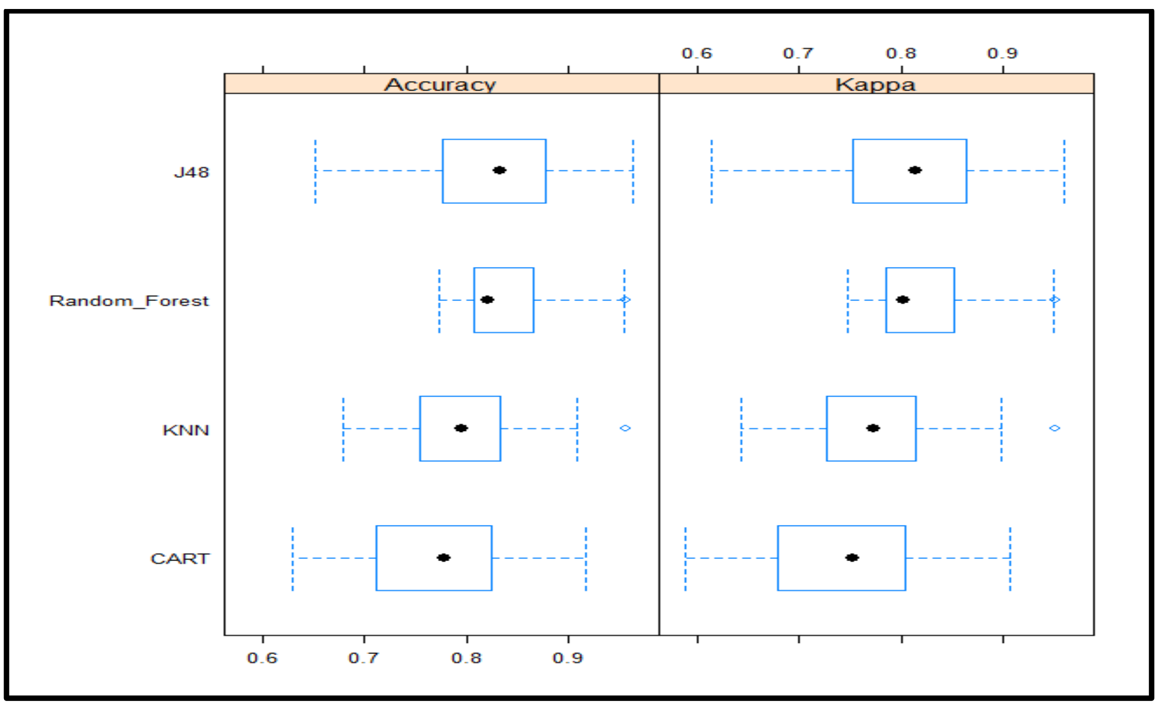

Figure 6.11 Box plot of Predictive accuracy and Kappa results for Statistical feature set for ventral side of the leaf image dataset

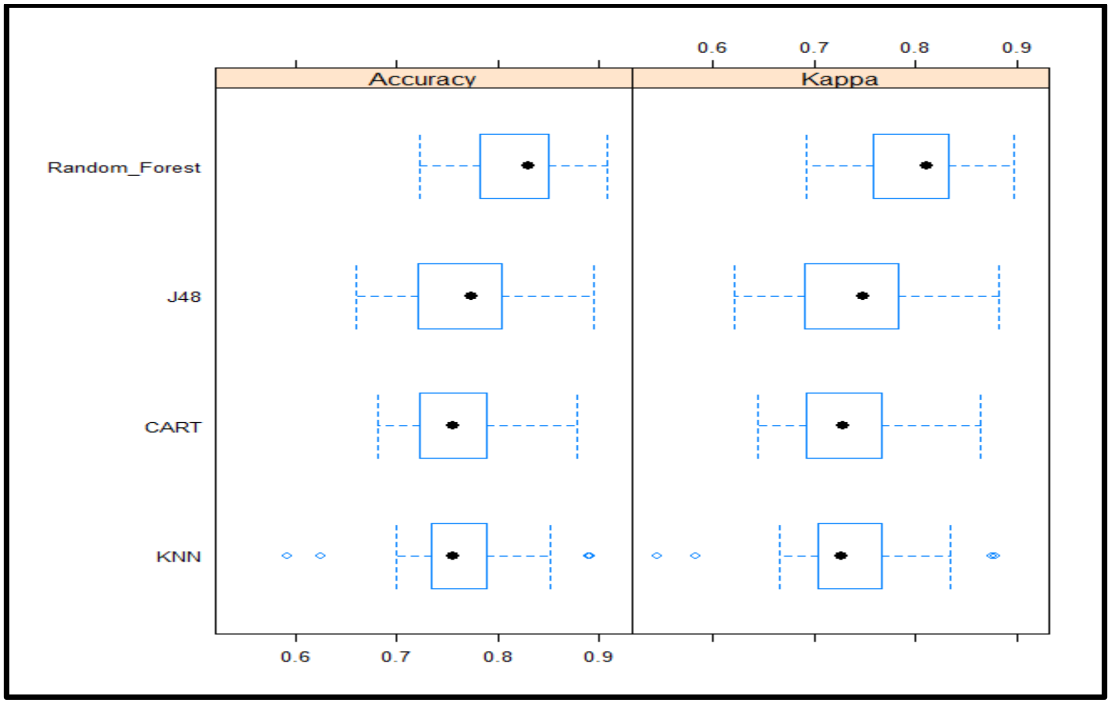

Figure 6.12 Box plot of Predictive accuracy and Kappa results for Statistical feature set for dorsal-ventral combined leaf image dataset

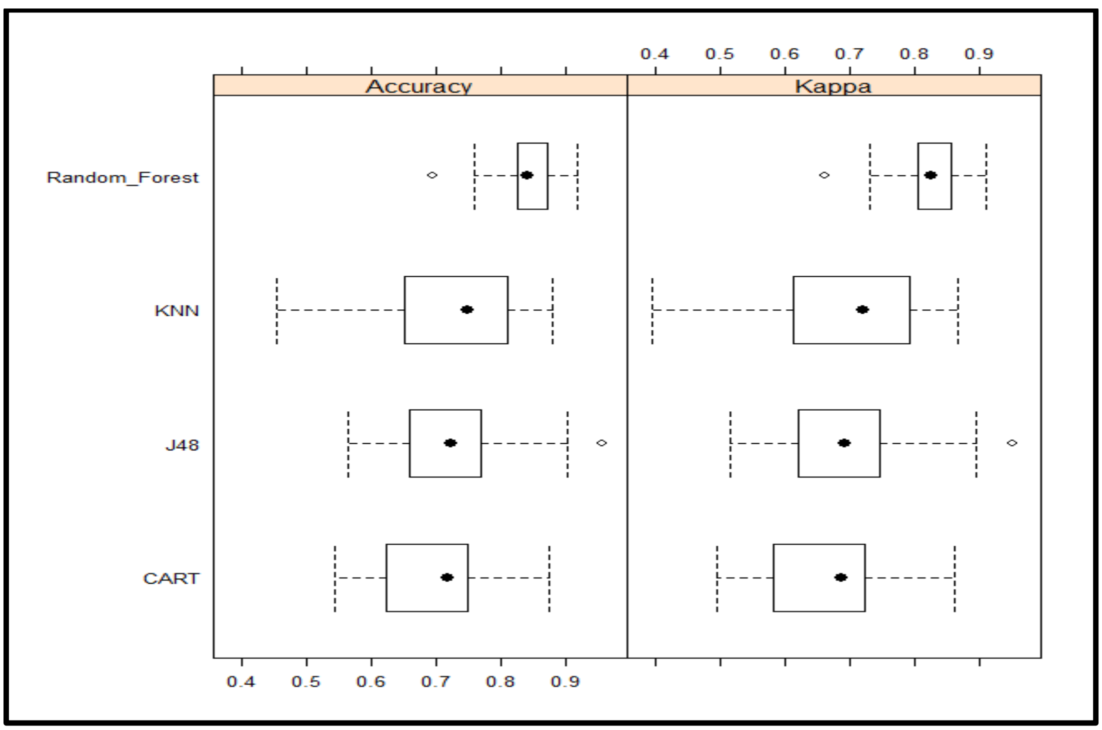

Figure 6.13 Predictive accuracy and Kappa results for Statistical-directionality feature set for dorsal side of the leaf image dataset

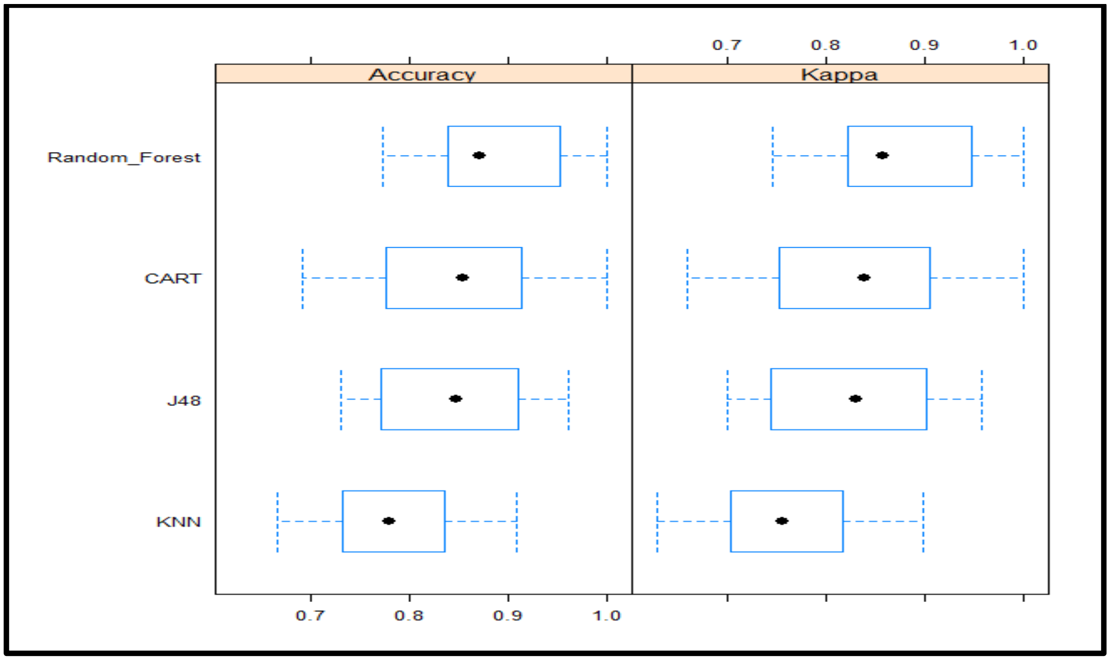

Figure 6.14 Predictive accuracy and Kappa results for Statistical-directionality feature set for ventral side of the leaf image dataset

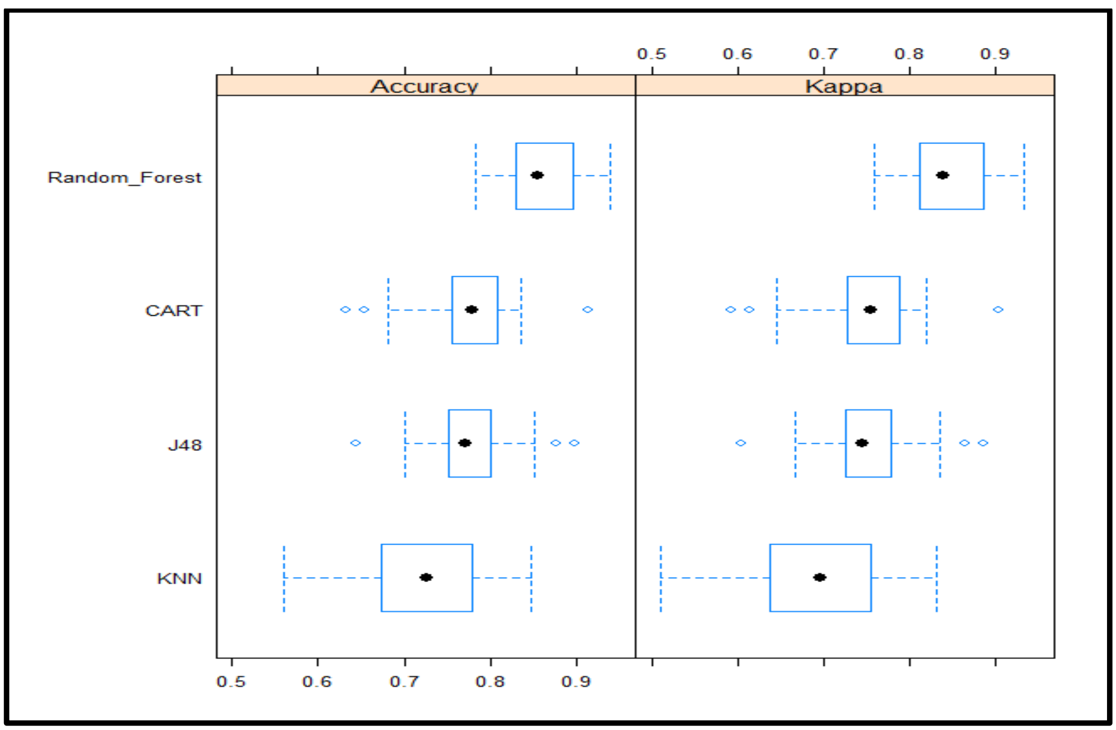

Figure 6.15 Predictive accuracy and Kappa results for Statistical-directionality feature set for dorsal-ventral combined leaf image dataset

The performance metric for the comparison of different classification algorithms (RF, J48,KNN, CART) is the resampling curve obtained for accuracy and kappa values. Figures 6.10, 6.11 and 6.12 show the resampling results using box plots for different classification algorithms for statistical features set for dorsal, ventral and dorsal-ventral combined side of the leaf image datasets respectively. Similarly, Figures 6.13, 6.14 and 6.15 show the resampling results using box plots for different classification algorithms for statistical-directionality features set for dorsal, ventral and dorsal-ventral combined side of the leaf image datasets respectively. On examining the box plots of the sampling distribution for four models, the RF modal outperforms all other classification algorithms.

6.3 Results and Discussion

6.3.1 Analysis on the basis of statistical features sets

As shown in Figure 6.16, the Random Forest (RF) classification algorithm is giving the highest accuracy values for dorsal, ventral and combined dorsal-ventral sides of the leaf images. Statistical feature set alone gives 83.92% accuracy for ventral side using Random Forest which is more than the accuracy of dorsal (78.87%) and combined dorsal-ventral (81.81%) as represented in Figure 6.16.

6.3.2 Analysis on the effect of directionality features combined with statistical features sets

By comparing the Figures 6.16 and 6.17, it is analyzed that the overall accuracy for classification of leaf image data has been increased with the addition of directionality features into the statistical feature set. As in Figure 6.17, the classification accuracy is 88.54% for ventral side, 86.18% for combined dorsal-ventral side and 84.05% for dorsal side of the leaf images as compared to accuracy shown in Figure 6.16 i.e. 83.92%, 78.87% and 81.81% respectively. Therefore the overall accuracy has been increased for all the datasets by adding the directionality features with the statistical feature sets. The directionality features added additional information extracted from leaf images which resulted in improved accuracy results in all the sides of the leaf images.

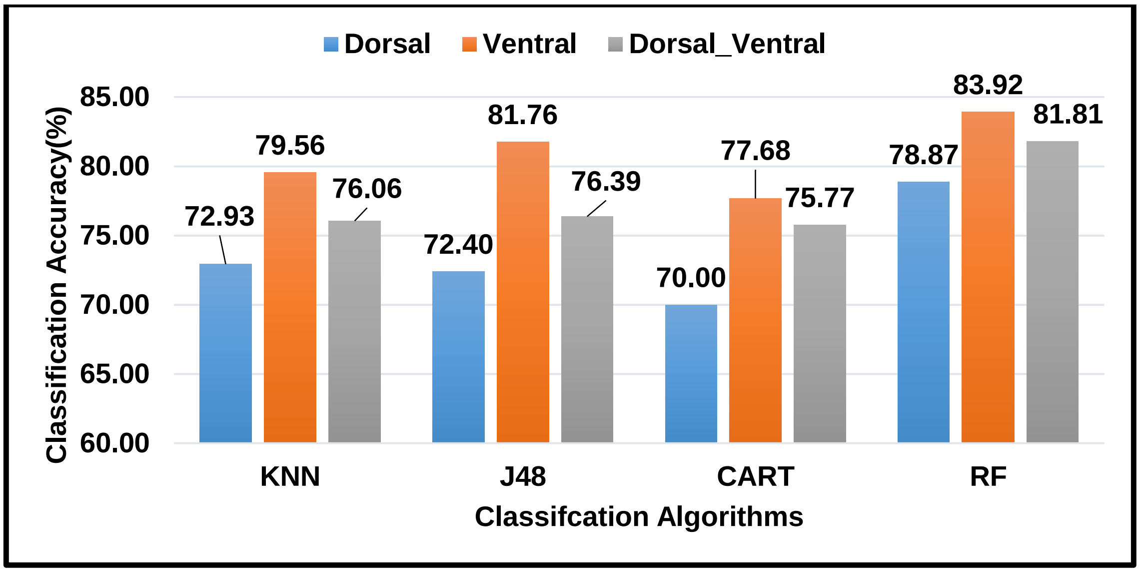

Figure 6.16 Classification accuracy for Statistical feature sets

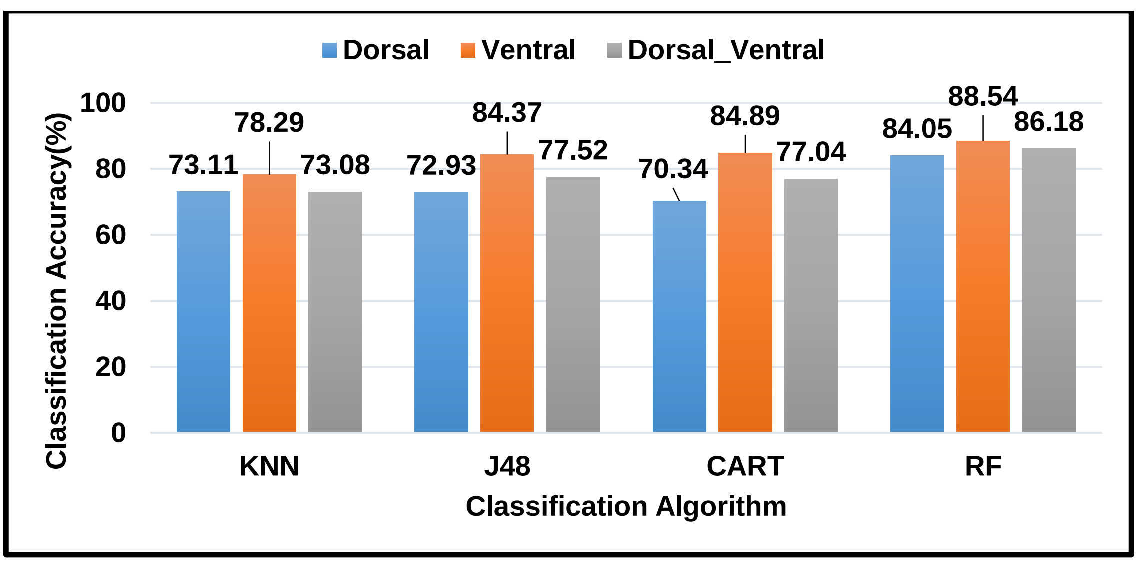

Figure 6.17 Classification accuracy for Statistical-Directionality feature sets

6.3.3 Analysis on the basis of sides of a leaf

The Random Forest algorithm is an ensemble learning technique used for classification and regression operations and based on the principle of constructing a multitude of decision trees at training time and it outputs the class that is the mode of the classes(in case of classification) or average prediction (in case of regression) of the individual trees. With the help of ensemble learning technique, it allows the algorithm to learn accurately both simple and complex classification features for the dataset.

As this work uses a large number of variables in a dataset, and each variable due to its interaction with the other variable creates its own importance. The Random Forest algorithm estimates the importance of the variables by finding out by how much the prediction error increases when out of bag data is presented to the algorithm. The computations are done tree by tree as the random forest is constructed. This methodology of RF algorithm [Dins Lab (2015)] makes it a better classifier as compared to other algorithms used.

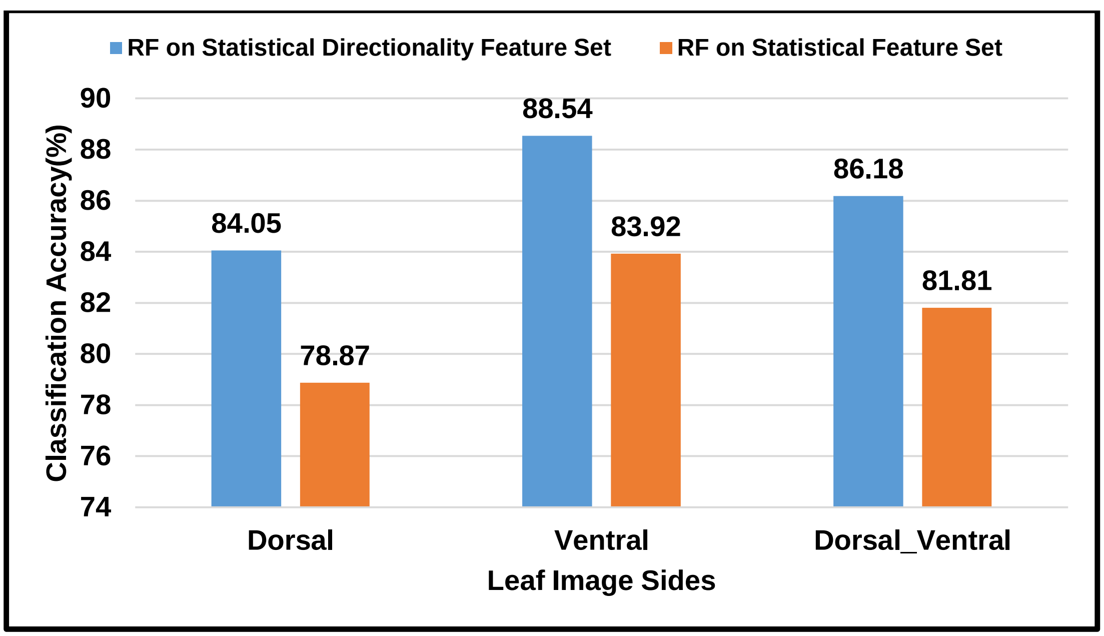

Figure 6.18 Comparison chart for classification accuracy of different sides of leaf images using RF

As shown in Figure 6.18, the ventral side is giving higher accuracy as compared to dorsal and combined dorsal-ventral sides of the leaf images for statistical feature set (83.92%) and statistical-directionality combined feature set (88.54%). This proves the assumption of this study, that ventral side can be considered for the classification purpose of the leaf images.

6.4 Conclusions

From section 6.3.2, and Figures 6.16 and 6.17, it has been observed that the directionality features with statistical feature sets improves the classification accuracy for dorsal, ventral and combined dorsal-ventral sides. On the basis of the results shown in Figure 6.18 and section 6.3.3, it is proposed to consider the ventral side of leaf images for the classification purpose which fulfills the objective of this research work.