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GLCM Features And Hybrid Manhattan Distance With SVM For Identification Of The Leaves Of Indonesian Herbal Medicines

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ABSTRACT

Herbal plants are those plants, which can be considered as a substitute for naturally healing diseases. The public still does not have the awareness about the presence of herbal plants. It is owing to the fact that there are several kinds of medicinal plants available and therefore, specialized knowledge is required for their identification. To get over this, an intelligent and precise herbal leaf recognition system is necessary. In recent work introduces one enhanced model for Indonesian Herbal Medicines identification. In which there are three techniques introduced. The first one includes the novel leaf feature framework. There are 16 distances between perimeter points and leaf centroid points, as well as seven median line connectors. The second project entails the creation of leaf feature extraction techniques and algorithms that allow for the production of 23 leaf shape attributes for any type of herbal crop. Thirdly, forming a prototype identification system or introducing herbal plants on the basis of morphological features of the leaf. The procedure of recognition is performed with the help of two mechanisms, which include MDs (Manhattan Distances) and Artificial Neural Networks. However in existing work foreground segmentation was not done based on any particular algorithm and its leads to poor segmentation results. Also ANN is about the executing with parallel processing, and therefore processors providing support to parallel processing is required, and therefore the ANNs exhibit hardware dependency.
To avoid those problems in this work introduced an improved model for herbal medicines plant leaf identification. In this pre-processing is done by using Image segmentation based on k means clustering to segment the foreground object, Image Filtering and Translation of RGB (Red, Green, Blue) images into Grayscale. Features are extracted using GLCMs (Grey Level Co-Occurrence Matrices) and Centre point based model. Finally the Indonesian Herbal Medicines plant leafs are identified based on those extracted features using Hybrid MDs with SVMs (Support vector machines). Experimental results shows that this proposed model produces better leaf identification accuracy than other state of the art models.

Keywords: Indonesian Herbal Medicines Identification, Recognition System, Feature Extraction, segmentation and Grey Level Co-Occurrence Matrix.

1.Introduction

Plants have an important part in human lives and contribute much towards the welfare of the living things worldwide. They constitute one among the primary sources of food, raw materials, medicines and so on. From time, various plants are popular for finding specific application in the form of a remedy to any illness or disease. A majority of the humans know their significance and have sought to attain more information on the ways to make use of particular plant for treating particular ailments. So far, a variety of plants, which includes the herbal medicine plants also have exhibited a huge effect on the health of individuals globally. As per the WHO (World Health Organization) report in 2009, 80% of the population worldwide still depend on plant drugs or medications [1,2,3].
Currently, there has been variety of declared promotions on using herbal medicine plants; and even health experts and other individuals in the scientific field have begun to understand their inherent benefits. One of the issues introduced with respect to herbal plants include their usage. Even though the presence of many herbal medicine plants and their popular usage is known to several; a majority still are incapable of identifying which one of these are medicinal plants out of the versatile plants growing in the world. Moreover, researchers in the domain of plant studies substantially endeavour for identification of plants[4,5,6].
In recent work introduces one enhanced model for Indonesian Herbal Medicines plant leafs identification. In which there are three techniques introduced. The first one includes the novel leaf feature framework. There are 16 distances between perimeter points and leaf centroid points, as well as seven median line connectors. The second project entails the creation of leaf feature extraction techniques and algorithms that allow for the production of 23 leaf shape attributes for any type of herbal crop. Thirdly, forming a prototype identification system or introducing herbal plants on the basis of morphological features of the leaf. The procedure of recognition is performed with the help of two mechanisms, which

include MDs and Artificial Neural Networks. However in existing work foreground segmentation was not done based on any particular algorithm and its leads to poor segmentation results. Also about the executing with parallel processing, and therefore processors providing support to parallel processing is required, and therefore the ANNs exhibit hardware dependency.
To avoid those problems in this work introduced an improved model for herbal medicines plant leaf identification. In this pre-processing is done by employing Image segmentation based on k means clustering to segment the foreground object, Image Filtering, Translation of RGB images into Grayscale which are then converted to their Binary forms. The process of feature extraction is done by employing GLCMs and Centre point based model. Finally the Indonesian Herbal Medicines plant leafs are identified based on those extracted features using Hybrid MDs with SVMs.

2.Related Work

Elhariri, et al [2014][7] studied about a classification technique founded on RFs (Random Forests) and LDAs (Linear Discriminant Analyses) for classifying plants. The study used pre-processes, feature extractions, and classifications as its three stages. As the leaves of a majority of the kinds of plants are distinct, the classification mechanism introduced in this research work relies on leaves of the plants. Leaves exhibit diversity in terms of features like the shape, color, texture and the margin. The study's dataset was obtained from UCI Machine Learning Repository and contained 340 photos of leaves of various plants. Their cross validations were suitable for both training and testing datasets where experimental results revealed that when shapes, first order textures, GLCMs, HSV colour moments, and vein features were combined with LDAs yield classification accuracy of (92.65 percent), whereas RFs yielded accuracy of (88.82 percent).
Mahdikhanlou and Ebrahimnezhad [2014][8] categorized plant leaves by employing centroid distances and axes of least inertia techniques. They accomplish this by converting RGB images into binary images. Prior to edge thinning, Canny operators detected image edges in binary images. Subsequently, image's boundaries were outlined for shape sampling procedures which minimized computational times and complexities. The centroid distance between these points were calculated, as well as the distance of sample sites from shortest inertia line's axis. The proposed technique was found to be invariant to picture modifications (translation, rotation, reflection, and scaling) and resilient to tiny deformities and obstacles by choosing a constant start point and then obtaining the normalized distances. In this work, PNNs (probabilistic neural networks) was used for classifications. The scheme was tested on two Swedish and Flavia leaf datasets. The outcomes of experiments corroborate the best performance achieved with the proposed feature in classifying the plant leaves.
Wang, et al [2014][9] described an innovative plant leaf recognition technique. For the extraction of unique features using the images of plant leaves and limiting chances of deformations, features were extracted based on LBDs (local binary descriptors) and dual-scale decompositions from images employed with disturbances, mess, or noises. Dual-scale decompositions had two stages where adaptive lifting wavelet methods separated plant leaf image into multiple sub-bands. Subsequently, Gaussian filter's variations filtered sub-bands. LBDs extracted from these filtered sub-bands encompassed textural, shape features, and histograms associated with LBDs at various scales. Diverse sub-bands were selected as features. To enhance the reliability and versatility corresponding to plant leaf identification more, a fuzzy *k*-nearest neighbors' classifier is presented for the purposes of matching. The outcomes of Experiments reveal that the proposed technique provides superior performance with respect to the classification accuracies in comparison with the benchmark techniques. It is also found that this technique exhibits considerable resilience to noise, obstruction and smoothing.
Tsolakidis et al [2014][10]proposed a technique that uses Zernike Moments and HOGs (Histogram of Oriented Gradients) for the classification of the images of plant leaves. After pre-processing, the leaf's shape features are computed applying Zernike Moments and texture features applying HOGs and later the SVM classifier is considered for classifying and identifying the plant leaf image. It was confirmed from the results of experiments that both Zernike Moments and HOGs were effective in classifying and identifying plant leaves from their images achieving good levels of accuracy. The validation of the technique has been performed on the Flavia and the Swedish Leaves datasets and also a hybrid dataset is used.
Naresh and Nagendraswamy [2016][11]proposed a symbolic mechanism to classify the plant leaves whose degrees of maturity, extractions, and environmental factors differ even within the same plant species. The study extracted textural features using MLBPs (Modified Local Binary Patterns) where clustering selected classes. Intra-cluster differences were determined using symbolic feature's interval values. A basic nearest neighbour classifier facilitated classifications. Extensive experiments were carried out on the newly produced UoM Medicinal Plant Dataset, as well as the Flavia, Foliage, and Swedish plant leaf databases. The study's proposed approach and current techniques were compared. The Outex dataset is also used for experimental purposes and potential outcomes are achieved with this handmade dataset also.
Le et al [2014][12] proposed a novel plant leaf recognition that depends on kernel descriptor (KDES). Bo et al proposed KDES quite recently. This is found to be reliable for various object identification problems. In this article, once more, the results of the experiments carried out on two plant leaf datasets prove that the performance of this technique excels the benchmark. Pradeep Kumar, et al. [2017][13] recognized leaves in their study using orthogonal moments as shape

descriptors for acquiring shapes of leaves while HOGs, and Gabor features were used as texture descriptors. The textural characteristics aided in acquiring inherent structures. Pre-processing of the binarized leaf picture improved its scalability, rotation, and translation-invariance. Krawtchouk moments were computed with the help of a scale and rotation normalised forms of images. Over a rotation normalised grey image, HOGs feature computations were performed and the classification of hybrid shapes and texture features were done using SVMs.

3. Proposed methodology

This section discuses the proposed model comprehensively. In this pre-processing is done by three steps first one is foreground Image segmentation based on k means clustering, second one is Image Filtering and third one is Conversion of RGB images into Grayscale. Feature extraction is computed by applying GLCMs and Centre point based feature extraction. Finally the Indonesian Herbal Medicines plant leafs are identified based on Hybrid MDs with SVMs. The overall schematic diagram of the proposed system is depicted in Figure 1.

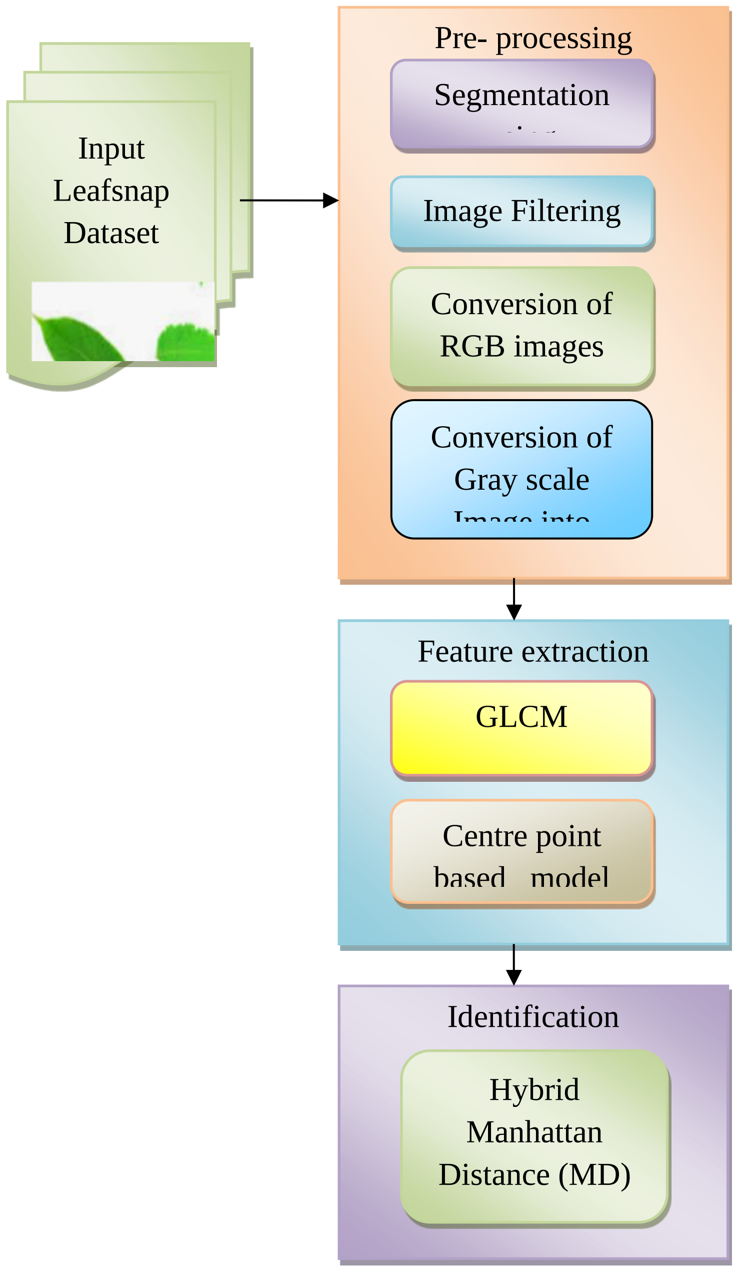

Figure:1.Overall schematic diagram of the proposed system

3.1. Pre processing

The second phase involves pre-processing the digital images belonging to medicinal plant leaves, where four approaches are undertaken in this pre-processing phase, as below

3.1. Foreground Segmentation using K means clustering

The background colours in the images of leaves is eliminated as segmentations aim at separating objects from digital images and without their backgrounds making it easier for analyzing the segmented objects. Well segmented images provide more information on object's edges. The images used in this study were segmented using K means clustering which is a segmentation method that splits a set of data into k categories. The algorithm iterates through the stages below in a loop. Each individual group or cluster's mean is calculated. The distance between each data point in each class and the cluster centre is then calculated. Finally, all of the data points are given to the cluster with the shortest distance. When the assignment is completed, the cluster centre is determined again, and a new distance vector is constructed based on that center [14,15].

Assume an image (X x Y) t needs to be divided into k clusters, with ck denoting the cluster's center. The k-means clustering algorithm is as follows:

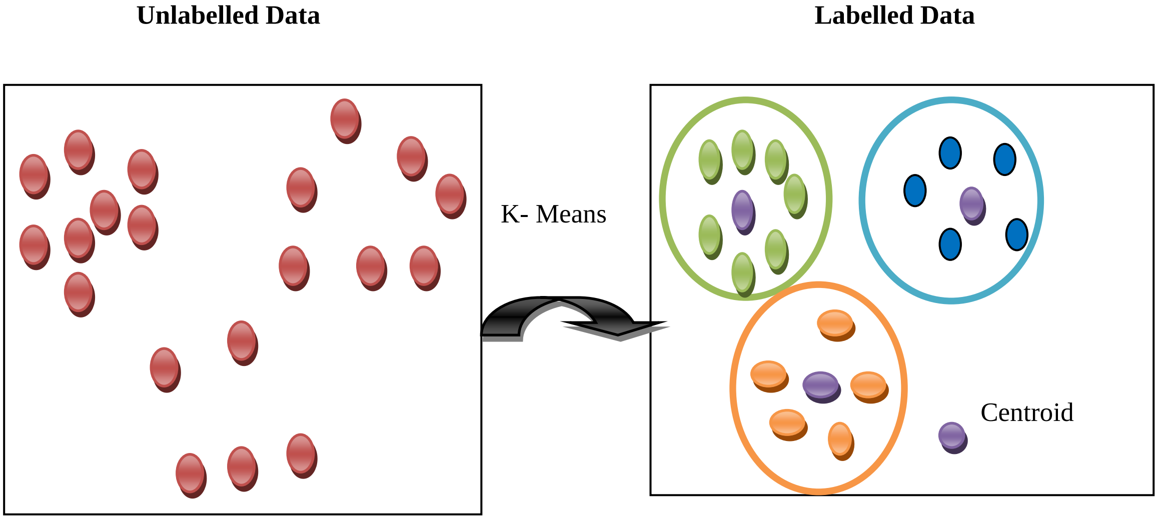

Figure:2 - K means clustering

Input: Leaf snap Dataset Output: Segmented foreground image Step 1: set initial count of clusters, k, and the centre of each cluster. Step two: Apply the expression(1) to compute distances between data points and cluster centre: $\mathrm{d} = \lVert \mathrm{p}(\mathrm{x},\mathrm{y}) - \mathrm{C_k} \rVert \quad (1)$ Step 3: Sort all of the data points into clusters based on their distance from each other, d. Step 4: After completing the assignment, re-compute new centre for each cluster using the formula(2): $C_k = \frac{1}{k}\sum_{x\in c_k}\sum_{y\in c_k} p(x,y) \quad (2)$ Step 5: iterate till convergence is achieved. Step 6: Allocate data points once more in accordance to reshape the image.

3.1.2.Image Filtering*:* This phase addresses quality recovery of objects in digital images in training. It aims at sharpening and fine tuning images.

3.1.3.Conversion of RGB images into Grayscale: In this methodology, digital images having three colour layers such as Red, Green, and Blue are simplified and converted into one colour layer and referred to as Grayscale.

3.1.4. Conversion of Greyscale Image into Binary Image: Once the RGB images have been converted to grayscale in the ultimate stage of pre-processing, the images are converted into their binary equivalents using specific threshold values also known as global thresholding.

3.2.Feature extraction

The second phase in this approach involves extracting the features pertaining to medicinal plant leaves, and this phase uses centre point based method and Gray Level Co-occurrence Matrix (GLCM).

3.2.1. Centre point based feature extraction:

This process is completed by three steps such as the determination of the median line connection, the centroid value, and 16 cardinal directions. The three methods are described in detail below.:

Centroid value: refers to the value of digital image object's midpoints (centres), where computing the centroid value aids in determining the distance between the digital image's midpoint and the point of the necessary object.

Method 16 Direction of the Wind Eye: This method is a main contribution of this work, and aids in determining the first centroid point and subsequent coordinate points, which start from east end's cardinal directions. This work uses 30 degrees as its primary angle which is applied between centre of a leaf image object to its boundary resulting in sixteen corner points for dividing the images along leaf edges. Telang leaves are one of 51 types of leaves investigated in this work, and one example of implementing the 16 cardinal directions approach in the binary object picture of telang leaves is shown.

Median Line Connector: The distances between seven horizontal lines at compass direction's point are computed and split using physiological vertical distances of the leaf. Median line connectors compute average values by dividing actual image sizes of medicinal plants leaves shown in figure.4. the results obtained in these executions using median line connectors on herbal plant leaf images (test object) is shown below.

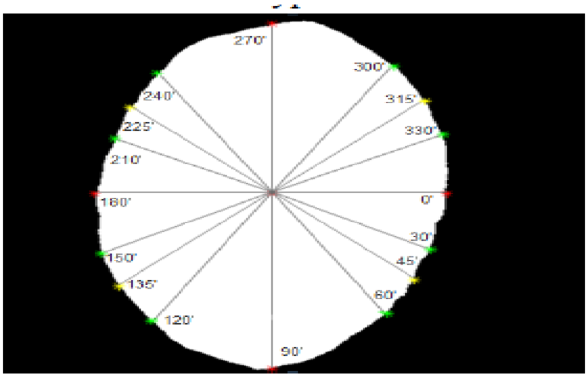

Fig. 3. Extraction of Telang Leaf Image with 16 Cardinal Directions

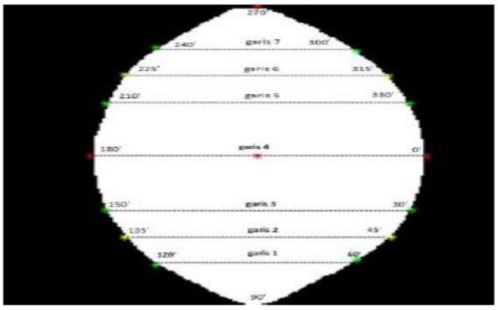

Fig. 4. Usage of Median Line Connector in Binary Image of Leaves

3.2.2. Feature extraction using GLCMs

GLCMs are helpful in estimating image characteristics and are associated with second-order statistics. With this GLCM technique, the texture features are computed as follows[16,17,18]:

Energy: Energy specifies the continuity found in the mammographic image. Typically, the computation of energy is done using the value of the mean squared signal. Its formula is given as

$$\text{Energy} = \sum_{i,j=0}^{n-1} p(i,j)2 \quad (3)$$

Contrast: The contrast provides the measure of the difference between the least and the highest values of a set of pixels close by. It computes the amount of the local differences present in the image

$$\text{Contrast} = \sum_{i,j=0}^{n-1} (i-j)^2 p(i,j) \quad (4)$$

Correlation: The correlation provides a measure of the correlation of a pixel with its neighbour over the whole image.

$$\text{Correlation} = \sum_{i,j=0}^{n-I} \frac{(i \times j)p(i,j) - u_i u_j}{\sigma_i \sigma_j} \quad (5)$$

σ2 = the difference between the intensities of each one of the reference pixels in the correlations, which are a part of the GLCM, expressed as below:

$\theta^2 = \sum_{i,j=0}^{N-1} p_{i,,j}$(i-u) (6)

Homogeneity, Angular Second Moment (ASM): ASM utilized for measuring the homogeneity of the image

$$\text{Homogeneit}\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \{p(i,j)\}^2 \quad (7)$$

Entropy: Entropy specifies the measure of the irregularity or complexity existing in the image. Entropy achieves the highest value if the values of P (i, j) are assigned quite evenly throughout the entire matrix. Entropy has ahigh but inverse correlation with Energy.

$$\text{Entropy} = -\sum_{i,j=0}^{n-1} p(i,j)\log p(i,j) \quad (8)$$

Where 'i' specifies the rows of the GLCM matrix, 'j' refers to the columns of the GLCM matrix, 'n' indicates the number of gray levels and P(i, j) refers to the cell denoted using the row and the column of the GLCM matrix. Based on these evaluations, the texture features are extracted.

3.3. Medicines plant leafs identification based on Hybrid MDs with SVMs

The phases involved with recognizing medicinal plant leaf images in this work are done by using Hybrid MDs with SVMs. The steps considered by researchers to utilize the MDs is as given :

Input: C: Extracted features

I:Results of leaf identification

1. Read training data utilising digital photos of herbal plants
2. Initialize the leaf image test data's characteristics (x)
3. Set up the features of the image data model for training (y)
4. Create a matrix with dimensions of 1 x y
5. Create a matrix with dimensions of x * y
6. Use MDs calculate the closest distance between two coordinate points:

$d(x, y) = \sum_{i=1}^{n} |(x_i - y_i)|$ (9)

The formula for computing MDs is as follows:

m is the number of images of herbal plant leaves in the test data.

y denotes single image's feature counts.

leaf image training data (xi)

yi = data from a leaf image test

7. On the basis of 23 features, compute herbal plant leaves test and training data co-ordinate differences.

SVMs

SVMs have been called as discriminative classifiers and offer increased accuracies when compared to several other classification models. SVMs have good generalizations as they use SRMs (Structural Risk Minimizations) for finding optimal separating hyper-planes as shown in Eq. (10), ensuring the most precise classifier in a variety of applications[19,20,21].

$$W.X + b = 0 \quad (10)$$

In Fig. 5, two sets of data points are available, indicated by void circles and darker circles, with some hyper-planes linearly separating them. Although an infinite number of hyper-planes (broken lines) may be created, only one hyper-plane (the long line) could be employed for the best separation of data points from different groups. This optimal separation hyper-plane is located between the maximal margin (d1 + d2 in Fig. 5) and the minimal margin.

SVs (Support vectors) are the data points that are closest to the ideally separated hyper-plane . There is a specific way of encoding the SVs for a specific set of training data points, and the maximum margin can be obtained by minimization of ½ $||w||^2$, as illustrated in Eq. (11).

$$\min\{1/2\|w\|^2\} \quad (11)$$

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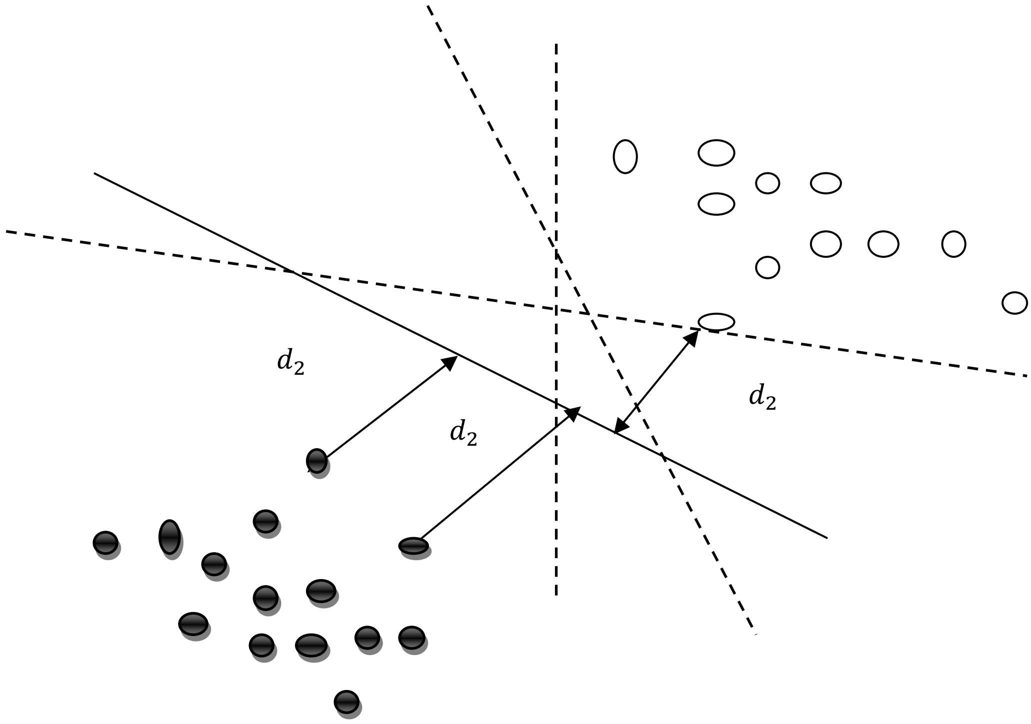

Fig. 5. Optimal separating hyper-plane.

Through the minimization of Eq. (11), training data points are isolated and the optimal dividing hyper-plane can be derived using the condition as shown in Eq. (12).

$$y_i(W.x_i + b) \geq 1, \forall i \quad (12)$$

Hybrid MDs with SVMs (HSVM –MD)

The underlying aim of this research work is to enhance the traditional MDs classification techniques using SVM's training to yield a combined classification mechanism in which the effect of accuracy is much less when parameter d is implemented, so that improved classification performance can be achieved, in comparison with traditional **MDs** and classical SVMs.

The SVM-MD hybrid classification technique proposed in this research study uses SVMs to limit training data point counts or SVs for classifications. MDs used calculate distances between new input data points and collected SVs. The right classes for input data points are determined by groups with least mean distances between their SVs and input data points. Since, SVM- MD measure distances between testing data points found to be the SVs of a single class, there is a need to decide on the optimum value for parameter d in traditional MDs which is reduced.

SVs that belong to groups are identified in training by SVMs in the training phase of the hybrid SVM-MD classification. The training data points are mapped into vector spaces and best separation hyper-planes are constructed where optimality of hyper planes are important to identifying a group's SVs. The best separation hyper-plane is located halfway between the greatest margin and the minimum margin. Margins are defined as the sum of distances between SVs and hyper-planes and while using classic SVMs in training. Thus, vector spaces of SVM-NN aids in the construction of optimal separation hyper-planes.

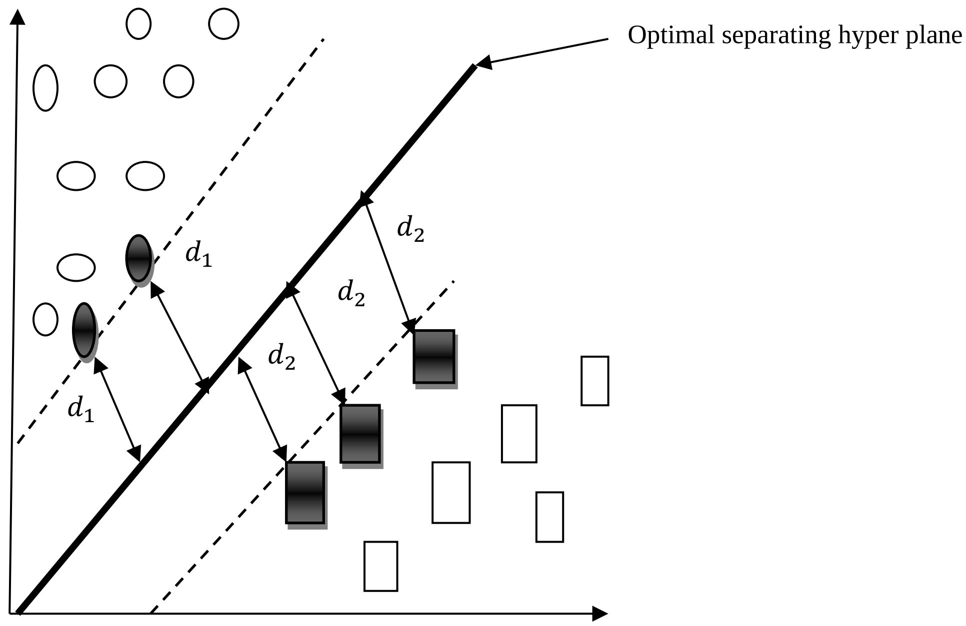

Fig. 6. Vector space of the SVM-NN technique during training phase

Fig. 6 shows an example in which two classes of data points, whose mapping is performed onto the vector space, as shown by the symbols "circle" and "square". The SVs of each class are represented by black coloured circles and squares. The optimal separating hyper-plane can be obtained by maximizing the margin of $d_1 + d_2$ margin, as shown in Fig. 6. The remaining training data points can be discarded on finding the classes for SVs. The optimum separating hyper-plane is not necessary during classifications, as Manhattan Distance Function decides on classifications. New data point that have to be classified are mapped as SVs within the same vector space, and then mean distances between SV classes and new data points are computed.

Algorithms of the HSVM-MD based leaf identification approach in training stage, and classification stage. **Input**: Extracted features **Output**: Leaf identification results **Training stage** I. Training data points are mapped onto the SVM vector space II. Support vectors belonging to every class are found, and the rest of the training data points are removed. **Classification stage** I. New unknown data point gets mapped onto the same vector space belonging to the support vectors acquired from the training step. II. Compute the mean distance for every class applying the Manhattan Distance equation III. Decide the class of new unknown data point on the basis of the shortest mean distance between the SVs of the class and the new data point.

4.Results and Discussion

This section discuses the results obtained with the experiments conducted with the proposed model. The proposed model is implemented using MATLAB. In this section proposed HSVM –MD model is compared with the current NN and MD in terms of performance metrics including precision, recall, accuracy and F Measure for the Leafsnap database (http://leafsnap.com).

Which consist of 23147 Lab images, and these are ofsuperior-quality images acquired of compressed leaves, obtained from the Smithsonian set. These images are visualized in moderated backlit and front-lit forms, with multiple samples for each species.7719 Field images, comprising of "common" images captured using mobile devices (generally iPhones) in external scenarios. These images exhibit different levels of blurring, noise, lighting forms, shadows, etc.The dataset presently provides a coverage for all 185 tree species obtained from the Northeastern United States.

Input Images

Figure:7. Halesia tetraptera lab image and field image

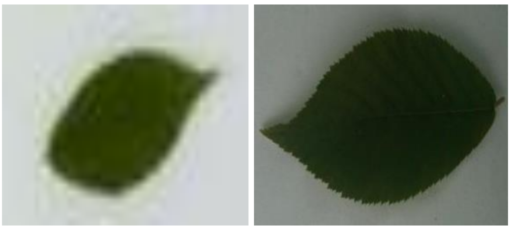

Figure:8. Ostrya virginiana lab image and field image

Figure:9.Nyssa sylvatica lab image and field image

Experimental metrics

1) Precision

Precision refers to the ratio of the results which show relevance and formulated as

$$\text{Precision}=\frac{\text{Truepositive}}{\text{truepositive+falsepositive}} \qquad (6)$$

2) Recall

Recall refers to the ratio of the overall relevant results that the proposed algorithm has correctly categorized, expressed as

$$\text{Recall}=\frac{\text{Truepositive}}{\text{truepositive+FalseNegative}} \qquad (7)$$

3) Accuracy

Accuracy refers to the metric that assesses the classification systems. In informal terms, accuracy is given by the ratio of predictions got right by this model. In more formal terms, accuracy is defined as:

$$\text{Accuracy}=\frac{\text{Truepositive+TrueNegative}}{\text{Total}} \qquad (8)$$

4)**F-measure**

The F-measure is calculated by the harmonic mean of precision and recall, yielding the same weighting to each one.

$$F_1=2.\frac{Precision.recall}{precision+recall} \qquad (9)$$

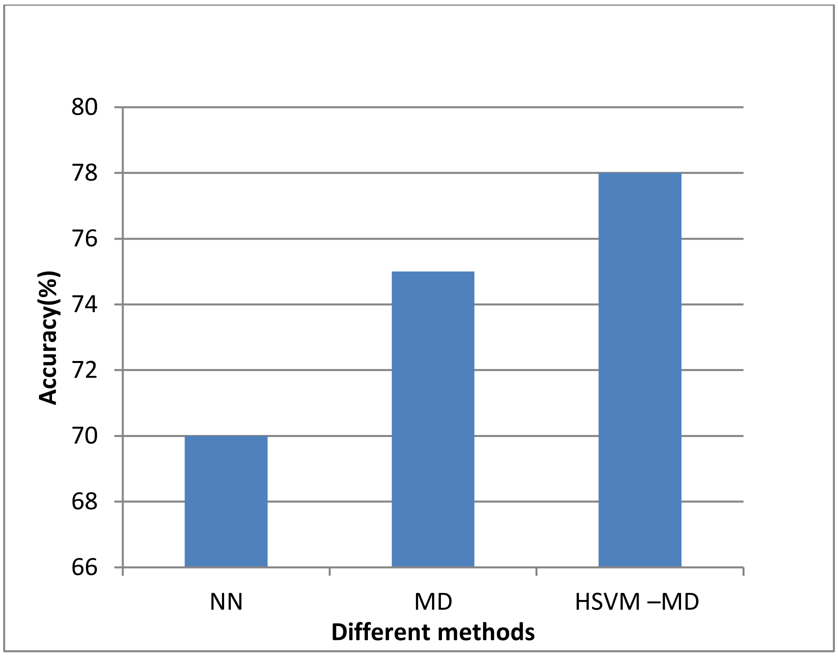

Figure:10. Accuracy results vs. Classification methods

The figure above shows the performance comparison performed between the existing classifier, NN, MD and the proposed HSVM –MD approach. In Proposed model, GLCMs based feature extractions are used and therefore improved accuracy of HSVM –MD is observed. In the above graph, X-axis depicts various techniques while their corresponding accuracies are plotted on the Y-axis. The result confirms that the proposed HSVM –MD framework yields improved Accuracy results of 78%, whereas the accuracy of NN and MD approaches is just 70% and 75% , correspondingly.

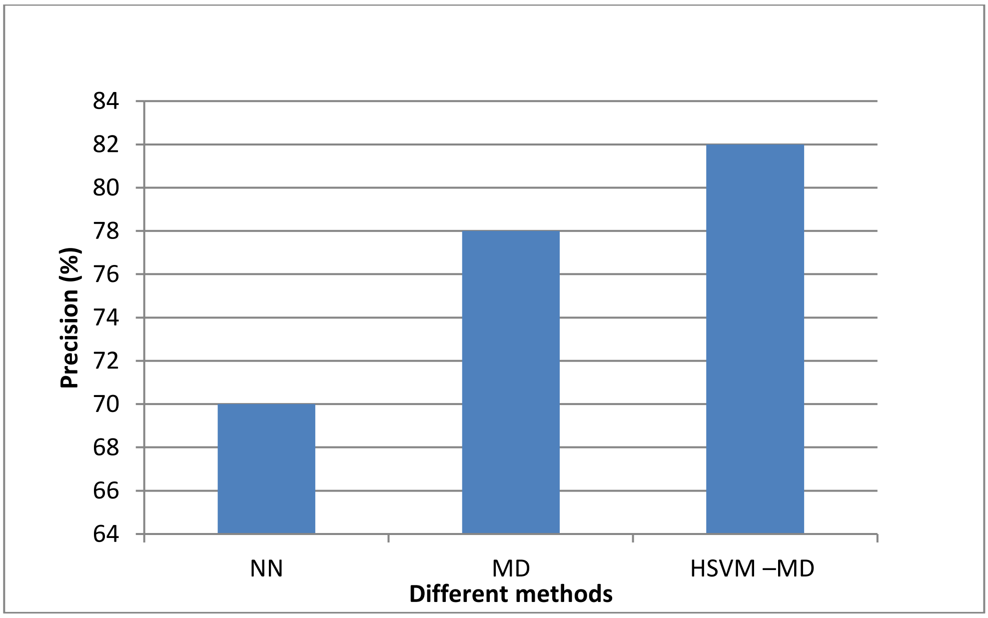

Figure .11: Precision results Comparison of different Classifiers

The above figures shows the efficiency of the proposed HSVM –MD by comparing it with the eixsting NN and MD techniques in terms of precision metric. Proposed work employs hybrid Classifier by which precision get improved . In the above graph, X-axis depicts various techniques while their corresponding precision values are plotted on the Y-axis. It can be inferred from the results, that the proposed HSVM –MD model yields precision values of 82% whereas the existing NN and MD techniques attains just 70% and 78% correspondingly.

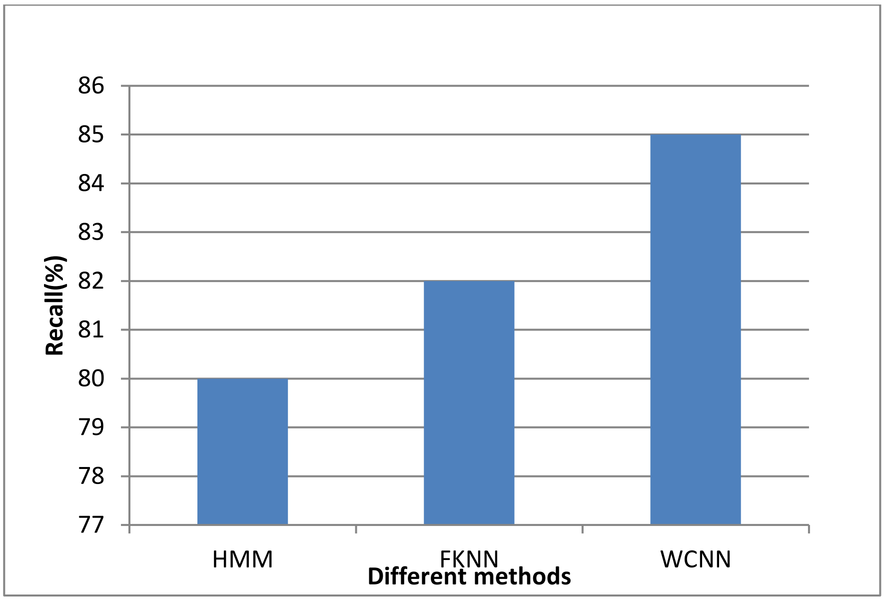

Figure: 12. Recall results vs. classification methods

In Figure: 7, the Performance comparison analysis between the available classifiers NN and MD and the proposed HSVM –MD approach is carried out in terms of recall metric. In the above graph, X-axis depicts various techniques while their corresponding recall values are plotted on the Y-axis. It can be inferred from the result, that the proposed HSVM –MD model produces higher recall values of 85%whereas the existing NN and MD techniques attains just 80% and 82% correspondingly.

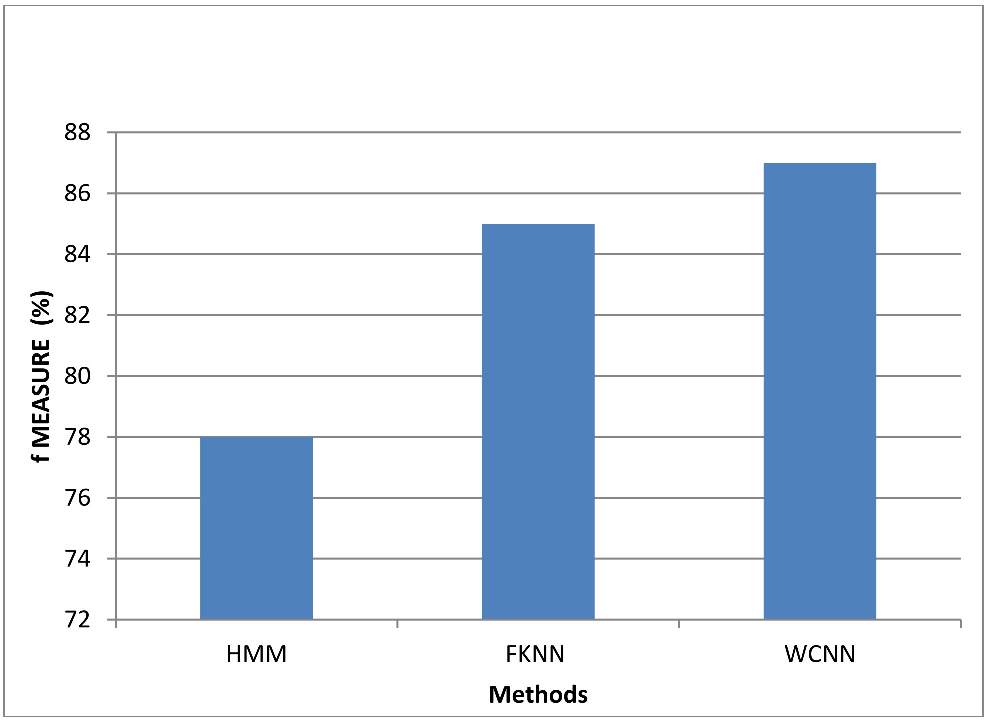

Figure: 13.F-Measure result vs. classification methods

In the above figure, the Performance comparison analysis between the current classifiers, NN and MD proposed HSVM – MD scheme in terms of F-Measure. In the above graph, X-axis depicts various techniques while their corresponding F-measure values are plotted on the Y-axis.It can be proven from the result,that the proposed HSVM –MD model produces higher f-measure results of 87% while available NN and MD techniques yields only78% and 85% respectively.

5.CONCLUSION AND FUTURE WORK

Plants are very important for the life of humans. Especially, medicinal plants have been used in prevalence as folk medicines by native humans from time immemorial. Generally, the identification of Herbs are done by experts on the basis of several years of experiences using personal sensory or olfactory senses. The current progress made in analytical technology have made considerable contribution towards herbal identification on the basis of scientific information. This helps several individuals, particularly those who lack experience in herbal identification. This work aimed to provide an improved plant leafs identification model. In this pre-processing is computed using Image segmentation depending on k means clustering to segment the foreground object, Image Filtering to eliminate the unwanted noise and to smoothen the data, translation of RGB images into Grayscale and translation of Grayscale Image into Binary Image. Feature extraction is done by applying GLCMs and Centre point based model. Finally the Indonesian Herbal Medicines plant leafs are identified based on those extracted features using Hybrid Manhattan Distance (MD) with Support vector machine (SVM). Results shows that this proposed model achieves higher leaf identification accuracy than other models. Dataset which taken for this work has more number of features this consumes more time for classification and this could be focused in near future.

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