Plant leaf disease detection using ensemble classification and feature extraction

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Abstract - It is a well-known certitude that agriculture and cultivation has a momentous part to play in the world in the economy of the world including the countries where agriculture is the sole source of income. Nevertheless, it is quite unfortunate that this is being affected by destruction caused by diseases. Plants form a considerable origin for energy for both man and animal. Leaves of the plants are the primary way the plants interconnect with the earth's atmosphere. Hence, it becomes prime responsibility of the researchers and academicians to look into the matter, develop schemes to pinpoint the leaves infected with diseases. This will help the farmers around the world to take timely steps to retain their crops from damaging to an ultimate extent and save the world and themselves from the possible economic crisis. Detecting the diseases laboriously may not be a right idea and hence a mechanized way to identify leaf diseases which can be a boon for the agricultural sphere which will also bloat the crop yield. This paper focuses on the use of ensemble classification along with hybrid features of Law's mask, LBP, GLCM, SIFT and Gabor in order to improve the results of classification. The proposed approach shows that ensemble of the chosen classifiers can perform much better as compared to individual classifiers. Since ensemble classification showed better accuracy, the choice of the features also matter to get the best possible results. The experiments have been performed on the diseased leaf images of bell pepper, potato and tomato of the PlantVillage dataset

Keywords – Leaf disease, ensemble classification, feature extraction

1. Introduction

1.1 Background

The utmost and one of the most critical task in agriculture is the timely contamination of plants leaves with diseases. It is surprising that in today's modern world also, the plant diseases are detected laboriously and hence it may not be feasible to do such a thing for the plants in bulk or in the field. Hence, the mechanism for the detection of infection was important that impelled the researchers to design such system which is more reliable in detecting diseases as compared to the manual system. Different datasets are available for this purpose in the form of images. The diseased areas on the leaves can be considered as the originating point [17] for disease. Hence, an appropriate information regarding the disease is very important. The disease identification of plants with the bare eyes is extremely cumbersome stuff and moreover such kind of detection is not always accurate [24]. Therefore, automated mechanism is of the utmost importance.

One of the modern methods to make machines capable of imitating humans is machine learning. A number of algorithms are involved in this. Using image processing approaches, the yield can be improved by developing a self-operating system which will be capable for classification of leaf diseases. The gathering of leaf images can be done with the help of a digital camera or any other appropriate device to capture the images. This is done in order to create a relevant dataset and identify the diseases spots. A mention is must for several image processing schemes that can be utilized for pinning down the diseased spots and suitable features can be extracted in order to analyse the scenario. To pin down the relevant diseased area, a stage called image segmentation is used. Later, the features are extracted in order to predict the disease with the help of different classification approaches. In order to communicate these issues with the researchers, the state-of-the-art techniques were examined and also the implementation was performed on a large dataset. The main focus of our paper relies on the way the productiveness can be controlled by taking into account the early observation of the deteriorating plant leaf fitness. The motive is to design an efficient system.

Contemplating the possible advantages of the various models in machine learning, the objective of this paper is to focus on the ensemble classification along with the use hybrid features.

1.2 Organization of paper

The paper is organized as follows. Section 2 provides an overview of the image processing techniques. Section 3 provides a deep insight into the related work and the literature. Section 4 provides the proposed methodology. Section 5 presents the experimental results of the proposed work. Section 6 mentions the conclusion and the future scope of the current work.

2. Overview of image processing

One of the widely accepted areas to monitor and classify the plant leaf diseases is machine learning. The have been a number of reach studies available in order to carry out the advanced research in the field of plant leaf disease detection.

2.1 Acquisition

It is the top-level step in image processing. This process is equipped with images from internet sources or HD cameras capturing high quality images. Most of the papers have referred to a benchmark dataset called PlantVillage dataset which is a benchmark dataset provided by Penn State University. The motive of this project is to provide solutions to smallholder farmers using the advances and recent trends in AI. Using multiple retail digital cameras [16], the images of the diseased plant leaves were captured in good resolution.

2.2 Pre-processing

Improving the image appearance involves a number techniques such as image filtering and image contrast enhancement. This is sometimes important to remove the unwanted details from the image.

2.3 Segmentation

Segmentation splits up the image into regions which are similar in nature. In order to focus only on the diseased part of the image, segmentation play a highly important role. If the image effectually segmented, then the extracted features will also be efficacious in differentiating between the infected and the non-infected parts. Edge based, threshold based, color based segmentation has been have been effectively used for leaf disease identification. Various edge based segmentation methods such as Sobel operator and canny edge detection have been used [13]. A number of techniques have been used for this purpose in several research papers. K-means clustering [31], Fuzzy c means clustering [25], Otsu algorithm [9] [19] are few of the popular segmentation techniques being used in image processing. Seeded region growing was also found to be effective [6].

2.4 Feature Extraction

This is the next most important step after segmentation in image processing. Commonly, the images are differentiated on the basis of their features such as color, shape and texture. Moments and histograms can be considered as a part of color features. Other features such as contrast, correlation, homogeneity can be considered as texture features. Shape features can comprise area, roundedness, convexity, rectangularity, etc. One of the most traditional feature extraction algorithm used in leaf disease detection is Gray Level Co-occurrence matrix (GLCM) which is meant to calculate different texture features such as entropy, energy, contrast, homogeneity, correlation, etc. [3]. For disease detection in an efficient way, features can be combined. Such an example can seen in [10], in which the researchers have combined discrete cosine transform (DCT), structure, Fourier transform, difference operators, and Wavelet packet decomposition. Efficient results were observed in [8] with the help of fourier based fractal descriptors. Many researchers have opted for combining texture, color and shape features in order to identify the leaf diseases [3]. Extraction based on Eigen vector has been observed in [7]. Several local descriptors such as speeded-up robust features (SURF), histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), dense SIFT (DSIFT), pyramid histograms of visual words (PHOW) have been considered to identify the diseases of soybean [18]

2. 5 Classification

The final step is the classification process. The classification part in image processing is one the most important parts. It is a process in which the plant leaf images are categorized as the detected diseases.

In different scenarios, the investigators have prospected a number of classification algorithms. Such kind of classification must be able to distinguish between an infected leaf image and a non-infected leaf image [18]. The several methods in machine learning are considered as supervised and unsupervised [44]. In supervised methods, the training set is required to have the inputs along with the corresponding label values. Alternatively, the unsupervised method, the label values are absent will itself build the inferences regarding the classification. In the field of leaf disease detection, there are a number of well accepted classification algorithms as shown in Fig.

3 Related work

Different researches have been carried out in the field of classification of leaf disease. These have been carried out using different datasets including the freely available datasets. Considerable research has been carried out with the real time datasets as well. With the help of 12 color features that includes mean, standard deviation, skewness, kurtosis, shape features that includes Hu moment variants, texture features using LBP and GLCM [42], an accuracy of 86.58% was achieved using XGBoost classifier and an accuracy of 81.67% using the SVM classifier for three rice diseases. In [30], Histogram of Oriented Gradient(HOG) has been used for feature extraction achieving the highest accuracy of 70.14% with Random Forest. [29] implemented technique with help of K-means clustering and feature extraction techniques such as GLCM, Haralick, Gabor and 2DWT. in order to differentiate between the healthy leaves and the infected leaves. Two datasets were used for this – Plant Village and IPM dataset. Even few optimization techniques have also been used for various purposes such as feature selection and optimized segmentation. [41] demonstrated that feature selection done with the help of newly introduced Spider Monkey optimization boosts up the computing efficacy and classification reliability when compared with other approaches for selecting the features. Here, only the consequential features are selected with spider monkey optimization since the unimportant features only lead to performance downgrade. [36] focuses on the improvement of segmentation and classification with the help of Particle Swarm Optmization and also it improved the accuracy results to a great extent. [35] proposed an optimized approach that uses the optimized extracted features in order to improve the classification accuracy. [20] used the concept of delta segmentation method, color histograms, LBP textural features, and trained classifiers in order to differentiate the area affected by diseases. [23] also introduced a novel algorithm for image segmentation technique. As per the proposed method here, the average accuracy was found to be quite more than the existing techniques. [34] proposed a technique using segmentation and feature extraction using SVM classifier. It also uses Gaussian filters, long transform and 2D DWT using a dataset of 500 images. [38] proposed a group of features that consists of a two feature set which further consists of 10 features. It used K means clustering algorithm in order to segment the diseased area. [31] used the K means clustering algorithm for segmenting the lesion from the image using the concept of super-pixel clustering and extraction of Pyramid of Histogram of Oriented Gradients(PHOG) features is executed on two image datasets of apple and cucumber. [37] adduced a methodology that uses One Class classifiers which is trained on vine leaves in order to identify four diseased conditions. [33] compared different machine learning approaches – Logistic regression, Naïve Bayes, decision tree and KNN on rice leaf to detect the diseases.

Table 1 refers to the comparison chart of the literature survey.

Table 1: Comparison chart

Researchers	Year	Dataset	Feature Extraction	Classifier	Accuracy

S. Gharge et al. [14]	2016	Soybean leaf image database used for training is taken from net. Total 30 leaf images of Soybean are used	GLCM	NN	93.3%
D. Pujari et al. [15]	2016	900 sample images used in this work was obtained from department of plant pathology, at the University of Agricultural Sciences, Dharwad, INDIA	Color and GLCM	ANN and SVM	87 with ANN and 92 with SVM
K. Ahmed et al. [33]	2017	https://archive.ics.uci.edu/ml /datasets /Rice+Leaf+Diseases	-	Logistic, KNN, Decision Tree, Naïve Bayes	Logistic - 70, KNN - 72, Decision Tree - 97, Naïve Bayes - 50
S. Zhang et al. [31]	2017	All diseased leaves in two databases were collected from the agricul-tural demonstration district of YangLing, Shanxi Province, China.	PHOG descriptors	Context-Aware Support Vector Machine (C-SVM) classifier with a radial basis kernel function	90.43% highest in case of Apple, 92.15% highest in case of Cucumber
M. Suresha et al. [22]	2017	Images have been captured in paddy fields, Shivamogga district, Karnataka state	Geometrical feature like Area, Major Axis, Minor Axis and Perimeter of diseased part of paddy leaves	KNN	The result 76.59% has been obtained for the proposed method

S. Kaur et al. [29]	2018	PlantVillage	Color, GLCM, Gabor, 2DWT	SVM	Approx. 90
S. Kumar et al. [41]	2018	PlantVillage	SPAM – 686 features	SVM, LDA, kNN, ZeroR	SVM 92.12 LDA 80.79 kNN 84.76 ZeroR 49.32
M. Sharif et al. [28]	2018	PlantVillage+local dataset	Color, GLCM, Geometric	SVM	The proposed technique outperforms the existing methods and achieves 97% classification accuracy on citrus disease image gallery dataset, 89% on combined dataset and 90.4% on local dataset.
M. A. Khan et al. [35]	2018	PlantVillage	LBP, Color Histogram features(RGB, HSV, HSI)	M-SVM	Black Rot - 98.10%, Apple Scab - 97.30%, Apple Rust - 94.62, Healthy - 98.0%
C. S. Hl et al. [26]	2018	PlantVillage	Statistical texture(SIFT) and color features	SVM	85.1%
L. Nair et al. [27]	2019	-	Colour based feature extraction techniques	SVM and ANN	SVM – 80 Optimized SVM with GA - 86 ANN – 80 Optimized ANN with GA - 86
G. Dhingra et al. [32]	2019	From PAU	Histogram information content (HIC), Bin binary pattern (BBP)	Decision tree, Naïve Bayes, KNN, RF, AdaBoost, Discriminant Analysis, GLM	Decision tree - 91.8%, Naives Bayes - 92.31%, KNN - 96.92, SVM - 90.8%, Random Forest - 98.4%, AdaBoost - 95.03%, ANN - 80.33%, Discriminant Analysis - 80%, GLM - 95.03

P. Sharma et al. [39]	2020	The images of leaves were collected from online sources such as GitHub, Kaggle and also some of the image's dataset consists of 20,000 images divided into 19 different classes.	-	Logistic Regression, KNN, SVM, CNN	Logistic Regression - 66.4 KNN – 54.5, SVM – 53.4, CNN - 98
Radhakrishnan et al. [40]	2020	PlantVillage	CNN	CNN and SVM	CNN – 95.8, CNN+SVM – 96.8
Y. Kurmi et al. [43]	2020	PlantVillage(Bell pepper, Potato, and Tomato)	SIFT	Multi-layer perceptron and SVM	94.35% accuracy
M. A. Azim et al. [42]	2021	Rice leaf diseases dataset from UCI	Color, shape and texture(GLCM)	XGBoost, SVM with RBF kernel	XGBoost – 86.58, SVM with RBF kernel – 81.67

4. Proposed methodology

Fig.1 depicts the methodology used for the proposed work.

4.1 Dataset Collection

The dataset considered is PlantVillage [29] [35] from which Bell pepper, Potato, and Tomato diseased leaves have been used for training and testing. Plant Village is actually an R&D part of Penn State University. It encourages smallholder farmers and uses low-cost technology in assisting farmers to grow better and more food. People from around the world are working in Plant Village to work for these farmers. The Plant Village dataset is based on the assumption that information related to growing food should be available to each and every one on earth.

4.2 Segmentation

Originally, segmentation is the phenomenon of splitting the digital image into well-defined regions that comprises the pixels having similar properties. In other words, this technique divides the image into several groups having similarity. There are a number of image segmentation techniques that can be considered. In our case, we have used the K means segmentation. The segmentation process makes it much easier for the feature extraction methods to extract the required features from the segmented or the clustered portions of the diseased leaf image.

4.2.1 K means clustering

K means clustering [31] is an unsupervised algorithm used for the purpose of segmenting the similar parts in digital images. It partitions the image under consideration into K clusters having K centroids. From unsupervised, it is clear that, it is used for untagged or unlabelled data. The objective of this algorithm is to reduce the sum of square of distances between all points and the cluster center.

Steps in K-Means algorithm:

1. Pick up the number of clusters K
2. At random, pick up K points(centroids).
3. Allocated the data points individually to the nearest centroid that builds K clusters.
4. Calculate and select the new centroid of the individual cluster.
5. Reallocate the individual data points to the nearest centroid. If there is any reallocation, go to step 4.

4.3 Feature Extraction

Feature extraction in image processing is enmeshed with a number of features such as spatial features, transform, features, edge, boundary, color, shape, and texture features. The features to be extracted from an image can be color, shape or texture. The values of these features may be humdrum under the same particular region and hence become a very powerful qualifier for identification in similar images. A texture feature is nothing but a recurring arrangement of information. It has found its use in a number of applications as medical imaging, plant disease detection, and remote sensing. In order to illustrate the distinctive features in an image, the process of feature extraction is used. Different feature extraction methods such as Law's Texture mask, GLCM, LBP, Gabor and SIFT have been used.

4.3.1 Laws texture features

Laws texture feature, has been used for research such as classification of wood defects [21], mammogram classification [12] and analysis of bone texture [4] is a method to determine the secondary features of the image. To determine the texture energy, a group of 5*5 convolution masks are used. It uses the filter masks within a specified size of the window. It has been chosen in order to extract the texture features of the image as it has a superior capability. There are 4 main characteristics of the image can be analysed: level, edge, spot and ripple.

L5 (level) = [1 4 6 4 1]
E5 (edge) = [-1 2 0 2 1]
S5 (spot) = [-1 0 2 0-1]
R5 (ripple) = [1 -4 6 -4 1]

4.3.2 Grey Level Co-occurrence matrix

GLCM [29] [28] is one of the oldest techniques for analysing textures. It represents a matrix that is generated over an image in order to show the distribution of pixels which are co-occurring. This technique is very helpful in image processing. It actually computes how frequently the pixel pairs having a particular value occur in an image. In other words, it computes the spatial relationship between the pairs of the pixels.

4.3.3 Local Binary Pattern

LBP is also a statistical based feature. LBP characterizes the texture with the finest primitives. LBP was developed for 2D texture patterns. LBP is a visual descriptor that was originally developed [1] in 1994. It is a very persuasive texture feature that has been used for the description of region of interest [5] and can reveal the fine details of the surface. It calculates a local exemplification of the texture. [2] shows that the texture measures using LBP are computationally easy. This local exemplification is formulated by comparing each pixel with the adjoining pixels. It is enmeshed with a number of steps. Elementary LBP is applicable to a 3*3 proximity of pixels. Initially, the image first needs to be converted into grayscale. 8 pixel proximity will be considered that will be around a central pixel. This central pixel will act as a threshold to formulate a group of 8 binary digits.

4.3.4 Gabor filters

Gabor filter [29], also called as the linear filter is utilized for texture analysis. It is mainly used for frequency content detection in peculiar directions in an image which are localized in a region. The representation of the Gabor filters is very close to human visual system.

4.3.4 Scale Invariant Feature Transform

SIFT [26] is used for texture features for the depiction of local features. It uses an image descriptor for image based recognition. It used key points in the image and these are then used with the descriptors for recognizing objects.

4.4 Ensemble Classification

The ensemble learning [45] techniques have always proven to be providing better performance as compared to individual or single classifiers. In the proposed methodology, classifiers such as RF, ANN, SVM, KNN, Logistic regression and Naïve Bayes have been used. Among all these, RF is itself and ensemble learning method. The Random Forest comprises an ensemble of decision trees and hence has been very successful over the years in multi- disciplinary fields. In the proposed methodology, a comparison is depicted between RF and an ensemble of ANN, SVM, KNN, logistic regression and naïve bayes classifiers.

4.4.1 Artificial Neural Network

Based on the concept of human brains, these are comprised of a huge number of simple computing elements which operate simultaneously. In image processing applications, the features of the images can be extracted and classified using ANN [15]. In order to carry out functions such as pattern recognition, the neural networks have the potential to adjust to their own responses using the automatic adaptation of the weights.

4.4.2 Support Vector Machines

SVM [29], used for both regression and classification problems, is a supervised learning technique. It has attracted a number of researchers all over the world owing to its higher classification accuracy as compared to other classification algorithms. Basically, it is used for classifying two classifiers with the help of a hyperplane in a feature space of high dimension. The main objective is to determine a hyperplane in an n-dimensional space that will differentiate the points into appropriate classes. Hyperplane can be represented as:

$$w.x+b=0$$

where w is weight vector and normal to hyperplane. b is bias or threshold. The kernel considered in our work is RBF.

4.4.3 K- nearest neighbour

KNN [22] is also a supervised learning algorithm for classification problems. It does not perform any learning at all. The major drawback is that it slows down as the size of the data increases.

4.4.4 Logistic Regression

Logistic regression [33] is also a supervised learning algorithm for classification. It is basically used for predictive analysis. It is used for predictive analysis and is built on the notion of probability. Logistic regression uses complex cost function called as the ‘Sigmoid function’. This function is used to map predictions to probabilities.

4.4.5 Naïve Bayes

These are the probabilistic classifiers based on the notion of Bayes’ theorem. [32]. It assumes independence between the features.

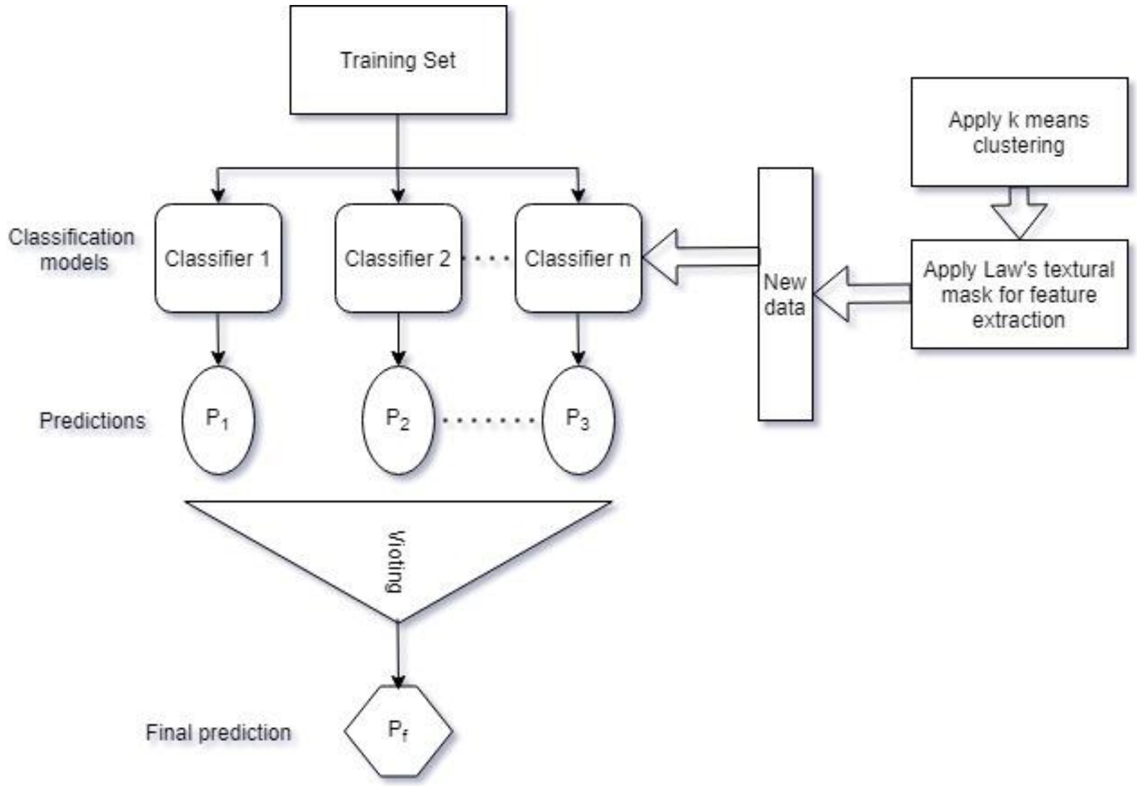

Fig 1: Proposed methodology

5 Experimental results

5.1 Leaf images dataset

The dataset consists of a total of 20,639 images comprising the 2 categories from Bell Pepper, 3 categories from Potato, and 10 categories from Tomato. Bell Pepper dataset comprises Bacterial Spot and healthy categories. Potato consists of Early Bight, Late Blight and healthy categories. Tomato consists of Target Spot, Mosaic Virus, Yellow Leaf Curl Virus, Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites and healthy category. 70% images have been used for training, and the rest 30% has been used for the testing purpose.

5.2 Evaluation Metrics

In order to measure the performance of the classification model, we used different evaluation metrics:

Accuracy = TP+TN/TP+TN+FP+FN,

Precision = TP/TP+FP,

Recall = TP/TP+FN,

where TP = True positive, TN = True Negative, FP = False Positive, FN = False Negative

Table 2, Table 3 and Table 4 show the results of the performance comparison of the proposed approach with the other existing approaches

Table 2: Accuracy comparison of the proposed approach with other approach

Approach	Pepper(2 classes)	Potato(3 classes)	Tomato(10 classes)
Proposed features Law's mask + SIFT + ensemble	82.65	89.12	86.23
Proposed features Law's mask + SIFT + Gabor + ensemble	87.23	93.156	88.45
Proposed features Law's mask + Gabor + ensemble	92.13	95.66	90.23
SIFT + Gabor + ensemble	81.23	86.23	84.23

SIFT + ensemble	86.23	88.23	83.12
Gabor + ensemble	80.12	84.23	82.12

Table 3: Precision comparison of the proposed technique with other techniques

Approach	Pepper(2 classes)	Potato(3 classes)	Tomato(10 classes)
Proposed features Law's mask + SIFT + ensemble	84.56	85.13	83.23
Proposed features Law's mask + SIFT + Gabor + ensemble	85.67	86.23	86.23
Proposed features Law's mask + Gabor + ensemble	86.12	88.12	87.45
SIFT + Gabor + ensemble	83.12	87.23	82.12
SIFT + ensemble	81.12	84.12	85.32
Gabor + ensemble	80	81.23	83.34

Table 4: Recall comparison of the proposed technique with other techniques

Approach	Pepper(2 classes)	Potato(3 classes)	Tomato(10 classes)
Proposed features Law's mask + SIFT + ensemble	80.12	76.12	84.23
Proposed features Law's mask + SIFT + Gabor + ensemble	86.12	84.34	86.13
Proposed features Law's mask + Gabor + ensemble	88.34	87.12	87.23
SIFT + Gabor + ensemble	85.12	83.34	81.23
SIFT + ensemble	84.12	82.12	84.23
Gabor + ensemble	79	80.34	82.12

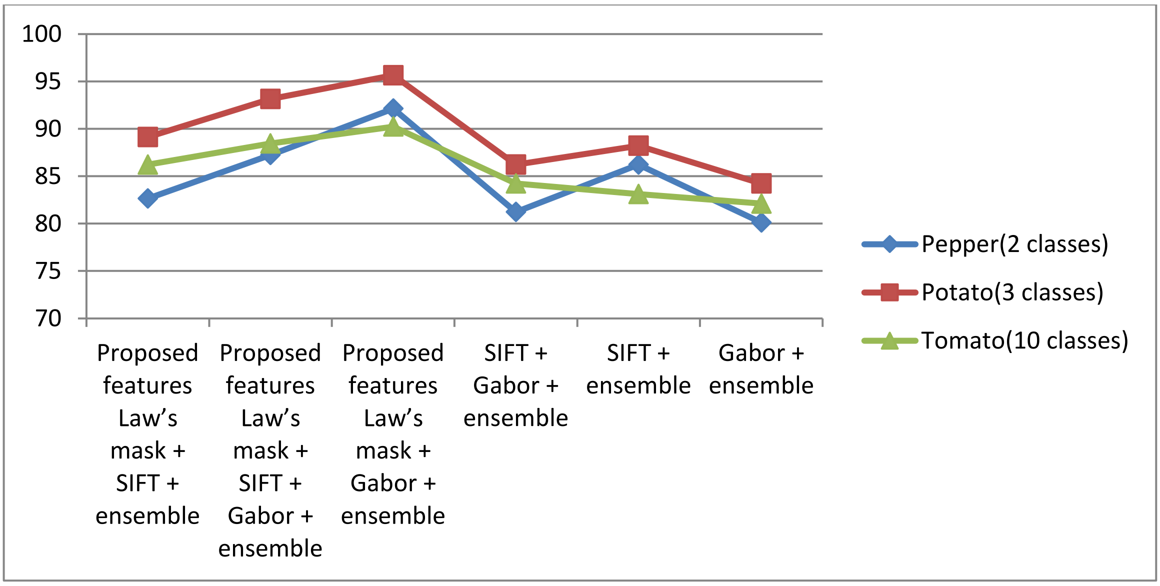

Fig 2: Comparison chart for accuracy for Pepper, Potato and Tomato using ensemble classification with the proposed approach as per Objective 1 along with Gabor features and SIFT features

From Fig 2, Proposed features Law's mask + Gabor + ensemble has the highest accuracy of 92.13% in case of 2 categories(Pepper), 95.66% in case of 3 categories(Potato), and 90.23% in case of 10 classes(Tomato).

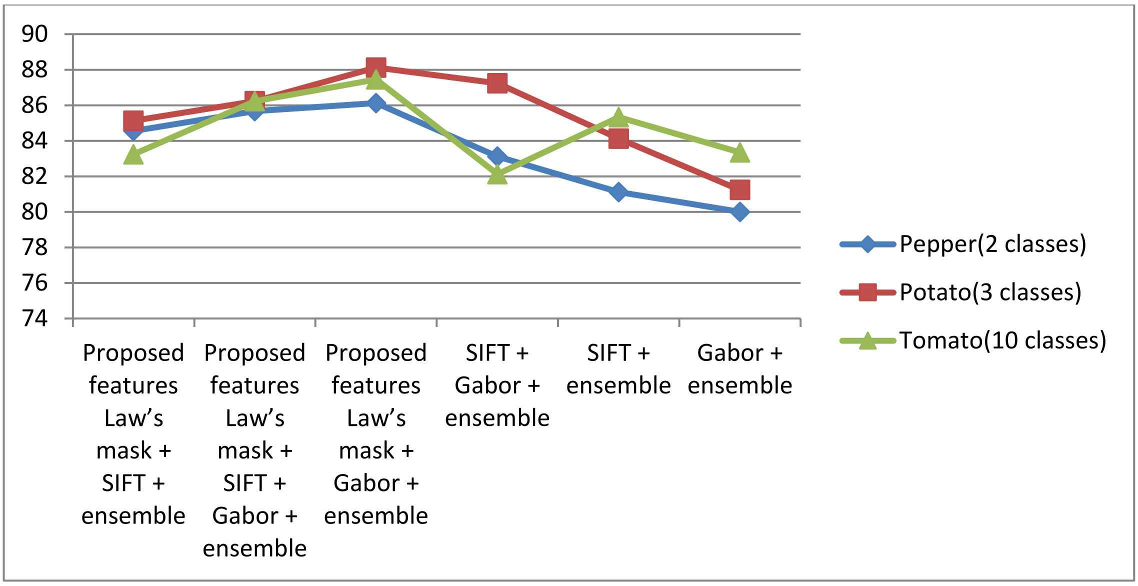

Fig 3: Comparison chart for precision for Pepper, Potato and Tomato using ensemble classification with the proposed approach as per Objective 1 along with Gabor features and SIFT features

From Fig 3, Proposed features Law's mask + Gabor + ensemble has the highest precision of 82.12% in case of 2 categories(Pepper), 88.12% in case of 3 categories(Potato), and 87.45% in case of 10 classes(Tomato).

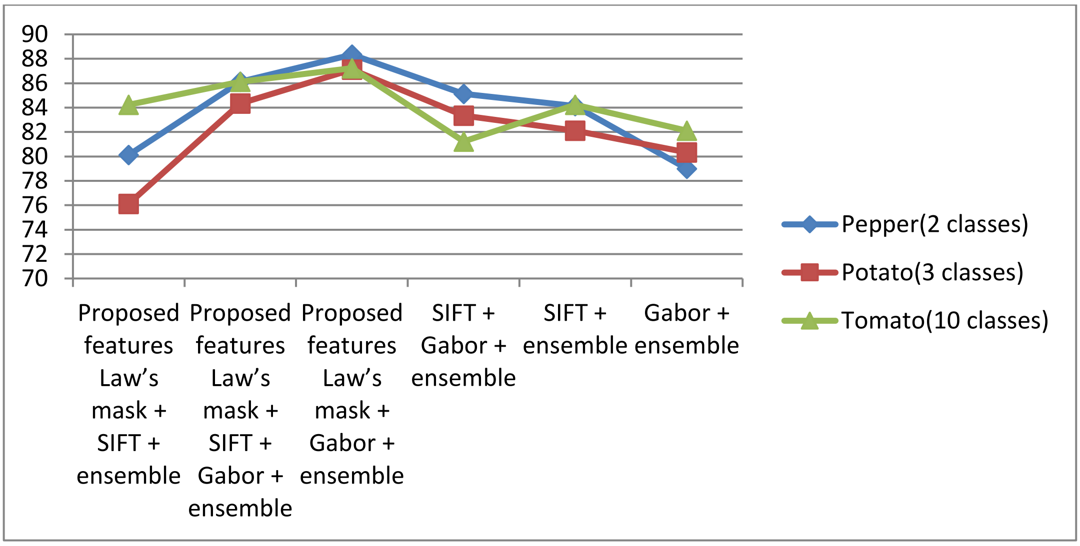

Fig 4: Comparison chart for recall for Pepper, Potato and Tomato using ensemble classification with the proposed approach as per Objective 1 along with Gabor features and SIFT features

From Fig 4, Proposed features Law's mask + Gabor + ensemble has the highest recall of 88.34% in case of 2 categories(Pepper), 87.12% in case of 3 categories(Potato), and 87.23% in case of 10 classes(Tomato).

6 Conclusion and Future Work

The principle contribution of the paper is to successfully design an ensemble classification approach along with different feature extraction algorithms. All the experiments have been performed on PlantVillage dataset consisting of 2 categories of diseases from Bell Pepper, 3 categories from Potato and 10 categories from Tomato. Steps such as image acquisition, segmentation, feature extraction and classifications are entailed but the entire focus is on feature extraction and classification phases. Feature extraction algorithms such as GLCM, LBP, Gabor features, and SIFT have been considered.

In order to make efficient ensemble classifier, the classifiers such as SVM, ANN, KNN, logistic regression, and Naïve Bayes have been used. The ensemble classification combined with different features has been implemented and their performance has been analysed. It has been observed that our ensemble classifier when used with proposed work provided us the best results in terms of accuracy, precision and recall. An accuracy of 92.13% has been observed in Bell Pepper(2 categories), 95.66% in Potato(3 categories) and 90.23% in Tomato(10 categories). The future studies for this work includes the use of deep learning in the form of convolutional neural networks in order to enhance the performance of the proposed model.

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