A REVIEW ON CROP DISEASE IDENTIFICATION AND CLASSIFICATION THROUGH LEAF IMAGES

J Sujithra[1] , M Ferni Ukrit[2]

[1] *School of Computing, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur-603203, Chennai, India.*

[2] *School of Computing, Department of Software Engineering, SRM Institute of Science and Technology, Kattankulathur-603203, Chennai, India.*

E-mail: sj1090@srmist.edu.in, ferniukm@srmist.edu.in

Abstract. Almost all over the world, the economy mainly depends on the production of food. Computer vision technology plays a pivotal role in the field of agriculture. The dream of this research is to produce successful crops in the agricultural sector. Successful farming can increase crop production in terms of both quality and quantity. The farming performs eight major phases which begin from crop selection to harvesting. At any of these phases, the disease and pest may destroy plants. However, the leaves are found to be the most damaged part in disease identification. A lot of articles are taken out for the survey that endorses the mechanism of image processing and deep learning for the detection and classification of diseases from the crop leaves. This survey provides an overview of the pros and cons of all such articles on various research aspects. The effectiveness of state-of-the-art methods is explored to identify the techniques that seem to work well across different crops. This paper indicates that algorithms like Support Vector Machine and Neural Network play an important role in the crop disease identification and classification.

Keywords: Crop disease, image processing, Feature Extraction, Segmentation, Classifiers.

1. Introduction

Agriculture is one of the most important sectors in the global economy. It provides food for humans and animals along with fabrics, materials for construction and paper products. As of September 2018, the total area planted with Kharif crops in India overtook 105.78 million hectares. India is the second biggest organic product maker in the world. Thus, an Indian economy greatly depends on farming products. Nowadays, farmers suffer a drop in production due to a lot of diseases and pests. Even though the farmers can identify the disease through naked eyes but they can’t recognize it in an overdue period which is a time-consuming problem. To avoid this condition and for a speedy recovery, the images of both healthy and infected parts of a plant are taken out. This identifies the infected regions using textural features of HSI and the set

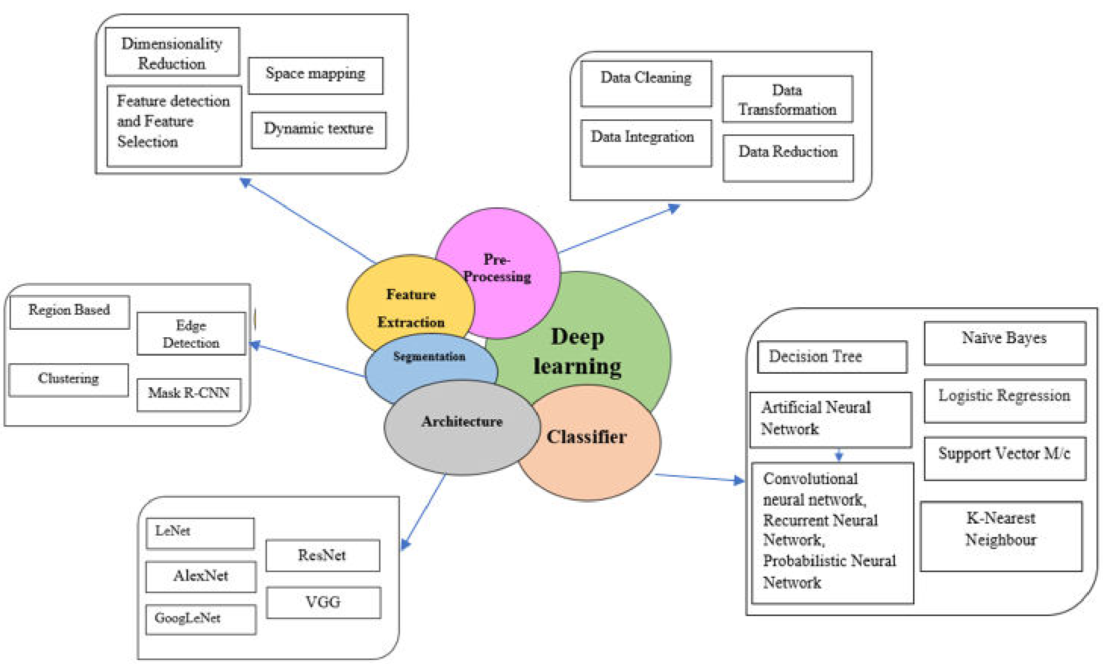
ISSN 2515-8260 Volume 07, Issue 09, 2020

of truncated feature models was created. This was used to determine the textural features in each image by using the CCM technique [1].

The utilization of crops can be classified into four different types such as cash, food, plantation, and horticulture. Plants get affected by two major diseases such as biotic and abiotic. Fungi, bacteria, and viruses in plants are caused by biotic disease [2], whereas abiotic can cause plants in terms of weather conditions, chemicals, etc... Leaves of different plants bear different diseases that have to be identified with the support of color, texture, and shape. Based on color intensity, the histogram technique was used on paddy leaves to identify the infected regions [3].

The disease detection mechanism involves several phases such as Dataset Preparation, Preprocessing, Feature Extraction, Segmentation, and classification. It consists of two major parts such as training and testing. The Training part begins with the collection of images from the stem, root, leaves, etc... These images are pre-processed by evacuating blur effect, noise effect and even correcting the RGB/grey level. In the phase of segmentation, it removes the background image from the ROI and also detects the affected part during training. Feature Extraction phase is used to extract the features and produce feature vectors. These feature vectors are utilized to train the classifier. In the training part, the test image goes through all phases and recognizes either infected or healthy from the trained classifier.

The effectiveness and compatibility of the model are evaluated using performance metrics. It is also called a recognition rate and success rate [4]. These rates depend upon the comparison of a model, type of classifier, techniques used and accuracy of recognition from one over another. Figure 1 explains about the basic deep learning techniques involved in the Leaf disease classification.



ISSN 2515-8260 Volume 07, Issue 09, 2020

Figure.1. Deep Learning Techniques for Leaf Disease classification

The rest of the paper is sorted out as follows: Section 2 exhibits about literature review on crops. Section 3 presents a discussion of crop diseases and their techniques in tabular form. Section 4 depicts the conclusion.

2. Literature review on crops

A crop is a plant that is grown or raised on a large scale so that it can be economically exchanged and extensively harvested for-profit purposes. The significant crops can be categorized into four major types depending upon their utilization. Figure 2 explains the Categories of crops.

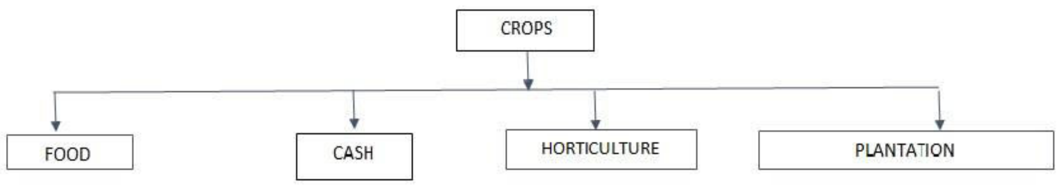


Figure.2. Categories of crops

2.1 Food crops

Food crops are derived from plants that refer to the world's food supply. These are intentionally grown with the key purpose of being eaten by people and livestock. The crops include maize, Rice, Millet, pulses, and paddy, etc… Figure 3 presents the categories of food crops and their diseases.

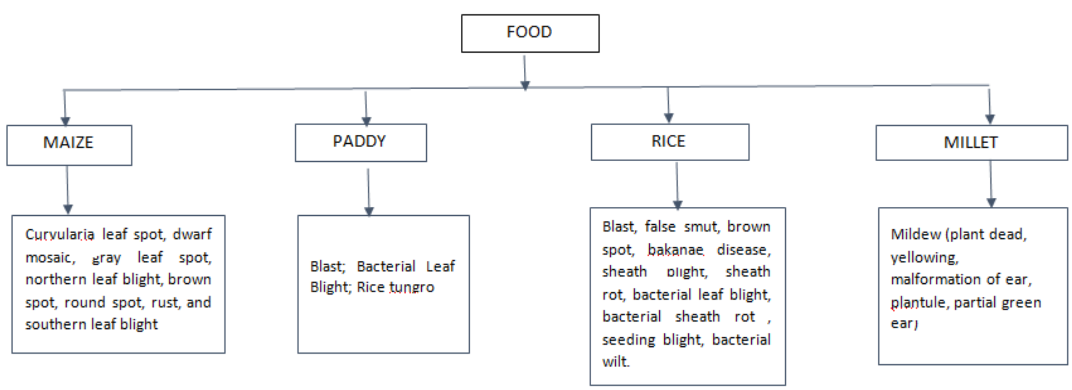


Figure.3. Categories of Food crops and their diseases

2.1.1 Techniques used

It is great significance as the accuracy of the framework lies in samples utilized for training. The 847 samples of paddy leaves were collected from several farms in West Bengal [3], which consists of three diseases such as blast, bacterial leaf blight and Rice tungro. The resized original RGB image was converted to a grey image using a color transformation technique and then the changing values were plotted using histogram technique.

Another research work negotiated with maize in [5] which 100 samples were collected from 5 kinds of diseases. Each kind consists of 20 diseases where segmentation technique was practiced to separate the diseased spots from the background image. This was done efficiently by obtaining an optimal threshold value through weighted Parzen-window.

To improve the precision of 500 maize samples that includes 8 diseases such as Curvularia leaf spot, dwarf mosaic, gray leaf spot, northern leaf blight, brown spot, round spot, rust, and southern leaf blight. The two improved models such as GoogLeNet and Cifar 10 were proposed to train and test by adjusting the parameters, adding up the dropout functions and ReLu functions, modifying the pooling combinations and reducing the number of classifiers in [6].

In [7], the dataset comprises 500 rice samples from 10 common diseases like blast, smut, brown spots, bakanae disease, sheath blight, sheath rot, leaf blight, bacterial sheath rot, seedling blight, and wilt. To avoid the problem of overfitting, the data augmentation method can be used to enlarge the datasets.

The research work was done with 124 images of millet leaves [8] which has Mildew disease like plant dead, yellowing, malformation of ear, plantule and partial green ear. The author has proposed a training network that was composed of feature extraction and a pre-trained model. This was used to extract features for any input for the third component.

2.2 Cash crops

Cash crops are crops that are produced for their commercial value rather than the consumption for humans or livestock. The crops include coffee, tea, sugar cane, tea, cotton, and spices. Figure 4 describes the categories of cash crops and their diseases.

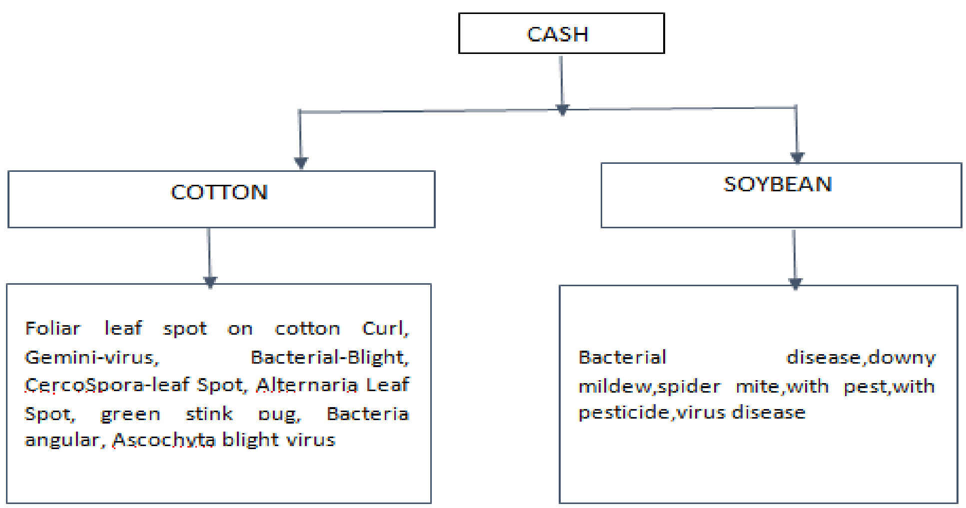


Figure.4. Categories of cash crops and their diseases

2.2.1Techniques used

The image data set of banana and plantain crops were obtained from the International Network for the Improvement of Banana and Plantain (INIBAP). The samples of cotton and soya were captured from the Department of Entomology at the University of Georgia, USA. The research work was done on identifying plant diseases through visual symptoms [9] by using the color transformation technique which converts an RGB image into H, 13a, 13b. Then, the processed images were fed into the segmentation phase, which was accomplished by determining

European Journal of Molecular & Clinical Medicine

ISSN 2515-8260 Volume 07, Issue 09, 2020

the threshold cut off value to identify the intensity of leaves using the histogram. 20 images from each crop variety have been taken for testing the model.

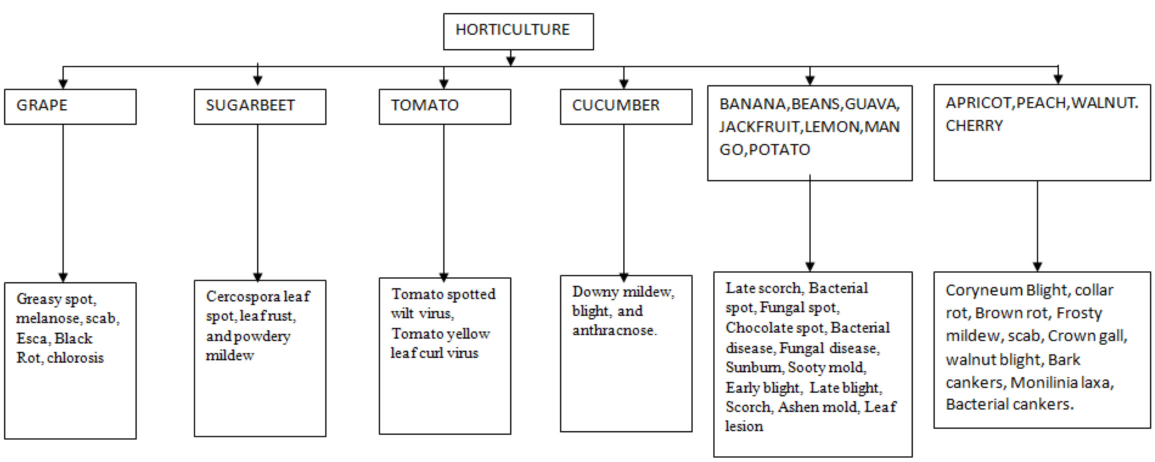
An image set of 117 samples from cotton crop [10] were acquired from the University of Georgia, the USA which consists of various diseases such as green stink bug, angular and blight virus. From those samples, the set of features was extricated. Each of them was utilized as the input to the support vector machine. It has been demonstrated that the texture related feature used as bias when the target image did not pursue the characterized shape and color.

Considering the diseases on cotton crop [11] in Foliar leaf spot on cotton Curl, Geminivirus, Bacterial Blight, CercoSpora-leaf, Alternaria spots were spotted and totally 20 diseased and 25 non-diseased samples were carried out for the detection and diagnosis using SVM. During segmentation, an anisotropic-diffusion technique can be utilized to protect the extracted pixel information and then the subsequent color pixels were grouped by an unsupervised SOFM network to obtain the cluster of the color image. Then, the classification was done using a backpropagation neural network.

The 1470 samples of soybean were collected from different farms of Northeast Agricultural University with the variation such as bacterial disease, spider mite, virus diseases, healthy leaves, downy mildew, leaves with pest and leaves with pesticide. Among all architectures, the Convolutional neural network with ResNet achieved optimal accuracy in finding diseases at the soybean crops [12].

2.3 Horticulture crops

Cultivation has been characterized as the farming of plants, for the most part for nourishment, comfort, beauty, and materials. Horticulture is the growing of fruits, vegetables, nuts and other ornamental plants for aesthetic uses which are used for medicinal purposes. Figure 5



explains the categories of horticulture crops and their diseases.

Figure.5. Categories of horticulture crops and their diseases

2.3.1 Techniques used

The image dataset of grapefruit leaves was collected from central Florida in late spring of 2002, which has four varieties of diseases such as greasy spot, melanose, scab, and normal citrus leaf. Each variety consists of 40 leaves samples in [1]. Each of the leaf sample's edges was detected byCanny's edge detector. The discrimination of affected and healthy leaves has been done using color co-occurrence techniques to identify whether the textural based (HSI) color features related to statistical classification algorithms.

The 15 plants of healthy and 15 plants of non-healthy [13] were taken as a sample for sugar beet, which consists of various diseases like leaf spot, leaf rust, and mildew. From the two classes, data was recorded using hyperspectral reflectance. SVM can be used as a classifier which produces low classification error. About 1434 samples of both sunflower leaves and weeds were collected. It was used to train the model in the splitting of 90 % training and 10% testing. To sort out the leaves, the proposed Posterior Probability Model Selection (PPMS) algorithm can be utilized in conjunction with the architecture of the Generalized Softmax Perceptron (GSP) neural network. It produces the classification outcome as either sunflower or weeds in [14].

Around 500 plant leaf samples of 30 diverse plant species from Tamil Nadu have been gained for the methodology of classifying plant diseases in [15], which has considered the common diseases like Late scorch, Bacterial spot, Fungal spot, Chocolate spot, Bacterial disease, Fungal disease, Sunburn, Sooty mold, Early blight, Late blight, Scorch, Ashen mold, Leaf lesion. The leaf samples were converted into HIS. Using co-occurrence matrix, features were derived and these values have undergone the classification with minimum distance criterion. Further, the accuracy was improved by SVM.

The 200 images of infected tomato leaves were obtained [16], which contains two diseases such as TSWV and TYLCV. SVM with various kernel functions were utilized for classification to recognize the two tomato viruses in leaf. The 300 images of cucumber leaves tainted with the sicknesses of downy mildew, blight, and anthracnose were collected for crop disease recognition. From each of the infected leaves, statistical and meteorological features were extracted [17]. The feature vector was created from these features and contributes to the Probabilistic neural network (PNN) to perform the classification.

The 90 images of apple leaves [18] affected by powdery mildew, mosaic and rust were transformed from RGB to HSI, YUV and grey models using color transformation structure. Based on the specific threshold value, the background image was evacuated and the diseased spot can be segmented using region growing algorithms. Based on color, texture, and shape, 38 classifying features were extracted. The combination of genetic algorithm and correlation-based feature selection can be utilized to choose the most significant features to improve the model efficiency.

The dataset of 106 leaf samples from banana, beans, rose and lemon was taken [19]. During training 15 samples from each species were used. After mapping the R, G, B segments of the input sample to the threshold images, the co-occurrence features were measured. Then, the infected clusters were formed by k-means clustering. The segmented components were processed using a Genetic Algorithm and classification has been performed to produce the output image with the amount of disease infected.

The 420 samples in cucumber [20] affected by Downy mildew, Bacterial angular, Corynesporacassiicola, Scab, Gray mold, Anthracnose, and Powdery mildew. The infected leaf samples were segmented using k means clustering. In training, the combined features of color and shape have been taken to form a dictionary and then form Sparse Representation of the image by the sparse model to attain the highest accuracy.

The vine leaves which have diseases like downy mildew, powdery mildew, and black rot were acquired [21]. The grab cut algorithm technique can be used in segmentation to separate the foreground and background images. The pixels were labeled and the histogram was derived using the Local Binary Pattern algorithm. Therefore, classification was performed using one-class classification and One Class SVMs. The conflicts were raised in one class SVM and it was resolved by the nearest support vector strategy technique to perform labeling according to proximity[26 - 29].

An open database of 87,848 images was taken to train a model. Among all, CNN performs better with VGG architecture in [22]. The 8900 leaf curl of papaya and 570 images of papaya mosaic were collected in [23]. It was resized as 224*224 RGB using an image processing technique. Both classification and feature extraction can be performed on CNN itself. At the outcome of CNN, the discrimination on healthy and diseased samples can be made[30-32].

2.4 Plantation crops

The plantation develops a large group of crops. It is concerned with farming where crops are grown for profit. Large land surfaces are much needed for this sort of agriculture farming. The plantation crops include coconut, oil palm, cashew, tea, coffee, rubber, and cocoa. Figure 6 presents the various categories of plantation crops and their diseases.

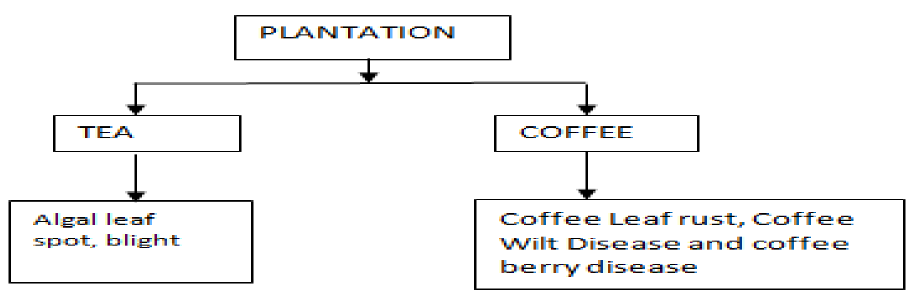


Figure.6. Categories of Plantation crops and their diseases

2.4.1 Techniques used

The 5 types of affected tea samples were taken [24], each type consists of 10 images. The tea leaves were preprocessed and undergone into the extraction phase. Pattern recognition can be done using Neural Network Ensemble (NNE) and the extracted features were fed into the Artificial Neural Network for training. The 9100 images of coffee leaves were acquired from Ethiopia, Jimma, and Zegie, which consists of three diseases such as leaf rust, berry disease, wilt.

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The data splitting of 70 % training and 30 % testing were used to improve the accuracy. There were two parts involved in [25], which is building a knowledge base system and image processing part. From the base system, an expert's knowledge can be extracted and a protocol was developed using decision tree methods. In the image processing part, the median filtering technique was used as a noise removal method and K means technique was used for segmentation. Then the feature extraction was carried to shorten the original data set, which discriminates the three types of diseases. Totally 17 features were extracted including GLCM, color, and Statistical features. Therefore the performance of recognition was tested using the BPNN classifier.

3. Analysis And Discussions

This section shows the comparative results of different crops on disease detection using computer vision techniques. The disease detection is mainly partitioned into two groups: firstly, it should follow up the steps like dataset preparation, preprocessing, segmentation and feature extraction. Secondly, it will drive into the classification and prediction results.

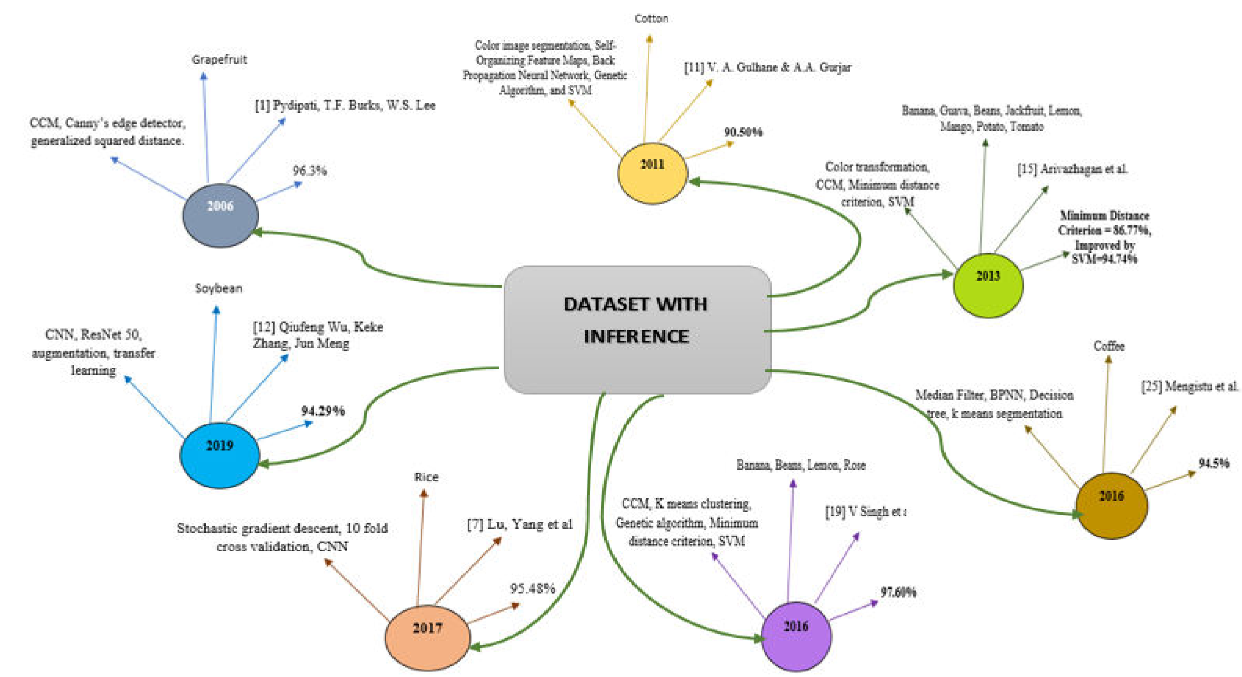

Figure.7. Review Map of Leaf Disease Classification

Figure 7 presents a summary of various techniques involved in leaf disease classification. It is categorized based on year which carries the article number, dataset applied, techniques adopted and accuracy. Since 2006, several researchers have been carried out to analyze the diseases in leaves.so, there are a number of studies related to this topic. In [1] generalized square distance technique was used in grapefruit dataset to classify the disease in leaves and showed the accuracy of 94.39%. With the progress towards technologies, algorithms like SVM [19], CNN [7], and K-Means [25] serve an indispensable function in leaf disease classification.

Table.1. shows various techniques and classifiers used to identify the crop diseases and presents the effectiveness of the algorithm through performance measures.

Table.1. Comparison on classifier's performance

[Ref No] year	Name of the crop	Crop type	Diseases have taken	Techniques used	Classifier	Performance measures (accuracy)
[1] 2006	Grape	Horticulture	Greasy spot, melanose, scab, and normal citrus leaf.	Color co-occurrence method, Canny's edge detector	Generalized squared distance	96.30%
[3] 2012	Paddy	Food	Blast; Bacterial Leaf Blight; Rice tungro	RGB to Grayscale conversion, histogram draw	Histogram draw	blast-87%, bacterial leaf blight-92%, rice tungro-90%
[6] 2018	Maize	Food	Curvularia leaf spot, dwarf mosaic, gray leaf spot, northern leaf blight, brown spot, round spot, rust, and southern leaf blight	Google Net and Cifar10	CNN, Google Net and Cifar 10	Google Net - 98.9% and Cifar10 - 98.8%
[7] 2017	Rice	Food	Blast, false smut, brown spot, bakanae disease, sheath blight, sheath rot, bacterial leaf blight, bacterial sheath rot,	Stochastic - pooling, CNN, SoftMax function,10-fold cross-validation strategy	CNN	95.48%

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			seedling blight, bacterial wilt.			
[8] 2019	Millet	Food	Mildew (plant dead, yellowing, malformation of ear, plantule, partial green ear)	Transfer learning, Optimizer= Stochastic Gradient Descent (SGD), Early stopping technique, Image Net, VGG 16 MODEL	CNN	95%
[10] 2009	Cotton	Cash	Green stink bug, Bacteria angular, Ascochyta blight virus	Image texture-CCM, fractal dimension-Box Bounting algorithm, lacunarity-Gliding Box algorithm, Cross-validation	SVM, Multi-class classification	93.10%
[12] 2019	Soybean	Cash	Bacterial disease, downy mildew, spider mite, with pest, with pesticide, virus disease	CNN, Google Net, Alex Net, ResNet 50, augmentation, transfer learning	CNN	CNN with ResNet50 = 94.29%
[24] 2015	Tea	Plantation	5 types of tea diseases	Neural network ensemble, negative correlation learning	Neural Network Ensemble and ANN	91%
[25] 2018	Coffee	Plantation	coffee leaf rust, coffee	Decision tree, k means	BPNN	94.5% accuracy

			berry disease, coffee wilt disease	segmentation, median filtering		(with tanh activation function)
[13] 2010	Sugar beet	Horticulture	Cercospora leaf spot, leaf rust, and powdery mildew	Multiclass classification- SVM (OAO), Cross-validation	SVM, Decision trees, ANN	1-2% diseased leaf area =65% accuracy for all leaves. More than 10% diseased leaf area by leaf spots=100 %. 6-9% diseased leaf area by rust = 95%
[15] 2013	Banana, guava, beans, jackfruit, Lemon, Mango, Potato, Tomato	Horticulture	Late scorch, Bacterial spot, Fungal spot, Chocolate spot, Bacterial disease, Fungal disease, Sunburn, Sooty mold, Early blight, Late blight, Scorch, Ashen mold, Leaf lesion	Color transformation structure, color co-occurrence method, minimum distance criterion, SVM	minimum distance criterion, SVM	Minimum Distance Criterion = 86.77%, improved accuracy= 94.74% by SVM
[16]	Tomato	Horticulture	Tomato	Image resizing-	SVM in	Classificat

2015			spotted wilt virus, Tomato yellow leaf curl virus	preprocessing, geometric and histogram features-feature extraction, K-means clustering algorithm, N-fold cross-validationtechnique	different kernel functions	ion accuracy-90% in general, highest classification rate-91.5 % using Quadratic kernel function.
[17] 2015	Cucumber	Horticulture	Downy mildew, blight, and anthracnose,	Region growing algorithm, PNN	PNN	91.08%
[18] 2016	Apple	Horticulture	Powdery mildew, mosaic, and rust	Color transformation, region growing algorithm, genetic algorithm, correlation-based feature selection	SVM	Training set= 95.48% ,testing set= 94.22%
[19] 2016	Banana, beans, lemon, rose	Horticulture	Early scorch, bacterial leaf spot, sunburn, a fungal disease	co-occurrence method, k means clustering, Genetic algorithm, minimum distance criterion, SVM	Minimum distance criterion, SVM	97.60%
[22] 2018	Apple, banana strawberry, blueberry,cabbage,celery,cherries,	Horticulture	Bacterial spot, early blight, late blight, powdery mildew, leaf	VGG model, Alexnet, Google Net, CNN	VGG model, CNN	99.53%

	corn,cucumber,eggplant,gourd,grape,orange,peach,beans,pepper,onion,potato,pumpkin,raspberry,soybean,squash,tomatoes		mold. Target spot, apple scab. Black rot etc...			

In figure 8, the Neural Network leads all other classifiers concerning frequent usage. Later SVM reaches close to the Neural Network. The leftover portions are chosen by other classifiers.

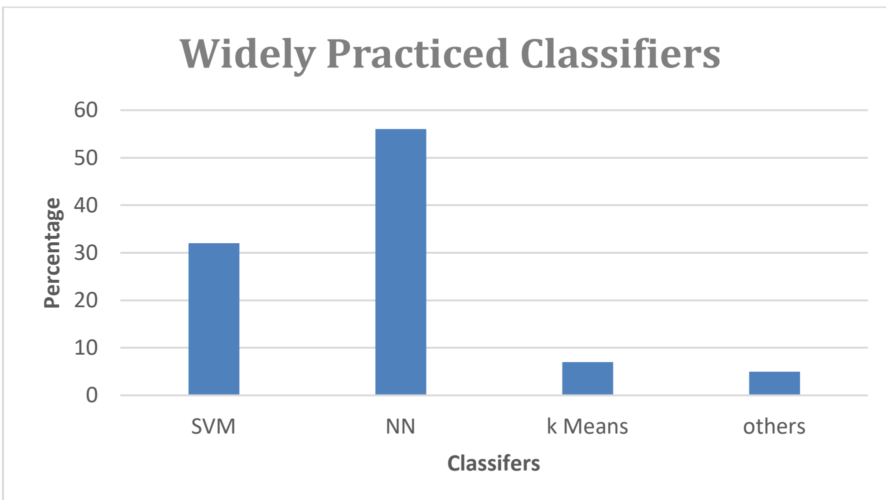

Figure.8. Analysis of Classifiers used

4. Conclusion

This paper presents a survey on the identification of plant diseases using image processing techniques. Various computer vision techniques were used to identify the plant diseases, but still, there is an impact on detecting all diseases using a single technique. From the survey, the results are compared with different approaches that end up with the algorithms like Support Vector Machine and Neural Network which plays an essential role and accomplishes more prominent performance in disease detection and classification. This approach provides an optimal solution for crop diseases. Researchers have done this work on a few plants only. Many more crop varieties are still there for diagnosis. Such varieties should be taken out for future work and the appropriate solution should be identified using different approaches.

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5. References

[1] Pydipati R, Burks T F and Lee W S 2006 Identification of citrus disease using color, texture features and discriminant analysis*Computers and electronics in agriculture*52 (1-2) p 49-59

[2] Husin Z B, Shakaff A Y B M, Aziz A H B A and Farook R B S M 2012 Feasibility study on plant chili disease detection using image processing techniques *Third International Conference on Intelligent Systems Modelling and Simulation* p 291-296 IEEE

[3] Mukherjee M, Pal T and Samanta D 2012 Damaged paddy leaf detection using image processing *Journal of Global Research in Computer Science*3(10) p 07-10

[4] Phadikar S, Sil J and Das A K 2012 Classification of rice leaf diseases based on morphological changes *International Journal of Information and Electronics Engineering* 2(3) p 460-463

[5] Zhang S W, Shang Y J and Wang L 2015 Plant disease recognition based on plant leaf image *J Anim. Plant Sci*25(3) p 42-45

[6] Zhang X, Qiao Y, Meng F, Fan C and Zhang M 2018 Identification of maize leaf diseases using improved deep convolutional neural networks *IEEE Access* 6 p 30370-30377

[7] Lu Y, Yi S, Zeng N, Liu Y and Zhang Y 2017 Identification of rice diseases using deep convolutional neural networks *Neurocomputing* 267 p 378-384

[8] Coulibaly S, Kamsu-Foguem B, Kamissoko D and Traore D 2019 Deep neural networks with transfer learning in millet crop images *Computers in Industry* 108 p 115-120

[9] Camargo A. and Smith J S 2009 An image-processing based algorithm to automatically identify plant disease visual symptoms *Biosystems engineering* 102(1) p 9-21

[10] Camargo A and Smith J S 2009 Image pattern classification for the identification of disease causing agents in plants *Computers and Electronics in Agriculture*66(2) p 121-125

[11] Gulhane V A and Gurjar A A 2011 Detection of diseases on cotton leaves and its possible diagnosis *International Journal of Image Processing (IJIP)* 5(5) p 590-598

[12] Wu Q, Zhang K and Meng J 2019 Identification of Soybean Leaf Diseases via Deep Learning *Journal of The Institution of Engineers (India)*: Series A100(4) p 659-666

[13] Rumpf T, Mahlein A K, Steiner U, Oerke E C, Dehne H W and Plümer L 2010 Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance *Computers and electronics in agriculture* 74(1) p 91-99

[14] Arribas J I, Sánchez-Ferrero G V, Ruiz-Ruiz G and Gómez-Gil J 2011 Leaf classification in sunflower crops by computer vision and neural networks *Computers and Electronics in Agriculture* 78(1) p 9-18

[15] Arivazhagan S, Shebiah R N, Ananthi S and Varthini S V 2013 Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features *Agricultural Engineering International: CIGR Journal* 15(1) p 211-217

[16] Mokhtar U, Ali M A, Hassanien A E and Hefny H 2015 Identifying two of tomatoes leaf viruses using support vector machine In *Information Systems Design and Intelligent Applications* (p 771-782) Springer New Delhi

[17] Yun S, Xianfeng W, Shanwen Z and Chuanlei Z 2015 PNN based crop disease recognition with leaf image features and meteorological data *International Journal of Agricultural and Biological Engineering* 8(4) p 60-68

[18] Chuanlei Z, Shanwen Z, Jucheng Y, Yancui S and Jia C 2017 Apple leaf disease identification using genetic algorithm and correlation based feature selection method *International Journal of Agricultural and Biological Engineering* 10(2) p 74-83

[19] Singh V and Misra A K 2017 Detection of plant leaf diseases using image segmentation and soft computing techniques *Information processing in Agriculture* 4(1) p 41-49

[20] Zhang S, Wu X, You Z and Zhang L 2017 Leaf image based cucumber disease recognition using sparse representation classification *Computers and electronics in agriculture* 134 p 135-141

[21] Pantazi X E, Moshou D and Tamouridou A A 2019 Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers *Computers and electronics in agriculture* 156 p 96-104

[22] Ferentinos K P 2018 Deep learning models for plant disease detection and diagnosis *Computers and Electronics in Agriculture* 145 p 311-318

[23] Veeraballi R K, Nagugari M S, Annavarapu C S R and Gownipuram E V 2018 December Deep Learning Based Approach for Classification and Detection of Papaya Leaf Diseases In *International Conference on Intelligent Systems Design and Applications* (p 291-302) Springer Cham.

[24] Karmokar B C, Ullah M S, Siddiquee M K and Alam K M R 2015 Tea leaf diseases recognition using neural network ensemble *International Journal of Computer Applications*114(17)

[25] Mengistu A D, Mengistu S G and Melesew D 2018 An automatic coffee plant diseases identification using hybrid approaches of image processing and decision tree *Indonesian J Electr Eng Comput Sci* 9(3) p 806-811

[26] R.Naresh, M.Sayeekumar, G.M.Karthick, P.Supraja, "Attribute-based hierarchical file encryption for efficient retrieval of files by DV index tree from cloud using crossover genetic algorithm",Soft Computing, Springer, Vol.23, No. 8, April 2019, Pp. 2561-2574.

[27] R.Naresh, P.Vijayakumar, L. Jegatha Deborah, R. Sivakumar, "A Novel Trust Model for Secure Group Communication in Distributed Computing", Special Issue for Security and Privacy in Cloud Computing, Journal of Organizational and End User Computing, IGI Global, Vol.32, No. 3, April 2020, Pp. 1-14.

[28] P.Vijayakumar, R.Naresh, L. Jegatha Deborah, SK Hafizul Islam, "An efficient group key agreement protocol for secure P2P communication", Security and Communication Networks, Wiley, Vol.9, No.17, pp.3952–3965, 2016.

[29] P.Vijayakumar, R.Naresh, SK Hafizul Islam, L. Jegatha Deborah "An Effective Key Distribution for Secure Internet Pay-TV using Access Key Hierarchies", Security and Communication Networks, Wiley, Vol.9, No.18, pp.5085–5097, 2016.

[30] R. Naresh, M Meenakshi, G Niranjana, "Efficient study of Smart Garbage Collection for Ecofriendly Environment", Journal of Green Engineering, Vol.10, No.1, pp.1-10,Feb 2020.

[31] M Meenakshi, R Naresh, S Pradeep "Smart Home: Security and Acuteness in Automation of IOT Sensors", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol. 9, No. 1 , pp. 3271- 3274 , Nov 2019.

[32] Rajakumar, S., Anakath, A.S., Naresh, R., Senthilkmar, S." A detailed study on security services in cloud environment", Proceedings - 2017 2nd International Conference on Recent Trends and Challenges in Computational Models, ICRTCCM 2017, pp. 13–18, 2017.

[33] Suchithra, M., Baskar, M., Ramkumar, J. *et al.* Invariant packet feature with network conditions for efficient low rate attack detection in multimedia networks for improved QoS. *J Ambient Intell Human Comput* (2020). https://doi.org/10.1007/s12652-020-02056-1.

[34] Dr.Ramkumar J, Dr. M. Baskar, Yash Harit, Aayush Gangwar. (2020). Effective Resource Segmentation for Centralized-RAN in 5G Networks. *International Journal of Advanced Science and Technology*, *29*(04), 1836 – 1843.

[35] Baskar.M, Gnansekaran.T "Developing Efficient Intrusion Tracking System using Region-Based Traffic Impact Measure Towards the Denial of Service Attack Mitigation", Journal of Computational and Theoretical Nanoscience, Volume No.14, Issue No.7, pp: 3576-3582, ISSN: 1546-1955 (Print): EISSN: 1546-1963 (Online) , July 2017.

[36] Arulananth, T. S., Baskar, M., & Sateesh, R. (2019). Human face detection and recognition using contour generation and matching algorithm. *Indonesian Journal of Electrical Engineering and Computer Science*, *16*(2), 709–714. https://doi.org/10.11591/ijeecs.v16.i2.pp709-714.

[37] Arulananth, T.S., Balaji, L., Baskar, M. *et al.* PCA Based Dimensional Data Reduction and Segmentation for DICOM Images. *Neural Process Lett* (2020). https://doi.org/10.1007/s11063-020-10391-9.