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PLANT LEAF DETECTION BY MULTI-CLASS SVM MODEL USING CCM AND HISTOGRAM FEATURES

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Abstract: - *Agriculture, serving as the cornerstone of civilizations, plays a pivotal role in providing sustenance and essential resources. Given its paramount significance in human life as a primary source of food, the detection of plant diseases has emerged as a critical concern. Although traditional methods exist for identifying such diseases, agriculture professionals and plant pathologists have traditionally relied on visual inspection alone to detect leaf diseases. However, this conventional approach to identifying plant leaf diseases can be subjective, time-intensive, financially burdensome, and necessitates a substantial workforce equipped with extensive knowledge about various plant diseases. This paper has proposed a model that classify the plant unhealthy leaf and identify the type of infected image. Paper has found that proposed model has increases the work detection accuracy by the use of Co-occurrence matrix and histogram feature. Extracted features were used for the training of multi class support vector machine. Experiment was done on real tomato plant leaf dataset and result shows that proposed model has increases the detection accuracy of multi class leaf diseases as well.*

Keywords: - Image Processing, Plant Leaf, Feature Extraction, Image Classification.

I. INTRODUCTION

Plants serve a critical function in global food supply, yet they face numerous environmental challenges leading to diseases and substantial production losses. Manual disease detection methods are prone to errors and time-consuming, making them unreliable for effectively identifying and containing plant diseases. Leveraging advanced technologies like Machine Learning (ML) and Deep Learning (DL) offers promising solutions by enabling early disease identification. Given the significant economic impact of crop cultivation, it's imperative to monitor crop health continuously, employing advanced technologies to pinpoint crop-specific illnesses caused by opportunistic pathogens.

Plant diseases and pests pose significant threats to both ecological balance and agricultural productivity. Thus, early detection and prevention strategies are pivotal for agricultural technology, especially in commercial farms and orchards. Traditional manual observation methods for disease diagnosis are inefficient, time-consuming, and incur high overhead costs. There's an urgent need for efficient and accurate disease detection systems to optimize crop yields.

In recent years, numerous research studies have proposed various ML and DL approaches for plant disease detection. However, most studies have focused on specific diseases or plant species, highlighting the necessity for more generalized and robust models applicable across different plant species and diseases. Moreover, the availability of publicly accessible datasets for model training and evaluation remains inadequate. Transfer learning, a technique involving fine-tuning pre-trained models on specific datasets, has emerged as a recent trend, facilitating enhanced DL model performance. Ensemble methods, which combine multiple models to improve overall performance and reduce reliance on a single model, have also gained traction in plant disease detection.

These approaches not only bolster the robustness and accuracy of disease detection models but also mitigate overfitting issues common in DL models. Additionally, employing data augmentation techniques to artificially expand dataset size through random image transformations enhances data diversity and diminishes the need for extensive labeled data. Such advancements hold promise for revolutionizing plant disease detection and management, ultimately ensuring global food security and agricultural sustainability.

II. REALTED WORK

Narayanan et al. [6] introduced a novel hybrid convolutional neural network architecture for the classification of diseases affecting banana plants. Their methodology involved preprocessing the raw input images without altering inherent information and maintaining standard image dimensions through the application of a median filter. The approach amalgamated Support Vector Machine (SVM) with Convolutional Neural Network (CNN) techniques. During the testing phase, a multiclass SVM was employed to discern specific infections in banana leaves, whereas in the initial phase, SVM was utilized to differentiate between healthy and infected leaves.

Jadhav et al. [7] pioneered a fresh histogram transformation method aimed at refining the accuracy of deep learning models by generating synthetic image samples from low-quality test set images. Their strategy encompassed enhancing images within the cassava leaf disease dataset using various methodologies such as Gaussian blurring, motion blurring, resolution down-sampling, and over-exposure, integrated with a modified MobileNetV2 neural network model. Synthetic images were synthesized with altered color value distributions to tackle data scarcity, thereby enhancing training outcomes.

M. Sowmiya et al. [8] proposed PLDPNet, a novel hybrid deep learning model designed for the automatic prediction of potato leaf diseases. This framework entailed several stages including image acquisition, preprocessing, segmentation, feature extraction, fusion, and classification. PLDPNet adopted an ensemble approach, amalgamating features from VGG19 and Inception-V3 models, and integrated vision transformers for the ultimate prediction. Training and evaluation were conducted on a publicly available potato leaf dataset comprising early blight, late blight, and healthy leaves.

Fizzah Arshad et al. [9] introduced IQWO-PCA, a pioneering approach combining Improved Quantum Whale Optimization with Principle Component Analysis, aimed at assessing tomato disease images for preemptive measures. They leveraged a variety of pretrained deep neural network architectures such as Alexnet, VGG16, ResNet50, and DenseNet121, optimizing hyperparameters systematically. The study focused on extracting primary features from the dataset and employing deep neuronal networks for enhanced disease classification.

Sabbir Ahmed et al. [10] presented a lightweight transfer learning-based methodology for the detection of tomato leaf diseases, leveraging a pretrained MobileNetV2 architecture and effective preprocessing techniques to refine image quality for subsequent classification. Runtime augmentation was employed to mitigate data leakage and address class imbalance issues, thereby ensuring robust performance in disease detection tasks.

R. Rashid et al. [11] introduced MMF-Net, a CNN-based architecture tailored for disease classification in plant agriculture. MMF-Net seamlessly integrated multi-contextual features using RL-block and PL-blocks, effectively amalgamating disparate model streams trained on diverse datasets. RL-block processed coarse grained images to extract local context, while PL-blocks extracted fine-grained global context and real-life environmental parameters as features.

S. S. Begum [12] proposed a comprehensive study comprising four pivotal stages: Pre-processing, Segmentation, Feature extraction, and Classification. They introduced techniques such as Improved Contrast Limited Adaptive Histogram Equalization (ICLAHE) for image enhancement and Kernelized Gravity-based Density Clustering (KGDC) for segmentation. Feature extraction and classification were performed using the Gated Self-Attentive Convoluted MobileNetV3 (GSAtt-CMNetV3) technique, with parameters optimized using the Osprey Optimization Algorithm (Os-OA) to enhance classification performance.

III. PROPOSED METHOD

Since In this section proposed plant leaf disease detection model PLDDM was detailed. This work uses Co-occurrence matrix feature for plant leaf texture analysis and histogram feature for the image color. Further image features were used for the training of multiclass support vector machine.

Plant Leaf Image Pre-Processing
Imagine input plant leaf image PL, have an of nxn which means it has n squared pixels in total In simpler terms there are n pixels in each row When read such an image it gets transformed into a matrix of the same nxn dimensions where each of the n squared values represents the color of a pixel [13].

$$PPL \leftarrow Pre\_Processed\_Plant\_Leaf(PL)$$

Fig. 1. Input image.

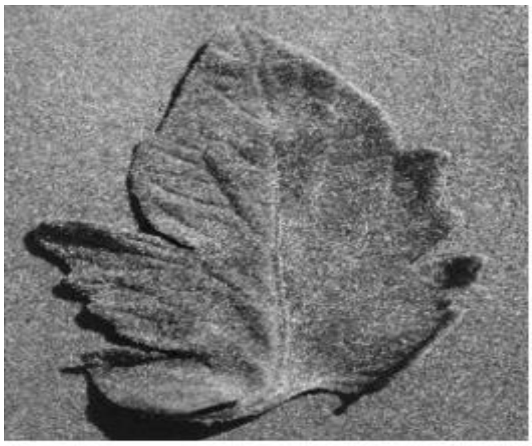

Fig.2 Pre-processed image for histogram features.

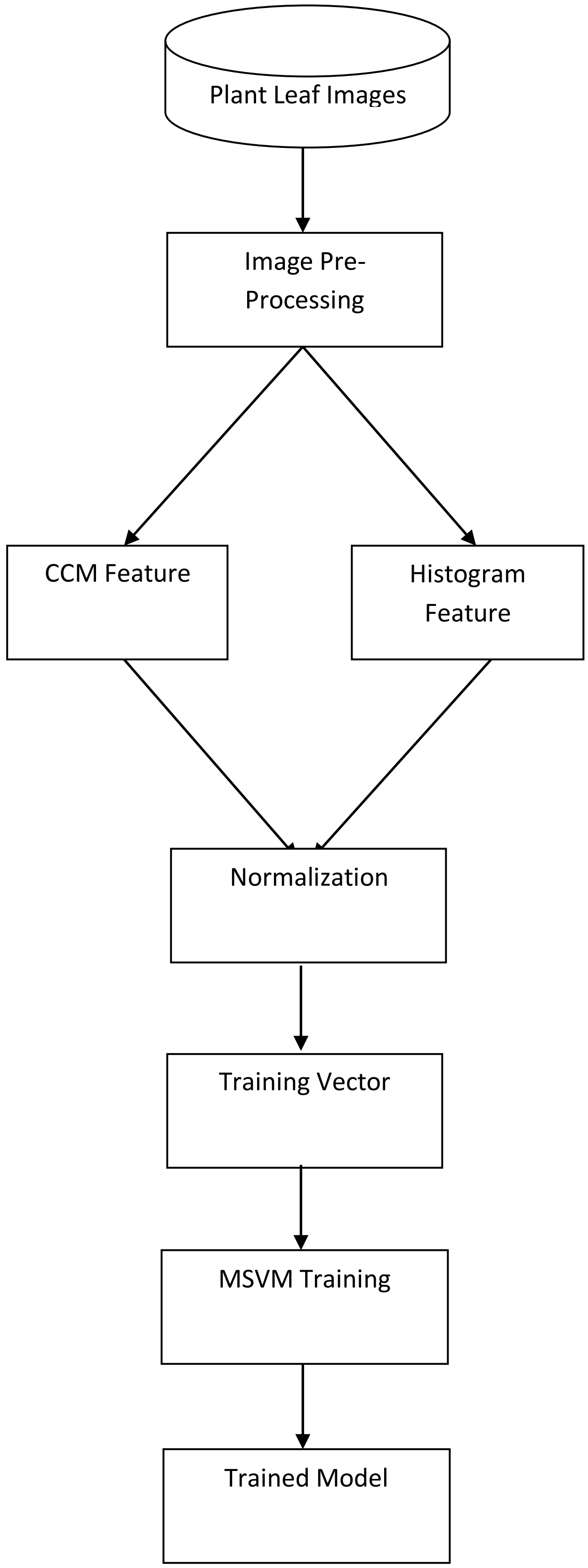

Fig. 3 Block diagram of proposed PLDDM.

Image Block In this study, the image was divided into smaller blocks measuring bxb pixels each. Since the entire analysis was conducted on grayscale images, the pixel values fall within the range of 0 to 255, representing different shades of gray. Consequently, each block in the analysis comprises a collection of 16 values, as detailed in the literature.

B←Plant_Leaf_Blocked(PL)

Feature Extraction The pre-processed image is then blocked into pixel values of a fixed nxn size. The features are extracted from the image that has been blocked. Histogram features were extracted from the image in the proposed model so as to increase the work efficiency. The CCM used in the model consists of 16 values.

Table 1. PLDDM notation table.

Notations	Meaning
PL	Plant Leaf
PPL	Pre-processed Plant Leaf
B	Block of leaf
b	Number of blocks in PPL
PCCM	Plant CCM Feature Vector
PH	Plant Histogram Feature
T_Vector	Training Vector
D_Class	Desired Class Vector
MSVM	Multiclass SVM

Co-occurrence Matrix (CCM) With a specific end goal to get the surface of the image one of the vital technique is co-occurrence matrix. Here co-occurrence matrix exhibit the surface property by the relationship of the neighboring pixels. It quantificational explains the surface component. In this paper four elements is chosen including contrast, energy, inverse difference, entropy [14].

$$ID = \sum_{i=1} \sum_{j=1} \frac{1}{(1+(i-j)^2} I(i, j)$$

$$Entropy = -\sum_{i=1} \sum_{j=1} I(i, j) \log[I(i, j)]$$

$$Energy = \sum_{i=1} \sum_{j=1} (I(i, j))^2$$

$$Contrast = \sum_{i=1} \sum_{j=1} (i-j)^2 * I(i,j)$$

Histogram Feature In this study, a histogram with B bins of values is employed. Consequently, the image feature is determined by the counting of pixels within specific ranges, such as [(1-B), (B+1 - 2B), … (PB-M)], where M represents the maximum pixel value and P is calculated as (M/B - 1) [15]. To illustrate, if an image has 256 different pixel values, the bins would range from [(0-15), (16-31), (32-47), … (250-255)].

PH←Plant_Leaf_Histogram(B)

Multi-class SupportVectorMachine

Multi-class Support vector machine (MSVM) falls under the category of supervised machine learningmodels. MSVM performs data analysis using two different methods named as classificationand regression analysis [16]. When training data are given, MSVM training algorithm creates amodelwhereeverynewinputisassociatedtooneofthetwom entionedanalysis method. MSVM performsnon-linearclassificationwithhighefficiencywhereinputsarebei ngmappedintohigh-dimensionalfeaturespaceswhichisknownaskerneltrick.SV Musuallyperformsitsanalysis by creating a hyperplane or set of hyperplanes in a high-dimensional space.

T_Vector←[PH, E Et, I, C]
D_Class←PLD // D_Class: Desired Class
MSVM←Train_MSVM(T_Vector, D_Class)

Functional margin is the distance between a hyperplane and its nearest training data pointof any class. The generalization error of the classifier is observed to be lower with largerfunctionalmargin andwhen thedistance isthe largest,a goodseparationisachieved.

Proposed PLDDM algorithm

Input: PLD // Plant Leaf Dataset

Output: MSVM

1. Loop 1:d // d: Number of images in PLD
2. PPL← Pre_Processed_Plant_Leaf(PL[d])
3. B←Plant_Leaf_Blocked(PL)
4. For 1:b //
5. [E Et I C]←PCCM(B)
6. PH←Plant_Leaf_Histogram(B)
7. EndLoop
8. T_Vector←[PH, E Et, I, C]
9. D_Class←PLD // D_Class: Desired Class
10. EndLoop
11. MSVM←Train_MSVM(T_Vector, D_Class)

As per desired class extracted features were used for the training of MSVM model. Trained model will be used for the testing plant leaf classification.

IV. RESULT

There In this section, experimental work was explained together with information on the implementation environment. This work's proposed model was also compared to other existing **MobileNetV2** models proposed in [10]. Different assessment parameters are used to compare models. It was discovered that the proposed model performed effectively over a variety of comparison parameters.

MATLAB software was used to build the proposed model and perform experiment on same.

Evaluation parameter

$$\Pr ecision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

$$\operatorname{Re} call = \frac{True\_Positive}{True\_Positive + False\_Negative}$$

$$F\_Score = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$$

Accuracy = (True_Positive + True_Negative)/(True_Positive + True_Negative+ False_Positive + False_Negative)

In above true positive value is obtained by the system when the classified image is same as in actual case or ground truth image class. While in case of false positive value it is obtain by the system when the classified image is not of same case as in actual in or ground truth image class.

Dataset

Experiment was performed on different image dataset size. Plant leaf image set have 256x256 dimension. Total image dataset is of 1500 images. Plant disease leaf detection dataset was taken from [], some of sample images were shown in table 2.

Table 2 Dataset of Skin Cancer.

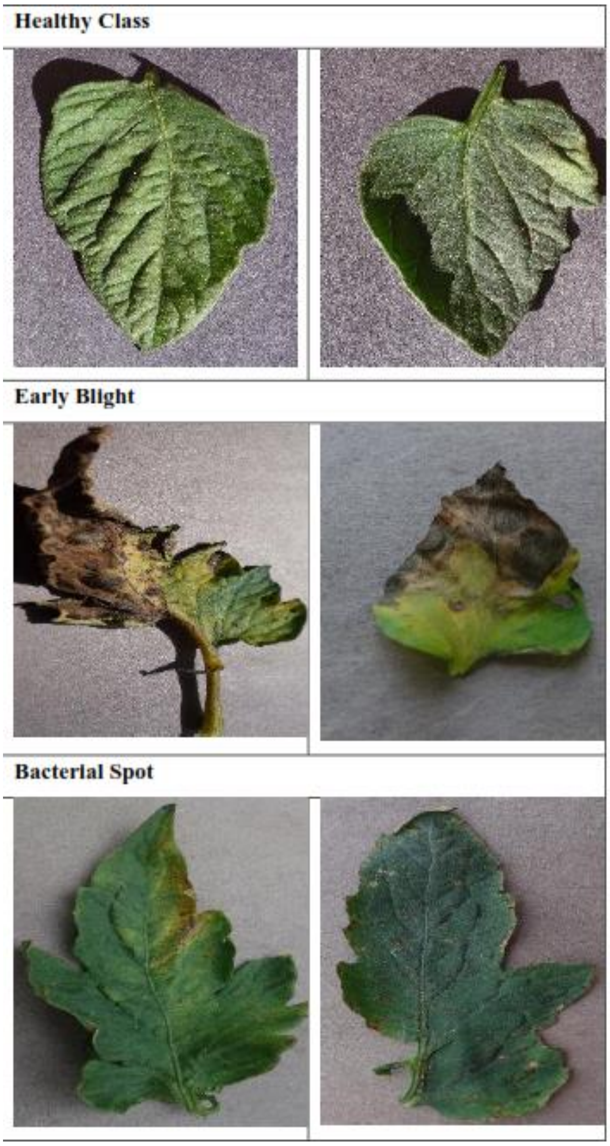

Table 3 shows that proposed PLDDM model has improved the precision value of the skin cancer detection. This model has uses the image features histogram and CCM feature for the training of MSVM. Use of hyperplane format for the learning of model has increase the detection of image class as well

Table 3 Plant leaf precision value based disease detection model.

Testing Image Set	**MobileNetV2**	**PLDDM**
36	**0.9133**	**0.9286**
75	**0.9231**	**0.9259**
150	**0.94**	**0.9608**
300	**0.9688**	**0.9468**

Table 4 Plant leaf recall value based disease detection model.

Testing Image Set	**MobileNetV2**	**PLDDM**
36	**0.5185**	**0.9286**
75	**0.4615**	**0.9259**
150	**0.4434**	**0.9074**
300	**0.4346**	**0.8241**

Table 4 shows that recall value of proposed PLDDM has increases by the use of transformed features for the training of model. It was found that proposed model has increases the recall value 26.98% as compared to existing model ADCN.

Table 5 Plant leaf f-measure value based disease detection model.

Testing Image Set	**MobileNetV2**	**PLDDM**

36	**0.6667**	**0.9286**
75	**0.6154**	**0.9259**
150	**0.6026**	**0.9333**
300	**0.6**	**0.8812**

Table 5 shows that proposed PLDDM model has improved the f-measure value of the plant leaf disease detection. This model has uses the image features histogram and CCM feature for the training of support vector machine. Use of combine features for the learning of MSVM has increase the f-measure of image class as well.

Table 6 Plant leaf accuracy value based disease detection model.

Testing Image Set	**MobileNetV2**	**PLDDM**
36	**66.67**	**95.24**
75	**62.96**	**95.06**
150	**62.2**	**95.68**
300	**61.96**	**92.59**

Detection accuracy of plant leaf disease detection was shown in table 6, Use of balanced feature histogram with 16 bins and CCM 4 matrix has increases the learning. Transformation of features for the learning has reduces the calculation of model.

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V. CONCLUSION

Plant leaf help to create food hence plays an important role for the healthy life. Sometime due to unfavorable conditions plants get infected by the disease, this reduces the production. This paper has proposed a solution for detection of unhealthy plant by its leaves. Use of color histogram features and texture CCM feature for the training of model was done by the work. In order to support multiclass leaf disease porposed model has trained a multiclass support vector machine. Experiment was done on real image plant dataset have multiple disease images. Result shows that proposed model has increases the work detection accuracy by 31.195%. Further it was found that proposed model has increases the work precision value by 0.44%. In future scholar can optimize the input image by removing the background noise.

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