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Water Melon Leaf Disease Detection and Fruit Quality Prediction using Machine Learning and Deep Learning Algorithms by Eye Visual Symptoms: A Review

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Abstract. This study conducted a systematic literature review to investigate machine learning techniques for water melon plant and fruit recognition, Leaf Disease analyzing 40 research articles from 2015 to 2024. The articles were searched across 10 databases and screened based on predefined inclusion/exclusion criteria. This study was performed on the aim of detecting the quality of the watermelon with eight features; sound, color, root, belly button, texture, sugar rate, density, and touch which were obtained from the Kaggle website and collected the data from water melon farmer. This was extracted to identify the techniques, accuracies, metrics, and applications. The results showed hybrid algorithms like convolutional neural networks(CNN) and support vector machines(SVM) achieved the highest accuracy of 95-99% for fruits like apple and banana. accuracy and precision were the predominant metrics used for evaluating model performance. The view concludes that deep learning approaches demonstrate effective capabilities for fruit and plant classification, disease detection, and yield prediction. accurate disease prediction is one of the key requirements in data science. Presently, machine learning based methods have improved prediction accuracy for plant leafs like grapes, pomegranates, maize. However, the disease prediction performance is still required to be improved in this challenging environment. existing disease prediction models require high computational time and storage facilities in the agriculture field. To overcome this, we have proposed a comparative study of Deep Learning for prediction and classification of water melon diseases to improve the efficiency of early prediction of water melon diseases.
Keywords: Deep Learning, Fruits, Plants, convolutional neural networks Deep Learning Image processing

1 Introduction

Disease on plant leaf will be the significantly reduced in both the quantity and quality agriculture water melon. For successful water melon production in the farm, need to monitor the disease and health on plant leaves. In earlier days, some experienced person was executed all these analyses and monitoring of leaf diseases manually, which is a time consuming process. Therefore, early identification of these diseases will be helpful to farmers to keep away from any losses. agriculture is the main part and support of the Indian economy, along with an income for Indian people. If agriculture had gone wrong, then nothing else would have an opportunity to go directly into the nation.

The quality of the fruits or vegetables plays an important role in customer consumption and thereby affecting the sale of those fruits. The concept of quality is wide and covers several aspects such as external appearance, nutritional aspects, and presence of health-related compounds, safety and security. The external appearance of the fruits is especially, the color and shape would make a prominent role in decision making. Further, the smell, texture and skin pattern make some impacts on the decision. However, the decision could vary according to the individuals with their human sensors. This manual prediction of the quality is time consuming and less effective and needs to learn from experience in choosing the quality and tasty fruits for their consumption. The quality prediction-based researches were conducted on several fruits. These techniques could be applied to the watermelon fruit, in detecting the quality. Some methods include optical properties, sonic vibration, nuclear magnetic resonance (NMR), machine vision technique, electrical properties detection, computed tomography and electronic noses technique and so on.

2. Literature Review

Borhani et al. (2022) developed a deep learning-based method for automated plant disease categorization utilizing a vision transformer in order to give farmers visual information. according to the scientists, the real-time automated plant disease classification method is built on Vision Transformer (ViT), making the deep learning technique very lightweight. For the categorization of plant diseases, conventional convolutional neural network (CNN) techniques and CNN + ViT combos have also been used in addition to the ViT. To speed up prediction, the model coupled CNN blocks with attention blocks. authors' approached model 3 and 4 for the corresponding wheat rot, rice leaf, and plant village datasets exhibit the maximum convergence accuracy. To generate a higher accuracy, the RGB version of the photos has been employed. But correctness of the model was missing in the study and convergence score also isn't an ideal metric in deep learning based experiment.

Bandi et al. (2023) proposed a model for plant leaf disease stage categorization and detection that operates according to the severity of leaf infection. You only look once version 5 (YoLov5) deep learning model is used to detect plant leaf disease. The background of the diseased leaf is then removed using U_2-Net architecture, and stage classification is then carried out using a vision transformer (ViT) to categorize. The apple leaf is the major focus of this work when executing stage categorization. With a confidence level of 0.2, the YoLo v5 can obtain a maximum f1-score of 0.57, whereas the vision transformer can reach a f1-score of 0.908 with or without a backdrop image.

Rethik et al. (2023) proposed attention-based mapping for plant leaves using Vision Transformer to categorize illnesses. In this study, researchers used Vision Transformer instead of CNN to categorize plant leaf diseases. The test accuracy attained by the three vision transformer models under comparison in this is 85.87%, 89.16%, and 94.16%, respectively. The models are ViT1, ViT2, and pre-trained ViT_b16. The findings demonstrate that the suggested model is capable of pinpointing the precise area of the leaf where the illness is present, giving farmers useful information.

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chougu et al. (2022) described plant-leaf diseases classification using CNN, CBAM and Vision Transformer. The authors developed four pretrained models using huge datasets like MobileNet, VGG-16, VGG-19, and ResNeT, and suggested a deep convolutional neural network architecture with and without attention mechanisms. additionally, authors' adjusted two ViT models: the Vit B32 from Keras and the Google base patch 16. The suggested model achieved a 97.74% accuracy rate. The accuracy of the pre-trained models was up to 99.52%. and the ViT models achieved up to 99.7% accuracy.

Sharma et al. (2023) presented a new deeper lightweight convolutional neural network architecture (DLMc-Net) to perform plant leaf disease detection across multiple crops for real-time agricultural applications. The passage layer and a series of collective blocks are added in the suggested model in order to extract deep characteristics. These advantages include feature reuse and propagation, which solve the vanishing gradient issue. convolution blocks that are point-wise and separable are also used to lower the number of trainable parameters. on eight metrics, including accuracy, error, precision, recall, sensitivity, specificity, F1-score, and Matthews correlation coefficient, experimental results of the proposed model are compared against seven state-of-the-art models. even with complex background conditions, the suggested model outperformed all other models, with accuracy values of 93.56%, 92.34%, 99.50%, and 96.56% on the datasets for citrus, cucumber, grapes, and tomatoes, respectively.

Hossain et al. (2023) addressed a study to analyze the effects of transformer-based approaches that aggregate different scales of attention on variants of features for the classification of tomato leaf diseases from image data. Four state-of-the-art transformer-based models, namely, external attention Transformer (eaNet), Multi-axis Vision Transformer (MaxViT), compact convolutional Transformers (CCT), and Pyramid Vision Transformer (PVT), are trained and tested on a multiclass tomato disease dataset. The result analysis showcases that MaxViT comfortably outperforms the other three transformer models with 97% overall accuracy, as opposed to the 89% accuracy achieved by eaNet, 91% by ccT, and 93% by PVT. MaxViT architecture is the most effective transformer model to classify tomato leaf disease because it achieves a smoother learning curve compared to the other transformers.

Thai et al. (2023) developed an efficient vision transformer for cassava Leaf Disease detection. The model Former Leaf, a transformer-based model for detecting leaf disease, and two strategies for improving the model's performance. To choose the most crucial attention heads for each layer in the Transformer model, the authors suggested the Least Important attention Pruning (LeIaP) algorithm. It might cut the size of the model by up to 28%, speed up evaluation by 15%, and improve accuracy by roughly 3%. In order to determine matrix correlation in the model, it also used sparse matrix-matrix multiplication (SPMM). Due to the model's complexity being reduced from o(n2) to o(n2/p), training time is cut by 10% but performance is kept the same.

Alshammari at al. (2022) developed a unique deep ensemble learning strategy that combines the convolutional neural network model with vision transformer model. This approach aims to identify and categorize diseases that may impact olive leaves. olive leaf disease was categorized using deep convolutional models-based binary and multi classification systems. The outcomes are encouraging and demonstrate the potency of combining CNN and vision transformer models. With an accuracy of roughly 96% for multiclass classification and 97% for binary classification, the model outperformed the competition. Zhou et al. (2023) proposed a residual-distilled transformer architecture in this study for feature extraction and prediction, a multi-layer perceptron (MLP) is fed with the residual concatenation of the vision transformer and the distillation transformer. on the dataset for rice leaf disease collected in paddy fields, experimental results show that the proposed method outperforms the current state of-the-art models and obtains a 0.89 F1 score and 0.92 top-1 accuracy.

Li et al. (2023) presented Shuffle-convolution-based lightweight Vision transformer for effective diagnosis of sugarcane leaf diseases named SLViT . The SLViT hybrid network is initially trained on the freely

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available disease dataset Plant Village and the independently created sugarcane leaf disease dataset SLD10k. The transformer encoder is converted to a flexible plug-in (LViT) and then integrated into several locations of a lightweight CNN architecture (SHDc). The experiments show that all of SLViT's modifications have improved the system's performance as a whole. on Plant Village, SLViT outperforms three specially created leaf-disease recognition models and six SoTa models in terms of speed (1,832 FPS), weight (2 MB), consumption (50 M), and precision (98.84%). on the SLD10k dataset, SLViT outperformed MobileNetV3_small with an accuracy boost of 1.87% and a size reduction of 66.3%.

Li et al. (2022) proposed an automatic pest identification method based on the Vision Transformer (ViT). The plant diseases and insect pests data sets are improved using techniques including Histogram equalization, Laplacian, Gamma Transformation, cLaHe, Retinex-SSR, and Retinex MSR in order to prevent training overfitting. according to the simulation results, the built-in ViT network has a test recognition accuracy rate of 96.71% on the publicly available Plant_Village dataset of plant diseases and insect pests, which is about 1.00% higher than the method for identifying plant diseases and pests based on conventional convolutional neural networks like GoogleNet and efficentNetV2.

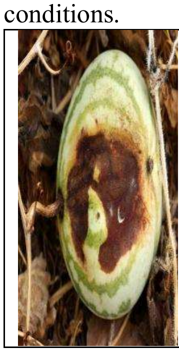
Yeswanth et al. (2023) proposed a novel Residual Skip Network-based Super-Resolution for Leaf Disease Detection (RSNSR-LDD) in the Grape plant. The super-resolution (SR) image is produced using a decoding block and a convolutional layer. For training, a brand-new collaborative loss function is suggested. The Disease Detection Network (DDN) receives the acquired SR picture in order to identify grape leaf disease. With numerous super-resolution scaling factors for different grape leaf pictures, the proposed model was thoroughly trained and evaluated on the PlantVillage, Grape 400, and Grape Leaf Disease datasets. The proposed model RSNSR-LDD attained accuracies of 97.19%, 99.37%, and 99.06% for the PlantVillage dataset, 96.88%, 97.12%, and 95.43% for the Grape400 dataset, and 100% for the Grape Leaf Disease dataset for various super resolution scaling factors like X2, X4, and X6.

4. Background

The main aim of this article is to present a comprehensive watermelon dataset that encompasses a wider spectrum of disease categories [1]. This dataset will be used to build a powerful machine vision-based recognition algorithm capable of diagnosing various watermelon diseases independently. This initiative aims to improve agricultural efficiency, raise output levels, and ensure food security.

4.1 Image acquisition

This is the first step of water melon leaf disease detection and classification. The purpose of this stage is to collect and prepare images dataset that will be used in the further process. This is done by capturing the images from mobile phone cameras, digital cameras, drones and UaV either on real time (site) or in controlled conditions.



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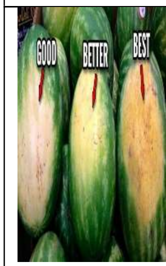
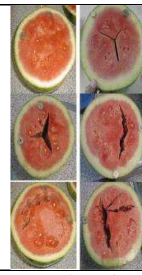
Fruit Diseases	Water melon disease	Watermelon Bacterial Fruit Blotch
		
Find the Fruit Quality	Detection of Internal Quality in Seedless Watermelon	Water melon fruit disorders

Fig.1 Water melon fruit diseases and Quality finding using parameters.

4.2 Image Preprocessing

Image preprocessing is very important to obtain the better results. To remove the noise color transformations were used. To reduce the size of the image acquired by digital cameras resizing techniques were used. It also helps to reduce memory size. The frequently used image preprocessing techniques in this literature includes cropping the leaves from the acquired images, color transformations, rescaling, background removal, image enhancement, flipping, rotating, Shear, and image smoothing.

4.3 Image Segmentation

Image segmentation plays an essential role in water melon leaf disease detection and classification. It splits the image into various parts or zones. It explores the image data to extract helpful information for feature extraction. Image segmentation can be done in 2 ways, one is based on similarities and the other one is based on discontinuities.

4.4 Feature Extraction

extracting the features of the substances of an image is called as feature extraction. The most common features found in plant and fruit disease detection and classifications are shape, color, sound and texture. The water melon diseases may differ in appearances of the image due to multiple classes. The water melon leaf disease system can easily recognize the diseases from the shape of the water melon leaf image. The second feature is color is an important. It distinguishes the water melon leaf diseases from each other. The last feature, texture portrays the various patterns of the color are spotted in the water melon leaf images. The common texture features are energy, entropy, contrast, correlation, sum of squares, sum entropy, cluster shade, cluster prominence, homogeneity.

4.5 Classification

Two types of classification methods were used to classify water melon leaf diseases: ML and DL. The important dissimilarity between traditional machine learning and deep learning methods is by means of feature extraction. In traditional ML, the features are not computed automatically whereas in DL the feature extraction automatically takes place and it is considered as learning weights. So, in DL the system itself learns the needed features by providing sufficient data. The most common machine learning algorithms used for classification of plant diseases are KNN, SVM, DT, RF, BPNN, NN, NB and ensemble learning. The frequently used deep learning algorithms present in the literature were CNN, CNN models which were Pre trained on ImageNet and used transfer learning.

chowdhury et al. proposed a plant disease detection and classification system, it uses transfer learning and deep feature extraction in. The authors were compared the obtained results of VGG16, GoogLeNet, ResNet50 CNN architectures with deep feature extraction by SVM and KNN. experiment results shown that classification with SVM and ResNet50 given best results (98%) than the remaining combinations. The authors also compared the results of traditional machine learning algorithms i.e. SVM and KNN, SVM shown better accuracy (80.6%) than KNN (71.8%) but it is lesser than the proposed.

5. Conclusion

This study represents a review for the emergence of smart agricultural solutions that incorporate in computer vision, vision transformers (ViT) are a relatively new and intriguing breakthrough. ViT can quickly classify and identify various plant-leaf diseases with high accuracy results and researchers have focused the strengths and weaknesses of some image classification and object identification models such as Vision Transformer (ViT), Deep convolutional neural network (DCNN), convolutional neural network (CNN), Residual Skip Network-based Super-Resolution for Leaf Disease Detection (RSNSR-LDD), Disease Detection Network (DDN), and YoLo(You only look once) Moreover, after the basic concept of Vit, there have also Least Important attention Pruning (LeIaP), ensemble (ViT + CNN), external attention Transformer (eaNet), Multi-axis Vision Transformer (MaxViT), compact convolutional Transformers (ccT), Pyramid Vision Transformer (PVT), SLViT and a ViT enabled CNN model called "PlantXViT" work well for high dimensional multicast image datasets. Deep learning-based system evaluation the performance of the models, different metrics such as accuracy, precision, recall, etc. were used in the existing studies. Finally, these technologies are aimed at addressing the challenge of early diagnosis and management of plant diseases.

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