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A Review on Fruit Disease Detection and Classification using Computer Vision Based Approaches

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Abstract:- Plant Diseases are one of the leading reasons of economic shortfalls in agricultural and farming sectors worldwide. It is the most essential element since it reduces crop quantity and quality significantly. Fruits are one of the largest essential nutritional resources from plants. Unfortunately, a variety of conditions might impair both the content and outcome of fruits. As a result, an autonomous Computer Vision (CV) -based approach for reliable Fruit Disease Detection (FDD) is necessary. CV is an Artificial Intelligence (AI) area that allows software and algorithms to extract relevant data from digital images. Over the past decades, advanced AI techniques such as Machine Learning (ML) and Deep Learning (DL) algorithms have been developed to predict and classify FDs early from different imaging modalities. The findings observed from these techniques can help farmers with FDD and treatment. This paper presents a detailed review of different ML and DL algorithms developed to predict and classify FDs from different fruit images. First, different FDD and classification systems designed by many researchers based on ML and DL algorithms are studied in brief. Then, a detailed analysis is carried out in order to identify the shortcomings of existing algorithms and to provide a novel strategy for properly classifying fruit pathogens.

I. INTRODUCTION

Agriculture has long been a key profitable area in terms of its societal influence, especially in impoverished nations. One of current primary issues is satisfying the ever-increasing needs and expectations for high-quality food items. Although the facts that numerous causes, including plant pathogens, climatic changes, and others, have a significant influence on agricultural productivity, crop infection has been recognized as one of the primary sources of food shortages, significantly hurting small-scale farmers. Small-scale farmers contribute nearly 80% of cultivations in poor nations, according to statistics, and yield losses are substantially heavier in these regions due to a scarcity of assets to handle insect infections and plant viruses [1].

Pomes, drupes, berries, melons and citrus fruits are examples of fruit plants that provide significant growth to productivity. FDs have an impact on fruit output; a decrease in fruit yield ultimately has an impact on a state's total revenue. It has the potential to affect not only cultivation but also the area economy. Besides from additional food shortages, infection destroys about 10% of crops every year, which can be significantly greater in underdeveloped nations relying on crop variety, environment, and agricultural traditions [2].

As a result, it is critical to diagnose and recognize these infections at an earlier phase in order to avoid substantial consequences. Earlier diagnosis and recognition of FDs can increase fruit quality and production. Pathology lab professionals are extensively relied on by farmers in poor nations to diagnose and control infections. Immediate infection identification is crucial for limiting infection transmission across the crop and area, especially in fruit trees. Fruit plant infection identification has always been tough for farmers who must maintain the total area by examining all crop growth. Because the physical identification method consumes a significant amount of effort and money, automatic computerized approaches must be implemented [3].

These computerized systems' key methods include preprocessing, clustering, feature extraction and selection, and categorization. To identify fruit infections, AML algorithms Neural Networks [4] have been suggested. For segmentation, K-Means clustering was used, which provides border pixels labels among objects. Image color, morphology, texture, and whole structure are used as feature vectors for disease diagnosis. Furthermore, certain programs for disease identification, such as Plantix [5] and GreenR [6], have been created employing cloud-based services. A DL-based strategy for reliably identifying the illness as well as its intensity degree has been presented [7]. Agriculture has also benefited from DL approaches. Advances in CV and AI can result in novel solutions. These approaches produce more precise forecasts than previous methods, allowing for more informed decision making. Because of advancements in hardware technology, DL techniques are now employed to solve complicated issues in a reasonable period of time.

Researchers have primarily focused on enhancing the efficiency of ML and DL-based techniques in FDD. The main goal of this manuscript is to provide a complete survey of ML and DL-based systems to detect and classify FDs for different fruit images. Also, a comparative study is presented to address the advantages and disadvantages of those methods in order to suggest future scope. The rest of the sections are prepared as follows: Section II discusses various methods designed to detect and classify the different types of FDs. Section III provides the comparative analysis of those methods. Section IV summarizes the entire survey and recommends the upcoming scope.

II. SURVEY ON DIFFERENT ALGORITHMS FOR FRUIT DISEASE DETECTION AND CLASSIFICATION

Muhammad Attique Khan et al. [8] devised a technique for diagnosing apple pathogens. Preprocessing, spot recognition with feature extraction, and categorization were the three pipeline procedures used. The apple leaf spots were upgraded in the initial phase using a layered system that used 3D box filtering, de-correlation, a 3D-Gaussian filter, and a 3D-Median filter. Following that, the fibroid areas were differentiated using a robust similarity-based technique and their findings were optimized by merging using Expectation Maximization (EM) classification. At last, the color histogram and Local Binary Pattern (LBP) features were fused, and the Genetic Algorithm (GA) was used to select more relevant features. The selected features were trained and classified by the Multi-Support Vector Machine (SVM). Since there are many stages, the computational complexity is high for this method.

BehzadNouri et al. [9] recommended employing the Electronic nose (E-nose) system's efficiency as a quick, non-destructive, and low-cost approach for determining the level of Alternaria fungus in pomegranate. Between healthy people and four phases of fungal infestation, the Back Propagation Neural Network (BPNN) technique performed better in terms of classification accuracy than Linear Discriminant Analysis (LDA) and SVM evaluation. Furthermore, it discovered that the E-nose system's prospective performance for pomegranate fruit quality detection was rapid, consistent, and non-disastrous. However, the approaches used were expensive and cumbersome.

Yogeswararao Gurubelli et al. [10] presented FF2DLDA, a fuzzy 2DLDA (F2DLDA) modification utilized to evaluate two-dimensional pomegranate fruit pictures. To solve the challenge of non-destructive pomegranate fruit grading and categorization, three known and one innovative mathematical feature extraction approaches were applied. By reframing the fuzzy among scatter matrix of F2DLDA as a fractional fuzzy among scatter vector, the approach retains the most discriminative properties. Finally, the Kernel SVM (KSVM) was used to determine which feature extraction strategy might provide the highest recognition score. However, the influence of the edge class problem on the collection of the best projection route was reduced.

Akshay Koushik et al. [11] proposed utilizing Convolutional neural network (CNN) to distinguish normal mangoes from diseased ones and to diagnose the infection. Mango illnesses were identified using an image categorization algorithm. Image enhancement was performed on the primary photos to artificially expand the database volume, proceeded by picture cleansing and preprocessing. The class were encoded one-hot and input into the CNN , which separates the mango pictures into distinct groups. However, there was a propensity for negative transfer in transfer learning, which might reduce the effectiveness of the current system, and there was also an issue of overfitting, which was problematic.

Na Yao et al. [12] developed an enhanced XceptionNet combined with the L2M error to categorize Prunus persica disorders. Additionally, 7 DL frameworks have been employed to recognize Prunus persica disorders from the variety of infected fruit photos. On the other hand, the considered database was limited and unbalanced.

Saiqa Khan et al. [13] developed an automated recognition and categorization of Solanum lycopersicum infections based on the super pixel-based optimized partition. Initially, the input photo was converted into the RGB photo to neglect the impacts of irregular lighting. Then, the compact areas have been generated from the converted photo by the super pixel function and the threshold has been adapted to the Histogram of Gradients (HOG) and color channels of super pixel to segregate the unnecessary surroundings from the leaf photo. K-means clustering has been employed to obtain the infected fruit photo. Besides, an improved HOG, pyramid of HOG with Gray Level Co-occurrence Matrix (GLCM) characteristics were considered to define the infected area. Moreover, Random Forest (RF) has been applied to categorize the infection types. But, this method was time-consuming because of choosing the initial seed.

Dhakshina Kumar et al. [14] suggested a Whale Optimization Based Artificial Neural Network (WOANN) for disease identification in tomatoes. Prior to condition categorization in tomatoes, color image extraction was performed by the Firefly Algorithm (FA) in order to achieve efficient disease detection at the end. ANN was used to categorise various types of illness. Whale Optimization Alogrithm (WOA) was utilized to analyze the effectiveness of the suggested system in this neural network for improving the weight variable. Some statistical characteristics were determined, including accuracy, precision, sensitivity, error index, and F1 score. Consequently, there are several phases to perform so the computation complexity of this approach was significantly high.

Jonah Flor et al. [15] presented an android mobile application to identify and diagnose jackfruit fruit which was destructed induced by pests (fruit borer and fruit fly) and infections (rhizopus fruit rot and sclerotium fruit rot). The consecutive type model was used that was primarily made up of three Convolutional layers, each of which was triggered by a Rectified Linear Unit preceded by a max pooling level, and lastly two dense strands. Furthermore, the programme can make suggestions to reduce, if not completely eliminate, agricultural production losses. However, numerous jackfruit pathogens were not addressed due to a lack of image collections.

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Patrick Wspanialy et al. [16] created a novel CV technology that could identify numerous illnesses autonomously. It also identifies previously unknown illness and determines intensity on a per-leaf basis. Several customized versions of Plant Village were used to train and evaluate the algorithms. The tomato dataset contains nine distinct forms of tomato pathogen, illustrating how varied leaf features influence disease identification. Furthermore, subsequent information gathering projects might increase the variety of their datasets by decreasing inadvertent bias, especially in their surroundings, by recognizing the limits of the Plant Village dataset and its image capture methodologies. However, the resolution is insufficient to detect minute variations in disease development.

Sivasubramaniam Janarthan et al. [17] suggested a compact, quick, and exact deep metric learning-based framework to diagnose citrus pathogens from limited data,. To precisely diagnose citrus illnesses, a patch-based classification structure was constructed in this approach, which includes a deep CNN-based embedded module, a K-means cluster concept unit, and a neural network classifier. However, it requires a huge storage capacity in order to retain more training factors.

Muhammad Attique khan et al. [18] presented a deep CNN-based technique for disease detection in the leaves of various fruits. Initially, deep attributes were retrieved using pre-trained deep networks such as VGG-s and AlexNet, which were modified using the transfer learning principle. Prior to the perference stage, a multi-level fusion mechanism based on an entropy-controlled threshold level generated by aggregating the identified attributes was also presented. However, single pre-trained model used in this method not enough to achieve good accuracy.

Jamil Ahmad et al. [19] offer an effective CNN-based disease detection framework in Plum for source-inhibited tools in actual field situations. In contrast to publicly accessible databases, the photos were utilized in this analysis were taken in this part while taking into account essential image-capturing equipment features such as angle, scale, orientation, and ambient constraints. Furthermore, considerable data enhancement was utilized to enlarge the dataset and make training more difficult. Recent architectural research has showed that transfer learning of scale-sensitive systems like Inception gives significantly better outcomes with such difficult datasets with massive data accretion. However, the approach delivers reduced accuracy for some instances of pathologies.

Guofeng Yang et al. [20] introduced the Location, Feedback and a Classification Network (LFC-Net) system, which comprises of three systems: a position structure, a feedback system, and a segmentation network. Simultaneously, a self-supervision technique in the model was presented, which can recognize relevant portions of tomato photos without the requirement for manual labeling such as bordering boxes/parts. A unique training procedure was developed that takes into account the image's class integrity as well as its formativeness. This approach, however, only considers a few types of pathologies.

AbdulMajid et al. [21] established an integrated DL framework for FDD. First, the Local Binary Pattern (LBP), colour, and deep ResNet50 features were extracted and concatenated into a single vector using the greatest mean cost serial technique. The merged vector was then refined using a threshold-function-based GA and put into the Ensemble Subspace Discriminant (ESD) algorithm for illness identification. However, the system's calculation time is long due to the irrelevant characteristics and the huge dimensionality of feature vectors.

Li Ma et al. [22] suggested a Deep CNN (DCNN) for the strawberry disease identification method. The strawberry disease image features were introduced to the training set after regular training of strawberry image feature expression in diverse situations, and eventually the attributes were classed and recognised to meet the aim of disease detection. Furthermore, the attention mechanism and central damage operation were introduced into the classical CNN to fix the issue that data of major characteristics in extant CNN classification techniques impacts the categorization consequence and further enhances the consistency of the CNN in image identification.

Rudresh Dwivedi et al.[23] suggested a Grape Leaf Disease Detection Network (GLDDN) that uses dual attention processes for feature assessment, detection, and categorization to classify esca, black-rot, and isariopsis illnesses in grape photos. It was used to multi-level characteristics layouts in order to create channel-wise attention, spatial recognition, and weighted adulation vectors, as well as to further analyse the attributes that would be input into the Region Proposal Network (RPN). Syndicate t raining entails pooling by cropping regions to identify and categorise items in order to determine whether they are diseased. However, it has a significant processing expense and is incapable of detecting all probable disorders.

HamailAyaz et al. [24] suggested a DCNN method for apple disease detection using deep synthetic images. This research used an end-to-end trained DCNN network with minimal variables to progressively modify a reference classifier. To train a DL model, a Deep Convolutional Generative Adversarial Network (DCGAN) structure was utilised to produce synthetic pictures. It outperforms previous models in terms of recognition performance (i.e.,ResNet, Squeeze Net, and Mini VGG (Net). The settings for the learning rate and optimizer constants, on the other hand, have a significant impact.

Ginne et al. [25] presented 10 categories of apple FDs that can be diagnosed using the Hybrid Neural Clustering (HNC) Classifier. In addition, the feature extraction matrix was fed into the algorithm. This proposed approach is divided into two stages. The initial stage was utilized to develop the photos by aggregating the vector points using K Means Clustering, and the second phase was utilized to evaluate them using the Feed Forward BPNN (FFBPNN). Furthermore, when the suggested approach HNC is compared to current algorithms such as Fuzzy logic, Nave

Bayes, and K-NN, it outperforms them. However, this approach only used a small range of image sequences.

Chang Hee Han et al. [26] created a MASK R-CNN-disease identification system that conducts both identification and segmentation of ailment signs in a fruit picture with the improved architecture of the neural networks. It was able to identify the condition in an accurate and reliable manner, exceeding the current state-of-the-art objection detection approach. Instead of a targeted query, it employs a region proposal network (RPN) to extract potential areas. It effectively constructs boxes of various sizes and aspect ratios by using a collection of preconfigured thresh holding known as anchor boxes. The attention technique enables a structure to use the global information of features, focusing on the most important characteristics and suppressing less important data, hence boosting the efficacy and potency of a network's characteristic depiction. However, this model was only tested on a restricted database. It must provide dependability by utilising massive datasets.

WaelAlosaimi et al. [27] created a Peach Net structure for pathogen detection in peach plants and fruits. The approach could also pinpoint the condition position and assist farmers in locating effective remedies to safeguard peach harvests. The VGG-19 design was used to identify illnesses in Peaches. For disease area localization, Mask R-CNN was used. The Regional Proposal Network (RPN) was another tool for determining disease regions. However, it was impossible to determine the infection location due to the class disparity issue.

Yunong Tian et al. [28] designed a new multi-scale DenseNet categorization model to recognize varieties of diseased malus domestica. Initially, the Cycle-GAN was employed to augment the photos of anthracnose and ring rot. Then, multi-scale DenseNet was applied to learn those photos and recognize the infected fruits for earlier diagnosis. But, there was a need to extract various traits from the photos to further improve the efficiency.

He Jiang et al. [29] developed a disease recognition model based on the DCNN with many convolution units for identifying and diagnosing malus domestica. To recognize the malus domestica fruit, the color modification of malus domestica fruit was observed. Then, many CNN with multiple layers were used and the final outcome was used to recognize the occurrence of the infection in malus domestica fruit photos. But, the training dataset was limited and needs individual feature selection process to improve the accuracy.

RajasekaranThangaraj et al. [30] proposed to enhance the recognition accuracy of avocado FD. The transfer learning in the Modified MobileNet CNN model effectively identified eight common diseases of avocado fruit through image recognition. Data Augmentation (DA) techniques such as flipping, rotation, scaling, and translation were used to reduce the over-fitting of the model by enlarging the size of the dataset. However, Modified Mobile Net cannot be deployed on all types of mobile devices.

Yanfei Li et al. [31] presented a new framework depending on the CNN to grade the malus domestica quality rapidly and precisely. First, different relevant features were extracted from the malus domestica photos. Then, CNN, InceptionV3 and HOG/GLCM + SVM have been applied to recognize the malus domestica quality. But, the hyper parameters were needed to optimize for further improvement.

TalhaIlyas et al. [32] designed a DL model to recognize Fragaria ananassa fruit infection categories. In this model, the Convolutional encoder-decoder structure has been implemented with various blocks. The initial block has been applied to dynamically handle the receptive lead dimension of the structure to recognize items of several dimensions. The other two blocks have been utilized to handle the flow of salient traits to the deeper units of the structure and handle the structure's computational difficulty, correspondingly. However, it was unable to isolate individual instances because of the nature of the semantic segmentation process. Also, it needs to make the dataset more dynamic by considering more class categories for the different diseases.

III. COMPARATIVE STUDY

In this section, a comparative scrutiny of the above studied ML and DL algorithms for FDD and classification according to their merits and demerits in Table 1.

Ref. No.	Algorithms	Merits	Demerits	Performance
[8]	GA for feature selection and One-vs-All M-SVM for classification, EM for segmentation.	It recognises microscopic indications from leaf pictures more correctly and fast than CNN and other techniques such as binarization.	Since have many stages, computational complexity is high for this method.	Black Rot Accuracy = 98.10% Apple Scab Accuracy = 97.30% Apple Rust Accuracy = 94.62% Healthy Accuracy = 98.0%
[9]	PCA, LDA, BPNN and SVM	Analyzed Good selectivity for detecting Alternaria spp. fungi in pomegranate fruit.	This process has high computational cost and time.	C-SVM Linear Validation = 90% C-SVM Sigmoid Validation = 76% C-SVM Radial basis Function Validation= 75%

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				C-SVM Polynomial Validation= 83%
[10]	Two dimensional feature extraction techniques, Fuzzy 2DLDA Fractional LDA	The suggested approach is significantly more capable of effectively evaluating pomegranate fruits than previous ways.	Fuzzy 2DLDA is not an appropriate method for assigning a binary class label.	FFR2DLDAAccuracy = 0.97 FFC2DLDA Accuracy = 0.97 FFB2DLDA Accuracy = 0.93
[11]	CNN	CNN has an advantage over other approaches in that it can recognise characteristics without the need for operator involvement.	Transfer learning can reduce the effectiveness of the subsequent system, and there was also an issue about overfitting.	Inception-V3= 95.1 ResNet-50 =71.2 ResNet-50 V2 = 97.7 Inception-ResNet-V2 =.4 99.6 Xception = 99.2 VGG-16 =33.6 DenseNet-121 =91.9 Proposed Model =94.3
[12]	DCNN and L2M Loss was used for classification	The suggested technology identifies Peach plant infections at an early phase, in a quick and efficient manner.	The observations in this database are unbalanced, and the instance size is limited.	AlexNet =4.05 ResNet50 =13.53 Xception =18.12 SENet154 =45.86 DenseNet169 =19.63 HRNet-w48 =2.26 MobileNetV3= 4.24
[13]	K-means clustering – for segmentation PHOG, GLCM Features , SVM, KBB, Bayesian and ensemble classifier	The features used in these methods are supported for various datasets.	Because of the first seed allocation, region-based fragmentation requires too long to complete.	Plant village accuracy = 97.42% Internet downloaded accuracy = 94% Real world accuracy =84.4% Combined accuracy =93.18%
[14]	FA and ANN and WOA.	The algorithms provide disease detections with minimal error rate	Since have many stages, computational complexity is high for this method. .	PNN accuracy = 0.9069 BPANN accuracy = 0.9152 K-NN accuracy = 0.9246 WOANN accuracy = 0.9411
[15]	CNN and ReLU	It may be used in smart phones to diagnose pest populations and pathogen conditions in real time.	Insufficient Image samples only used ,many jackFDs not covered	Success rate = 97.87% TP healthy = 108 TN healthy = 408 FP healthy = 0 FN healthy = 0
[16]	Disease detection techniques and ResNet.	The models have less computational costs with high precision	The granularity is insufficient for detecting minute alterations in disease development.	Baseline (color-masked-binary) =0.987 Bacterial Spot = 0.994 Early Blight = 0.997 Late Blight = 0.961 Leaf Mold= 0.997 Mosaic Virus = 0.997 Septoria Leaf Spot = = 0.991 Spider Mites = 0.788 Target Spot = 0.774 Yellow Leaf Curl Virus = 0.998
[17]	Metric learning, DCNN and Siamese network	The method has high accuracy for detecting various diseases from fruits and leaf images.	Deep models size of this method consumed more memory space	Citrus precision = 0.9549 Citrus recall = 0.9547 Citrus F1 score = 0.9541 Citrus accuracy = 95.04
[18]	DCNN and Multi-class SVM	Entropy method only selected high ranked features. So that this method obtained high accuracy with less time consumption	Single pre-trained model used in this method not enough to achieve good accuracy.	Sensitivity = 97.6% Accuracy = 97.8%, Precision = 97.6% G-measure = 97.6%
[19]	DCNN, Inception-v3 and Data Augmentation	This is more robust model, can support resource constraint devices.	The method provides lower accuracy for few types of diseases	Brown rot accuracy = 87.12% Healthy= 90.43% nutrient deficiency = 84.04% shot hole = 92.15%

				shot hole on leaf = 88.34%
[20]	LFC-Net, Multi-network, Self-supervised	The proposed method detects to find small discriminative features between different tomato diseases effectively.	Only few type of diseases only considered in this work	Random selection 373 accuracy = 94.1% Plant village accuracy = 94.8% Data augmentation = 95.1%
[21]	Feature extraction using ResNet50, features fusion, features selection using GA, SVM, KNN, ensemble bagged trees and ESD	This method provides high disease detection accuarcy	Computational time of the system is high due to the irrelevant features and high dimensionality of feature vectors.	Precision = 99.7% Sensitivity =99.5% F1 score = 99.6% maximum accuracy = 99%
[22]	DCNN	It has a significant classification probability and a quick identification velocity, allowing it to resist ambient surroundings disturbance to the greatest level possible.	This technique does not compensate for the various illness features at each stage of the disease's progression.	Verticillium wilt = 96% Black spot = 83% Bacterial wilt = 76% Anthracnose = 86% Fruit rot = 97% Malformed fruit = 98% Snake eye = 93% Root rot = 90% Graymold = 94% Powdery mildew = 85%
[23]	GLDDN	It is computationally efficient, simple and accurate by reducing the manual intervention.	It has a significant processing expense and is incapable of detecting all probable diseases.	DCNN accuracy = 93.4% CNN accuracy = 99.53% DenseNets accuracy = 99.75% VGGNetaccuracy = 83.2% GoogLeNet and Cifar 10 accuracy = 98.9% and 98.8% AlexNet and SqueezeNet accuracy = 95.65% and 94.3% Faster R-CNNaccuracy = 99.93%
[24]	DCGAN and CNN	It can achieve higher statistical significance and accuracy by learning non-linear features.	The hyper-parameters such as learning rate and optimizer variables are properly chosen which influences the accuracy.	DCNN-Adam = 99.99% DCNN-Adamax = 96.66% DCNN-Nadam = 93.00% DCNN-Adadalta = 88.00%
[25]	HNC Classifier and Feed Forward FFBPNN	It classifies the infected area from overall surfaces o that computational complexity is less.	This method utilized only small number of image samples only	Fuzzy logic accuracy = 90.48% Naïve bayes = 85.71% KNN accuracy = 92.38% HNC proposed = 98.1%
[26]	Mask RCNN, RPN	It has a high degree of performance in identifying and localising illness symptoms.	This strategy is only tested on a tiny collection of data. It must provide dependability by utilising huge databases.	Mask R-CNN = 77.67% SSD = 63.29% Retinanet = 64.13% YOLOv3 = 73.56% Proposed Network = 82.30%
[27]	PeachNet,Mask RCNN, RPN	The performance was high for largely available disease types	The class imbalance problem makes unable to locate the disease region.	Peach scab=0.99 Shot hole disease = 0.86 Peach leaf curl 0.83% Plum pox virus = 0.99 Accuracy = 0.94%
[28]	Cycle-GAN, for data augmentation ,Multi-scale DenseNet for	Cycle-GAN can produce new training samples in the super-pixel region and efficiently boost	To improve efficiency, it must examine the visual	Healthy apple leaf = 95.63 General apple scab = 93.18 Serious apple scab = 93.45

	disease detection	the quality of the trained database.	features of various diseases.	Apple gray spot = 92.1 General cedar apple rust = 92.80 Overall = 94.31
[29]	CNN with different Convolutional ,Pooling and Fully Connected Layers (different architectures)	Higher recognition rate than ML techniques like SVM	Training the networks requires a large dataset.	Outcomes implied accuracy = 98%
[30]	Modified MobileNet CNN model and Data Augmentation (DA) technique.	Small, low latency, low power model of MobileNet can run more efficiently in mobile devices	Not deployed in all type of mobile devices.	Accuracy 93.3% for Sunbloch, 99% Scap and 90.9% for cercospora diseases
[31]	CNN , Google Inception v3 model and HOG/GLCM + SVM	Shortest times for training process, High accuracy in classification.	Some fundamental guidelines must still be followed while configuring the specifications.	Overall accuracy = 95.33% Training and Validation accuracy = 99% and 98.98%
[32]	Dynamic Attention-based Convolutional encoder-decoder network	It may be used in real-world plant settings. Because of its effectiveness in a changing and adaptable environment	This method was unable to isolate individual instances	Precision = 92.45%. Recall = 75.35% for Overgrown disease with confidence threshold 0.5

Table.1 Comparison of Different Fruit Disease Detection and Classification Algorithms using Fruit Images

IV. CONCLUSION

In this paper, a detailed comparative study on different FDD and classification systems based on ML and DL algorithms using fruit images was presented. From this comparative study, it was observed that many researchers have experience in designing AI-based algorithms to predict and classify FDs efficiently. Among these fruit pathogen detection systems, the adaptive attention-based convolutional encoder-decoder system outperforms the others in dealing with extremely obstructed instance situations. Because of its effectiveness in a changeable and reactive surrounding, it is capable of being used in real crop conditions. It will also assist to avoid the propagation of FD by detecting and eradicating affected fruits as soon as possible. However, due to the nature of the semantic partitioning process, it may be unable to identify particular occurrences. Also, it is necessary to make the database with more flexible range by taking into account of more condition label groupings. So, the future work will focus on enhancing the accuracy of predicting multiple FDs simultaneously by improving the localization and recognition of individual fruit instances from more dynamic datasets.

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