Comprehensive Review on Automated Fruit Disease Detection at Early Stage

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Abstract— Fruits are now cultivated in many different countries, which has increased global fruit output to 2,914.27 thousand tons. Numerous countries want to increase their fruit production in the next years, thus the number of countries producing fruits is expected to keep growing. But despite this, a variety of challenges and problems are still experienced while growing crops. These include problems with the fruit's general quality, the cost of manufacturing, the state of the seed, and the fruit's own illness. The main causes of fruit diseases' detrimental impacts are microbes and fungus. Early fruit disease detection is used to foresee fruit disease, which helps farmers save money by lowering the amount of capital they have to spend. To stop fruit illnesses in their early stages, it is crucial to figure out the best way to identify fruit infections. Many studies on a variety of fruits, including the papaya, apple, mango, olive, kiwifruit, orange, etc., have employed deep learning approaches. This study compares several ways for image capture, pre-processing, and segmentation as well as deep learning techniques. The study discovered that the best deep learning strategy for a particular collection of data may change depending on the system's computational power and the data being used. The results of this study show that a convolution neural network is more accurate and can predict a wide range of fruit diseases.

Keywords- Fruit Disease Detection, Feature extraction, Feature selection, Papaya fruit, Deep Learning Techniques, Classification

I. Introduction

In every part of the globe, agriculture plays a significant part in the development of economies and general growth [1]. The transport of agricultural products from one part of the globe to another is continually beset with a myriad of critical obstacles. Farmers in the modern day need to be provided with the instruments of decision-making and advancements in automation that can more effectively integrate their commodities, skills, and services in order to increase their production, efficacy, and profitability [2]. The idea of "smart farming" is summed up in this phrase. The purpose of increasing the fruit yield is to boost the total quantity of fruit that is produced and, as a result, contribute to the growth of the agricultural economy. Agriculture plays a vital part in performing an important function as a key driver of economic growth, labor, as well as import and export industries. This role is crucial for the economy as a whole. It is vital to secure the long-term sustainability of fruit farming in relation to the prevention of diseases [3, 4] in order to increase the amount of fruit that can be produced from the land..

The minerals and nutrients that are found inside fruits, such as apples, oranges, grapefruits, pomegranates, and plums, play a key part in the techniques that are used to cultivate these fruits. Fruits are an excellent source of essential minerals such as magnesium, copper, phosphorus, calcium, potassium, and nitrogen. Iron is also one of the minerals that may be found in fruit. When there is an insufficient supply of essential nutrients, the growth of the fruit, the production, and the quality are all significantly affected. In the course of one year, the infrastructure of the cold chain is responsible for the waste of an average of 16% of the fruits that are transported through it. Precautions need to be taken in order to recognize the illness in its early stages so that they may be taken in order to prevent the fruits from being infected with the sickness. If this is done, it will be feasible to stop the illness from spreading to other kinds of fruit and keep it from becoming widespread. Some of the illnesses that have a detrimental effect on fruit output include canker, anthrax, black spot, rot, and thread blight. Other diseases include black spot and rot. The procedures of harvesting, pruning, and spraying within the agricultural industry have not made use of agricultural automation technology in recent years. Both the early diagnosis of fruit illnesses and the precise prediction of the time at which diseases are linked to fruit play a vital role in the effective growth of fruit production [11, 16].

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It is now possible to send many different types of fruit all over the world because to developments in cold storage and transportation, and this pattern is anticipated to continue in the foreseeable future. It is now an imperative need to maintain the highest possible level of export efficacy, which is achieved mostly via visual inspection carried out by qualified specialists. Inspection of fruit with the naked eye by people who are informed about the illness being sought after is the conventional approach of finding and naming it. This is not only difficult but also expensive to do because of the farms' distant locations.

In some sections of the worlds less developed countries, consulting experts may be exceedingly expensive and time consuming due to the distant locations in which they are accessible. This can be the case because of the high expense of travel. It is very necessary for there to be automated identification of fruit illnesses so that indications of diseases may be swiftly recognized as soon as they emerge during the growth of fruits [19]. When the fruit is picked, it is probable that illnesses in the fruit may cause significant losses, not only in terms of quantity but also in terms of quality. If one want to have even the slightest chance of avoiding financial setbacks the following year, it is very necessary to have an accurate comprehension of what is being observed. Additionally, there is an infection that may spread to other areas of the tree, which can result in the infection of the tree's leaves, branches, and stems [6]. Apple scab, apple rot, and apple blotch are just a few examples of the more common diseases that have the potential to destroy apple orchards. Scabs on apples are scaly regions that might be brown in color [4]. Apple rot infections lead to the formation of slightly depressed, circular brown spots that may be encircled by a red halo. These patches may be found anywhere on the apple. Fungi are responsible for the disease known as apple blotch, which appears as discolored, uneven, or lobed edges on the outermost layer of the fruit's flesh [24, 25]. Apple blotch is caused by the fungus scabies. In the industry, fruits are already subjected to visual inspections performed by computer vision; this procedure is already computerized in terms of both their size and their color. However, it is still difficult to identify defects since there is a naturally occurring variety in the color of the fruit's skin across different kinds of fruits, there is a huge range in the types of imperfections, and there is either a stem or a calyx present. It is crucial to monitor the general state of a fruit and to search for any indicators of illness that may be present inside it. By implementing the right management procedures, such as applying fungicides, insecticides, and other chemically-based treatments, an individual is able to boost control of diseases, which in turn increases the efficacy of the therapy. There is a wide variety of approaches that may be used [22, 23] in order to enhance the prevention and control of plant diseases. Methods such as spectroscopy and imaging are two types of examples of these types of techniques.

II. GENERIC STEPS OF DETECTING FRUIT DISEASE

Taking into account the fruit is the best way to classify the disease. Deep learning (DL) and Machine Learning (ML) methods for detection can be applied in order to determine which fruits are afflicted with the disease. There are six primary stages involved in the methodologies of deep learning. Initially photos will need to be gathered, then preprocessing, segmentation, feature extraction, and classification will take place, and finally, the type of disease will be forecasted. Figure 1 illustrates the block diagram of the generic steps for detecting fruit disease using DL classifiers

- **Image Acquisition**: The process of acquiring images is the initial step of the system intended for identifying diseases in fruit. Photographs taken by sensors, drones, or cameras typically have the highest possible quality. The photos that were collected are in RGB format. After the creation of the color conversion framework for the RGB fruit picture, a device-independent hue conversion is then applied to the color conversion framework.

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- **Image Pre-processing:** There are a number of different ways that can be utilized in order to eliminate additional objects or noise from a picture. To clip a photograph, first crop the picture of the Fruit to obtain the area that is relevant in the image. A smoothing filter is applied whenever there is a need for smoothing. The enhancement of the image is performed in order to increase the contrast, then color conversion is used to transform pictures with RGB values into grayscale images, and finally, histogram equalization is utilized so that the intensities of the pictures are distributed evenly.
- **Image Segmentation:** The term "segmentation" refers to the process of splitting a picture into multiple components that have the same characteristics or have some similarities. Different methods, such as the otsu' method, k-mean clustering, turning RGB images into HIS models, and many others, can be utilized in the segmentation process.
- **Feature Extraction:** Extracting Features is a technique that is utilized to assess the overall effectiveness and quality of an image by utilizing features such as color, surface texture, shape, and other similar characteristics. It is possible to extract features from a picture using a variety of methods, such as the Global Color Histogram, Color Coherence Vector, Local Binary Pattern (LBP) and Complete LBP.
- **Classification:** The last phase in this process is classifying various fruit diseases through the use of DL techniques. There are a few different approaches to classifying things: Support Vector Machine (SVM), Multiclass SVM, Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Backbone Propagation Neural Network (BPNN), Feed forward Back propagation Neural Network (FFBPNN) etc.

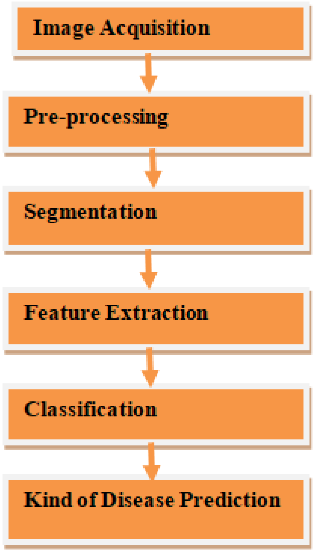

Figure 1: Generic Steps of Detecting Fruit Disease

III. LITERATURE SURVEY

The model that was suggested by Asad Khattak et al. [1] was known as Convolutional Neural Networks (CNNs), and an integrated method was used to complete the task. The objective of the CNN model that has been described so far is to differentiate between citrus leaves and fruits that are in good condition and those that have common citrus illnesses such as black spot, canker, blister, greening, or Melanose. The architecture for the CNN that has been developed takes use of the integration of several layers in order to extract specific properties that complement one another. On both the Citrus and Plant Village datasets, the CNN technique was evaluated against a significant number of innovative DL approaches. According to the results of the studies, the CNN Model is superior to its competitors in a number of the measuring metrics that were examined. Because it has been shown in testing to have an accuracy of 94%, the CNN Model is an important tool for citrus farmers to use as a decision support tool when they are trying to detect illnesses that harm the fruit or the leaf.

Muhammad Zia Ur Rehman and colleagues [2] established a brand new strategy for the classification of citrus ailments that is predicated on DL. Throughout the course of our investigation, we made use of two different DL algorithms, each of which had received prior training. Image improvement strategies are put into action in order to broaden the scope of the citrus dataset that had been used before. In addition, a hybrid stretching of contrast has been applied to images in order to improve the photographs' overall visual quality. In addition, transfer learning is used so that models that have already been trained may be retrained, and feature fusion is used so that the feature set can be expanded upon. Both of these methods are used so that the models can be improved. The combined feature set is optimized for the best possible performance by the use of a meta-heuristic strategy known as the Whale Optimization approach (WOA). Citrus fruits are susceptible to a total of six different illnesses, each of which may be classified according to one of the qualities that were selected. The strategy that has been proposed yields a classification accuracy rate of 95.7% with enhanced outcomes when compared to other approaches that have been developed in recent years.

This article by Ashok kumar Saini et al. [3] gives an overview of the many ways that may be used to diagnose and classify illnesses that damage the leaves of citrus plants. In addition to this, a comprehensive taxonomy of illnesses that damage the leaf tissue of citrus fruits is presented here. Within the scope of this research is also a probe into the automated detection and categorization of ailments. Several distinct methodologies, including preprocessing, classification, the extraction of features, and the aggregation of features, are all now under investigation here.

Shiv Ram Dubey and colleagues [4] came up with a technique that may be used for the detection of fruit diseases, and this approach was subsequently verified via experimentation. The image processing-based method proposed consists of the following primary stages: in the first phase, a K-Means clustering method is utilized for the defect segmentation; in the second phase, certain state-of-the-art features are obtained from the categorized image; and in the final phase, the images are categorized into any of the classes through the utilization of a Multi-class support vector machine (SVM). Scab, blotch, and rot are the three kinds of apple diseases that were taken into account and evaluated when utilizing apple diseases as a laboratory case. Apple diseases were used as a model in this study. The outcomes of their trials indicate that the approach that was presented is able to provide significant support for the accurate identification and automated detection of fruit illnesses. With the assistance of the supplied method, a correct classification of up to 93% of the items in question is possible.

Han, L. and colleagues [5] developed a one-of-a-kind system that is based on computer vision and is capable of automatically identifying agricultural illnesses. The classification of watersheds in this system is controlled by markers, and feature assessment and classification are determined using superpixels. The findings of the studies indicate that the approach that has been presented is able to effectively detect illnesses of crops, establish the severity of the diseases, and determine how severe the diseases are while maintaining a speedy pace of processing.

By adjusting the values of the parameters in a CNN framework, Metin et al. [6] were able to generate an updated version of their Faster R-CNN framework. A Faster R-CNN architecture is also described for the purpose of automating the detection of leaf spot infections in sugar beets. 155 photos were used to train and test the method that was created for the detection of the severity of an illness by imaging-based systems with expertise. The results of the testing showed that the overall correct classification rate was 95.48 percent, which demonstrates that the strategy was effective. Additionally, the approach that was shown proved that altering the CNN parameters in accordance with the picture and the regions that needed to be detected would enhance the efficacy of the Faster R-CNN framework. This was proven by the fact that the method was offered. In compared to the methods that are currently being used, the results that the recommended strategy achieved for the important variables were better. It would thus seem likely that the strategy would reduce the length of time necessary to determine the scope of the sugar beet leaf spot disease in the key growing regions. In addition, it is expected that the method will reduce the amount of time necessary to identify the severity of the condition and how far it has progressed.

D. Lorente and colleagues [7] studied the use of reflectance spectroscopy in the visible and near infrared (NIR) ranges in order to automatically detect citrus fruit that had degraded as a result of the Penicillium digitatum fungus. Reflectance spectrum of sound and disintegrating surface sections of mandarins cv. 'Clemenvilla' were obtained in two spectral regions such as 650–1050 nm (visible–NIR) and 1000–1700 nm (NIR). These are examples of spectral ranges. Both of the spectrum ranges exhibited significant differences in the spectra between the sound and the skin that was disintegrating. Principal component analysis (PCA), factor analysis, and Sammon mapping are the three manifold learning approaches that were used to transform highly dimensional spectrum data into understandable pictures of reduced dimensionality containing vital data. These techniques were utilized to accomplish this goal. A supervised classifier that is based on linear discriminant analysis employs low-dimensional representations of information as feature vectors in order to differentiate between healthy skin and skin that is deteriorating. Evaluation of factors based on NIR spectra led to the production of the most accurate categorization results, with a maximum accuracy in classification of 97.8%, as well as 100% and 94%, respectively, for well-classified specimens that were sound or deteriorating. Because of these discoveries, industrial citrus fruit sorters now have the ability to employ reflectance spectroscopy to determine whether or not citrus fruit has rot.

An improved version of the CNN method was used by Jahanbakhshi, A., and colleagues [8] to locate flaws in sour lemon fruit, assign grades to those problems, and develop an efficient system. In order to locate any errors, photographs of sour lemons were first classified as either healthy or damaged. After the first processing, pictures were classified using an improved CNN method. The results of CNN were enhanced thanks to data augmentation and stochastic pooling. In order to compare the model that was presented to existing approaches, feature extraction methods as well as k-nearest neighbor (KNN), artificial neural network (ANN), fuzzy, support vector machine (SVM), and decision tree (DT) classification methods were utilized. The accuracy of CNN was confirmed to be 100%. Therefore, CNN and image processing contribute to the reduction of waste and the promotion of sour lemon grading.

Deep convolutional neural networks (CNNs) and algorithms for object recognition were used by Qimei Wang et al. [9] in order to identify tomato illness. Tomato infections are identified using Faster R-CNN, whereas Mask R-CNN detects and segments the afflicted portions of the tomato. In order to determine the strategy that is most effective for recognizing tomato diseases, researchers utilize four deep CNNs as well as two algorithms that recognize items. When conducting investigations, data from the Internet are segmented as follows: training data, validation data, and test sets. The recommended methods are able to rapidly and accurately distinguish 11 kinds of tomato disease and differentiate between the places in which they are found and the morphologies they exhibit.

Researchers Inzamam Mashood Nasir and colleagues [10] used a contour feature-based Deep Neural Network (DNN) to categorize fruits and illnesses. A fine-tuned, pretrained DL classifier (VGG19) was retrained with the use of a plant dataset, and it successfully extracted significant attributes. After that, the pyramid histogram of oriented gradient contour features was recovered, and a serial-based approach was used to combine those features with the deep features. During the fusing process, unnecessary qualities were included, and thereafter, a "relevance-based" technique for optimization was used to choose the most useful traits from the fused vector so that it could be classified definitively. The recommended strategy outperformed prior approaches, with an accuracy rate of 99.6% when using several categorization strategies.

The work of Jamil Ahmad et al. [11] presents a CNN-based illness detection method in plum that has shown to be useful under real-world conditions, even when applied to devices with limited resources. In contrast to publicly available datasets, the photographs used in this inquiry were taken in the field and careful consideration was given to location, size, orientation, and other environmental considerations. Significant data improvement resulted in an increased dataset, which made it more difficult to conduct effective training. Recent findings shown that scale-sensitive algorithms like as Inception perform much better with difficult datasets that include substantial data improvement. Inception-v3's performance on devices with constrained resources was significantly enhanced via parameter quantization. Using the most accurate method available, mobile devices were able to differentiate between good and diseased leaves and fruit with an accuracy of 92%.

Almetwally M. Mostafa et al. [12] use color-histogram equalization and unsharp masking in conjunction with a deep convolutional neural network to identify guava plant species. Nine different perspectives out of a total of 360 degrees were employed to enhance the plant pictures. These improved data were accumulated using contemporary classification networks. The recommended method began with the standardization and preparation of the data. The experimental evaluation makes use of a dataset on guava disease in Pakistan that was obtained locally. The inquiry that is proposed makes use of AlexNet, GoogLeNet, ResNet-50, and ResNet-101 NN in order to identify different species of guava plants. ResNet-101 was able to classify with an accuracy of 97.74%, which is higher than the accuracy of other classifiers.

Williams, H.A. et al. [13] designed and tested a multi-arm kiwifruit harvester bot that was intended for use in pergola-style plantings. Gathering kiwifruit in a secure manner requires four specifically built robotic arms, each of which is equipped with a different end effector. The most recent developments in deep neural networks (DNNs) and stereo matching have made it possible for vision technology to detect and find kiwifruit under natural lighting conditions. During the harvesting process, the four arms are organized by a one-of-a-kind adaptive fruit scheduling system. An industrial orchard was used to test the harvester, and the results showed that it could gather 51% of the orchard's kiwi fruit in 5.5 seconds per fruit.

Modern CNNs, as shown by Santos, T.T. et al. [14], have the ability to recognize, segment, and monitor wine grape bunches, despite the fact that these clusters might vary in shape, colour, size, and compaction. A F1 score of 0.91 was reached for classification in an experimental set of 408 grape clusters that were photographed on a trellis-system vineyard. This enables for more exact evaluations of fruit size and shape. A dataset that is publicly accessible and has 300 grape clusters that have been sufficiently annotated as well as a one-of-a-kind segmentation technique for complex objects in real photos has been supplied. Agricultural patterns in photographs may be annotated, trained, evaluated, and monitored with the help of the pipeline by a wide variety of crops and production systems. It has the ability to produce sensor components that may be used for agricultural and environmental applications.

Mask Region CNN (Mask-RCNN) was developed by Yu, Y., and colleagues [15] with the purpose of improving the efficiency of computer vision in the process of detecting fruits for use in a strawberry harvester equipment. It was decided that Resnet50 would serve as the network's backbone, and the Feature Pyramid Network (FPN) architecture would be used for the purpose of extracting features from the network. Comprehensive training was provided from the very beginning to the very end for the Region Proposal Network (RPN), which was done so that it could create proposals for regions for each attribute map. After the work of making mask images of ripe fruits had been finished using Mask R-CNN, an image localization strategy for strawberry harvesting areas was carried out. The results of identifying fruits in a set of 100 test photographs revealed an average accuracy rate of 95%, a rate of recall of 95%, and a mean intersection over union score for fruit

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classification of 89.85%. These results were based on an average accuracy rate of 95% and a rate of recall of 95%. The results of the forecasting of 573 ripe fruit picking places indicated that the mean inaccuracy was 1.2 millimeters less than what was projected. This was shown by the fact that the mean error was less than what was predicted.

Deep Orange, DL is a system that was introduced by Ganesh, P. et al. [16], and it is capable of detecting and pixel-wise segmenting fruits by applying the most powerful instance segmentation technology that is presently available, which is called Mask R-CNN. The solution that has been developed takes use of information that comes from many sources, such as RGB and HSV photographs of the scene. The constructed architecture is evaluated using images that were shot in their natural settings in an orange orchard in the state of Florida. In the investigation, photographs in the RGB color space as well as the RGB+HSV color space are used in order to evaluate the efficacy of the algorithm. When just RGB data was used, the accuracy was only 0.89, but adding HSV data brought it up to 0.9, which is an improvement over the previous accuracy of 0.89. The overall F1 score that may be achieved in the RGB+HSV color space is really close to 0.89.

Liu, Z. et al. [17] applied the widely deployed Faster R-CNN model VGG16 with transfer learning for the goal of identifying kiwifruit using imagery collected from two distinct methods, RGB and NIR pictures. This was done in order to accomplish the aim of kiwifruit identification. With the use of a Kinect v2 device, a bottom view of the NIR and RGB photographs of the kiwifruit canopies was obtained. The near infrared image, which has one channel, the red, green, and blue pictures, which each have three channels, and the near infrared image, which has one channel, have been positioned and put next to one another to form a picture with six channels. In order to get an image with six channels, the input area of the VGG16 needs to have its settings modified. Image-Fusion and Feature-fusing had been the two types of fusion procedures that had been used for the purpose of acquiring features. On the input layer of the network, an application called Image-Fusion was used to mix the RGB and NIR photos. After the updated networks had been trained end-to-end using reverse propagation and stochastic gradient descent techniques, they were compared to the originally formed VGG16 networks, which only received RGB and NIR image input. This comparison was carried out in order to determine which of the networks was superior. According to the findings, the average precision of the original VGG16 alongside RGB and NIR picture input only had been 88.4% and 89.2% respectively; the average precision of the 6-channel VGG16 making use of the Feature-Fusion technique got to 90.5%; the average precision of the 6-channel VGG16 making use of the Image-Fusion technique attained the maximum possible value of 90%; and the quickest speed of detection was achieved at 0.134 sec/picture.

Ge, Y., et al. [18] offer a method that may be used for the identification, instance segmentation, and enhanced localization of strawberries. This method makes use of a Deep Convolutional Neural Network (DCNN). Deep learning is the core of the approach that will be taken here. The DCNN algorithm determines that there are four unique classes, three of which correlate to the various phases of ripeness that may be found in strawberries, while the fourth class is designated for strawberries that have an aberrant form. The research indicates that ripe strawberries can be differentiated from the other four categories with the least amount of work. After that, a method called bounding box refinement was used in an effort to boost the accuracy of the localization results. In this method, the identification of blocked fruits and the determination of real fruit sizes were accomplished by the use of boundaries. A similar refining strategy based on the firmness of the mask shape was recommended in order to discover the edge of the fruit that was hidden, and the measurement of the width to height ratio (WHR) of outputting masks was employed in order to detect obstacles. This allowed for the identification of the edge of the fruit that was concealed. In the third phase, which is the refining of the obscured side, the occluded section was compensated by utilizing the median WHR of the strawberries that were not obscured. This step brings the total number of steps up to three. The 'Lusa' strawberry variety was used in an experiment to try out the refining approach, which reveals that it is able to both identify and recover the real dimensions of the object. The test of comparison demonstrates that the amount of overlap between the raw identified and the ground fact is 0.68, but the bounding box intersection between the enhanced and the ground fact is 0.87. It would seem from the data that the revised technique is capable of discovering fruits with a greater degree of accuracy.

The authors Altaheri, H. et al. [19] describe a computer vision method that is both efficient and effective for dating fruit harvester bots. The system is comprised of three distinct classification algorithms that are used to classify photographs of date fruit in real time depending on the kind of date fruit, its degree of ripeness, and the decision to harvest it. These factors are taken into consideration while classifying images of date fruit. In the classification models, Deep Convolutional Neural Networks (DCNNs) are employed, in addition to Transfer Learning (TL) and fine-tuning on previously published approaches. An vast picture collection of date fruit groups in an orchard is created so that a dependable vision system may be built from the ground up. This collection includes over 8000 photographs of five unique types of dates at various stages of pre-maturity and maturity. The considerable amount of variation that is present in the dataset is a direct result of the intrinsic challenges that are present in the environment of a date orchard. These challenges include shifting viewpoints, dimensions, and lighting conditions, as well as date bunches that are wrapped in sacks. It was determined that the date fruit classification algorithms that were suggested had an accuracy of 99%, 97%, and 98.5%, with categorization durations of 20.6, 20.7, and 36 msec, respectively, for the kind, ripeness, and harvesting choice task classifications.

Deep-3DMTS is a strategy that Zapotezny-Anderson, P., et al. [20] describe with the goal of constructing a single-perspective approach to 3DMTS. This technique makes use of a convolutional neural network (CNN). After developing the one-of-a-kind method, we put it through its paces in a simulation to see how it stacks up against the conventional 3DMTS strategy. It has been demonstrated that the Deep-3DMTS method achieves effectiveness that is comparable to that of the standard 3DMTS baseline when guiding the ultimate effector of an automated arm for the purpose of improving the perspective of an obscured fruit. This includes an end effector ultimate position that is within 11.4 millimeters of the baseline, as well as an increase in fruit size in the picture by a factor of 17.8 in comparison to the baseline of 16.8 (on average).

Lin, G. et al. [21] creates a fruit recognition and estimate of posture technique in order to conduct out autonomous, collision-free choices using a low-cost red–green–blue–depth (RGB-D) detector. Their goal is to carry out selections without causing any damage to the fruit. In the first stage of the procedure, a cutting-edge fully CNN is used to segment the RGB image in order to produce a binary mapping of the fruit and branches. This step is the beginning of the process. After the fruit binary mapping and the RGB-D depth image have been applied, the next step is to apply Euclidean segmentation in order to arrange the focus point cloud into a collection of individual fruits. In the subsequent stage, a method is developed for identifying multiple fragments of line in three dimensions in order to rebuild the broken branches. This is done in preparation for the next step. In conclusion, an approximation of the 3D posture of the fruit is created by making use of the information on the location of the fruit's core as well as the piece of the branch that is closest to it. A dataset was gathered in an orchard that was situated in the outside area so that it could be used to evaluate how well the proposed technique worked. In quantitative testing, it was discovered that guava identification had an accuracy of 0.98 and a recall of 0.94, respectively. It was determined that the 3D posture inaccuracy was 23.4 degrees and 14.1 degrees, and that the implementation time per fruit was 0.5 seconds. The results provide proof that a bot designed to gather guavas can effectively apply the method that was developed.

Orchi H. et al. [22] offers a current assessment of inquiry that has been carried out over the course of the last ten years in the field of disease detection of different crops. They do this by using techniques such as machine learning (ML), deep learning (DL), methods for image processing, the Internet of Things (IOTs), and hyperspectral analysis of pictures. The identification of diseases in a variety of crops was the focus of this research project that was carried out. In spite of this, research on the parallels and divergences that exist between various methods for the diagnosis of plant diseases has been carried out. In addition, this article discusses the numerous challenges that need to be overcome, as well as possible solutions to these issues and their associated concerns. Following that, a variety of suggestions for addressing and overcoming these challenges are provided. In conclusion, the results of this study provide a prospective for additional research that offers enormous potential to develop into an incredibly useful and major source for scientists who work in the field of crop disease diagnosis.

Abbas et al. [23] presented a method that was based on DL and was used to detect illnesses that affect tomatoes. The method employs the Conditional Generative Adversarial Network, often known as the C-GAN, in order to generate fabricated pictures of the leaf surfaces of tomato plants. A DenseNet121 model is constructed on simulated and real photographs using TL in order to classify images of tomato leaf diseases into ten separate categories. These categories are determined based on the appearance of the photos. The aforementioned model has been constructed and rigorously verified using the dataset provided by PlantVillage, which is available to the general public. The recommended strategy had a success percentage of 99.5%, 98.6%, and 97.1% when it came to classifying photos of tomato leaves into five categories, seven categories, and 10 classes, respectively. The methodology that has been offered indicates its superiority to the methods that are presently being employed in the situation.

H. Wang et al. [24] demands apple, peach, orange, and pear as study components and offers a model using Mask R-CNN to recognize illness spots on the outermost layer of fruits. These spots are often caused by a fungus or a virus. After the collection robot has located and identified the fruit, this model makes an accurate assessment of any defects that may exist on the surface of the fruit's skin. These problems are brought about by the present approach for identifying fruit surface diseases, which has a low level of accuracy, a sluggish speed, and a high burden associated with quality classification. In order to improve the fusion of high-level and low-level features, the framework of the feature pyramid (FPN) that is used by Mask R-CNN has been adjusted to incorporate a bottom-up horizontal linking route. This change was made in order to improve the fusion of high-level and low-level features. The improved Mask R-CNN approach has a detection rate that is more than 95% for each of the four different kinds of fruit exterior spots, and its detection rate increases to 2.6 frames per second when the GPU is used. This is a lot quicker than the Fast R-CNN and SSD techniques, and it has excellent detection efficiency as well as durability.

S. R. used a wide range of color, texture, and form feature combinations to create the artwork in this piece. An image processing technique was proposed by N. M. Ayyub et al. [25] with the purpose of finding and categorizing illnesses that may affect apple fruit. The proposed procedure begins with the classification of pictures, then continues on to the retrieval of characteristics (color, appearance, and form), then continues on to the combining of those attributes, and finally concludes with the diagnosis of apple disease and the classification of apples using a multi-class support vector machine as either healthy or diseased. There is potential for the accuracy of the suggested strategy to be raised to as high as 96%.

N. Saranya and other authors [26] If photos are processed, they may be used to detect and classify illnesses that might harm banana plants. This is one of the most important things for farmers to be aware of, thus doing a study of the growth of the plant can be done easily, effectively, and at a low cost. Image processing would be used at the beginning of this suggested system so that illnesses could be identified, and subsequently artificial neural networks (ANN) would be used so that the diseases could be categorized. The proposed system incorporates a variety of operations, such as image capture and preprocessing, feature extraction, illness detection, and disease classification using an artificial neural network (ANN).

S. M. Jaisakthi et al. [27] developed an automated technique for diagnosing illnesses in grape vines that makes use of image processing and ML method. The method uses a grab cut segmentation approach to differentiate the leaf, also known as the Region of Interest, from the background image. This is accomplished by cutting off the leaf. Starting with the piece of the leaf that has already been separated, the diseased component of the leaf is further segmented according to two different methods, one of which is global thresholding, and the other is the use of semi-supervised technique. Both of these methods begin with the same section of the leaf. In order to obtain characteristics from the segmented afflicted area of the plant and then categorize it as either healthy, rotten, infected with esca, or impacted by leaf rot, a number of machine learning (ML) algorithms were applied, including SVM, adaboost, and Random Forest tree. These strategies were used in order to acquire the attributes. The accuracy was brought up to 93% by using SVM, which really helped in the process.

R. Ramya and colleagues [28] describe the detection and assessment of fruit ailments that are accessible in the plant areas. In addition to this, they examine the saving of data about the agricultural sector and information about farmers in a dataset, as well as the recovery of the information using Cloud computing. The surrounding environment, the amounts of minerals, insects that reside in the agricultural region, and a variety of other variables are all contributing to a rise in the number of fruit illnesses that are manifesting. Image processing is used to determine the found data obtained from the plant area, and this information is then kept in the database. Image processing is used to ascertain the discovered data gathered from the plant region.

TABLE TYPE STYLES

Title	Algorithms used	Gap Analysis
Automatic Detection of Pomegranate Fruit and Leaves Diseases Using DNN Model[1]	CNN	Intensive computational work for the construction of two layers
Classification of Pomegranate Fruit Diseases Using Deep TL[2]	DCNN	Only useful for the image of the citrus fruit.
Detection and Classification Techniques of Pomegranate Leaves Diseases: A Survey[3]	ML and DL methods	Method determined by surveys; no specifications of accuracy is provided
Adapted Approach for Fruit Disease Identification using Images[4]	Multi-class SVM	Multi class issues with classification caused by information im-balancing
A Novel Computer Vision-based Approach to Automatic Detection and Severity Assessment of Crop Diseases[5]	ML	Low degree of accuracy in detection
Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms[6]	R-CNN	When it comes to dealing with heterogeneous datasets, it has an issue with excessive fitting.
Visible-NIR reflectance spectroscopy and manifold learning methods applied to the detection of fungal infections on pomegranate fruit[7]	Segmentation, histogram classification	High levels of computing are generated via redundant feature selection.
Classification of sour lemons based on apparent defects using stochastic[8]	DCNN	Computation requiring a long time
Identification of Tomato Disease Types and Detection of Infected Areas Based on DCNN and Object Detection Techniques[9]	DCNN, R-CNN	When it comes to module training, only the RGB characteristics are taken into account; no additional characteristics are included because each has a negative effect on accuracy.
DL-Based Classification of Fruit Diseases: An Application for Precision Agriculture[10]	DCNN and PHOG	Dependence on the internet of things for data collecting, which results in massive, noisy information.
Disease Detection in Plum Using CNN under True Field Conditions	Inception V-3 and GAN	There is no provision for identifying objects that can be carried out with a diverse dataset.
Guava Disease Detection Using DCNNs: A Case Study of Guava Fruits	DCNN	Low accuracy is achieved using AlextNET and GoogleNET
Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms	Enhanced VGG-16 called FCN-8S	Low accuracy of 70% is obtained of the fruit kiwi
Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association	Enhanced ResNeT	Strict since each piece of data may be assigned to only one class.
Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN	Resnet-50	Limitations imposed on the amount of time spent storing and processing data
Deep Orange: Mask R-CNN based Orange Detection and Segmentation	Resnet-101	Not applicable when the data have a lot of noise.
Improved kiwifruit detection using pre-trained VGG16 with RGB and NIR information fusion	VGGNET-16	To get a sparse appearance, pruning methods need to be utilized.
Instance Segmentation and Localization of Strawberries in Farm Conditions for Automatic Fruit Harvesting	Convolutional Neural Network with ResNet	It takes a longer time to conduct tests, it is costlier for evaluating each instance, and it is vulnerable to both noise and output.
Date fruit classification for robotic harvesting in a natural environment using deep learning	Convolutional Neural Network with AlexNet and VGG-16	Overfitting is a problem that arises when an intricate model contains numerous variables.
Towards Active Robotic Vision in Agriculture: A DL Approach to Visual Servoing in Occluded and Unstructured Protected Cropping Environments	Convolutional Neural Network with ResNet Modified	There is a possibility that conditional independence will lower accuracy.

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Towards Active Robotic Vision in Agriculture: A DL Approach to Visual Servoing in Occluded and Unstructured Protected Cropping Environments[23]	RCNN	Mask R-CNN almost never succeeds in detecting objects that have been affected by blurred motion at poor resolution.
Guava detection and pose estimation using a low-cost RGB-D sensor in the field[24]	SVM, ANN	The most obvious drawback of ANN is that it is less efficient than SVM due to the fact that it is a classifier that is binary. High degrees of non-linearity are attainable by its utilization.
Guava detection and pose estimation using a low-cost RGB-D sensor in the field[21]	VGG-16, GoogLeNet	Costs of computation are high
Tomato plant disease detection using transfer learning with C-GAN synthetic images [23]	Feed Forward Neural Network	The binary data that they output are highly susceptible to interruptions caused by noise.
Research on Detection Technology of Various Fruit Disease Spots Based on Mask R-CNN[24]	SVM	Slow implementation.
Detection of Quality in Orange Fruit Image using SVM Classifier[25]	Inception V-3 and GAN	There is no provision for identifying objects that can be carried out with a diverse dataset.
A DNN based disease detection scheme for Citrus fruits[26]	DCNN	Low accuracy is achieved using AlextNET and GoogleNET
Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight.[27]	Enhanced VGG-16 called FCN-8S	Low accuracy of 70% is obtained of the fruit kiwi
Grape Leaf Disease Identification using ML Techniques.[28]	Enhanced ResNeT	Strict since each piece of data may be assigned to only one class.

IV. CONCLUSION

Controlling fruit infections is essential because agriculture is vital to the running of the economy as a whole. Although early problem detection is crucial, manual inspections are time-consuming, error-prone, and require a lot of effort. With the use of AI, we can extract data about a fruit's outward look, shape, or structure, which aids in the detection of pathogens. In this study, we do a comprehensive literature review of feature-based and DL approaches. Highlighting its potential to reshape agriculture and contribute to a more secure and sustainable food supply chain. It is an exciting journey that combines science, technology, and a commitment to feeding the world while preserving our environment. We need to find the future holds the promise of even more precise, accessible, and impactful solutions for fruit disease detection.

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