ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 02 (2024)

CITRUS DISEASES DETECTION & CLASSIFICATION USING DL AND ML MODELS: A SYSTEMATIC REVIEW

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Abstract - Citrus fruits, including lemons, mandarins, oranges, tangerines, grapefruits, and limes, are widely cultivated around the world. Citrus manufacturing enterprises generate a substantial amount of trash annually, with fifty percent of citrus peel being lost to various plant diseases. This paper provides a survey of the various methodologies applicable to the detection and classification of citrus plant leaf diseases. The page provides a comprehensive classification of citrus leaf diseases. Initially, the difficulties of each stage, which affect the accuracy of detection and classification, are described in depth. In addition, a comprehensive literature assessment of strategies for automated disease identification and classification is offered. In order to accomplish this, several picture preprocessing, segmentation, feature extraction, feature selection, and classification techniques are investigated. Discuss the significance of feature extraction and deep learning methods as well. The survey provides a detailed assessment of studies, analyzes their merits and weaknesses, and identifies more research concerns. According to the survey results, automated detection and classification approaches for citrus plant diseases are still in their infancy. To fully automate the detection and classification processes, therefore, new technologies are required. Comparative analysis of deep learning models currently used for citrus disease detection and classification. The creation of an updated model containing new characteristics and classifiers. Improvement of the proposed model's accuracy in the identification and classification of citrus illnesses. Citrus production and export have increased gradually over the past three decades, albeit at a slower rate than rival products such as mangoes, avocados, and melons. Citrus fruit production is severely affected by illnesses in its growing stages. The diseases develop not only on foliage but also on fruits. Hence, the presence of faults degrades the quality of fruits. The citrus fruits are evaluated in two ways, based first on the color of their skin and then on their size. So, it is necessary to assess citrus illnesses in order to prevent output losses. In addition, citrus fruit must be graded to facilitate its packaging in terms of its quality, so that the correct Citrus fruit values can be generated. This research examined and assessed various machine vision-based citrus disease prediction and postharvest citrus fruit grading approaches reported between 2010 and 2022. This study discusses the present successes, limits, and recommendations for future research on citrus illnesses and fruit grading.
Key words –Citrus Disease Detection, Plant Disease Detection deep learning, Machine learning, Citrus Disease, CNN, Feature Extraction, Segmentation

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I INTRODUCTION

Citrus is an important source of nutrients such as vitamin C for plants around the world. Citrus contains numerous economically significant species. Few species are cultivated commercially in India, including grapefruit, lemons, limes, sweet oranges, and mandarins. Citrus is indigenous to Southeast Asia. Several citrus species, such as mandarins, are native to the North East of India. In central India's Vidharbha region, Nagpur Santra is cultivated on a big scale. Similarly, the Brahmaputra Valley and Dibrugarh district are renowned for their production of mandarins in Assam. Khasi mandarin is a notable Nilgiri hills cultivar. In addition to mandarins, limes and lemons are also grown everywhere. India. Pests and illnesses are the two most influential influences on citrus yield. Many citrus pests and illnesses exist in nature. Several of them have a similar look, making it challenging for farmers to identify them in a timely manner. In recent years, advancements in machine learning algorithms have significantly advanced computer vision. These new network topologies have allowed researchers to achieve great precision in picture classification, object detection, and semantic segmentation [1]. Thus, some studies have applied the machine learning approach to determine the disease category based on an image. As a significant contributor to the agricultural economy as a whole, the citrus industry requires proper disease control in citrus groves to prevent losses. Melanoses, greasy patch, and scab are the most destructive citrus diseases [3-4]. Ensuring fruit quality and safety, and boosting the citrus industry's competitiveness and profitability, would be technologies that easily identify these pathogens. The objective is to examine the viability of pattern classification algorithms for detecting disease lesions on citrus leaf surfaces. Based on the disease, the leaves are divided into four categories: scab, melanoses, greasy patch, and normal leaf [3].

Citrus production: Around 923.2 thousand hectares are devoted to citrus cultivation in India, with an estimated output of 8,607,7 thousand metric tons. Agriculture entails substantial production risks, and numerous variables must be taken into account when making decisions [5]. For management strategies and development programs to be effective, it is necessary to have a thorough understanding of the variables that have the most direct impact on output. Comprehending the behavior of variables is challenging due to the complexity of relationships and the number of relevant elements.

Citrus Diseases: Citrus fruits, including lemons, mandarins, oranges, tangerines, grapefruits, and limes, are widely cultivated around the world. Citrus manufacturing enterprises generate a substantial amount of trash annually, with fifty percent of citrus peel being lost to various plant diseases. [6] Currently, citrus exports to international markets are significantly hampered by fruit illnesses. Citrus diseases negatively impact citrus fruit yield and quality.

Taxonomy of Citrus Diseases: In the agriculture industry, plant diseases are primarily responsible for the decline in productivity that results in economic losses at the national level. Grapefruit is an important global source of nutrients such as vitamin C. Unfortunately; citrus diseases severely impacted citrus fruit supply and quality. Many citrus lesions, including anthracnose, citrus scab, black spot, melanoses, and canker greening, afflict citrus plants such as lemons, oranges, grapefruits, and limes [7-8]. Included below are brief descriptions of several citrus illnesses.

Anthracnose- Anthracnose is a disease of citrus plants caused by a fungus (Colletotrichum gloeosporioides) and characterized by twig blight of mature tips, leaf spots, and fruit stains, spots, or rots. It can spread rapidly during wet seasons.

Canker- It is a highly serious citrus disease, primarily affecting limes. Sickness manifests itself on leaves, twigs, and fruits. It shows as yellow dots on leaves. Which progressively increase in

ISSN:2731-538X | E-ISSN:2731-5398
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size, grow rough and brownish, and become elevated on both sides of the leaf? These specks have a yellow halo surrounding them. The sores on the fruit's peel grow tough and corky. Kagji limes and grapefruits are extremely vulnerable.

Citrus Scab- Acne scabs on citrus leaf and fruit are composed of fungal and organism tissue. The color of a scab lesion is dirty grey and yellow-brown. Tiny, dark brown, rough, uneven, elevated lesions appear, predominantly on the undersides of the leaves. Fruits and branches are also infected.

Citrus black spot - Citrus black spot is caused by the fungus Guignardia citricarpa. This ascomycete fungus affects citrus plants in subtropical climates, reducing both the quantity and quality of the fruit. Symptoms consist of both fruit and leaf lesions, with the latter being crucial for inter-tree dispersal.

Melanose- Melanose is caused by Phomopsis citric fungus. On leaves, branches, and fruits, it appears as dark circular depressions with yellow edges. Subsequently, the dots grow rough and elevated, and their light brown and yellow edges vanish. The surfaces of leaves and fruits develop a sandpaper-like roughness.

Greening:- It is caused by bacteria and shows as many, rigid, erect branches and buds. The leaves shrink and become speckled. Early defoliation and branch dieback are observed.

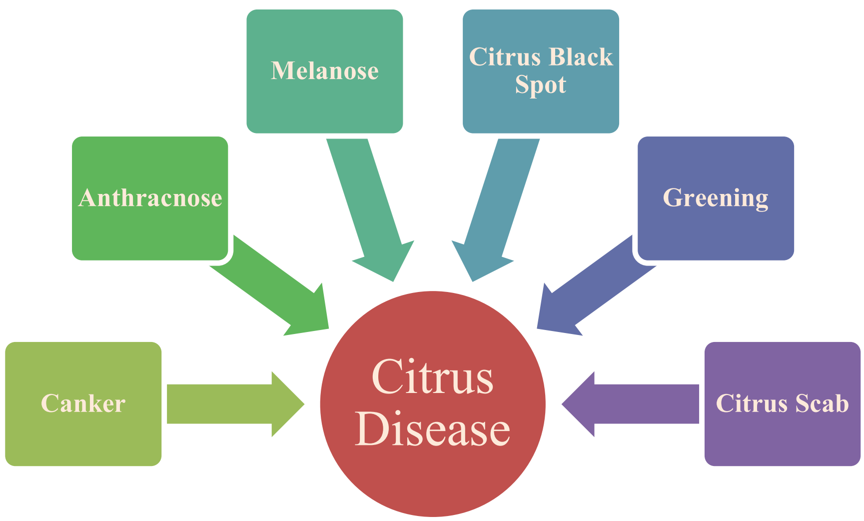
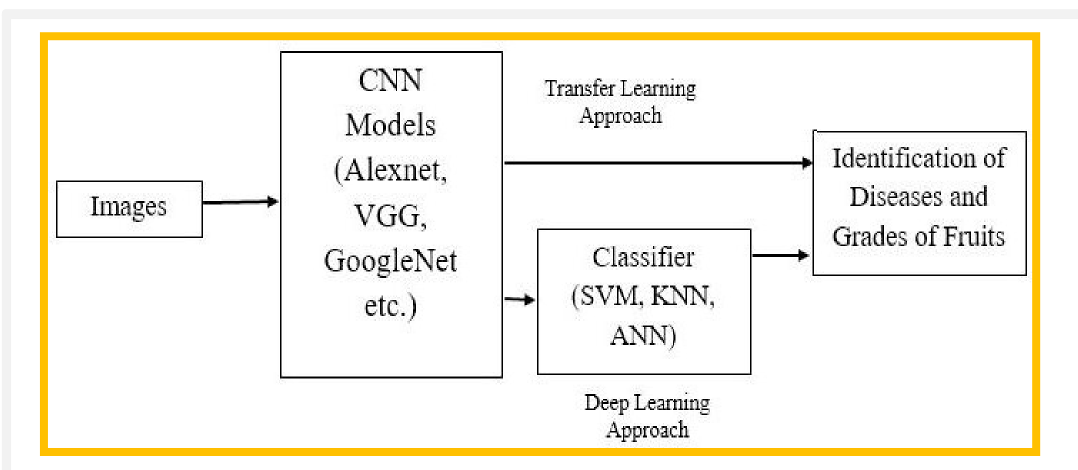


Figure 1 different types of citrus disease

Major Challenges in Disease Detection and Fruit Grading of Citrus based on Machine Vision-Machine vision, which integrates cameras, processing gear, and software algorithms, allows for the automation of regular visual inspection tasks. With machine vision, these include location, identification, verification, measurement, and flaw detection. The fundamental purpose of machine vision in this crop is to detect defects (diseases), classify diseases and citrus fruit kinds, and evaluate fruit quality and size. (1) Optical consistency; (2) separation of the disease from the background; (3) the presence of irrelevant features; and (4) the absence of big datasets are significant challenges in citrus disease identification and diagnosis. [9]

Machine vision mainly relies on preprocessing to improve the optical consistency of the incoming images. Included in the preparatory procedures are image enhancement, color space conversion, image resizing, and image filtering. Many challenges, including lighting, brightness, and contrast issues, can therefore be eliminated. These factors have a direct effect on the accuracy of disease classification. For the identification of plant diseases, numerous preprocessing techniques are utilized. They include image enhancement, scaling, image correction, and the elimination of shadows. Segmentation is the second primary process for separating the disease's fragments. Color change, substantial diversity in colors, changing lighting circumstances, variations in the size of the sick portion, the volume of fruits, and estimation of disease area and fruit size are some of the most typical obstacles for segmenting diseased parts in an image [10-11].

Due to these flaws, the accuracy of detection and grading is weakened, and the system as a whole suffers. Using various methods, such as K-means and thresholding, crop disease diagnosis and fruit grading are possible. Preprocessing and segmentation techniques assist with crop defect classification. In order to evaluate illness and fruit grades, feature extraction and categorization are also required. An essential objective of feature extraction methods is to diagnose diseases based on the texture, size, and color of lesions. Dealing with challenges such as enormous dimensions of extracted features, irrelevant information, lengthy computation durations, redundant data, and changeable lighting conditions and characteristics that are not invariant under scaling and rotation are phases of the feature extraction process. As each disease has a specific hue that is utilized to identify it, the majority of studies concentrate on color. Other properties, such as texture and shape, contribute in the detection of disease in agricultural plants [12]. The conclusion of machine learning is classification. In agricultural operations, SVM, KNN, and ANN [13-14] are frequently employed for disease classification and fruit grading. The main cause of the classifier's low performance is the lack of feature selection and feature reduction algorithms. Figure 2 depicts the machine learning technique to disease detection and fruit grading. Recently, there has been a great deal of interest in machine learning regarding deep learning (DL) (ML). When applied to big datasets, deep learning (DL) enhances agriculture's precision and productivity. Similar to ANN, DL provides a hierarchical data representation in the form of convolutions. Deep learning is defined by the automated extraction



of features from raw data (DL). Hence, DL solves complex problems more rapidly and with fewer errors. DL techniques are not used in the literature for citrus disease classification for a number of important reasons, including the availability of a big dataset. A huge number of data points are needed to train a machine learning model. Other plants, including apple, tomato, and general plant leaves, are classified [15-20]. Figure 3 displays the typical deep learning methodology for disease identification, as well as the citrus crop's fruit grading. Taking into account all demanding elements and available methodologies, these two approaches are more attentive for disease detection. The most suited strategies for generating high dimension feature vectors from a short dataset are the feature fusion techniques. Thus, citrus disease diagnosis and

ISSN:2731-538X | E-ISSN:2731-5398
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fruit grading performance may be improved. [21-24]

Figure 2. Framework based on Machine Learning.

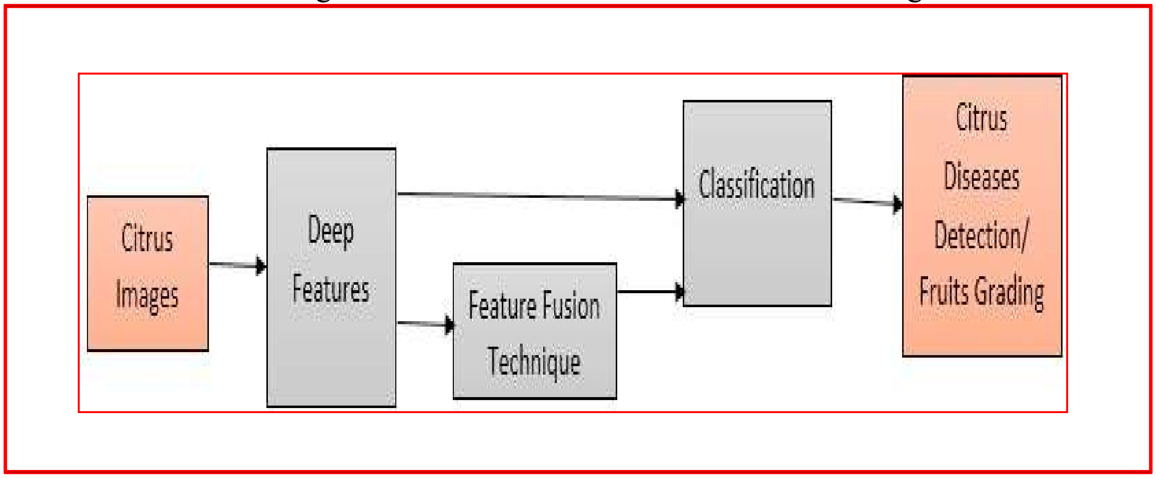

Figure 3. Framework based on Deep Learning.

II RELATED WORK

Citrus Disease Detection Using Machine Vision The typical approach for detecting citrus diseases is time-consuming and requires a thorough understanding of the problem, making it a hot topic among researchers. With machine vision, it is possible to detect citrus diseases. Greening illness and know & mandarin citrus were found for the first time in 2017 [25] by H. Ali et al. Using an algorithm based on the color difference of E, the sick area was isolated. Textural characteristics and a color histogram were used to classify diseases. They used fine KNN, Cubic SVM, Boosted tree, and Bag of trees to achieve 99.9% precision. A method has been devised for diagnosing diseases such as Black Spot and Citrus Scab. Preprocessing, segmentation, feature extraction, and classification are all components of their research. K-means clustering is used for segmentation, whilst SVM and KNN are used for classification, according to Pandey et al. Muhammad Sharif et al. [27] created a hybrid illness detection and classification strategy few years ago. Some of the ailments include black patches, canker, greening, and melanoses.

Multiclass SVM (M-SVM) is loaded with the appropriate features to categorize citrus illnesses. The proposed classification approach was 95.8% accurate. Six CNN architectures, including AlexNet, GoogLeNet, Inception v3, ResNet-50, ResNet-101, and SqueezeNet, were tested to identify Grapevine yellow (GY). Comparing accuracy and training expenses, they determined that the ResNet-50 model was the most effective. 2018 [28] paper by Konstantinos P. Ferentinos et al. describes a method for identifying Huanglongbing disease.

GoogLeNet and VGG architectures were also utilized. VGG had the highest success rate, at 99.53 percent. “ According to Mrunalini R. Badnakhe et al., 2018 [29], the Gummosis disease can be identified and predicted throughout time in citrus. "Huanglongbing (HLB), melanoses, oleocellosis (oil spot), wind scar, Leafminer, and dust mites had their spectral signatures found by Yao Zhang et al. 2018 [30] using support vector regression (SVR) and multilinear regression (MLR) approaches. The study includes an ant colony optimization (ACO) algorithm and variable selection concepts. For the first time, scientists have identified an effective method for identifying citrus huanglongbing (HLB) disease. Many AI tools, including decision trees, SVMs, k-nearest neighbors, and direct discriminant examinations, can be used to identify groups of unwell individuals.

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The results indicated that critical hyper spectral reflectance can be used to effectively categorize objects. While the SVM's three-way classification accuracy was 90.8%, its two-way classification accuracy was 96%. (healthy versus asymptotic HLB leaves). Diseases can be utilized to identify citrus fruits and leaves, according to Hafiz Tayyab Rauf et al. 2019[31]. Diseases include Blackspot, Canker, Scab, and Melanoses. The Toys for Tots Program Using a CNN model proposed by Arnal Barbedo et al. in 2019 [32], citrus variegated chlorosis, sooty form, leprosy, halo scourge, citrus mosaic, and scab were recognized. 62% of the time, citrus fruit diseases can be accurately recognized. [33] Victor Patel and his coworkers have created a technique for identifying citrus illnesses. CNN's model was utilized. These disorders are known scientifically as Huanglongbing, or "citrus greening." Using two CNNs, psyllids were recognized, and debris fell from the tree with 80% and 95% accuracy and precision, respectively. Utpal Barman et al. 2020 [34] suggested techniques for distinguishing citrus leaf diseases.

Citrus leaf diseases were discovered and categorized using MobileNet and Self-Structured (CNN) classifiers of CNN models. MobileNet CNN fared the best with a 98% preparation accuracy. The project's design will incorporate images taken with a mobile phone. Zongshuai Liu et al. 2020 [35] developed techniques for diagnosing agricultural diseases. MobileNetV2 was utilized to arrange the study and evaluate the speed, model complexity, and precision of various network models in comparison to MobileNetV2. These methods lowered the system's complexity, and it is now time to calculate it. Citrus huanglongbing was discovered by Yubin Lan and colleagues in 2020 [36].

SVM, k-nearest neighbor (kNN), logistic regression (LR), naive Bayes, and ensemble learning models were compared to sound and HLB-contaminated samples following boundary advancement. All models were shown to have the most precise and comprehensible PCA characteristics when paired with CN (computerized numbers) esteem. Utpal Barman et al. LR and ANN are used to forecast citrus leaf chlorophyll content. ANN was more accurate than LR in forecasting citrus chlorophyll levels in this instance. Sue Han Lee et al. 2020 [38] were able to identify plant pathogens using a novel approach. Orange fruit exhibits the citrus greening disease, according to researchers. CNN models GoogLeNet, VGG16 (16 layers), and InceptionV3 were utilized (48 layers). The VGG16 performed better on tests. Yiannis Ampatzidis et al. 2020 [39] discovered that employing small Unmanned Aerial Vehicles (UAVs) equipped with a variety of sensors makes surveying simpler, faster, and less expensive. To process, analyze, and visualize data gathered from unmanned aerial vehicles (UAVs) and other platforms, the Agroview cloud-based artificial intelligence (AI) tool was developed (e.g., small planes, satellites, and ground platforms)

Using this user-friendly and interactive tool to: I locate plants (and plant gaps) and plant inventory (measure plant height/canopy size); and (ii) generate maps displaying the health of plants in a specific area (c). Using this Agroview application, the phenotypic characteristics of citrus trees can be analyzed (as a case study). This emerging technique detected citrus trees with a mean absolute percentage error (MAPE) of 2.3% in a commercial orchard of 175 977 trees. Vijai Singh et al. et al. evaluated the identification of plant diseases in 2020 [40]. Citrus diseases include canker, oily patch, insect damage, melanoses, wind scar, and scab. Using PCR and spectral information divergence, diseases can be discovered. Using these procedures, the results are accurate 95,2 percent of the time. A approach developed by David Argüeso and colleagues in 2020 [41] can identify citrus greening disease.

Using CNN and SVM, they were able to detect 90% of the disorders they sought. In plant leaf disease classification, the efficientNet deep learning architecture introduced by Umit Atila et al.

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2020 [42] was compared to other state-of-the-art deep learning models. The detection accuracy of these models for diagnosing huanglongbing disease in citrus was determined to be 99.97% accurate. SVM, Random Forest, Stochastic Gradient Descent (SGD), and DL (Inception-v3, VGG-16, VGG-19) have been investigated for the search for citrus plant diseases, as demonstrated by R. Sujatha et al., 2021 [43]. Due to the fact that DL tactics outperform ML methods in disease discovery, the infection classification accuracy (CA) acquired through trial and error is exceptional. Among the top three are RF-76.8%, SGD-86.5, SVM-87, VGG-19, Inception-v3, and VGG-16. VGG-16 has the best CA, however the RF receives the least consideration.

Using machine learning and deep learning, Utpal Barman and his colleagues 2021 [44] built a computerized system to identify citrus leaf diseases. Citrus Greening and Citrus Tristeza Virus (CTV) have been identified as diseases. For detection and classification, Deep Neural Networks (DNNs) and K-Nearest Neighbor (KNN) classifiers are utilized. The KNN classifier's accuracy is 89.9%, whereas the DNN classifier's accuracy is 99.89% with an error of 0.0219. Morteza Khanramaki et al. 2021 [45] suggested an intelligent technique based on deep learning to detect three prevalent citrus pests: citrus Leafminer, Sooty Mold, and Pulvinaria. Their research utilized ResNet50, Inception ResNet v4, AlexNet, and VGG16. The proposed ensemble outperforms rival CNN algorithms with a 99.04 percent accuracy advantage.

Ngugi et al. 2021 [46] identified leaf diseases using image processing and deep learning techniques. Classification of diseases using the GoogLeNet model. Sooty Mould of Citrus, Alternaria Brown Spot, Canker, Greasy Spot, and Algae. Develop an automated model for detecting and categorizing plant leaf diseases by employing a CNN based on the ideal mobile network (OMNCNN). Preprocessing, segmentation, feature extraction, and classification are all suggested workflow processes for the OMNCNN model. The damaged leaf image regions are identified using bilateral filtering (BF) and thresholding-based image segmentation. An algorithm created by Vaibhav Tiwari et al. in 2021 [48] can be used to detect citrus diseases.

DenseNet and MobileNet-v2 discovered Citrus Black Spot, Canker, and Greening. The findings of the experiment indicate a cross-validation accuracy of 99.58 percent and a test accuracy of 99.199 percent. Ahui Xue and colleagues presented early detection of Citrus (Huanglongbing) HLB and the regulatory mechanism of the Phenylpropanoid Pathway in 2021 [49].

III METHODOLOGY

- The purpose of this systematic review is to provide an overview of the various machine-learning and deep learning algorithms employed in the diagnosis of citrus fruit diseases using photographs of sick citrus trees. The review technique consists of the following steps.
- Data Collection
- Searched databases

  Science Direct, Scopus, Springer, ACM (Association for Computing Machinery), and IEEE (Institute of Electrical and Electronics Engineers) were utilized to analyze this body of literature (IEEE Explore Digital Library). This survey utilized the years 2000 to 2020 as its time frame.

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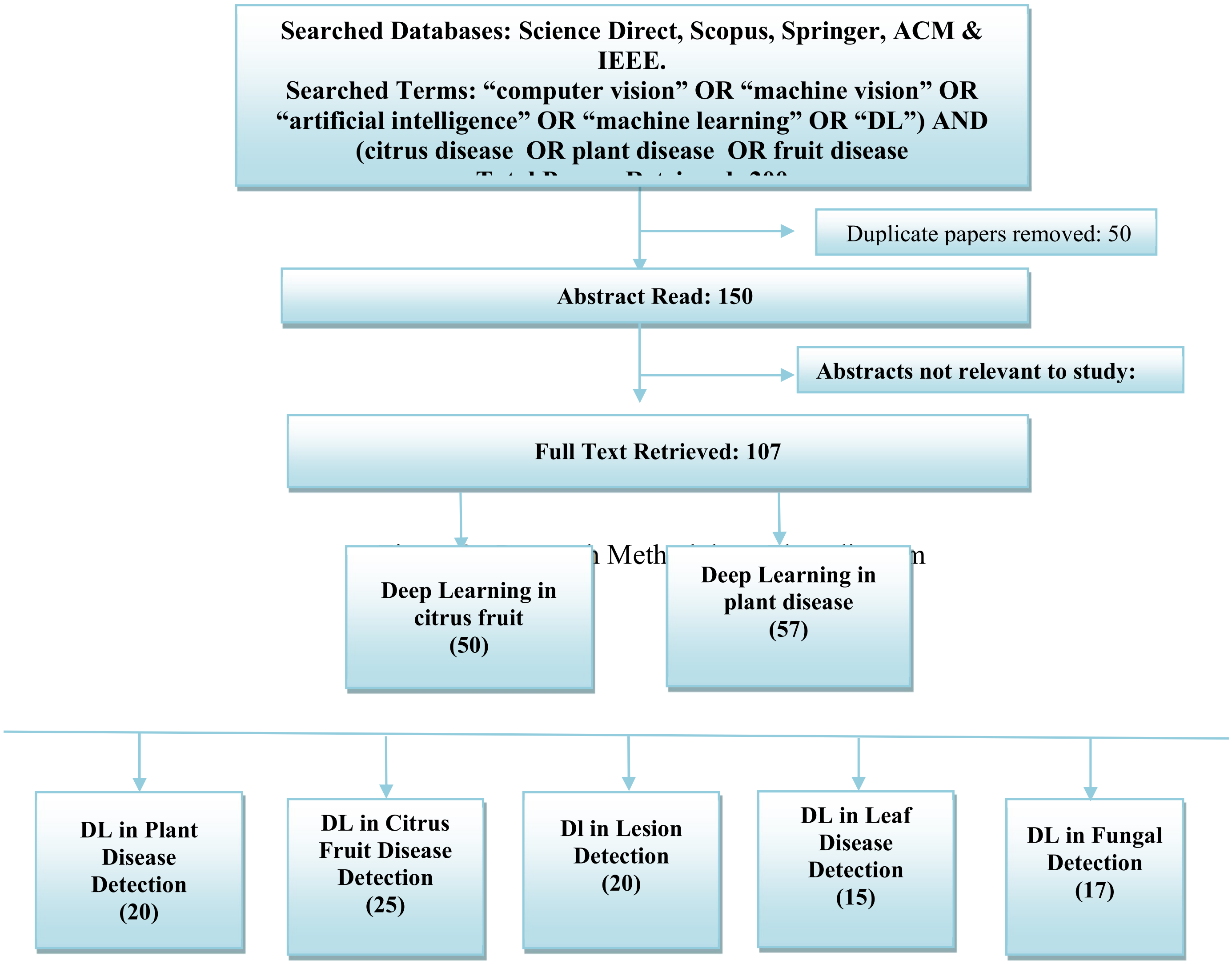

Searched Terms: For the survey of papers, the following search expression was defined: ("Convolutional Neural Network" OR "Machine Learning" OR "Artificial Neural Network" OR "Deep Learning") AND ("citrus Plant Diseases" OR "Crop Diseases Detection&Classification"OR"citrus fruit disease Classification" "lemon/orange/mango/Grape/Tomato/Grapevine/Peach/Pear Diseases Detection").
Inclusion criteria: To find the paper meeting desired criteria Titles and Abstract represented the first selection step, and then duplicate papers were removed.

- **Exclusion criteria**: The study omitted articles that did not particularly deal with citrus fruit or other plant disease detection and classification using deep learning/CNN.
- **Data Analysis:** After choosing more than 107 papers deemed eligible for the evaluation, data analysis was conducted with the following factors in mind:

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- **Year of Publication:** Researchers' interest in CNN/Deep learning for citrus disease diagnosis has increased over the past few decades. So, knowing the publishing year is essential for determining when this interest has increased.
- **Purpose of the study:** Several sorts of tasks, such as discoloration & lesion detection, classification, segmentation, etc., were done for various citrus illnesses in the study for diverse reasons, including discoloration & lesion detection.
- **Deep Learning** Architecture: Deep learning architectures such as Deep Neural Network, Convolution Neural Network, and Recurrent Neural Network have been applied to the identification of a variety of crop diseases.
- **Process of Article Selection -** This study's article search and selection procedure consists of the four phases listed below. Figure 4 illustrates this process. Table 1 displays the search terms and phrases for the initial phase of document research. This collection of publications is the result of a search of common internet databases. Among the applied electronic databases are Scopus, IEEE Explore, Springer Link, Google Scholar, ACM, Elsevier, Emerald Insight, MDPI, Taylor and Francis, Wiley, Peerj, JSTOR, Dblp, DOAJ, and ProQuest. Also discovered are periodicals, conference papers, books, chapters, notes, technical studies, and special issues. Stage 1 produced 200 documents. Figure 3 depicts the publisher's paper distribution (see Table 1).
- It is difficult to employ machine learning-based techniques, such as deep learning, for accurate diagnosis of numerous citrus diseases due to the restricted availability of diseased samples that have been labeled. In addition, a lightweight architecture with low computational complexity is required to classify citrus diseases on devices with limited resources, such as mobile phones. This makes it possible for farmers to effectively monitor diseases using their own mobile devices on their farms using the architecture. Hence, a lightweight, rapid, and accurate deep metric learning-based architecture for the identification of citrus illness from sparse data.

Table 1 publisher's distribution of the papers.

Journals	Number of Papers
Other Journals	30
MDPI	10
Elsevier	15
Springer	15
ACM	12
Hindawi	15
IEEE	10

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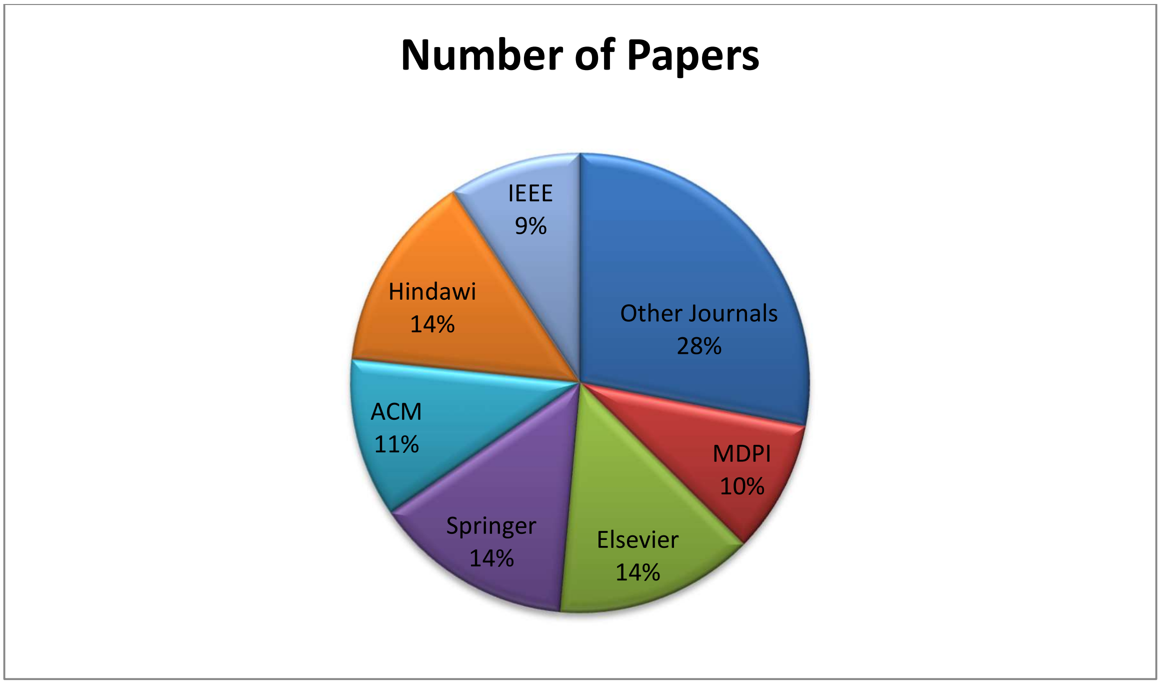

Figure 5: percentage of publisher's distribution of the papers

Fig shows the distribution of the chosen articles by their publishers. Other publishes most selected articles (28%, 30 articles).MDPI taken 10 article 10% ,Elsevier taken 15 article 14% ,Hindawi taken 15 article 14%,IEEE taken10 article 9%,ACM taken 12 article 11 %,

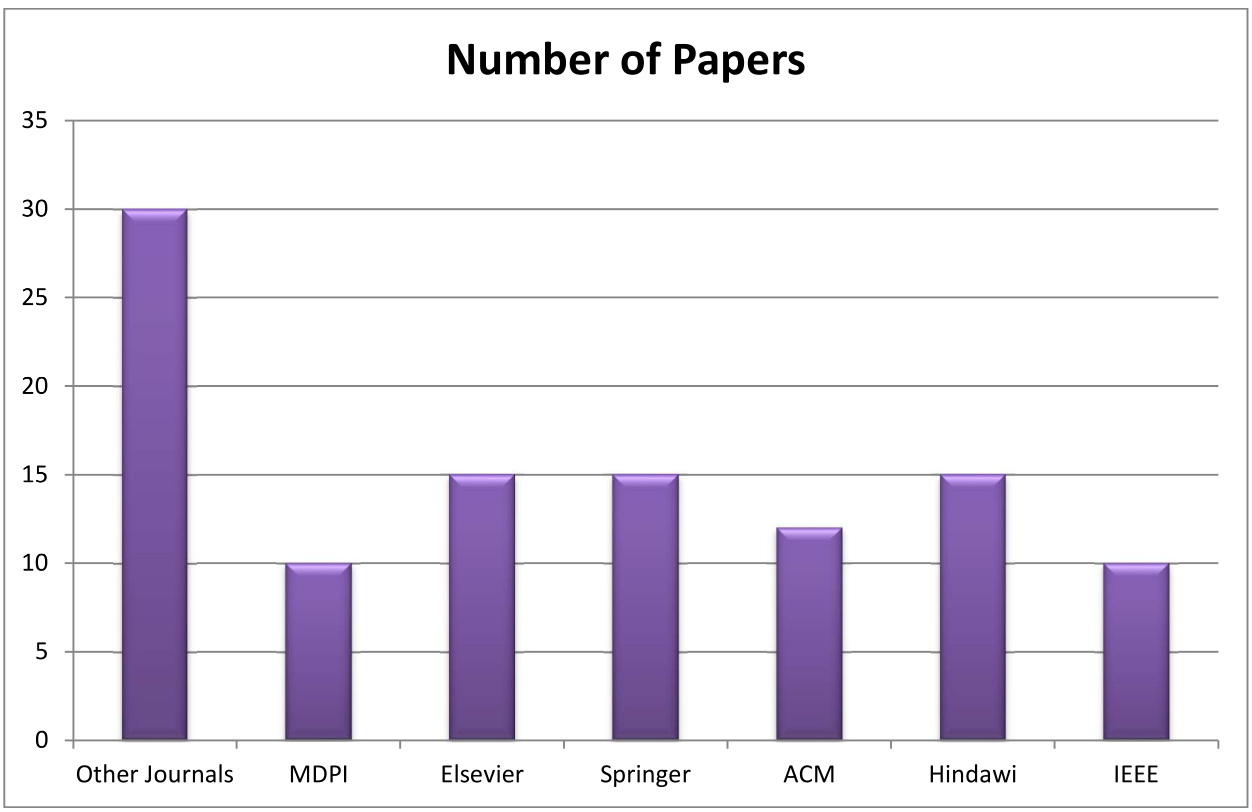

Figure 6: number of papers distribution of the papers by publisher's

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Selected Articles	Number of Articles.
Computer Method And Programs In agriculture	10
Neural Computing Applications	23
Other Journals	25
Soft computing	15
IEEE	11
Computer vision	12
Knowledge Based System	14
IEEE Transaction agriculture disease	13

Table 2 journal distribution of the selected articles

Figure 7 illustrates the periodicals that publish the pieces. The journals Applied Soft Computing and IEEE Access publish the most articles.

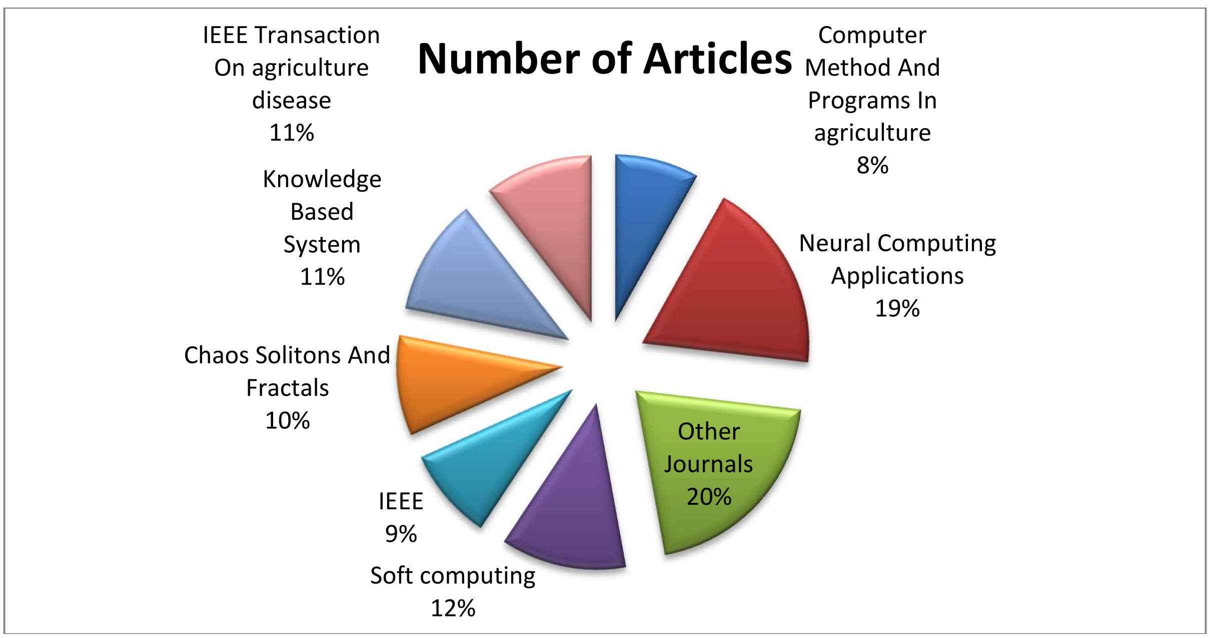

Figure. 7. Journal distribution of the selected articles.

Table:3 Different types of citrus diseases detection using DL

Citrus Disease	Number of paper
Melanoses	20
Greening	10
Citrus Black Spot	50
Anthracnose	10
Canker	10
Citrus Scab	12

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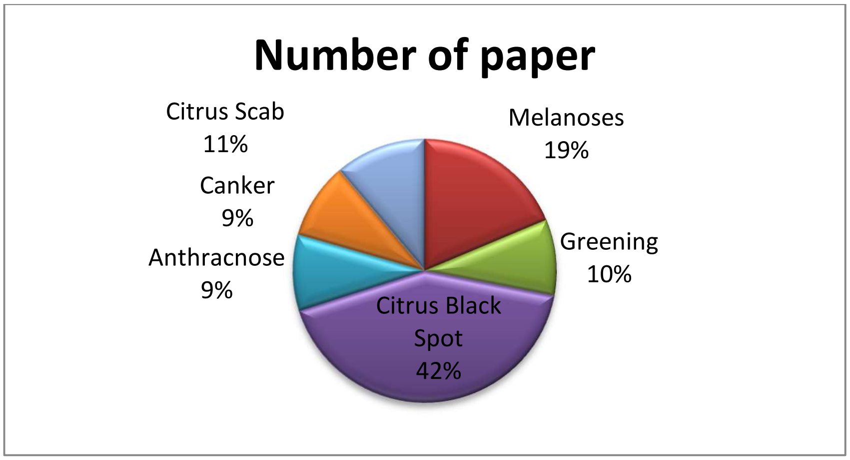

Figure 8: Different types of citrus diseases detection using DL

Table 4 Summary of the DL models used to detect Different types of citrus disease

Models	Number of Articles
ResNet	15
SVM (M-SVM)	8
GoogLeNet	8
CNN Models	10
VGG	5
K-Nearest Neighbor (Knn)	10
Mobilenetv2	12
Inception-V3	7
Squeeze net	5
Other Deep Learning Models	19
Other Machine Learning Models	8

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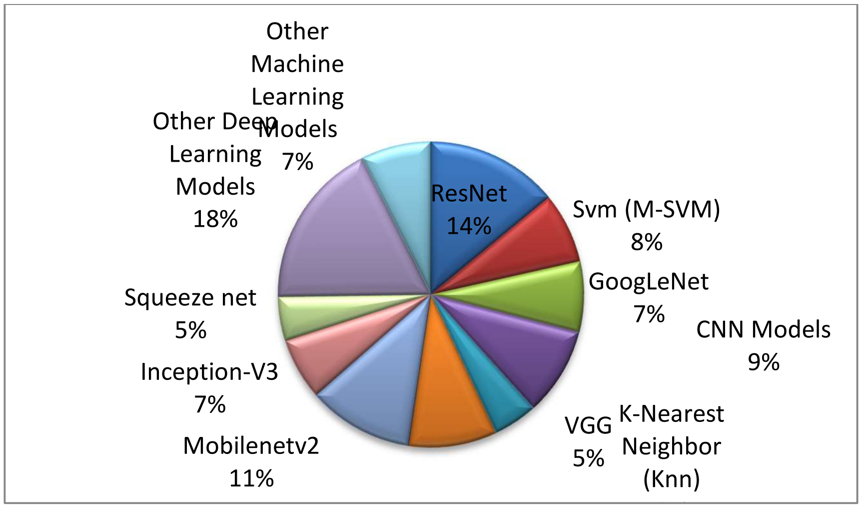

Figure 9: Summary of the DL models used to detect Different types of citrus disease

Table 5 Summary of the Research papers of Citrus disease detection and classification.

Reference	Problem	Diseases and Dataset	Methodologies	Accuracy
[50]	"Citrus disease detection and classification in agriculture using optimum weighted segmentation and feature selection"	Anthracnose (100), black spot (80), canker (120), scab (100), Greening (100), and melanose (70).	Multiclass SVM(M-SVM), EBT, K-nearest Neighbors (KNN), DT, and Linear Discriminant Analysis (LDA)	**95.8%**
[51]	Evaluation of Citrus Gummosis disease dynamics and predictions with weather and inversion based leaf optical model	Citrus Gummosis	Support vector regression (SVR) and multilinear regression (MLR)	**N/A**
[52]	"Non-destructive recognition and classification of citrus fruit blemishes based on ant colony optimized spectral information."	Huanglongbing (HLB), melanose, oleocellosis (oil spot), wind scar, Leafminer, and dust mites (30 fruit images for each)	Ant colony optimized spectral information, SVM	**98.4%,90.8%,95.2%,92.0%,90.8%, 95.2%and9 6.8%**

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[53]	Field detection and classification of Citrus Huanglongbing based on hyperspectral reflectance	Huanglongbing (108)	logistic regression, decision tree, SVM, k-nearest neighbor, linear discriminant analysis, and ensemble learning	**96%**
[54]	A citrus fruits and leaves dataset for detection and classification of citrus diseases through ML	Black spot (19, 171), Canker (78, 163), Scab (15), Greening (16, 204), and Melanose(13)	Top-hat process and then Gaussian function, weighted segmentation and Saliency map, skewness, PCA, and Entropy methods	**N/A**
[55]	Plant disease identification from individual lesions and spots using DL	Algal spot (254), Citrus greasy spot (281), Canker (236), Citrus variegated chlorosis (335), Sooty mould (152),	CNN	**62%**
[56]	Automated vision-based system for monitoring Asian citrus psyllid in orchards utilizing AI	Huanglongbing	CNN	**N/A**
[57]	Image Recognition of Citrus Diseases Based on Deep Learning	Anthracnose, Huanglongbing (HLB), Canker, Scabies, Blackspot, and Sandpaper rust.	Deep Learning Network, MobileNetV2	**87.28%**
[58]	Comparison of machine learning methods for citrus greening detection on UAV multispectral images	Greening	SVM, KNN, logistic regression (LR), naïve Bayesian ensemble learning	**97.28%**
[59]	“Zero- and few-shot learning for diseases recognition of Citrus aurantium L. using	Anthracnose (92), Blackspot (171), Canker (251), Greening	Vgg19	**N/A**

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	conditional adversarial autoencoders"	(204), Leaf miner (116), Sandpaper rust (98)		
[60]	Smartphone image-based digital chlorophyll meter to estimate the value of citrus leaves chlorophyll using Linear Regression, LMBP-ANN, and SCGBP-ANN	the chlorophyll of leaf (360)	Linear Regression (LR) and ANN	**N/A**
[61]	New perspectives on plant disease characterization based on deep learning	Huanglongbing (5507)	GoogLeNetBN, VGG16, InceptionV3, GoogLeNet	**N/A**
[62]	Agroview: Cloud-based application to process, analyze and visualize UAV collected data for precision agriculture applications utilizing artificial intelligence		Unmanned Aerial Vehicles (UAVs) are equipped with various sensors	**N/A**
[63]	Few-Shot Learning approach for plant disease classification using images taken in the field	Citrus Greening (5507)	CNN, SVM	**90%**
[64]	**Performance of deep learning vs. machine learning in plant leaf disease detection**	**Black spot (171), Canker (163), Greening (204), Melanose (13)**	**ML (SVM, Random Forest (RF), Stochastic Gradient Descent (SGD)) & DL (Inception-v3, VGG-16, VGG-19)**	**89.5%**

IV LIMITATION

Citrus is one of the important fruits grown in more than 50 countries of the subtropical and tropical regions. Different kinds of citrus plants, like oranges, acid limes, and lemons, are grown in these areas. These citrus plants can get sick from fungi, bacteria, and viruses, among other things. Citrus canker, a disease caused by bacteria, is seen as a very big problem for the growth of citrus plants. The signs of citrus canker are small spots on plants that are surrounded by an

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oily, water-soaked edge and have a yellow halo around them. Citrus canker is mostly a disease that causes spots on the leaves and on the skin of the fruit. [65-70]. Several types of image processing methods are talked about so that plant diseases can be found. It has four main steps, such as preprocessing, segmenting, extracting features, and classifying. The comparison is made for each step based on how it is done, how well it works, and what its pros and cons are [71]. The preprocessing techniques help to improve the accuracy of segmentation. Also, the Means method is the most common way to divide up plants that have been infected. Also, the texture features of an image show disease most clearly, and Support Vector Machine (SVM) and Neural Network use these features (NN). So, they need to work on making a system that works quickly, accurately, and automatically to find diseases on citrus leaves that haven't been affected. [72-80]

V DISCUSSION

In this review paper, we looked at recent studies that used DL models to find 50 different kinds of rice plant diseases, such as Anthracnose, Canker, Citrus Scab, Citrus Black Spot, Melanose, Greening, and Leaf Spot Disease. 10 of the papers surveyed are about finding Anthracnose disease, 10 are about finding Canker disease, 12 are about finding Citrus Scab disease, and 45 are about finding Citrus black spot disease. Also, 20 papers are about finding Melanose disease, and 10 are about finding Greening disease. 20 papers on finding plant diseases were looked at, 03 papers on the leaf segmentation method for classifying plant leaf lesions, Five papers look at how to use different segmentation methods to tell the difference between the shape and intensity of plant damage. Two of the papers are about detecting Cassava mosaic, and one is about detecting leaf spot disease. Eight studies look at how CNN uses transfer learning, and twenty studies look at how learning algorithms can be used to classify things. 16 papers on machine learning were looked at. Fifteen of the papers were studies on how to classify diseases using the SVM classifier, and 11 were studies on how to classify plant diseases using an artificial neural network. After reading these papers, we came to the conclusion that many researchers have done important work in the field of deep learning to find diseases in rice plants. 15 studies have been done on how to find diseases on plant leaves. From leaf spot detection, we can find, identify, and classify different kinds of diseases. The topic of 15 papers is segmentation to figure out the shape of a spot on a plant leaf. 10 papers were written about using clustering techniques to measure the uniformity and shape of plant leaves. 10 papers were written about using DL to find rice diseases. 15 papers were read about convolution neural networks.

Any improved method can be used to improve the recognition and classification of rice plant diseases and get the best results by reducing the number of false classifications. Increase the amount of data on rice diseases and make a full tool for diagnosing citrus diseases. This method also has some problems, but it is clear that when there isn't much data available, it leads to more reliable results. Before training a model with machine learning, images will need to be pre-processed. This will be a good way to get good results. [81-85]

When there are not enough samples, the data augmentation method will be used to build a good classifier. Look into other deep neural network architectures and use the deep learning algorithms to their fullest to improve the accuracy of classification and make the rice disease diagnosis systems more reliable and stable[86–95]. By adding more images to the dataset and adjusting the parameters of the machine learning model, the accuracy of classification can be improved even more. But it is still a research challenge to find the best parameters for a machine learning model. In a review of some of the literature, it was found that there is still not a lot of data available[96–100]. The proposed solution not only increases the size of image datasets by a lot, but it can also increase the variety of the data by taking into account the natural differences in each image by dividing it into smaller regions[101–107].

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VI CONCLUSION

This paper looks at almost all papers published between 2010 and 2022 that deal with citrus diseases and how to grade fruit. This survey gives information about the signs of citrus diseases. Also, the techniques that the researcher used to understand citrus diseases and grade the fruit are looked at. These include image processing, machine learning, and deep learning. The pros and cons of the current state of the art are shown in a table. This paper also gives a brief overview of techniques for pre-processing, segmentation, feature extraction, and classification. Most of the time, a hybrid approach is suggested for automatically predicting citrus diseases and grading them. Deep learning and machine learning are both parts of the hybrid approach. Researchers in this field might also be very interested in an attempt to make such a system. In this survey, different ways of using image processing to find out what kind of disease is affecting a plant are talked about. This survey has four main steps, such as preprocessing, segmentation, feature extraction, and classification. The comparison is made for each step based on how it is done, how well it works, and what its pros and cons are. From the results of the survey, we can say that preprocessing techniques help improve the accuracy of segmentation. Also, we think that Kmeans is the most popular method for dividing up plants that have been infected. Also, the texture features are the most important for showing disease in an image, and both SVM and NN use these features. So, they need to work on making a system that works quickly, accurately, and automatically to find diseases on citrus leaves that haven't been affected. This paper does a comparison of the different kinds of Convolutional Neural Network and Deep Learning models used to find and classify different rice plant diseases. It does this by looking at research from the last five years that was published in an internationally indexed journal. This article also goes into detail about the different kinds of data sources. After this study, we found that most researchers were able to find citrus diseases more accurately when they used the Convolutional Neural Network model of Deep Learning. The goal of this research is to look at all of the different Deep Learning models and find the best one for getting better accuracy and precision.

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