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Exploring Deep Learning Approaches for Citrus Diseases Detection and Classification: A Review

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Abstract:- Citrus diseases pose significant threats to global agriculture, impacting crop yield and quality. In recent years the integration of deep learning models has surfaced as a hopeful method for classifying and detecting diseases. This review critically analyzes and synthesizes 25 research works that explore various deep learning models applications in citrus disease detection and classification. The methodology involves a systematic literature search, filtering based on relevance, publication date, and language. The selected works are categorized, and each is analyzed for contributions and limitations. The review identifies limitations, notably the reliance on limited datasets leading to issues of generalization and class imbalance. Data augmentation, while employed, lacks comprehensive evaluation. Practical implementation in real-world agricultural settings remains a challenge, demanding scalable, adaptable, and robust solutions. Future research directions are proposed to address limitations. Emphasis is placed on curating larger and diverse datasets, actively mitigating class imbalance, and rigorously evaluating data augmentation techniques.

Keywords:- *Citrus Diseases, Deep Learning, Disease Detection, Disease Classification.*

I. INTRODUCTION

Presently, citrus stands as the predominant fruit tree crop globally, accounting for 104 million tons over 7.1 million hectares. This production is predominantly concentrated in countries such as Brazil, China, India, the USA, Mexico, and Spain. Including numerous other tropical and subtropical areas across the globe. (Agusti et al., 2013).

Contemporary technologies have empowered human society to generate sufficient food to satisfy the needs of over 7 billion individuals. Nevertheless, food security continues to face threats from various factors, with climate change being a significant concern (mohanty et al., 2016).

The current challenges in citrus production include; adverse weather conditions or climate changes, pest and diseases, availability of arable land, access to technology, lack of government support etc (Christopher & Udoh, n.d., 2020)

Citrus diseases pose significant threats to global agriculture, affecting crop yield and quality. Over the past few years, the incorporation of deep learning models has surfaced as a promising method for detecting and classifying these diseases. this literature review aims to critically analyze and synthesize 25 research works that delve into the utilization of diverse deep learning models in the context of detecting and classifying citrus diseases.

Deep learning finds widespread application not only in image processing, recognition, and classification but also extends its influence to various domains, including agriculture. In comparing to earlier artificial neural network approaches, deep learning demonstrates superior accuracy in recognition and effectively tackles challenges related to image classification and visualization. Consequently, it is currently recognized as the most promising technology in the contemporary agricultural sector. (liu et al., 2021).

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In this review, our objective is to illuminate the strengths and weaknesses of various approaches, ultimately contributing to the development of effective and reliable solutions for the detection of citrus diseases. The subsequent sections will delve into the methodologies employed, summarize key findings, and critically assess the limitations of each reviewed research work.

II. RESEARCH METHODOLOGY

To ensure a comprehensive review, an exhaustive literature search was conducted across reputable academic databases including the Institute of Electrical and Electronics Engineers (IEEE), Association for Computing Machinery (ACM), Science Direct, ResearchGate, Google Scholar, PubMed, Scopus, SpringerLink, and Tech Science that addressed citrus disease detection using deep learning models, we eliminated any repetitive entries that resulted from database searches. The following criteria were used for the selection of research works:

➢ *Relevance:*

Articles were selected if they specifically addressed citrus disease detection and classification using deep learning models.

➢ *Publication Date:*

Preference was given to recent publications between the year 2019-2024 to capture the latest advancements in the field.

➢ *Language:*

Articles published in the English language were included to facilitate a standardized review process.

Upon completing the initial search, the identified articles underwent a thorough screening process. Relevant information from each selected research work was systematically extracted, including details on deep learning models employed, datasets used, experimental setups, and key findings. 25 research work were selected and were categorized based on common themes and methodologies. This categorization aimed to facilitate a structured review by identifying patterns and variations across the studies. Each category was then analyzed in terms of its contributions, strengths, and limitations.

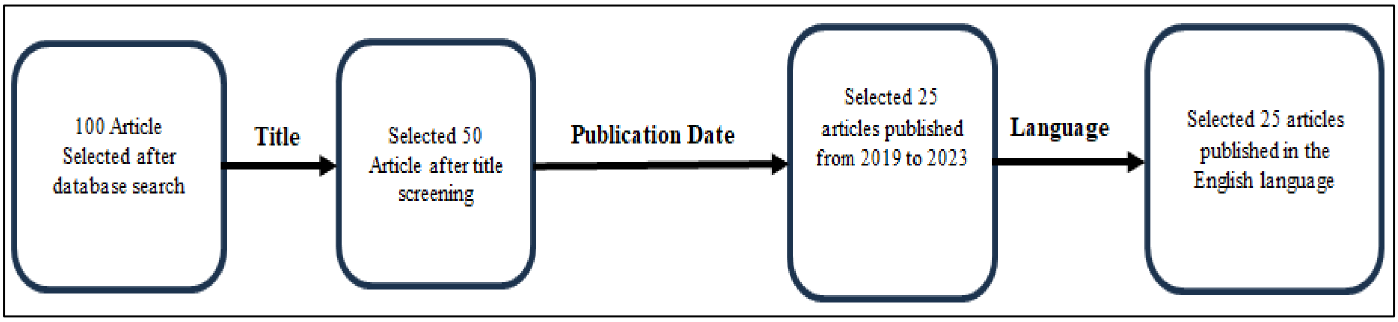

Fig 1 Research Selection Process

III. RELATED WORK

(Syed-Ab-Rahman et al., 2022) Introduced a dual stage deep convolutional neural network (CNN) model designed for the detection and classification of citrus diseases through the analysis of leaf images. The model comprises a feature extractor and Region Proposal Network, ROI pooling, and a classifier. It attains a disease detection accuracy of 94.37% and an average precision of 95.8%. The dataset includes three categories of citrus diseases: black spot, canker, and Huanglongbing and a healthy class. The proposed model uses Faster R-CNN with ResNet101 as the feature extractor. The RPN extracts potential diseased areas, and ROI pooling and the classifier classify the regions.

(Raaj & Selvy, n.d.) Introduced a detection system for citrus fruit and leaf diseases using the YOLO classifier. The proposed YOLO classifier model targets common citrus diseases and demonstrates superior performance compared to other deep learning approaches. The methodology involves a CNN, Gaussian Feature extraction and YOLO Classifier, with training images undergoing grayscale conversion and binary image classification.

(Firdaus et al., 2023) proposed a convolutional neural network (CNN) model employing the DenseNet-169 architecture in two scenarios include one utilizing original features and another incorporating a combination of features. The study focuses on classifying four categories: canker, greening, blackspot and healthy plants, all sourced from the same dataset as (Syed-Ab-Rahman et al., 2022). Augmentation techniques were applied to the dataset to augment the quantity of training data in other to overcome overfitting and improve the overall detection accuracy. The DenseNet-169 model incorporating feature combination achieves a 96.66% accuracy rate, achieving superior performance compared to the model utilizing only original features 91.33%.

(Çetiner et al., 2023) introduced a three deep learning models employing three distinct approaches for the classification of citrus leave diseases, proposed denseNet, basic denseNet201 and 21-layer convolutional neural network models were used. The study utilizes a dataset containing Images depicting diseases in citrus leaves, including HLB (Huanglongbing), CBS (Citrus Black Spot), and CBC (Citrus Canker) with preprocessing steps like

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resizing, standardization, and data augmentation. An accuracy of 95% was achieved for the proposed denseNet201 while 99% accuracy was achieved for the CNN model.

(Luaibi et al., 2021) introduce a two ways conventional neural network, AlexNet and ResNet architectures both with and without the application of data augmentation, which focuses on the early detection of citrus leaf diseases. A self-compiled dataset comprising 200 images encompassing healthy leaves and diseases such as nutrient deficiency, Phyllocnistis citrella and scale insects is used. The Results reveal that models trained with the incorporation of data augmentation achieve the highest accuracy, with ResNet at 95.83% and AlexNet at 97.92%.

(Khattak et al., 2021) employed a convolutional neural network model with the aim to distinguish between healthy fruits and leaves and those affected by prevalent citrus diseases such as black spot, greening, canker, scab, and melanose. The convolutional neural network architecture includes preprocessing, two convolutional layers, max-pooling, flattening, and classification. With a Citrus and PlantVillage datasets, the model demonstrated a commendable test accuracy of 94.55%.

(Mudholakar et al., 2022) introduced a CNN model for the detecting citrus fruit and leaves diseases. The proposed system integrates various image processing steps and employs a convolutional neural network to differentiate healthy citrus plant and the ones with diseases, such as canker, citrus blight and black spot. The convolutional neural network model, inspired by AlexNet architecture, achieves promising training and validation accuracies above 85% and 90%, respectively. The system was implemented using the Django framework for a user-friendly interface.

(Çetiner, 2022b) introduce A distinctive CNN-based architecture developed for the detection and classification of black spot, greening and canker diseases. Using a publicly available Citrus Leaves Prepared dataset and employs preprocessing techniques, including histogram equalization and data augmentation, the proposed model achieved high average values of 95% for F1-score, 96% for Precision, 95% for Recall, and 96% for Accuracy.

(Senthilkumar & Kamarasan, 2021) proposed a segmentation process based on Otsu using an Inception ResNet V2 based approach to detect and classify citrus The methodology was evaluated on the dataset from citrus image gallery, showcasing a notable accuracy of 99.13%. The key processes involved in the proposed model are preprocessing, segmentation, extracting features through the Inception ResNet v2 model and performing classification using a Random Forest (RF) classifier.

(Liu et al., 2021) used a mobileNet V2 as the main network and conducting a comparative analysis with other networks based on model accuracy, speed and speed. The study involves dataset enhancement techniques and compares MobileNetV2's performance with other networks. Results show improved accuracy through data augmentation, and MobileNetV2 proves effective for real-time disease identification. The model was able to achieve an accuracy oof 87.28%.

(Elaraby et al., 2022) suggested AlexNet and VGG19, using transfer learning to enhance efficiency. The process involves scaling and augmenting disease images, The proposed approach is assessed using both the citrus disease image gallery dataset and the combined dataset, which includes citrus image datasets of infested scale and Plant Village. The approach achieves 94% total performance.

(Dai et al., 2023) Proposed an improved FastGAN (FastGAN2) for image generation and an Enhanced EfficientNet-B5 (EfficientNet-B5-pro) for classification. FastGAN2 is designed to generate diverse and realistic citrus disease images, overcoming issues of small and unevenly distributed datasets. The proposed EfficientNet-B5-pro incorporates Arcface loss and adversarial weight perturbation, enhancing its performance in disease classification.it demonstrates that FastGAN2 can be trained with only 50 images, producing 8000 images with improved quality. Classification networks, trained exclusively on images generated by FastGAN2, achieve high accuracy rates exceeding 93%. EfficientNet-B5-pro exhibits superior performance compared to EfficientNet-B5, with accuracy, scores of 97.04%.

(Yadav et al., 2022) employed hyperspectral imaging along with an artificial intelligence algorithm to classify eight distinct peel conditions on citrus fruit. The method involved selecting discriminative bands using Principal Component Analysis (PCA) and training a custom CNN modeled on the VGG-16 architecture designed for classification. The PCA-selected bands achieved high accuracy (99.84%), sensitivity (99.84%), and specificity (99.98%). Additionally, a CNN using randomly selected bands demonstrated slightly lower but still substantial performance achieving an accuracy of 98.87%.

(Dhiman et al., 2023) introduces an efficient model design for predicting diseases in citrus fruit by fusing LSTM and CNN with edge computing. Using citrus dataset form Kaggle with 2950 images, the proposed CNN-LSTM model demonstrates superior disease detection capabilities. With Magnitude Based Pruning and Post Quantization technique the model attained an accuracy of 97.18% and 98.25%, surpassing the baseline CNN method. The multi-phase approach involves data collection, pre-processing, re-scaling, data augmentation, and image segmentation. Evaluation parameters like accuracy, recall, precision and F-score highlight the model's effectiveness across various disease classes, ranging from 94.65% to 99.05%.

(Faisal et al., 2023) introduced an automatic system aimed at detection and classification disease of citrus plant, utilizing deep learning models, particularly focusing on transfer learning. Four pre trained CNN models (EfficientNetB3, MobiNetV2, ResNet50 and InceptionV3) were utilized to the citrus dataset, demonstrating improved

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accuracy and reduced computational complexity. The suggested methodology involves data collection, data augmentation, image pre-processing, extracting deep CNN features through transfer learning, and final classification. The study identifies EfficientNetB3 as the most effective model, achieving training, validating, and testing accuracies of 99.43%, 99.48%, and 99.58%, respectively.

(Shermila et al., 2024) Proposed a customized CNN-based model, integrating CNN with LSTM, to automatically detect and classify diseases in citrus fruits and leaves. The research focuses on identifying illnesses such as fruit blight, fruit greening, fruit scab, and melanoses. The suggested model demonstrates excellent performance, achieving a 96% accuracy in identifying and classifying citrus fruit and leaves. The dataset encompasses both healthy and diseased citrus leaves and fruits from diverse origins. The architecture of CNN-LSTM incorporates convolutional layers, max-pooling layers, fully connected layers, and an LSTM layer.

(Janarthan et al., 2020) Presented is a compact deep metric learning architecture tailored for precise detection of citrus diseases, specifically crafted for devices with limited resources such as mobile phones. The suggested framework comprises a classification network based on patches, featuring an embedding module, cluster prototype module, and a neural network classifier. The process involves pre-processing, embedding calculation, K-Means clustering, and patch embedding computation. Evaluation on citrus and tea leaf datasets demonstrates the model's efficiency, achieving a 95.04% detection accuracy.

(Jasim et al., 2022) Introduce a CNN model for recognizing citrus diseases using a dataset that comprises of 2450 sample of images with seven disease classes. The CNN structure comprises pooling, convolutional and fully connected layers. The system achieves an 88% recognition accuracy for citrus diseases, and the study discusses the impact of optimization algorithms and data augmentation on model performance.

(Huang et al., 2023) presented a proficient diagnostic system for citrus fruit diseases based on CNN. The model integrates the Inception module with EfficientNetV2 to improve multi-scale feature extraction. VGG replaces the U-Net backbone, resulting in enhanced segmentation performance. Findings demonstrate a recognition accuracy exceeding 95%, with VGG-U-Net achieving the highest segmentation accuracy at 87.66%. The dataset encompasses 800 images of citrus fruit affected by black spot and canker diseases. Transfer learning is employed, utilizing pre-trained weights from ImageNet, to enhance classification performance.

(Ur Rehman et al., 2021) proposed a pair of pre-trained models, MobileNetV2 and DenseNet201 for the classification of citrus plant disease, image augmentation, and feature fusion. The technique achieves a notable classification accuracy of 95.7%. It addresses data scarcity through image augmentation, optimizes features using the Whale Optimization Algorithm, and outperforms individual models. The experiments involve a dataset of 279 images, six disease classes, and various classifiers, demonstrating the efficacy of the proposed framework in enhancing citrus disease classification accuracy for practical agricultural applications.

(Shireesha & Reddy, 2022) Suggested a DenseNet-121 model with the objective of discerning between healthy citrus leaves and fruits and those afflicted by diseases such as black spot, greening, scab, and canker. The dataset included images from the Plant Village Dataset and Citrus Dataset, classified into black spot, canker, greening, scab, and healthy categories. By employing the DenseNet-121 architecture and pre-training with ImageNet over 50 epochs, the model achieved a commendable accuracy of 96%, effectively tackling challenges like degradation and vanishing gradient.

(Kalim et al., 2022) Introduced a hybrid model, integrating a CNN for feature extraction and a Random Forest (RF) for classification. The dataset comprised 58 images of healthy and 536 images of unhealthy instances involving Black Spot, Canker, and Greening. The VGG16-Random Forest algorithm demonstrated optimal performance, achieving an accuracy of 87%, outperforming ResNet50-Random Forest (83%) and InceptionV3-Random Forest (80%). The model's flow involved CNN as a feature extractor, utilizing VGG16, ResNet50, and InceptionV3, followed by RF for classification.

(Subramani et al., 2023) focuses on identifying and categorizing diseases in citrus leaves using deep learning architectures, including ResNet50, ResNet101, VGG16, and VGG19. With a dataset of 609 images featuring Black Spot, Greening, Canker, Melanose and Healthy classes, the pre trained ResNet50 achieves a very good accuracy of 96.8% and negligible loss (0.1573). The ResNet models, known for deep convolution and skip connections, prove powerful in addressing the vanishing gradient problem.

(Challagundla et al., 2023) Proposed Inception V3, VGG16, SqueezeNet and machine learning classifiers (Neural Network, Random Forest, KNN, Gradient Boosting, SGD). A dataset with 759 images (80 healthy, 679 diseased) of citrus diseases is used. Image embedding is performed using pre-trained CNN models, and machine learning classifiers are applied for disease prediction. The neural network utilizing Inception V3 attains the highest average accuracy of 96.6%.

(Khan et al., 2021) proposed a deep learning approach to categorize six distinct citrus diseases affecting the yield and quality of citrus fruits. The dataset undergoes data augmentation to enhance it, subsequently used for the retraining of two lightweight pre-trained deep learning models: SqueezeNet and MobileNetV2. Features are extracted and optimized using the Whale Optimization Algorithm (WOA). SqueezeNet surpasses MobileNetV2, achieving a classification accuracy of 96%.

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IV. LIMITATIONS

The primary goal of this study is to gain a comprehensive grasp of the existing scenario in citrus diseases detection and classification by employing deep learning models. One notable limitation across the reviewed research works is the reliance on limited datasets for training and evaluation. Many studies faced challenges associated with dataset size, diversity, and representativeness. The use of small datasets may hinder the ability of deep learning models to generalize effectively to the wide range of citrus disease scenarios encountered.

Many studies faced challenges related to class imbalance in the datasets, where certain citrus diseases were underrepresented. This imbalance can impact the model's capability to sufficiently learn and distinguish between different disease classes, leading to biased predictions and reduced overall performance.

While data augmentation techniques were employed in some of the research to enhance dataset diversity, the impact and effectiveness of these techniques were often not rigorously evaluated. The extent to which data augmentation contributes to improved model generalization and performance remains an area of concern and requires further investigation.

A common limitation identified is the gap between experimental results and practical implementation in real-world agricultural environments. The transition from controlled experimental setups to dynamic field conditions poses challenges in terms of scalability, adaptability, and robustness of the proposed models.

V. DISCUSSION

One prominent similarity among the reviewed papers is the widespread adoption of deep learning architectures for citrus disease detection. Various models, including convolutional neural networks (CNNs), DenseNets, Inception modules, and YOLO classifiers, were employed across different studies. These architectures demonstrate the versatility and effectiveness of deep learning in handling complex image data and extracting meaningful features for disease classification.

Preprocessing techniques also emerged as a common theme across the reviewed papers. Authors consistently applied resizing, standardization, and data augmentation to enhance the quality and diversity of the input data. Data augmentation, in particular, played a crucial role in artificially increasing the diversity of the training dataset, thereby addressing concerns related to overfitting and improving the generalization capability of the models.

However, despite these commonalities, notable differences were observed in the methodologies and experimental setups employed by the reviewed studies. For instance, some studies focused on specific citrus diseases, such as black spot, canker, or greening, while others addressed a broader range of diseases. Additionally, variations were observed in the choice of datasets, with some studies utilizing publicly available datasets, while others collected and curated their own datasets.

VI. CONCLUSION

The significance of citrus cultivation in global agriculture cannot be overstated, and the challenges posed by climate change, pests, and diseases underscore the need for innovative solutions. this literature review has provided a comprehensive analysis of 20 research works focused on citrus disease detection using deep learning models. By examining the methodologies, key findings, and limitations, several common themes and variations have been identified. the common themes observed across the research highlight the versatility of deep learning in citrus disease detection, along with persistent challenges related to datasets and the need for models to transition effectively from controlled settings to real-world agricultural contexts. These findings provide insights for future research endeavors and the advancement of more resilient and applicable solutions for the management of citrus diseases.

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