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Enhancing Citrus Plant Health through the Application of Image Processing Techniques for Disease Detection

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Abstract - The foremost task in agriculture is the decisive identification of citrus plants and the timely identification of diseases in the plants with the aim of improving the quality of crops and the yield. In this work, a machine learning algorithm focuses on image processing of citrus to solve issues that are significant and cause concern in agriculture. This work focus on the machine learning models like VGG 19 and VGG 16. In addition, dataset curation, data augmentation and various other methods were employed. The dataset used in this research is a composed one which is recorded in a comprehensive manner including the data of both the affected and healthy pieces of citrus fruits. The ensemble model utilised here to ensure the improvement of trained datasets. Reviewing the research on machine learning models indicates a possibility for accurate classification of the fruits and disease detection models of the fruit. The three contenders performed admirably, with VGG 19 dominating with 95.5% accuracy. In second place was CNN with 93.4% and VGG 16 trailing at 91.2%. Such models are recognisable, because they perform well in agricultural environments, thanks to their precision, recall, and F1 scores, which are all balanced properly. The models' capacity to lessen the number of false alarms and misses is further assessed with the use of confusion matrices, which are of utmost importance in disease control. New developments in early disease diagnosis and detection of citrus fruits in agriculture may greatly enhance the health and productivity of crops. This research can be critical in increasing agricultural productivity while ensuring the environmental sustainability and health of growers and citrus crops in the long run.

Keywords— Artificial Intelligence, Plant Disease Identification, Deep Neural Network, Convolutional Neural Network, Prediction

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1. INTRODUCTION

Agriculture is the foundation of the economy, especially considering the spike in population and its relevance to food security, and the growing of colourful fruits like citrus is rather helpful for the agricultural sector However, the cultivation of citrus plants is problematic because diseases can cause grave harm to these economical plants and these

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damages can lead to loss in revenue [1, 2].

The diligence and skilfulness of a human being is as tedious as it is vital. Diseases can spread rather quickly and so can their impact; therefore, identifying them early on is crucial to taking prompt action. Unfortunately, the optimisation of disease identification and fruit classification is given less attention than it should, and as a result, humans have to rely on outdated methods that are futile at the end. With the technologies like machine learning and image processing, we can make the processes more efficient [3, 4].

2. LITERATURE REVIEW

This paper presents an in-depth analysis of the application of machine learning-based image processing algorithms to tackle the two problems of citrus fruits detection and plant disease recognition. To achieve our goals, we employ advanced machine learning algorithms along with a superset of a carefully handpicked dataset [5, 6]. Our objective is to enhance the accuracy of early disease detection and robust classification of citrus fruits. With these measures being set in place, we aim to promote agricultural sustainability and productivity [7, 8].

The adoption of machine learning has recently received a great deal of attention due to its prospect of completely transforming the best practices in agriculture. Machine learning techniques have been employed in the prevention and control of plant diseases, which is one of the things that have caught [9, 10] attention. Support vector machines and neural networks, two types of machine learning algorithms, have successfully demonstrated powerful disease detection performance in many types of crops. The research effort in [11, 12] demonstrated how neural networks can be used for disease diagnosis, which is important for the early diagnosis of cassava disease using deep learning methods.

The disease that afflicts the citrus fruits the most is citrus canker, followed by citrus greening and black spot. These conditions degrade the quality of citrus goods while leading to a decrease in the output of the fruits themselves. Preventive diagnosis and therapy of many diseases are fundamental for the well-being of the citrus plants. Sensing from a distance and analysis of images are among the methods that have been of aid in the early detection of certain diseases of citrus crops. But the use of models based in machine learning in this space is a new trend.

Mostly used in image processing tasks, Convolutional Neural Networks (CNNs) greatly surpass computer vision challenges in their performance. By nature, CNN's are suited for tasks such as image classification, because they excel at picking out intricate features and patterns within images. There is ongoing research on the use of CNNs in the agricultural image-processing domain due to their versatility. [13, 14].

For machine learning models to work effectively, they must work with good quality data sets of various types. Researchers have pointed out that ensuring data is well representative of the population of the study is key to successful implementation of models. Besides, a number of data augmentation methods such as flipping, rotating and changing colour of images have also been used to augment the data set and improve the model performance. [15, 16].

There are numerous computer aided technologies which were used to identify plant diseases with a high degree of sensitivity. In sickness recognition not deep learning model adaptation can succeed, but also transfer learning, which means making changes to models that were previously taught, can also succeed. Plant disease detection methodology using Visual Geometry Group (VGG) 16, VGG 19 and CNN models have been developed with great success. Although there are several Artificial Intelligence (AI) based image processing technologies that can offer excellent solutions to agricultural problems, many barriers still remain. Some of them are the creation of high-quality datasets, the implementation of monitoring tools and the explainability of AI models. Other goals for future research are to create user friendly applications for farmers and use drones for data collection and remote monitoring.

Researchers have explored various machine learning and pattern detection methods to improve the accuracy of disease diagnosis in crops like wheat, rice, maize, and corn. Wuterich et al. [17] employed a support vector machines (SVM) and fluorescence imaging system to detect Citrus canker and Huanglongbing (HLB), achieving a classification accuracy of 97.8% for Citrus canker and scab, and 95% for HLB and zinc deficiency. Golhani et al. [18] examined neural network techniques for identifying and classifying diseases from images of plant leaves and fruit. Patel et al. [19] applied K-Means segmentation to detect diseased regions in pre-processed orange images, where colour, texture, and shape features were extracted and classified with an SVM classifier. The attained accuracy of their GLCA model was 67.74%.

Padmavathi and Thangadurai [20] proposed the Recursively Separated Weighted Histogram Equalization (RSHE) method for image quality enhancement in the process of Citrus disease detection, followed by noise suppression in the citrus images. In 2020, Singh et al. [21] studying the diseases of citrus leaf, used SVM, Linear Discriminant Analysis (LDA), K-Nearest Neighbours (KNN), and Multi-Layer Perceptron (MLP). They used K-means clustering to segment affected areas and Analysis of Variance (ANOVA) F-test to select relevant features, yielding precision rates of 84.32% for LDA, 81.36% for MLP, 77.12% for KNN, and 80.93% for SVM from a sample of 236 diseased citrus leaves. B. Doh et al.'s work on citrus disease diagnosis through the use of colour and texture parameters was optimised, and their experimental results showed enhanced classification accuracy.

In recent years, applications of deep learning in agriculture, such as image recognition and disease diagnosis, have seen a significant boost in interest. Barman et al. [22] investigated MobileNet and Self Structured CNNs, with the latter better validating accuracy where it scored 99% against MobileNet's 92%. In parallel, Xing et al. [23] designed a weakly thick linked convolutional network elucidating on the uses of citrus diseases and pest recognition with the NIN-16 model and achieving 91.66% accuracy in test environments. Liu et al. trained MobileNetV2 to classify six common citrus diseases, demonstrating its effectiveness in terms of model accuracy, size, and validation speed compared to other network architectures.

Kukreja and Dhiman [24] developed a robust CNN algorithm for detecting visible citrus fruit diseases, showing that data augmentation and preprocessing improved damage detection accuracy to 89.1%. Khanramaki et al. [25] suggested using CNNs to detect citrus pests such as Citrus Leafminer, Sooty Mold, and Pulvinaria, testing their method on 1,774 citrus leaf images. The CNN ensemble approach achieved an accuracy of 99.04% in a 10-fold cross-validation experiment. Partel et al. [26] designed an automated system using machine vision and artificial intelligence to monitor Asian Citrus Psyllid (ACP) in citrus groves, employing a tapping mechanism and camera grid to capture images of insects. Their system demonstrated 80% accuracy and 95% recall in detecting ACPs on 90 young citrus plants.

3. RESEARCH METHODOLOGY

As shown in Figure 1, the step one involves adding a few methods in which a unique multi-tiered approach to machine learning is capable of parsing citrus images to first tackle the objectives of identifying citrus fruits and detecting diseases in its associated plant. This approach and its steps are divided in a way where each step is crucial and significant towards the overall aim of the study.

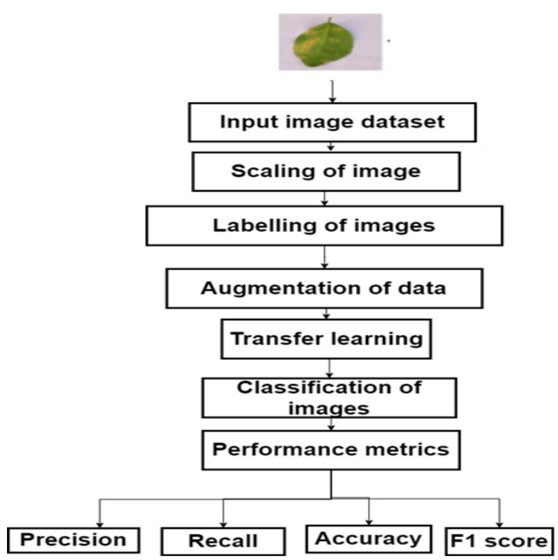

Figure 1. Architectural Diagram of the Proposed Model on Citrus Plant Disease Detection

The system in this case has the citrus leaves and fruits images as the first data set to the investigation. This set of images formation serves as the baseline for every other image analysis and model formulations that will be done later on. Due to its nature of being the starting point of the network, its accuracy and effectiveness is essential. The first aspect of the refinishing is scaling down the components of the photo. When the size of an image is altered in order to fit it to a specific size, the process is referred to as image scaling. This standardization is necessary because it ensures that there is uniformity among the images making later processes easier. By decreasing the size of the images to a uniform size, the differences in picture size are reduced and details are easier to analyse and compare.

After scaling the images, the next step is labelling. Labelling images with relevant information like what type of citrus fruit or leaf the image shows is very important for the branching of machine learning known as supervised learning. Without this specific annotation, the machine learning models will not be able to identify different classes of citrus and even classifying symptoms of possible diseases is very hard. Another very important step is data augmentation, which comes after image augmentation. Data modification is done in a controlled manner so that the image dataset is more diverse and robust. These changes of visual appearance may include but are not limited to rotations, flips and the addition of random noise. Data augmentation increases the model's ability to handle the nuances of real-world Agricultural conditions, which makes it very useful for simulating real-life situations.

The stage of extracting features of a photograph such as patterns, lines, and even colours, is an important stage of the machine learning model. Shaped features are geometric properties like curves and outlines and are used to register the outline of an object. Size characteristics examine the amount of each citrus fruit and foliage noticed within the image while texture features observe the details within the image. Later machine learning models are built using the features that were extracted from the images. The data rich in features are then transferred to the algorithms for machine learning. This process is depicted where the system can use and modify previous models to fit the current task. The use of transfer learning allows for the improvement of smaller models, such as the model of the citrus fruit and illness dataset depicted in Figure 2. Large datasets are used to make smaller models more efficient and effective.

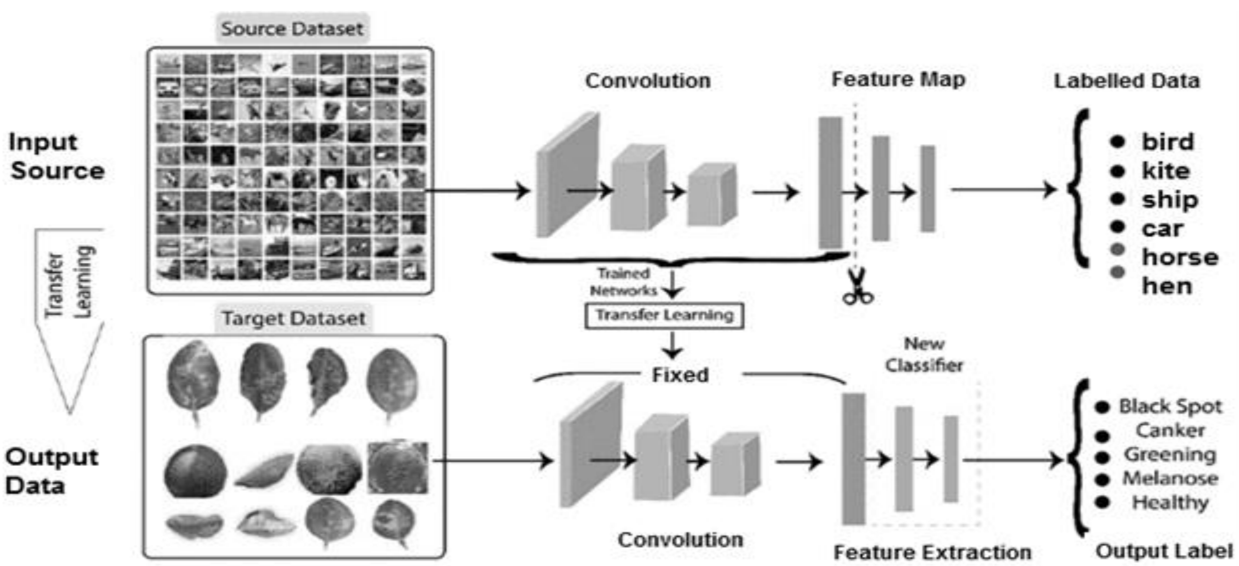

Figure 2. Working of Transfer Learning

In the process of categorization, it is necessary to distinguish between images with and without plants diseases. Classifiers are attached to images containing medical diagnoses using transfer learning-based approaches with machine learning algorithms trained on the collected features. To assess the system's performance, an extensive range of assessment measures are employed in the study to offer a more holistic evaluation of the system's performance. For measuring system performance during the accurate identification of citrus fruits and plant disease diagnosis, additional metrics like precision, recall, and F1-score are calculated. Some assessment metrics are crucial for controlling and maximizing the effectiveness of the developed system.

3.1 Classification Model

Within this research, different models and methods from the domain of deep learning are utilised to identify plant diseases accurately. Each model has its unique set of skills and advantages. AlexNet, which is a highly regarded model, is a deep CNN architecture that employs algorithms which are as developed as modern-day complex facial recognition systems. AlexNet has gained worldwide attention for the leaps he made in deep learning and image classification. Due to the high number of convolutional layers, fully linked layers, and rectified linear unit (ReLU) activation functions, AlexNet is particularly good at feature-based image retrieval and classification. In this research, however, he is particularly favourable for plant illness diagnosis due to his unique architecture that has lots of learnable parameters that make him able to detect fine details and intricacies in images.

The VGG network's version VGG 19 is yet another useful model that can be used for research purposes. VGG 19 is appreciated for its intricacy and sophistication. It possesses 19 weight layers (three of them are fully connected layers while the other 16 are convolutional layers), all of which are capable of identifying minute details within an image. This trait is essential for detecting small signs of plant disease. Due to its homogeneous construction from small max 3x3 convolutional kernels and max-pooling layers, VGG 19 displays improved adaptability to different plant conditions because it can learn and model the hierarchical features present in the images.

The analysis also utilizes the VGG 16 model, which is a part of the ensemble of machine learning models used in the study. The construction of VGG 16 and VGG 19 is similar, with the former having 16 less layers which allows it to achieve a balance between accuracy and processing power. Because plants exhibit a wide range of symptoms on different scales, VGG 16’s ability in gathering both low-level and high-level data makes it especially useful in diagnosing diseases in the plants. The efficiency of VGG 16 and the fact that it is not computationally expensive makes it a great option for scenarios that need plant disease diagnostics.

Finally, this study has a reasonable amount of coverage concerning the use of CNN. Their structure enables them to learn patterns and relationships in images which makes them highly effective for image processing. These methods consist of a series of stages where images are progressively analysed to extract features and reduce their size or spatial resolution through the use of convolutional layers, activation functions, and pooling layers. CNNs have positively impacted many application domains in computer vision, such as developing algorithms for plant disease detection. They handle these tasks remarkably well due to their great diversity and the level of detail contained in the images.

4. RESULTS AND DISCUSSIONS

4.1 Description of Dataset

The dataset used consists of 1232 images that are a combination of the Kaggle dataset and other images collected manually (750 Images from the Kaggle dataset and 482 images collected relatively manually) depicting healthy and unhealthy citrus plants. The images of the citrus leaves are labelled as Dark Spot, Greening, Cranking and Healthy, and they form the basis of our study for the detection of diseases in citrus fruit and plants using machine learning based image processing. The dataset comprised of high-quality images of the different views of the citrus fruits and foliage. The images have each been obtained, sorted and annotated with specific details allowing for an in depth understanding of the dataset. The photos in the collection are grouped into two categories: one includes images of citrus fruits and the other, images of plant diseases. These divisions are vital as they help focus our research towards accurately identifying citrus fruits and finding plant diseases.

Every variety of citrus fruit, such as oranges, lemons, grapefruits, and limes, is captured under the “Citrus Fruit Images” heading and each fruit is accompanied by a collection of photographs showcasing it. Each of the photographs contains a comprehensive list of characteristics which enables the users to identify various fruits precisely and consistently. The granularity of the image description of these citrus fruits in our collection yields the following essential facts: Oranges and other citrus fruits are available in different shapes – spherical, oval, irreguous named. The parameters which describe the shape of different fruits, though, have to be robust. The advanced machine learning models that our unique dataset contains are artificially trained to understand and differentiate between the various species of fruit based on the detailed description of the shape parameters. A citrus fruit has a distinct colour that sets it apart from other fruit types. To paint an all-round picture of the different colour variations these fruits bear, the collection focuses on multiple colouring such as orange, yellow, green and their combinations.

- Size: Citrus fruits’ quantitative metrics for classification purpose are numerous and can vary drastically. The size of these fruits has been carefully measured which aids in proper classification.

- Shape: The types of fruits are also distinguished based on important qualitative attributes such as texture of the citrus fruit skin. The skin has features such as smoothness, roughness and skin dimples that helps us build a dataset to train machine learning models to differentiate various species of fruits.

Fruit such as this can be classified as either unripe (green) or overripe (having brilliant colours). Our specific dataset has got images of every stage of these fruits ripeness, therefore making it easy for the algorithms to assess the condition of the fruit. In addition to images of diseased plant leaves and citrus fruits, the Plant Disease Images category includes images of citrus leaves and fruit Plant Diseases which helps broaden its scope Furthermore, these photos provide the necessary information on the symptoms that the disease manifests for an accurate diagnosis and targeted therapies. Signs for different diseases may show symptoms such as aberrations, lesions, wilting, or discolouration. All these symptoms have been compiled into this dataset, making it easier for machine learning algorithms to detect the visual clues associated with specific diseases. The information brought here pinpoints the exact parts of the citrus plant that are infected with the diseases which may include, stems, leaves or fruits. By having this information, it is easier to comprehend the disease pattern and the way it spreads. To depict the level of influence each disease has, our dataset measures the range of severity within the disease. With this severity level, interventions for disease management can be highlighted as a priority.

4.2 Data Enrichment with Augmentation

In addition to the detailed processes of data gathering and data mapping, this study involves an important process we called data augmentation. Through data augmentation, the variety and the lifespan of the dataset can greatly be improved, which is a prerequisite for effective training of machine learning models. To augment data set means to strategically implement certain changes, alterations, or updates to the existing data. These alterations mimic real scenarios where change in temperature, lighting, and manifestation of plant diseases might occur. A pivotal part of this study’s original effort was the generation of additional variations using the first 350 photographs, which extended the dataset remarkably to 1232 photos.

- The dataset was augmented using a number of alteration methods, including those listed below.
- These provided different rotations of fruit and leaf images.
- Flipping: These were done by also rotating the images sideways and upright to get different aspects of the picture.
- Zooming: These were achieved by zooming in and out of the subject matter to different levels.
- Noise Introduction: Some noise was added to the images to imitate flaws that would be present in real life such as sensor distortions or noise from equipment.
- Colour Adjustments: Adjusting the saturation and balance of the added noise allows for lighting and colour representation changes, which in turn helps for colour adjustments.

The enhanced dataset allows for a larger variety of images, making it easier to use while training machine learning models. This also increases the model’s performance because they are able to handle the subtleties and intricacies of real agricultural environments while classifying citrus fruits and diagnosing plant diseases.

4.3 Evaluation Results

The study ends with evaluating the performance of the identified method in detecting citrus fruits and plants disease. The accuracy, effectiveness, and performance of the system in real farming practices will be measured by the outcome of the evaluation. For a full check on the performance of the system, a range of standard measurements are employed such as: accuracy, sensitivity (recall), F1 score, precision, etc. One of the bottom lines of this report is the extent to which the system is able to classify an image correctly. This is the numerator out of total provided cases that are being evaluated and categorised. High performance means that the technology identifies various types of citrus fruits, healthy and damaged plants with high accuracy.

The term recall refers to the sensitivity of the system, which provides a distinction between plant diseases and non-disease conditions. Sophisticated monitoring systems can be measured by early detection or negative avoidance strategies and even plant disease diagnosis techniques can be evaluated. The balance between precision and recall is elegantly reconciled in the F1 score, allowing one to have a more complete picture of system performance. F1 Score is especially useful when dealing with false positives and false negatives as one side of the equation is larger than the other. A strong F1 Score means that the system managed to perform these vital calculations correctly. A measure of precision attempts to reduce the consequences of the most severe false predictions. It is calculated by determining what fraction of all positive predicted values are truly positive. In scope of our research, precision is an important item because it increases the confidence in the plant diagnosed as ill, while reducing the chance of a healthy plant being incorrectly identified.

Covered in Figure 3 is sample selection from our dataset that has been blotted out for our detailed analysis.

Figure 3. Diseased Leaf and Fruit Used in the Analysis

In this work, the performance of three different models, VGG 19, CNN, and VGG 16 was compared for the effectiveness of citrus crop plant disease detection. These models performance in terms of accuracy, precision, recall, F1 score and other key metrics all listed in Table 1. The best scores belong to VGG 19 who scored also on the accuracy metric with 95.5%. It is followed by CNN and VGG 16 with scores of 93.4% and 91.2% respectively. VGG 19 scored the highest in precision at 96.2%, meaning it is able to distinguish between disease-positive and other conditions exceptionally well. The model does exceptionally well with recall too, scoring 94.8% while identifying actual diseased plants in the real world. As those metrics show, VGG 19 is accurate and its F1 score of 95.5 indicates balanced performance. CNN also performed exceptionally rings with all metrics above 93% which put VGG 19 on top with a 93.4% score, but still yields amazing results. VGG 16 rounds out the group of effective models with a score of 91.2% on the precision metric.

Table 1. Comparative Analysis of Evaluation Models

Models	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG 19	95.5	96.2	94.8	95.5
CNN	93.4	94.1	92.7	93.4
VGG 16	91.2	92.0	90.5	91.2

These measures provide an insight into the effectiveness of these machine learning algorithms in identifying plant diseases. VGG 19 is exceptional in its accuracy and F1 score and is therefore the most reliable option. The fact that all three models exhibited a high degree of reliability suggests that artificial intelligence image processing can enhance the management of citrus crops and the detection of diseases at an early stage.

In Figure 4, we can analyse the confusion matrices and gain valuable insights into the practical aspects of each machine learning model created to detect diseases in citrus crops. From our experiments, we found that VGG 19 is effective at capturing sick plants because it has a rather large (30 instances) of false negatives. The system demonstrates a remarkable low (20 instances) of false positives, labelling plants as sick that are actually healthy. The confusion matrix of CNN show a similar pattern with low false negatives (32 instances) and low false positives (35 instances).

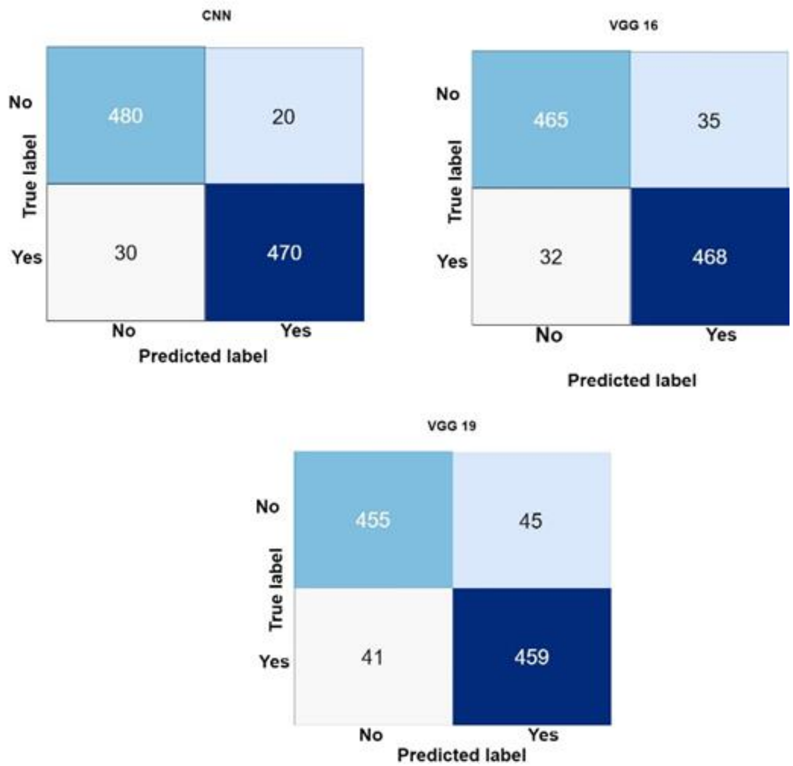

Figure 4. Confusion Matrices of Classification Models Utilised for Citrus Plant Disease Detection

The evaluation demonstrates that the model is competent in diagnosing the plant diseases and subsequently categorizing them. Although VGG 16 is quite accurate, it has a marginally higher number of false positives (45 cases) and false negatives (41 cases). This indicates that its accuracy in distinguishing disease-free plants from plants with diseases is somewhat lower than those of VGG 19 and CNN.

5. CONCLUSION

As a resultant of this work, a comprehensive and advanced methodology for the image-based detection of citrus fruits and plants diseases using machine learning techniques is provided. Encouraging outcomes have been achieved with the strategy applied, which includes careful user-controlled dataset specification, data additional synthesis, and the application of various modern machine learning techniques. Due to the fact that we collected essential characteristics on citrus fruit and disease symptoms, our work is well-supported. In addition to that, our dataset was also augmented to increase its size, and diversity and strength which is vital for effective training of the machine learning models. VGG 19, CNN, and VGG 16 were trained and confirmed to be efficient in classification of citrus fruits and recognition of plant diseases. The VGG 19 secured first with an accuracy of 95.5% and CNN second at 93.4% followed by VGG 16 with 91.2%. These models presented good accuracy and reasonable precision, recall and F1 scores which confirmed their applicability against real agricultural tasks.

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AUTHOR CONTRIBUTIONS

C. Pabitha: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
B. Vanathi: Project Administration, Writing – Review & Editing;
K. Revathi: Project Administration, Supervision, Writing – Review & Editing;
S. Benila: Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflicts of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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