

DEEP NEURAL NETWORK BASED IDENTIFICATION AND CLASSIFICATION OF SWEET ORANGE LEAF DISEASES

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Abstract

Historically and currently, more than 60% of the world's population relies on agriculture to earn a living, making it an important source of livelihood for them. Plant diseases are still a major problem, however, and are responsible for up to 25% loss in agricultural production annually. In this study, a novel approach was taken using Convolutional Neural Network (CNN) and transfer learning for the detection and classification of sweet orange ailments. The structure of the proposed method is inspired by EfficientNet-B0 pre-trained model with the addition of a new set of fully connected (FC) layers and a final layer for fine tuning the model for the new task. The model was trained under various sets of image classes, such as binary classification, six and eleven classifications, and each image class had a moderate number of images. Prior to training, preprocessing and augmentation techniques (rotation, flipping, etc.), were applied to enhance the dataset. The model trained was then tested with new, unseen images. The results of the evaluation reveal that the proposed method can accurately classify the sweet orange leaf diseases, with average accuracy of 96.20%, 97.45%, and 96.54% for binary, six-class and eleven-class classifications, respectively. These results demonstrate the model's strength and stability at various classification levels, and its 2.17% accuracy improvement over the latest state-of-the-art models. The proposed leaf ailment detection method can be an effective and secure way to reduce losses from leaf ailments and food security. The model is able to detect multiple types of plant diseases even at the initial stage of infection. The findings of this study may point to the use of a deep learning technique in the early detection of plant diseases, which will help to control the ailments in the crop sector effectively and automatically.

I. INTRODUCTION

The role of producing oxygen is essential for humans to breathe and that is why plants and trees are called the "lungs of the Earth. In addition to producing oxygen, they are the main source of food and energy for both animals and people [1]. They also have a big impact on the distribution of rainfall and add to the earth's natural beauty. In short, trees and plants are one of the most significant creatures of the earth. They do become sick, just as people and animals do. Since they supply a significant amount of food and money, agricultural goods are a crucial component of many economies in developing nations. Almost 60% of individuals worldwide are employed in agriculture, which provides a lot of individuals with a significant source of revenue and nutrition [2].

Plant ailments are one of the common challenges in agricultural production across the globe which lower the quality and quantity of agricultural crops produced. Data from a 2019 study by the Food & Agriculture Organisation (FAO) indicate that illnesses in plants can lose 20%-40% of crop production every year; and pathogens causing crop anomalies are responsible for economic losses of up to USD 220 billion worldwide each year [3]. This effect can be seen in the production of citrus crops, especially sweet oranges which are one of the most cultivated and nutritional fruit crops in the world, and they are a significant source of vitamin C [4-5]. Plant diseases negatively affect yield, and are brought about by organic organisms including algae, fungi, bacteria and other harmful organisms. Other nonliving factors also contribute to plant diseases, such as a

climatic change, chemical toxicity, lack of minerals, too much or not enough water, and inadequate fertilization [6].

Citrus fruit production and quality are affected by a number of diseases, including sweet oranges, and can severely affect plant growth and yield. Early detection of these diseases in the diagnostic phase is very important.

The condition of plant foliage is usually good measure of the physical condition of the plant, particularly for fruiting plants like the sweet orange trees. A sick or malnourished plant will show signs on the petals as its first line of defence, and as a warning for potential hazards. Thus, inspection of these leaf components will give all information regarding a tree's health and the influence of any disease on the tree [7]. Plant pathologists have been traditionally the ones to diagnose ailments and have relied on their knowledge, experience and sometimes simple diagnostic tools. But, in the case of the conventional method of disease diagnosis, human error, potential human error and dependability issues, particularly on large farms or orchards, are fundamental constraints. The wrong diagnosis of a disease can lead farmers to misuse or overuse pesticides which damage production and plants. The alternative of conventional methods is to use advanced AI techniques which can automatically identify abnormalities in leaf images using diseased patterns. These models can be well trained to provide accurate results and can identify the symptoms of disease at an early stage [8]. In the conventional approach, the plant leaf disease is diagnosed by the method shown in Fig. 1.



FIGURE 1. Plant leaf disease diagnosis using conventional approach [9].

The proposed study will be aimed to gather a massive amount of sweet orange leaf images to optimize and train an efficient CNN framework to accurately identify and categorize multiple patterns of common sweet orange leaf diseases automatically. Sweet oranges (*Citrus sinensis*) are a popular fruit, prized for their sweet taste, bright color and versatility. They are a hybrid of pomelo and mandarin, and are sometimes used to make

jam, marmalade and juices. Lemon peel and zest can be used in a variety of recipes and desserts. Sweet orange juice is a good source of vitamin C which promotes healthy skin and a stronger immunity. Fruits have antioxidants and these nutrients can help decrease inflammation. Since they have lots of fiber, grains help promote digestion [10].

Sweet orange are used for their fruit and also numerous skin products or cosmetics. Many lotions, skincare products and aromatherapy formulas contain orange essential oil because of its scent and beneficial antioxidants, extracted from the peel. The peel is often used as the exfoliating scrub to whiten and clean the skin. By-products such as orange pulp, peel, can be used as organic fertilizers or feed for animals through composting. Orange oils and extracts are used as flavorings in the food and beverage sectors, and its fresh, citrusy scent is used in cleaning goods and perfumes by the fragrance industry. Besides culinary applications, sweet oranges are indispensable for industrial, cosmetic and health applications [11].

Early diagnosis of diseases and precise species identification is essential to the prevention, reduction and control of disease in the agricultural industry [12-13]. Improvements in deep learning and computer vision demonstrated the significance of detecting and categorizing infections in an era of more than ever before seamless integration of farming innovations and technological advances. In the last few years DL, an extension of ML, has had the potential to be very successful in several areas. The use of neural algorithmic deep learning has shown great potential in various fields including, but not limited to, visual data interpretation problems [14-15]. One of the critical steps in identification of plant diseases is vital to facilitate early diagnoses of insect and pest problems, disease prevention and agricultural production growth, among other benefits. Sweet orange trees are often afflicted with disease on the leaves. To do this, picture pre-processing techniques are applied to a plant leaf in order to quickly and accurately detect any irregularities. Thus, for agriculture, using a DL based approach for pest and disease identification can make a huge leap forward and minimize losses in agricultural production and save time with even more accuracy and precision. This will help plant pathologists and landowners to diagnose plant diseases without any knowledge of plant disease diagnosis and also be able to diagnose and

control plant diseases before it affects the crop yield both in terms of quality and quantity and in turn help the farmer economically. [16].

CNNs are DL-based approaches which are widely adopted for image data and superior at important features extraction, generalization accuracy, flexibility and with deep learning ability. Due to these special features, CNNs are the most suitable for numerous computer vision tasks and are considered the most advanced and creative way of understanding images and defining their essential features. Thus, most of the previous studies adopted CNN-based techniques to identify plant leaf diseases [17].

Monitoring and detecting leaf diseases of sweet oranges are essential to prevent them from reducing the rate of photosynthesis, fruit quality and production. Although most farmers are still relying on manual method of sickness observations which is time-consuming and sometimes error prone. Traditional diagnosis of disease requires specialist knowledge, and requires physical examination at the site, making it costly and unpleasant [18]. To overcome such issues, many latest studies have been carried out to make use of innovative technologies to automate plant disease diagnosis and classification. In addition to the advancement of computer tools, a growing number of devices that incorporate cameras, cellphones, drones and Internet connections made machine learning and image processing techniques possible, enabling automatic identification and diagnosis of crop diseases [19-20].

CNN based image identification has recently proved to be of great importance in the early detection of disease and insect infestation in plants [21]. One of the common challenges for image processing specialists is however to acquire suitable, comprehensive, and high resolution sets of images for CNN techniques to generate accurate disease diagnosis results. International scientist researchers have developed open access datasets of numerous plant diseases, available for other academic researchers. Fig. 2 shows plant leaf disease diagnosis based on deep learning approach

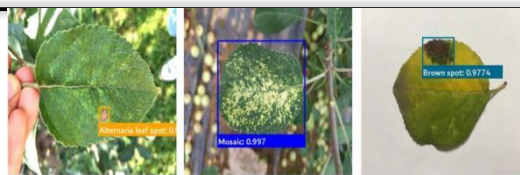


FIGURE 2. Plant leaf disease diagnosis using deep learning approach [22].

Sweet oranges are a familiar fruit in the agriculture sector and the global citrus industry plays a critical role in food security and strengthening economies. Disease prevalence, however, is a serious risk to crop quality and productivity, resulting in large financial losses. An accurate and timely diagnosis is important to implement sustainable farming practices and to be successful in disease management. The traditional diagnostic methods are often labour intensive, time consuming and require specialized expertise and knowledge which is not always available. One of the best ways to automatically identify illnesses precisely and effectively is to apply DL developments, particularly CNNs. In order to overcome these issues and guarantee a more accurate and generalized approach for automatically identifying sweet orange leaf ailments, this study aims to use advanced CNN models.

The previous disease identification method was the naked eye or traditional method, which had a high labor intensity, low applicability for large amount of data and identification error. Moreover, little research has been conducted specifically on sweet orange and most studies focus on one or two diseases. This leaves a gap in the research that needs to be filled with an automated and robust classification framework which can cope with several sweet orange leaf diseases in wider classes.

The purpose of proposed study is to build an efficient CNN based model to detect the sweet orange leaf diseases at early stages by achieving high accuracy with lightweight model for the use on resource constrained devices. A large set of sweet orange leaf photos will be collected, followed by advanced image processing and augmentation strategies to tackle the problem of over fitting, a common issue with DL models and improve generalization. The study also aims to increase the number of target disease types compared to the previous studies.

This study's research goals are as follows:

To accurately and universally detect early symptoms of sweet orange leaf diseases based on CNN model.

- To gather a large training set from various sources (Internet, images etc.) and then annotate/label the images.
- To use advanced preprocessing and image augmentation techniques to improve model training performance in various and real-life scenarios.
- To build a new CNN network for solving the issue of over fitting which is one of the important issues in network generalization with transfer learning technique.
- To test the model with new unseen images from real-field situations.

Our work is a lightweight CNN model with transfer learning, which is used to automatically recognize the sweet orange leaf diseases. The model was based on a pre-trained network EfficientNet-B0 as backbone and a dense layer with 1024 neurons and 30% dropout ratio in combination with a softmax activation function as a final classifier. The model was trained using various sets of image classes such as binary classification, six classes and eleven classes with moderate number of images per class. Preprocessing and augmentation were used to augment the dataset before training. A new set of unseen images was then used to test the trained model. The proposed approach has been evaluated and the results show that the proposed method has high accuracy with average accuracy of 96.20%, 97.45%, and 96.54% for binary, six-class and eleven-class classifications respectively in the recognition of various sweet orange leaf diseases. The proposed transfer learning based model outperforms some of the well known pre-trained networks and also gives high accuracy of 96.85%. The aim is to develop a robust and generalizable model that can accurately detect issues, to ensure a healthy ecosystem and boost yield.

The present study has the following main contributions:

- A large set of training data of sweet orange leaf images was collected based on multi-class classification.
- It was fine-tuned and trained using an efficient approach (the EfficientNet-B0) and it was found to be useful in various scenarios, namely binary classification, six-class classification and eleven-class classification.
- In addition, the model was trained with potato leaf data set and it was found to achieve a reasonably good accuracy when compared with the previous work.

This study is limited to the detection of sweet orange leaf diseases using an efficient CNN model based on transfer learning with a lightweight model and high accuracy, but can be expanded to other plants with ease. The proposed study aimed at early detection of the various leaf diseases of sweet orange plants, which lead to a decrease in the yield of fruit. It can be deployed on web applications, smartphones and drone cameras and can be used by laymen without the involvement of plant experts, providing quick services to farmers and ensuring a reduced amount of pesticides. The performance of the model was tested in two different problems: binary classification, six-class classification, and eleven-class classification, which can be easily adopted as per the end user's requirement. The present study was conducted on the disease symptoms on the leaves only and can be extended to the root, stem and fruit infections with ease. The developed model is designed to support the research, agronomists, and farmers by providing a quick and accurate disease diagnosis solution, lessen the reliance on manual inspection, and lessen the danger of misdiagnosis.

This book includes a background study on plant diseases in Chapter 1, followed by automated disease identification through the use of AI in Chapter 2. There was previous work related to plant disease detection based on ML and DL that was presented in Chapter 2. Chapter 3 contained the detailed information regarding the proposed methodology, such as data collection, preprocessing techniques, data augmentation and the proposed model's structure. The training environment, the measurements, the conclusions and the discussion were included in chapter 4, while chapter 5 is the conclusion of the thesis,

consisting of a short summary and suggestions for future directions.

II. LITERATURE REVIEW

In recent years, deep learning has shown great progress in agricultural disease monitoring and detection, surpassing traditional methods [23]. Nowadays, prompt detection of plant diseases via deep learning can play a key part in improving crop yields. By utilizing deep learning-based methods in plant disease recognition, quick decisions can be made that can mitigate the shortcomings associated with conventional manually operated diagnosis of diseases, leading to more endeavor than DL and also encountering subjectivity challenges [24].

B. Plant Disease Identification Using Physics and Engineering

Basavaiah et al. [25] proposed a novel strategy that utilized extracting and integrating features to diagnose five kinds of tomato leaf illnesses from 500 pictures using machine learning techniques such as decision tree (DT) and random forest (RF). The accuracy rate of the two proposed classifiers was 95% for the RF approach, and 91% for the DT approach. Alanni et al. [26] created an enhanced feature identification methodology using Improved Gene Expression Programming (IGEP) and gain ratio (GR) in gene pattern identification. The proposed approach was trained with 8 sets of training data with SVM and leave-one-out cross validation (LOOCV). Compared with the previous feature identification algorithms, the proposed algorithm was found to be an efficient approach to capture the complex features and hence results in high detection rate.

Al-Gaashani et al. [27] proposed a technique for tomato ailment recognition using conventional techniques like principal component analysis (PCA) and logistic regression for classification while pre-trained CNN networks were used for low level feature grabbing, resulting in an improved detection rate of 96.90% for 1150 pictures that contained six groups. The training images were collected from an online website called PlantVillage. One of the studies conducted by Yang et al. [28] was to propose a machine learning method for detecting leaf deformity in plants. They found tea plant diseases with a large-resolution infrared thermal imaging tool called the Fluke TiS20. Some of the major preprocessing steps are converting RGB images

to HSV, thresholding, splitting color channels, color assessment, conversion of images to binary form and noise removal, etc.

B. Plant Disease Identification Using Hybrid Approach

Çinar & Cengil [29] proposed a deep neural network and transfer learning based hybrid structure. The researchers used pre-trained networks like Xception, ResNet-50, Inception-v3, VGG-16, AlexNet and VGG-19 as their backbone and machine learning-based algorithms as their classification layer at the end. The suggested approach was validated with multi-class data from PlantVillage with 4976 pictures and the accuracy achieved was 98.30%. For the detection of the severity of tomato diseases, Moussa et al. [30] have proposed a model with multi-class classification. The authors used publicly available data that was provided by PlantVillage to train the data set. The overall segmentation result of the leaf pictures by modified U-Net and the extraction of leaf features and identification of the target tomato diseases by a pre-trained Residual Network achieved an accuracy of 97% based on 10 categories of leaf pictures (one healthy and nine diseased classes).

M. S. Anari [31] had suggested the model for early detection of various plant leaf diseases. The scholar used an enhanced DL framework with transfer learning, which was equipped with the preprocessing and augmentation methods to extract complex features in the input images. They used several support vector machine (SVM) models to boost processing and classification accuracy. The kernel parameters for radial basis function (RBF) were optimized in the process of training the model. The model is trained and tested with six different image datasets of cotton, grape, apple, maize, rice and pepper leaves from PlantVillage and UCI repositories, with around 90,000 images for each variety. The outcomes showed significantly high classification accuracy, thereby indicating the ability of the framework to contribute towards the future of automatic leaf disease detection in agriculture. An accurate model called GreenVit was built by Perez et al. [32] to identify leaf diseases in a variety of plants. The researchers gathered and used two datasets of plant leaf images from PlantVillage and the Data Bank of Leaf Image to train the recommended model. The modified version of

Vision Transformers, GreenVit, attained 99% recognition as regards the accurate distinction between healthy and unhealthy photos of plant leaves.

C. Plant Disease Identification Using CNN Models

Symptom classifications in plant disease is challenging because of subtle differences in plant symptoms, overlapping symptomologies and variation in leaf texture. This can result in misclassifications and over fitting. Early and accurate symptom detection to reduce losses in agriculture is crucial. Deep CNNs have been found to be useful in identification and detection of diseases in plants, though there are still challenges such as the requirement of large amount of training data and the need to tune the parameters. In [33] the authors presented a new Transformer block using the transformer architecture for the long-term features and soft partitioning token embedded to extract as much info as possible from pixels. Fine-grained pattern identification is enhanced by fusion structure and cross channel attributes acquisition.

In [34] a CNN-based method was used to detect and diagnose 9 types of tomato diseases and one healthy type with a detection rate of 90.98%. In order to train the model, 10000 images were collected from a well-known repository called PlantVillage. To tackle this issue, the authors of [35] proposed an improved CNN-based approach to detect tomato diseases with an attention block, which achieved an accuracy of 96.81% on the open-source image database from the PlantVillage repository. There were 4585 training images in ten categories and multiple augmentations produced a final training set of 22,925 images. Khan et al. [36] compiled a special image set and developed a unique training set to recognise abnormalities in wheat crops such as brown and yellow rust. Currently most of the research was performed with high resolution cameras and deep learning algorithms to classify crop diseases, which makes the process of gathering training sets and determining the disease difficult and expensive.

S. Rahman et al. [37] classified and localized citrus diseases using a CNN-based object recognition model that was modified from Faster R-CNN. The technique was able to classify and identify various citrus diseases, such as bacterial canker, black spot, and Huanglongbing (HLB),

with a high accuracy of 94.37%. The method enhanced the image quality of the images used to train the model using several image processing techniques. All the shots were subsequently converted to greyscale using the histogram equalization technique with similar intensity ranges to produce comparable images. Using a technique known as thresholding, greyscale images were transformed into binary images in the second preprocessing stage. Abade et al. [38] thoroughly evaluated CNN algorithms used for the detection of plant diseases. They studied 122 articles published between 2011 and 2020, and found that TensorFlow was the most common framework used in this field, and that PlantVillage was the most important dataset.

By collaboration with plant experts, Dhaka et al. [39] explained the procedure of detecting plant disease from plant leaf images using CNN algorithm. The algorithms, the preprocessing techniques and the systems of CNN were compared. In order to assess the efficacy of these designs, their study additionally looked at performance measures and datasets. Just like data scientists, Nagaraju et al. [40] analysed datasets, data preprocessing methods and deep learning methods for plant disease identification. After analyzing 84 articles, they discovered that a lot of DL techniques needed efficient preprocessing techniques in order to function as effectively as possible.

In [41] researchers engaged in agricultural improvement research used DL methods to solve several agribusiness issues. Their analysis indicated that DL systems had better performance than traditional photo interpretation methods, which could result in better farming practices. In the study of controlling weeds in croplands, Quintanilla et al. [42] studied both on the ground and aerial imaging technologies. Efficient weed surveillance is crucial for weed management, they concluded, and they forecasted that sensor data saved in the public spaces will be crucial in enhancing crop security in the future.

Lu et al. [43] have performed a study on plant disease identification using CNNs. They assessed how well CNNs performed in this area and emphasized how crucial it is to have more varied and in-depth datasets for superior outcomes. Golhani et al. [44] presented a model for detection of leaf diseases using hyper spectral

images. They explained the problems and potentials of hyper spectral data. The article provided a brief overview of the development of SDI based on the Artificial Neural Network approach.

Plant Leaf Disease Classification using CNN based model was identified by Bangari et al. [45]. With many convolution layers, FC layers, and a last layer for categorization, they employed a deep CNN structure. They came to the conclusion that CNN-based models are the best models for jobs involving images.

D. Plant Disease Identification Using CNN with Transfer Learning

It is a good idea to train a CNN model from scratch, as it provides the basis for training the CNN and the knowledge acquired by the model is relevant to the domain; but training from scratch requires a large amount of training data. It also requires increased strength of hardware resources as compared to transfer learning. Therefore, transfer learning is a good choice if there is a small or moderate size of training data. Transfer learning also guarantees a quick training convergence, ensuring less use of computing resources, including training time. To classify all the maize leaf diseases, Priyadarshini et al. [46] adapted the LeNet algorithm to create a CNN based approach. They trained their method on a set of maize leaf images from PlantVillage. They showed that their accuracy for the model was 97.89%.

For maize leaf diseases classification, Waheed et al. [47] optimized and fine-tuned DenseNet structure to classify the maize leaf illnesses as northeastern leaf destruction, common rust, grey leaf area and healthy leaves. Their approach had an accuracy of 98.06%. Wu et al. [48] developed a CNN based disease diagnosis system that was able to detect Northern leaf rot in the leaves of maize using UAV photos. They used the framework of ResNet trained earlier to extract features, then fed the extracted features into a simple linear classifier. Accuracy of this model was 95.1%. Scholars have also explored the classification and prediction of plant diseases using a hybrid model of the combination of CNNs and attention mechanisms.

In investigations for crop disease detection [49] used a residual CNN enhanced by self-attention to enhance the performance of the architecture. Zeng and Li [49] used a residual

CNN, with self-attention added to improve performance, in investigations for crop illness detection. Their method achieved 97.95% success rate on the MK-D2 image set and 94.93% success rate on the AES-CD9214 image set, which is impressive. To identify rice leaf diseases, Chen et al. [50] adopted an already trained MobileNet-V2 network, pre-trained on ImageNet data, and added attention mechanism, achieving a success rate of 98.48%.

Most of the earlier research on the genus citrus has been conducted for the other species, primarily mango, lemon and orange, with only a few studies conducted on sweet oranges. The majority of earlier studies have been conducted on other citrus plants like oranges, mangoes and grapes with comparatively small training sets (maximum 4 disease classes). The datasets are small in size, which can make it difficult to achieve good generalisation and the risk of over fitting is high, especially when using more complex deep learning algorithms that require large datasets to perform well. The proposed study is aimed at incorporating wider classes of diseases while obtaining more accuracy and generalization by the use of CNN model with lesser training parameters for deployment on the resource-constrained device.

III. RESEARCH METHODOLOGY

The present study provides an in-depth analysis and summary of the entire detection system of sweet orange leaf disease using a novel CNN approach. Previous approaches, like machine learning, required manual feature engineering and are more time-consuming and less accurate.

CNN based methods, however, are known for their ability to extract and identify intricate properties from input information, particularly image information. They can easily identify abrupt changes that can lead to a valuable decision making regarding plant diseases and they can extract and pick up the vital information related to domain task. The recommended sweet orange leaf disease diagnosis approach was to use EfficientNet, which is a pre-trained network, and add a single FC layer with softmax as the last layer (as shown in Fig. 3).

A. Training Dataset

In the field of AI, especially in the area of supervised learning, the training data is the most important element of DL-based techniques. With the help of big and quality data, the DL-based models can be trained effectively with better performance and accuracy. The integration of DL and automatic interpretation of agricultural image data has received a lot of attention nowadays but also needs a well-created and large data set related to the task at hand. In the proposed study we focused on multiclass classification of sweet orange leaf disease. To support our research we chose a large collection of leaf images from the website www.mendeley.com, which is widely known to collect many and comprehensive agriculture-related images [51]. Table 1 shows the distribution of images belonging to 11 classes in the dataset with brief detail, which amounted to 5813 images. Some examples of sweet orange leaves in the training set are shown in Fig. 4.



FIGURE 4. Sample images from the training dataset.

TABLE 1. CLASS-WISE DISTRIBUTION OF CITRUS LEAF IMAGES

S No.	Class	Images
1	Citrus Canker	588
2	Citrus Greening	254
3	Citrus Mealybugs	603

4	Die Back	434
5	Foliage Damage	690
6	Spiny Whitefly	677
7	Powdery Mildew	598
8	Shot Hole	560
9	Yellow Dragon	407
10	Yellow Leaves	310
11	Healthy leaves	594

B. Image Processing

After collecting the data, the image data needs to undergo preprocessing, which is an important step and common process in the training of a CNN model. It optimizes the use of hardware resources and detection performance. The preprocessing of the sweet orange leaf images is critical in order to train the model and to provide good classification of the leaf diseases. In this regard, the quality and type of images play an important role in the classification result.

The following actions were taken to make the training process and image better.

All the training photographs were inspected manually and excluded from the training set if they were not suitable.

For CNN algorithms to be trained, the pictures that are fed into the network have to be uniform. Consequently each picture was resized to a size of 256 x 256 pixels.

Another important pre-processing step that practitioners follow when training CNN models is rescaling which helps positively in model convergence. All of the input images of the proposed study were normalized to the range [0,1]. In this study, 80% of the training set was used for training and 20% of the training set was used for validation. Using these aforementioned image preprocessing techniques, we were able to achieve reasonable growth in the training process

while maintaining high accuracy and minimizing over fitting.

C. Data Augmentation

The process of enlarging and adding diversity to the training images is called data augmentation. There are two forms of augmentation – offline and online augmentation. Online augmentation is a technique that is known to be easy to implement and was used in the proposed study. Enhancing images is a frequently used and vital procedure for CNN training. Data augmentation is used in computer vision and NLP to improve training procedures—and thus the generalization of the model. The data augmentation technique benefits CNN model training in two prime ways: diversity in the training images and a higher number of training data, which ensure the generalization of the CNN model in real scenarios. In the proposed research work, the whole training data set was augmented using a pre-built module from the Keras library. In this study, multiple data augmentation techniques were employed such as brightness, shear, flipping, rotation, and zooming. There were several steps in the augmentation process in this study. The validation of our suggested CNN-based method for the classification of sweet orange leaf diseases has been enhanced in this multidimensional augmentation, both in terms of avoiding over fitting as well as the ability to generalise to new unseen data.

D. Proposed Model

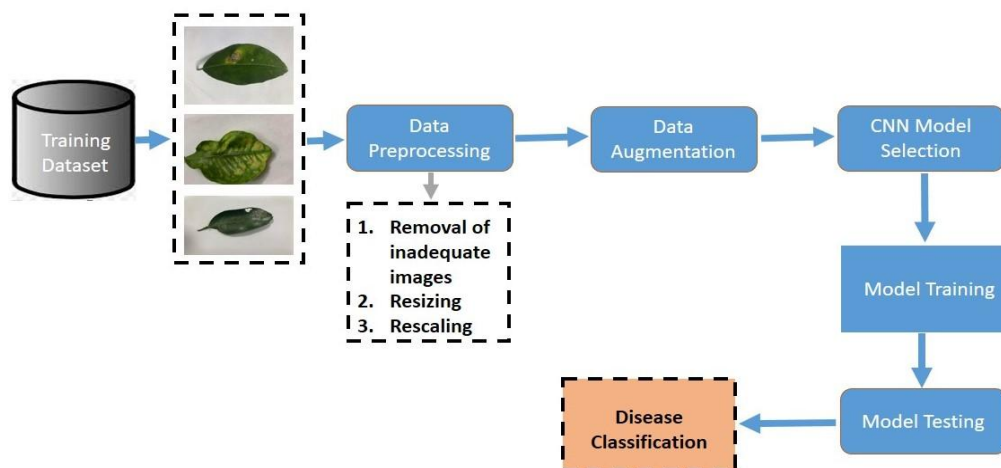


FIGURE 3. Workflow of the proposed work.

In the proposed framework, a deep CNN model was employed whereby sweet orange leaf disease was automatically recognized using the method of transfer learning. To develop the proposed model a pre-trained network called EfficientNet-B0 was fine-tuned with new set of FC layers. The proposed method was optimized with fully connected FC layer of 1024 neurons and a softmax output layer for multi-class leaf classification and 11 categories of leaf images were used in the experiments (10 diseased and 1 healthy leaf). A drop-out rate of 30% is applied after the dense layer to decrease the chance of over fitting. The EfficientNet-B0 model ([52] 2019) is the base model in the EfficientNet family and is efficient by design. It is arranged to maximize both precision and computational efficacy through a technique called compound scaling that try to ensure balance among network depth (No. of layers), width (neurons per layer), and input image size. Efficient-Nets are different from older models, which scale these dimensions separately, because these networks can be scaled using a single strategy, offering better performance with lower computational cost. The most important innovations are the introduction of the novel feature of Compound Scaling, which uniformly scales the depth, width, and resolution of the network for better accuracy and efficiency; new Mobile Inverted Bottleneck Convolutions (MBConv) that reduce computational cost without compromising performance; the Swish activation function that increases model non-linearity and gradient flow; and the novel Swish attention mechanism Squeeze-and-Excitation (SE) that adaptively recalculates channel-wise feature

responses. Finally, an optimized architecture was identified using Efficient Neural Architecture Search (ENAS) for automated discovery of high performing model structures. Unlike previous networks, which scale the depth (No of layers), width (No of neurons per layer) or input size to the network, EfficientNet scales all three dimensions systematically and balancedly through the use of compound scaling. This approach provides more efficient trade-off between accuracy and computational cost. Scaling Equations are given as follows:

$$d = \alpha^{\phi}, w = \beta^{\phi}, r = \gamma^{\phi} \quad (1)$$

$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \quad (2)$$

Where:

- d represents the depth of the model,
- w denotes the width of the model,
- r corresponds to the input image size,
- α, β, γ are scaling coefficients, and
- ϕ is a user-defined factor used for scaling that controls the overall network size.

In order to decrease computation cost, MBConv semi-blocks are employed instead of conventional convolutional layers, which are taken from the Mobile-Net family. These blocks use separable convolutions using depth wise and an enlargement strategy to enrich feature collection from the input data. Further, the regular ReLU function is replaced by another function called the Swish, which is defined as:

$$\text{Swish}(x) = x \cdot \sigma(x) \quad (3)$$

In this case, $\sigma(x)$ represents the sigmoid function. The Swish activation function does not clamp negative values as in the case of ReLU, thereby promoting a more fluid flow of the gradients and increasing the model's accuracy. EfficientNet-B0

also adopts SE blocks that learn and dynamically adjust the values of the channel-wise attributes by calculating the global attention values, which improves the model's representation capability. Moreover, it was designed automatically by the Neural Architecture Search (NAS) method to achieve optimum efficiency, rather than by hand. These developments allow EfficientNet-B0 to outperform its competitors in terms of detection rate and require fewer parameters, making it a more powerful option for image interpretation tasks. Transfer learning: Fine tuning a pre-trained network, trained on a different similar task, for the current task is called transfer learning. During transfer learning, only dense layers of the model are fine-tuned when learning from the new set of images, rather than training from scratch. It has several benefits, such as less training time, and more generalisation on a moderate number of images than training from scratch. This study involves pre-trained models, like EfficientNet-B0, that are trained on large image datasets like MS COCO and ImageNet,

and have huge amounts of image data. Originally, EfficientNet-B0 was trained using the popular ImageNet image collection. Typically the convolution part of the new model is pre-trained and the higher layers for identification have to be trained completely from scratch. High-level characteristics common to all objects, such as boundaries, contours, and solid patterns, are included in the pre-trained networks of transfer learning. Transfer learning can also be helpful to alleviate over fitting and shorten training time when training sets are moderate sized [53].

E. Fine-tuning

To improve the proposed network, after the pre-trained network, a flatten layer was added with a 30% dropout. A dense layer with 1024 neural connection was employed in head of the model. To identify sweet orange leaf illnesses with multiclass classification, a softmax activation mapping was carried out in the last layer. Table 2 shows the main architectural components of the proposed framework.

TABLE 2. CONFIGURATION DETAILS OF THE PROPOSED CLASSIFICATION MODEL

S No.	Layers	Neurons	Parameters	Value
1	Backbone	EfficientNet-B0	Learning rate	0.001
2	Flatten layer		Optimizer	Adam
3	Dense layer	1024	Loss	Categorical Cross Entropy
4	Dropout	0.30	Data Split	80%, 20%
5	Final layer	11	Epochs	35
6			Batch Size	32
7			Input Size	(256 x 256 x 3)

F. Limitations of the Study

The aim of the proposed study was to create an improved DL-based approach to automatically detect the primary symptoms of diseases that are likely to affect the leaves of sweet oranges. The CNN based model proposed in this work, using transfer learning is more accurate than previous SOTA approaches, however there are still some drawbacks that can be addressed in future iterations of this study. Given that CNNs are

thought to be data greedy, the training dataset's size is adequate but requires additional samples. The second limitation is the imbalanced dataset, while the third is that the images used for training were collected from an Internet repository, not accurately reflecting real-world situations, which are important for evaluating the model's generalization performance. This shows the power of the data set in Fig. 5 as the difference in images per class is clearly evident.

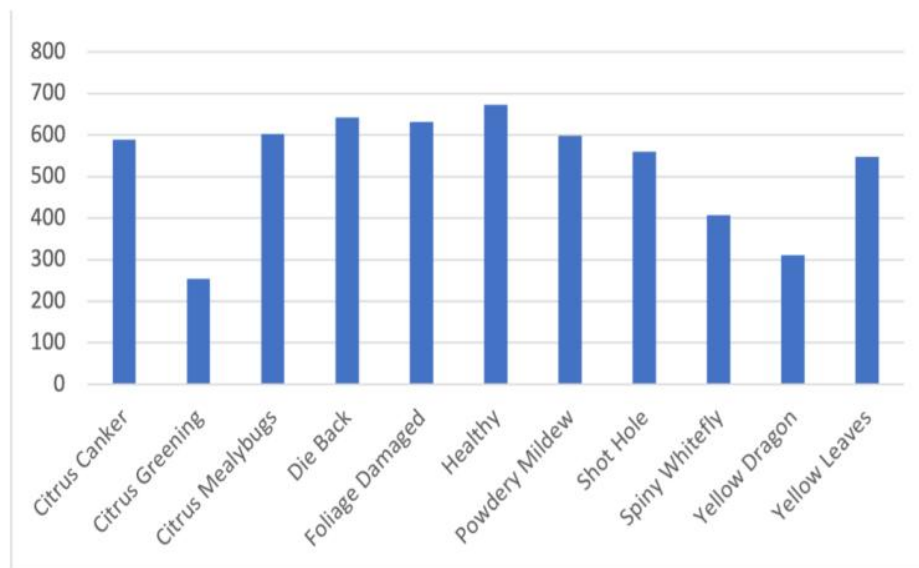


Figure 3.2: Statistical view of dataset

FIGURE 5. Class-wise (statistical) view of the training dataset.

IV. EXPERIMENTS AND RESULTS

Scientists are working to bring innovative AI-powered tools and technologies to a higher level of precision agriculture. In order to detect sweet orange leaf illnesses early, with cellphones and without the need of plant pathologists, a new CNN-based approach was developed, trained and evaluated. Specific findings from the evaluation of the model are shown in this section.

A. Training Environment CNN-based techniques that are used for picture analysis and identification need a powerful computer using a large amount of memory and processing units such as graphical processing units (GPUs) instead of central processing units (CPUs). In this investigation, the easy-to-use system Google Colab with Tesla T4 GPUs and sufficient Google Drive was used. Additionally, it provides Jupyter notebooks which come with pre-installed tools like Matplotlib, Keras and TensorFlow so that researchers can build, train and test deep learning models for a variety of tasks without worrying about spending a lot of money on hardware resources need for AI models.

B. Evaluation Metrics The performance of the proposed framework has been measured using various evaluation metrics including precision, accuracy, recall and F1 measure. Accuracy calculates the proportion of correct predictions to overall cases during the evaluation and is probably best estimated when the number of images is uniform across each class. Precision is

the number of positive cases that are predicted to be correct, and this is important if the false positive cases are costly. Recall refers to the framework's performance in capturing every positive example, meaning it's essential when minimizing false negatives is necessary and it needs to be focused. If both the false negative cases and false positive cases are equally significant, the harmonic mean of "recall" and "precision" is called "F1-score" and provides a general performance summary. The metrics are provided here:

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \quad (4)$$

$$\text{Precision} = TP / (TP + FP) \quad (5)$$

$$\text{Recall} = TP / (TP + FN) \quad (6)$$

$$\text{F1-score} = 2 \cdot (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (7)$$

True Positive (TP): cases correctly predicted, which are part of the same class as the target class. The model incorrectly classifies other classes as the target class is called False Positive (FP). Some of the examples where the model gets it wrong and classifies the target class as a different one are called False Negative (FN).

C. Results and Analysis

A novel approach, transfer learning, was used in this research to progress with precision agriculture. One of the hottest areas of precision agriculture is the early detection of plant diseases specifically focusing on sweet orange diseases. This investigation focused on the detection of ten sweet orange leaf diseases, as it is essential to

protect this important crop from disease and to augment production. The study used this Efficient-B2 model as a pre-trained model and fine-tuned and trained a CNN approach using the transfer learning method that achieved a high

accuracy and performance against over fitting. For proposed study, separate set of test images were used where 100 number of images were used per class. Table 3, shows the results of the suggested framework on new unseen images.

TABLE 3. RESULTS OF THE PROPOSED MODEL ON TEST IMAGES

Metric	2-Class Classification	6-Class Classification	11-Class Classification
Accuracy	96.20 %	97.45 %	96.54 %
Precision	95.35 %	96.35 %	96.35 %
Recall	97.10 %	97.10 %	96.10 %
F1-score	96.27 %	96.70 %	96.30 %

To depict the performance of the model for a single class in each experimental iteration, Fig. 6, Fig. 7, and Fig. 8 contain the accuracy and loss

graphs of the model's training progress. While Fig. 9 shows the confusion matrix of the model on eleven-class classification.

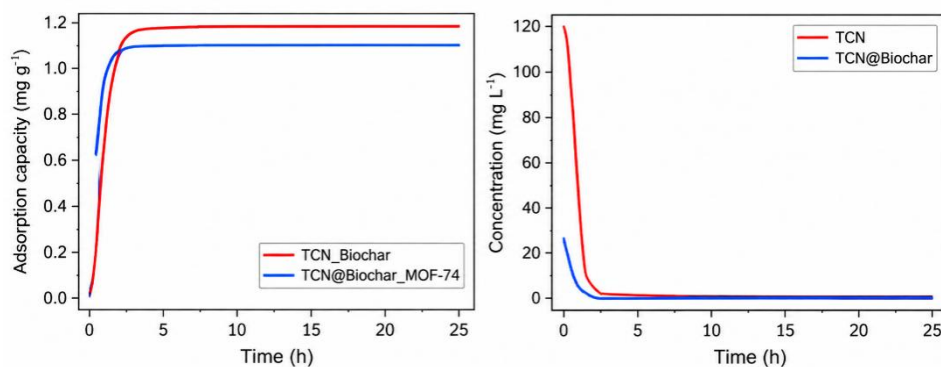


FIGURE 6. Training progress (binary classification): (a) accuracy (b) loss.

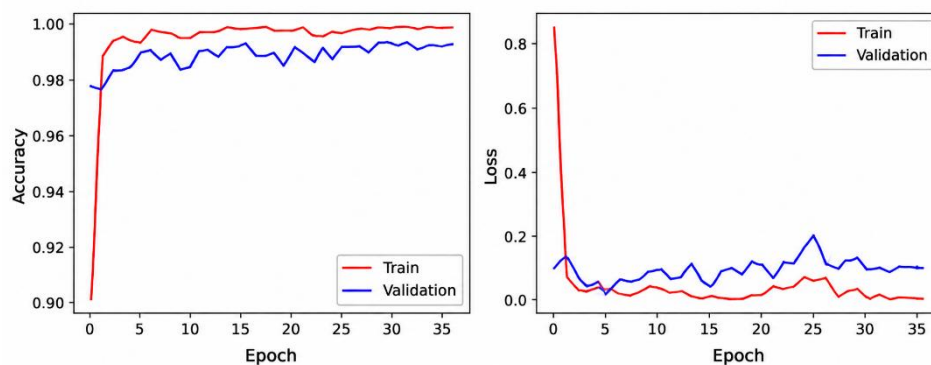


FIGURE 7. Training progress (six-class classification): (a) accuracy (b) loss.

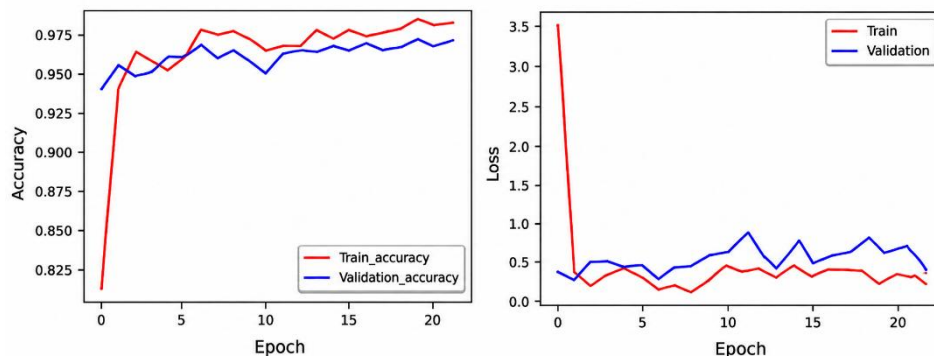


FIGURE 8. Training progress (eleven-class classification): (a) accuracy (b) loss.

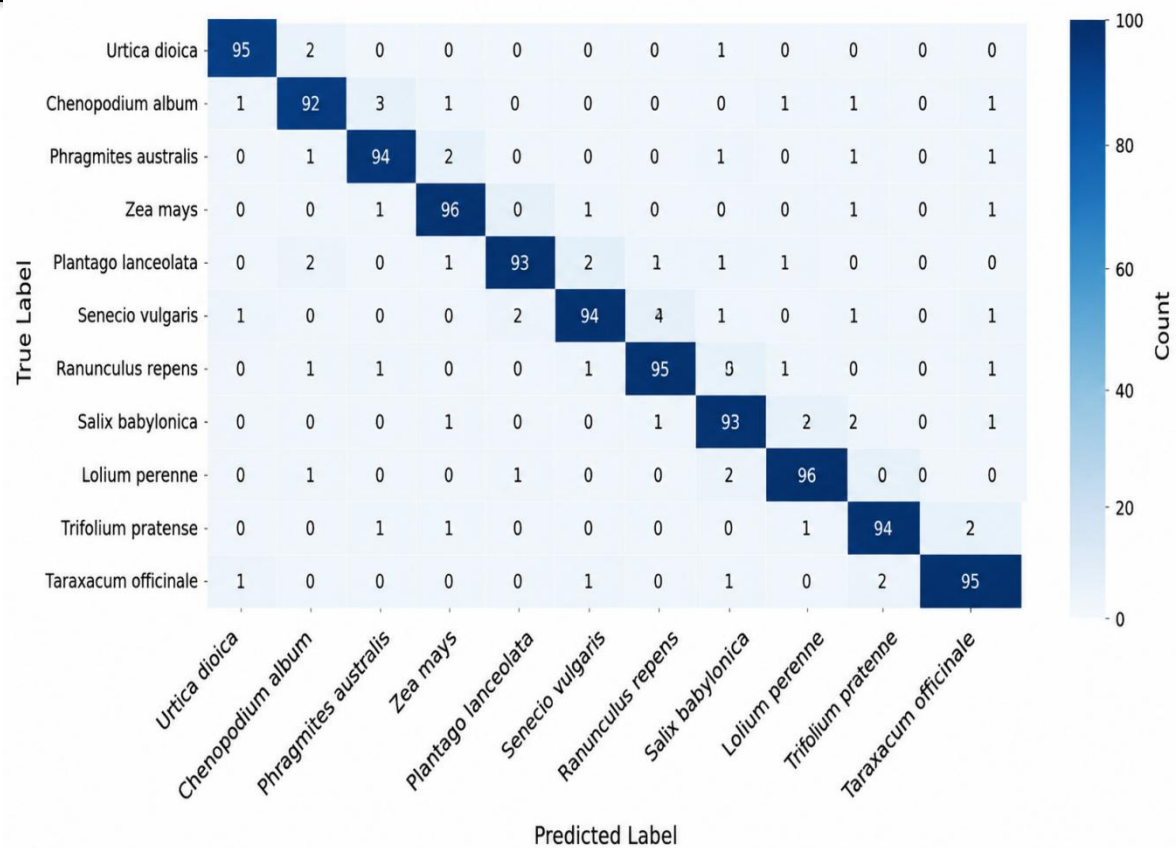


FIGURE 9. Confusion matrix of the proposed model.

D. Comparison with Other Well-Known Pre-Trained Networks

This is compared with three popular pre-trained models, DenseNet-121, MobileNetV2 and ResNet50. With the same parameters and FC layers, these networks were further optimized by

transfer learning on a similar set of images. Although they were able to achieve good results, they were found to have low accuracy in answering the EfficientNet-B0, as stated in Table 4 and also the results are shown in Fig. 10.

TABLE 4. RESULT COMPARISON WITH OTHER PRE-TRAINED NETWORKS

Network	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)
ResNet-50	96.05	96.81	96.36	96.24
MobileNetV2	95.55	95.42	95.10	95.83
DenseNet-121	95.90	96.68	96.68	96.28
EfficientNet-B0	96.35	97.10	97.45	96.70

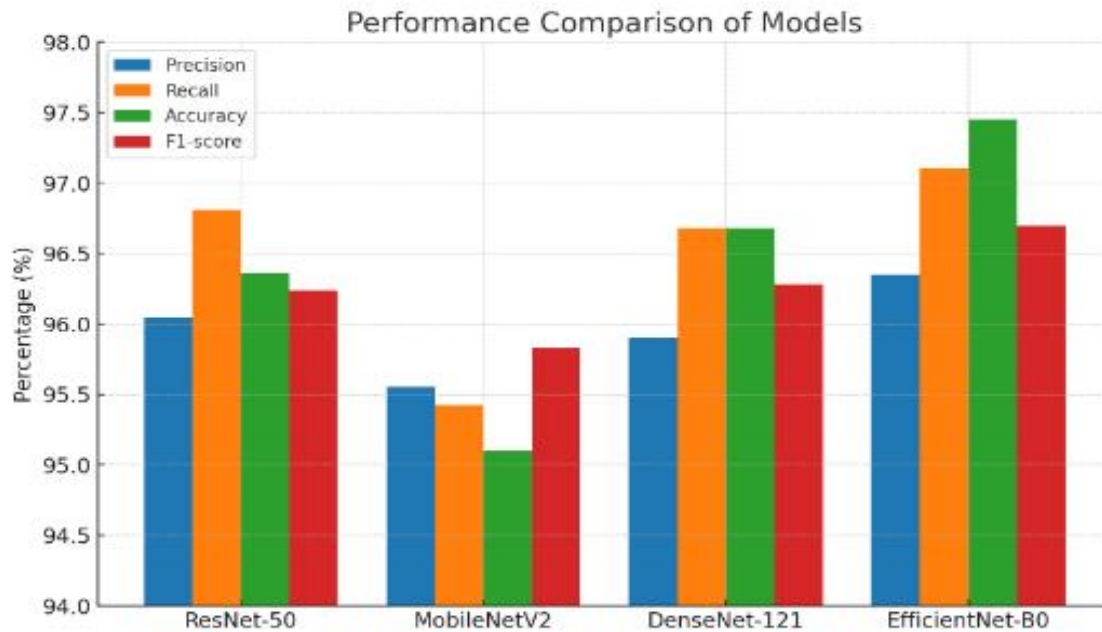


FIGURE 10. Performance comparison of models.

E. Comparison with Previous State-of-the-Art (SOTA) Models

To benchmark the performance of the proposed model, the results are compared with other well-

known latest previous work in this domain. Table 5 shows the detailed comparison.

TABLE 5: PERFORMANCE COMPARISON OF THE PROPOSED MODEL WITH PREVIOUS SOTA MODELS

Ref#	Images	Diseased Classes	Proposed Approach	Accuracy (%)
[37] (2022)	596	Three	CNN	94.37
[54] (2024)	1800	Single	YOLOv8	83.14
[55] (2024)	525	Single	CNN-SVM	92.10
[56] (2023)	588	Single	CNN-SVM	94.03
[57] (2025)	1810	Four	Modified YOLOv8	93.20
Proposed Model	1182	Binary	Fine-Tuned EfficientNet-B0	96.20
Proposed Model	3163	Six	Fine-Tuned EfficientNet-B0	97.45
Proposed Model	5813	Eleven	Fine-Tuned EfficientNet-B0	96.54

F. Performance Measurement of the Proposed Model on Potato Dataset

To promote the adaptability and generalizability, the proposed model was trained with another crop dataset comprising of 2110 potato leaf images from two classes of diseases and a healthy class. The model exhibited enhanced precision in classifying plant leaf diseases using the potato leaf

disease dataset, highlighting its ability to recognize complex patterns. This is an indication of the enhanced generalizability and adaptability of the proposed approach, thereby promising to make a substantial impact in the agriculture sector. The test results of Proposed model for potato leaf dataset is displayed in table 6.

TABLE 6. PERFORMANCE ASSESSMENT OF THE PROPOSED MODEL ON POTATO DATASET

Reference	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
[58]	PlantVillage	97.85	98.40	96.67	97.45

G. Comparison with State-of-the-Art Approaches (Potato)

With the potato leaf image sets being publicly available, many studies have been carried out in recent years on the automatic disease identification

of these crops' diagnosis by employing machine learning and deep learning methods. The output of the proposed approach is compared with the previous state-of-the-art approaches in Table 7.

TABLE 7. COMPARISON WITH EARLIER WORK

Reference	Year	Method	Test dataset	Crop	Accuracy (%)
[59]	2019	VGG-16	PlantVillage	Potato	96.00
[60]	2021	SVM+ GLCM	PlantVillage	Potato	95.99
[61]	2022	VGG-19	PlantVillage	Potato	97.30
[62]	2023	Dense-Net	PlantVillage	Potato	97.20
[63]	2020	Custom CNN	PlantVillage	Potato	96.80
Proposed Model		EfficientNet-B0	PlantVillage	Potato	97.45

H. Discussion

Requires a lot of knowledge about the CNN model, such as many of its parameters, in order to train the model. In this study, custom CNN structures were used, but due to the moderate size of the dataset and imbalanced nature, their outcomes were not so good. The alternative way of model training called transfer learning was opted for. We used various structures of pre-trained networks and continuously examined their performance on the proposed dataset. In order to achieve the goal of the study, we gradually added dense layers to the framework and systematically and carefully changed the training parameters several times. Though multiple pre-trained models were used, some of them were effective as indicated in Table 6, the proposed model has surpassed all the other models except the most near to the aim of the research study. The proposed model, EfficientNet-B0 (1024 neurons) with FC layer followed by softmax was trained in various environments with classification classes, binary classification (6 classes), 6-class and 11-class classification, and the accuracy is very high and is stable. To clearly depict the performance of the model, training graphs and confusion matrices are also added to the result section.

The model was also trained and tested with potato leaf diseases as well as compared potato results with earlier latest publications as there is ample literature on potato leaf disease identification for the proposed approach to be adopted to other plant diseases. The results of this study proved the

efficiency of DL architectures and specially the customized EfficientNet-B0 approach, which was a significant improvement in precision agriculture field. Carefully designed experiments and comprehensive analysis of results make this study at the forefront of the attempt to bring about a revolution in the practice of smart agriculture.

V. CONCLUSION AND FUTURE DIRECTIONS

A. Conclusion

The proposed study is to enhance the automatic diagnosis of plant diseases especially the sweet orange leaf diseases. To be used in this way, EfficientNet-B0 is a pre-trained network that has been fine-tuned and trained with an FC layer (1024 neurons) followed by a softmax activation layer. To improve the training process, image preprocessing and data augmentation techniques were used. To prevent the problem of over fitting a dense layer was added after it. A training set of 11 classes and 5813 sweet orange leaf images was used to fine-tune and train the model. The proposed approach had a higher detection rate of 97.47 % on test data. The model was trained using several sets of diseased classes (binary, 6 and 11) and yielded extremely consistent performance in all scenarios. The model was also trained with potato leaf images and obtained comparable results, thus guaranteeing the model's performance on other plant species. This comprehensive approach showed the significance of the model as an intelligent disease detection system for sweet orange trees, enabling accurate classification and

assessing the adaptability and strength of the network in various categories of leaf diseases. The aim of the study is to help simplify the process of plant disease identification using deep learning techniques to make precision agriculture a reality.

D. Future Work

For future work, more image data for training will be used to increase the accuracy and generalization ability. Enhancing data balancing in real-world settings and adding more disease categories in addition to the standard photos will also be helpful. In addition to the existing CNN architecture, it should also contain other state-of-the-art methods, including the classification and localization of affected regions, the assessment of temporal progress of the anomalies. The study could also be extended to other plant species and diseases to further increase the range of use for the recommended strategy.

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