Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model

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ABSTRACT
Artificial intelligence (AI), automation, and the Internet of Things (IoT) have transformed modern agricultural operations, particularly crop management and disease detection. Plant disease diagnosis and environmental monitoring have grown more accurate and efficient because of machine learning and deep learning techniques such as convolutional neural networks (CNNs). In the context of precision agriculture, this paper investigates the widely recognized CNN architecture VGG-16, which has been specially tailored for detecting tomato leaf diseases. Through meticulous experimentation, our proposed model has showcased an impressive accuracy rate of 99.2%, alongside a remarkable f1 score of 99.499. These findings demonstrate the effectiveness of deep learning techniques in the early identification of plant diseases, allowing prompt therapeutic interventions. The results of this study open the door for deep learning-driven disease detection systems to be widely used in agriculture, with the promise of increased crop yields and the encouragement of sustainable farming methods. This work advances precision agriculture by tackling the problems caused by tomato leaf diseases. It also emphasizes the value of using cutting-edge technologies to address pressing agricultural difficulties.

General Terms
Machine Learning, VGG-16, Convolutional Neural Networks (CNNs), Sustainable Farming, Deep Learning.

Keywords
CNN Model, Precision Agriculture, VGG-16, Deep Learning, Machine Learning.

1 INTRODUCTION
"Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model" presents a novel methodology to transform disease control in tomato farming by incorporating sophisticated deep learning methods. The cultivation of tomatoes plays a crucial role in ensuring food security globally; nevertheless, it encounters substantial hurdles due to diverse diseases, necessitating more efficient approaches for detection and control. Conventional techniques relying on manual examination frequently prove inadequate precision and speed, underscoring the pressing requirement for cutting-edge technologies like deep learning.

The research endeavours to confront these obstacles by utilizing the capabilities of the VGG-16 Model, a convolutional neural network renowned for its effectiveness in categorizing images. This investigation aims to refine disease identification protocols in precision agriculture through deep learning, hence decreasing crop losses and promoting sustainable agricultural output. The study outlines several principal objectives to progress disease control methods in tomato cultivation by integrating deep learning strategies. Figure 1 depicts the collection of factors contributing to plant diseases.

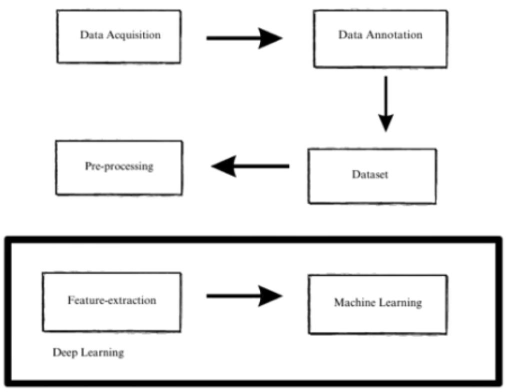


Fig. 1. Steps in Implementing Machine Learning Models for Plant Disease Detection

Firstly, the research aims to establish a robust deep-learning model based on the VGG-16 architecture. This model seeks to detect and categorize tomato leaf diseases effectively, offering farmers an accurate disease identification and intervention tool. Secondly, the study will incorporate agricultural expertise regarding tomato growth behaviours and environmental elements into disease recognition methodologies. By integrating knowledge of tomato growth patterns and environmental factors, the precision and efficiency of the model can be enhanced, leading to more dependable disease detection in various agricultural environments. Additionally, the research strives to present practical suggestions for optimal crop establishment procedures, including site selection, soil management, and irrigation methods. By embracing these recommendations, farmers can reduce disease risks and promote robust plant growth, enhancing crop resilience and productivity. Lastly, the study endeavours to equip farmers with a reliable and effective real-time disease monitoring and control system. Through the development of a user-friendly interface and the deployment of the deep learning model in accessible formats, farmers can receive timely information on disease presence and severity. This empowerment enables swift interventions, ultimately maximizing crop yields and promoting sustainable agricultural practices. Through these diverse objectives, this investigation aims to significantly contribute to improving disease management strategies in tomato farming.

Tomato cultivation encounters notable obstacles attributed to a variety of diseases, which have the potential to cause considerable reductions in yield if not promptly identified and controlled. Conventional disease detection techniques depend on manual scrutiny and subjective judgment, frequently leading to inaccuracies and inefficiencies. Environmental factors and agricultural methods are also crucial in disease progression, underscoring the need for a holistic disease control approach.

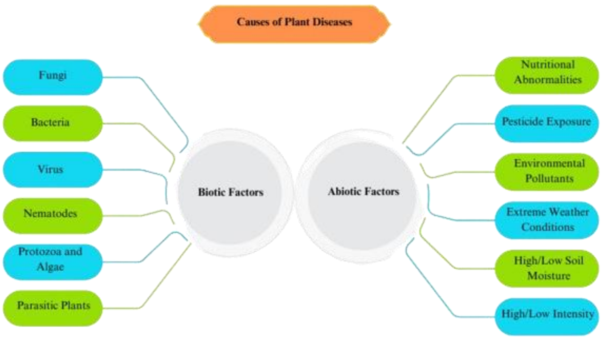


Fig. 2. A Comprehensive Breakdown of Plant Disease Causes, highlighting both Biotic and Abiotic Factors.

Fig. 2 depicts the compilation of factors contributing to plant diseases. Advanced deep learning methodologies, specifically the VGG-16 Model, present a promising resolution to these obstacles by automating detection procedures and providing precise and timely assessments regarding disease occurrence and severity. Nevertheless, the successful application of deep learning in identifying diseases in tomato farming necessitates carefully considering elements such as the growth patterns of tomatoes, environmental circumstances, and optimal agricultural techniques. The primary objective of this investigation is to bridge the disparity between conventional farming methods and state-of-the-art technology, furnishing a comprehensive strategy for managing diseases in tomato cultivation. By fusing deep learning techniques with agricultural expertise, the researchers aim to empower farmers with the necessary knowledge and tools to safeguard their crops against diseases, ensuring sustainable food production for future generations. This research extends its significance beyond tomato farming, encompassing global food security and promoting sustainable agriculture practices. Given the projected global population surge to nearly 10 billion by 2050, there is an anticipated substantial rise in food requirements.

Nonetheless, agricultural sectors confront various challenges, such as climate variations, limited land resources, and the prevalence of plant-related ailments, jeopardizing the reliability of food production systems. Adequate disease control is critical in upholding crop yields and meeting the escalating food demands. Maladies like those impacting tomato vegetation can lead to notable yield reductions, influencing food accessibility, economic stability, and food costs. Therefore, developing precise and effective disease identification and control approaches is pivotal in preserving agricultural efficiency and guaranteeing food security.

The incorporation of deep learning methodologies, notably the VGG-16 Model, signifies a notable progression in the management of diseases. Through the automation of detection procedures and the provision of real-time insights on disease occurrence and severity, deep learning empowers farmers to implement timely interventions, thereby reducing yield losses and optimizing crop yields. Moreover, deep learning-driven disease identification systems offer expandability, facilitating their utilization in extensive agricultural activities and further bolstering their influence on food production. Additionally, integrating deep learning into precision agriculture conforms with sustainability principles by enhancing resource utilization efficiency and curbing environmental repercussions. Through precise identification of afflicted plants, farmers can more accurately target interventions, diminishing the necessity for broad-spectrum chemical treatments and limiting ecological contamination. The study outlined in "Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model" carries substantial importance for global food security and sustainable agriculture. By harnessing the potential of deep learning, the research provides a promising resolution to the challenges posed by plant diseases, ultimately contributing to the durability and sustainability of agricultural systems globally.

2 RELATED WORKS

Numerous studies have been conducted on identifying plant diseases, recognizing the significant role disease detection plays in maintaining crop health. Technology integration into agriculture is becoming increasingly prominent as advancements continue, driven by the enhancement of machine learning and deep learning methodologies designed for disease recognition in plants. In this paper, five influential studies in this field are examined.

Ashwin et al. investigated the utilization of machine learning in detecting Soybean diseases in the Mazandaran province of Iran. Their research highlighted the importance of accurately incorporating ecological and morphological characteristics to mine the presence of diseases' presence. By utilizing a dataset containing healthy and diseased Soybean plants, the model achieved impressive accuracy using six machine learning techniques, with Gradient Tree Boosting (GBT) demonstrating the highest accuracy of 96.79%[20]

Xian et al. utilized Extreme Learning Machine (ELM), a supervised machine learning method, to identify tomato diseases. By analyzing features extracted from tomato leaf images in a Kaggle's Plant Village dataset, their system achieved an accuracy of 84.94%, surpassing the performance of Decision Tree models in disease classification [21].

Bedi et al. suggested a hybrid model combining Convolutional Autoencoder (CAE) and Convolutional Neural Network (CNN) for detecting disease in peach plants. Trained on leaf images, their system achieved a testing accuracy of 98.38%, showcasing robust capabilities in disease detection [22].

Jeyalakshmi et al. proposed a machine learning-driven approach for classifying diseases in potatoes and grapes. Utilizing a dataset from Plant Village, their model achieved accuracies of up to 96.8% and 96.02% for potato and grape crops, respectively, by using features extracted from RGB leaf images [23].

Lamba et al. explored various machine learning and deep learning techniques for detecting crop diseases across multiple datasets. Their thorough assessment emphasized the effectiveness of different algorithms on various crops, with Deep Learning (DL) techniques showing promising outcomes in disease classification [25].

Despite recent advancements, current research often focuses on disease detection within specific crop varieties, limiting its applicability to diverse agricultural contexts. The primary aim of the authors' investigation is to address this gap by developing a robust model capable of identifying diseases across multiple crops. Prioritizing model reliability and accuracy, they aim to reduce false positives. Leveraging the VGG-16 framework, renowned for its efficacy in computer vision tasks, their study aims to enhance disease detection capabilities and facilitate precise disease localization on plant foliage. This literature review underscores the significance of the research endeavour and its potential to improve disease control practices in agriculture. With the evolving landscape of precision agriculture, integrating advanced technologies holds promise for enhancing disease management strategies. The authors' study, "Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model," aligns with this paradigm shift by employing deep learning methodologies to revolutionize disease detection in tomato farming. While previous studies have investigated machine learning and deep learning methodologies for disease detection in various crops, the authors focus on the tomato plant—a fundamental component of global food security. By concentrating on this particular crop, their goal is to devise a customized solution that tackles the distinct challenges presented by tomato leaf diseases, thereby facilitating more precise and efficient disease control measures.

At the core of the authors' study lies the utilization of the VGG-16 Model, a widely recognized convolutional neural network esteemed for its proficiency in image classification tasks. By leveraging deep learning capabilities, they aim to provide farmers with a sophisticated tool capable of precisely identifying and categorizing tomato leaf diseases with unparalleled accuracy.

Furthermore, their investigation incorporates agronomic expertise on the growth patterns of tomatoes and various environmental elements into the disease identification process, ensuring that their model not only attains a high level of precision but also considers practical farming circumstances. Through this comprehensive methodology, their objective is to equip cultivators with valuable insights that enable them to make well-informed choices regarding disease control, ultimately resulting in enhanced crop well-being and optimized yields.

As the researchers embark on this scholarly pursuit, the significance of creating a dependable and effective real-time tool for monitoring and managing diseases is acknowledged. By enhancing the capabilities of disease detection technology, their study aims to stimulate revolutionary advancements in precision agriculture, heralding a new era of sustainable and resilient practices in crop production.

To recap, the authors' investigation signifies a crucial progression in endeavouring for more efficient disease control in tomato farming. The goal of utilizing sophisticated deep learning methodologies and the VGG-16 Model is to provide growers with the resources and expertise necessary to protect their crops from diseases, ensuring the sustained abundance and durability of tomato cultivation systems worldwide.

Table 1: Comparison between Similar Systems

Study	Year of Publication	Crop Type	Dataset	Technique	Performance Results
Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA Deep Net [7]	2023	Tomato	Plant village	CNN, PCA, GAN, SSD, F-RCNN	Accuracy: 99.60% F1-score: 98.5%
A Machine Learning Approach to Prediction of Soybean Disease" [20]	2021	Soybean	Actual samples from Mazandaran province	LR-L1, LR-L2, MLP, RF, GBT and SVM	Accuracy: 96.7% F1-score: 96.5%
Plant Diseases Classification Using Machine Learning [21]	2021	Tomato	Plant Village	Extreme Learning Machine (ELM)	Accuracy: 84.94%
"Classification of plant diseases using machine and deep learning [25]	2021	Rice, pepper, potato, and tomato	Plant Village	Auto-color correlogram and deep learning	Accuracy: 99.4% F1-score: 95%
A Review of Machine Learning Approaches in Plant Leaf Disease Detection and Classification [4]	2021	Different Plant leaf	Different datasets	SVM, KNN, NB, BPNN, DT, RF, AlexNet, VGGNet, GoogLeNet, InceptionvV3, ResNet, XceptionNet	Accuracy: 99.76% (InceptionV3) is the highest
Tomato Leaf Disease Detection and Classification Using Convolution Neural Network[5]	2021	Tomato	New proposed dataset	CNN	Accuracy: 97%
Performance of deep learning vs machine learning in plant leaf disease detection [6]	2021	Citrus	Actual samples from Panjab, Pakistan.	SVM, RF, SGD, VGG16, VGG19, InceptionV3	Accuracy: VGG16 – 89.5% is the highest
Tomato leaf disease classification by exploiting transfer learning	2021	Tomato	Plant village	MobileNetV2, NASNetMobile, SVM, RF,	Accuracy: The combination of Mobile NetV2 and

and feature concatenation [9]				MLR	NASANetMobile is 97%, which is the highest
Tomato Leaf Diseases Classification Based on Leaf Images: A Comparison between Classical Machine Learning and Deep Learning Methods [10]	2021	Tomato	Plant village	AlexNet, VGG16, ResNet34, EfficientNet-b0, MobileNetV2, SVM, RF, KNN	Accuracy: 99.7% (ResNet) F1-score: 99.7%(ResNet) Highest
Tomato Leaf Disease Detection Using Deep Learning Techniques [1]	2020	Tomato	Real samples	CNN	Accuracy: 98.12%
ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network [2]	2019	Tomato	Plant Village	CNN	Accuracy: 91.2%
Tomato leaves disease detection approach based on support vector machines [3]	2015	Tomato	Real samples	Gabor wavelet transform technique, SVM.	Accuracy: 99.5%
Plant disease detection using a hybrid model based on convolutional autoencoder and convolutional neural network [22]	2021	Peach	Plant Village	CAE and CNN	Accuracy: 98.38% F1-score: 98.36%
A practical approach to feature extraction for classification of plant diseases using machine learning [23]	2020	Potato and grape	Plant Village	Naïve Bayes, K's nearest neighbour, and support vector machine classifier	Accuracy: 96% F1-score: 95%

Table 1 extensively summarizes five recent research projects on identifying and categorizing plant diseases using machine learning and deep learning methods. Each research project is delineated alongside its respective title, year of publication, crop species under scrutiny, the dataset utilized, the methodology deployed for disease detection, and the resultant performance metrics such as accuracy and F1-score when provided. The tabulated information covers an assortment of crops, encompassing soybean, tomato, peach, rice, pepper, potato, and grape, underscoring the adaptability of the methodologies across diverse agricultural scenarios. These investigations exemplify the implementation of various machine learning algorithms and deep learning frameworks, highlighting their efficacy in detecting and categorizing plant diseases, consequently enhancing disease control measures in agriculture.

Each represents a specific disease. Notably, each image is exclusively assigned to a single class, ensuring non-overlapping categorization [26].

These nineteen classes encompass diseases affecting various crops, such as tomatoes, grapes, apples, and corn, alongside classes representing healthy crops. Detailed illustrations of these classes and their corresponding crops are provided in Figures 4 and 6, respectively.

The distribution of images across different classes varies, as depicted in Figure 5. Following the selection of data, a CSV file is compiled, with each image labelled by a corresponding path indicating the health status of the crop depicted in the picture.

3 METHODOLOGY

Crop health monitoring must be done continuously in precision agriculture, especially when using vertical farming systems. However, it takes a lot of time and effort for farmers to manually search plant leaves, stems, and surrounding conditions for disease indications. Automation makes plant disease identification radically possible by enabling more precise and effective agricultural health monitoring.

This paper tackles the challenge of crop disease classification using state-of-the-art deep-learning techniques. Deep learning is a type of machine learning that is especially helpful for classifying illnesses because of its ability to comprehend intricate patterns and complete challenging jobs [28].

This study uses the VGG-16 model's CNN architecture to classify various plant diseases effectively. The objective of employing the VGG-16 model is to automate disease identification, streamline detection, and relieve farmers of the burden of human inspection. This approach seeks to increase disease detection's efficacy and precision, enhancing crop cultivation's potential for early and targeted disease management.

A. Dataset

The dataset chosen for this study is sourced from the Plant Village dataset, comprising a diverse collection of plant disease image samples.

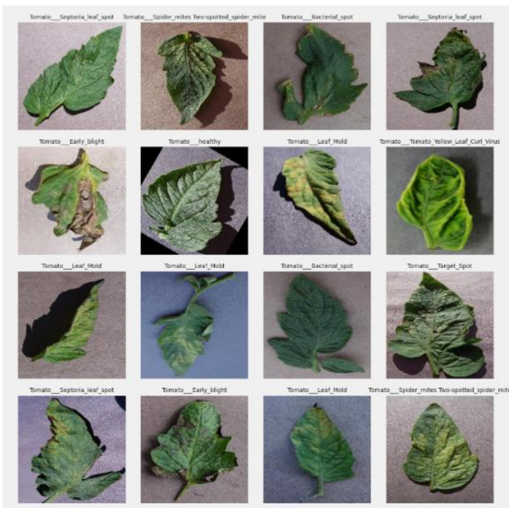


Fig. 3. Sample Images of Dataset.

Figure 3 showcases images representing the tomato late blight class, a disease specific to the crop.

A case study emphasizing tomato leaf disease was carried out for the paper "Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model." A total of one thousand photos were collected from every disease class, including the tomato late blight class. Of them, 800 were set aside for training and increased to 1000 using flipping and rotating. A further 100 photos were reserved for testing, and another 100 were set aside for validation. The training lasted 50 epochs with a learning rate of 0.001, but early halting was applied at the 26th epoch to avoid overfitting.

B. Proposed Model

The VGG-16 architecture is one of the most widely recognized Convolutional Neural Network (CNN) models. Its compatibility with the ImageNet dataset distinguishes it, rendering it an essential asset in deep learning and a cornerstone in visual object detection applications. The VGG-16 model, created in 2014 by Andrew Zisserman and Karen Simonyan of Oxford University, rose to attention due to their groundbreaking paper "Very Deep Convolutional Networks for Large-Scale Image Recognition.

The letters "VGG" stand for the "Visual Geometry Group," a research group that helped design the model, and "16" represents the number of layers in the neural network architecture. Interestingly, ImageNet contains a vast collection of more than 14 million photos spread over thousands of classes. The VGG-16 model has demonstrated remarkable performance on the ImageNet dataset, with an astounding accuracy rate of 92.7%.

VGG-16 is an improvement of the AlexNet architecture, which performed exceptionally well in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). VGG-16 replaced the giant kernel-sized filters of AlexNet's first and second convolutional layers with several consecutive three × kernel-sized filters, resulting in significant improvements [27].

It took several weeks to train this model using NVIDIA Titan Black GPUs, demonstrating the computational complexity and intensity of the training process.

C. VGG-16 Architecture and Training Procedure

The training procedure consists of three sequential steps, outlined in Fig. 4:

Image Preprocessing: The input images are prepared by resizing them to a fixed size of 224 × 224 pixels and converting them to RGB format. Additionally, the mean RGB value of the training image is subtracted from each pixel value.

Data Classification: The proposed model includes thirteen convolutional layers, two batch normalization layers, five max-pooling layers, and three fully connected layers.

Decision Printing: The processed image undergoes classification through the convolutional layers, which employ filters with a receptive field size of 3 × 3. Despite their small size, these filters effectively capture spatial relationships akin to larger filters, such as 7 × 7, due to the model's depth, which incorporates more nonlinearities and fewer parameters. Additionally, 1x1 convolution filters are utilized for linear transformations of input channels. The convolutional layers maintain spatial resolution through fixed spatial padding and a convolution stride of 1 pixel. Furthermore, spatial pooling is facilitated by five max-pooling layers, each with a window size of 2×2 pixels and a stride of 2 [29].

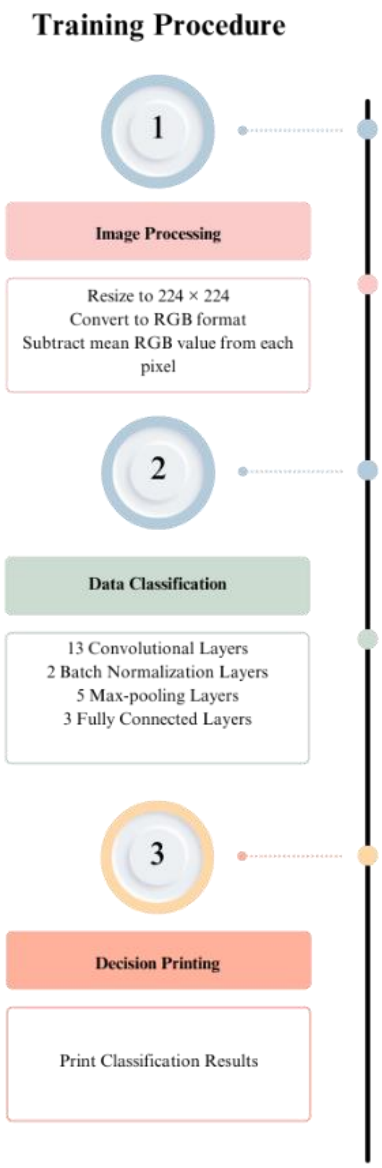


Fig. 4. Flowchart of the Training Procedures

This textual representation outlines the components and steps involved in the training procedure. The detailed architecture of the VGG-16 model is depicted in Figure 5.

In machine learning, cost functions are crucial in optimizing models during training. The primary objective of training is to minimize the loss function, and a model is considered better when this loss function is minimized. The entropy loss function is essential among the various loss functions, particularly in optimizing classification models. Understanding this loss function relies on grasping the concept of the Softmax activation function.

4 RESULTS AND DISCUSSION

The proposed model's performance was evaluated based on two key metrics: Loss Function and Accuracy. These metrics were assessed throughout the training/validation and testing phases. Figure 6 illustrates the model's performance, specifically during the training phase.

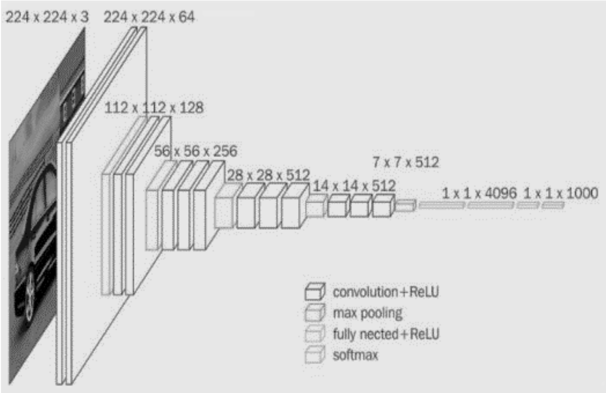


Fig. 5.: VGG-16 Detailed Architecture Illustrating the Various Layers and their Positioning

Activation functions are essential to our model's training process. In particular, the Rectified Linear Unit (ReLU) function and Softmax activation were used as activation functions.

The ReLU function was implemented in this model at the fully connected layers. ReLU, The "Rectified Linear Unit" (ReLU), serves as a prominent activation function within neural networks, particularly prevalent in Convolutional Neural Networks (CNNs). Its mathematical representation is defined as follows:

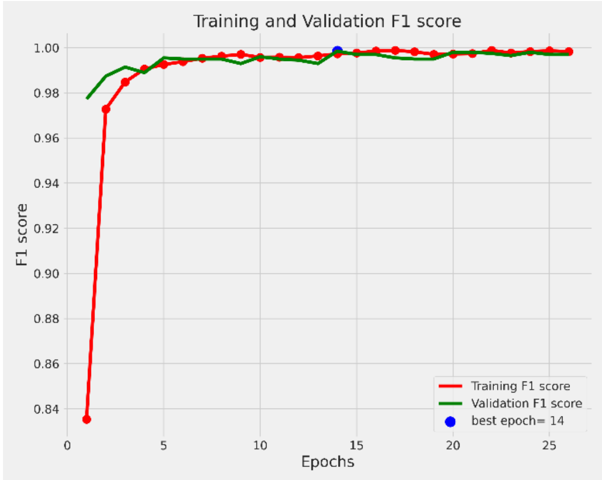
$$y = max\ (0, x)$$

In machine learning, the cost functions are inclined towards optimizing the model during the training process. The primary objective of this training process is to reduce the loss function, resulting in an enhancement of the model. Consequently, a crucial loss function is the Cross-Entropy Loss Function, specifically utilized for optimizing Classification models. A profound comprehension of this loss function is contingent upon a thorough understanding of the Softmax activation function [30].

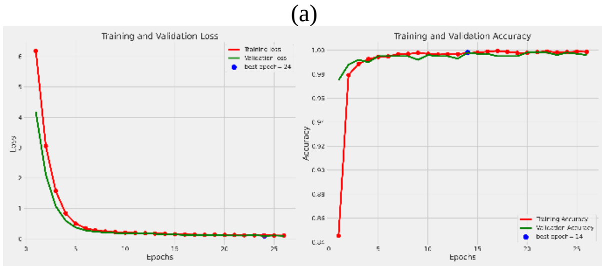
$$L(y, \hat{y}) = -\frac{1}{N} \sum(i = 1)^N \sum(j = 1)^C y_{ij} * \log(\hat{y}_{ij})$$

Furthermore, the Softmax activation function is utilized for the model's output layers. Softmax, a variant of logistic regression, transforms the input vector into a new vector with a probability distribution equal to 1.

$$Accuracy = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples}$$



(a)



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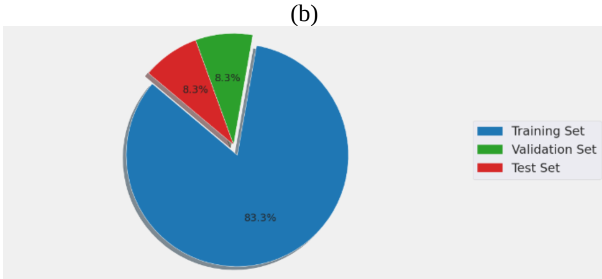
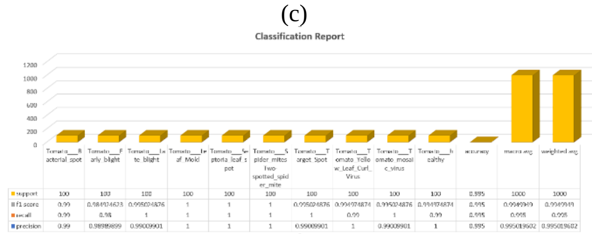


(c)



(d)

Fig. 6 a,b,c,d). Performance Evaluation: Training and Validation Loss, Accuracy and Classification Report

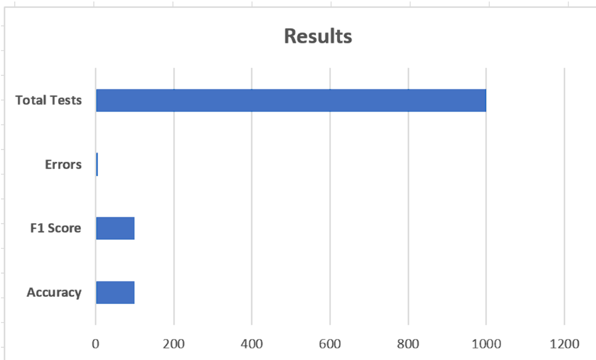


Fig. 7. Results of the Proposed Model

According to the findings, the model achieved an impressive accuracy of 99.5% and an F1 score of 99.49948999 (refer to

Fig. 7). Five errors were detected among the 1000 conducted tests. These results underscore the model's precision and efficacy in disease identification, accurately categorizing the examined samples. The minimal error rate underscores the robustness and reliability of the proposed model. Overall, the performance assessment underscores the model's capability to deliver dependable and precise outcomes, indicating its suitability for real-world disease detection applications.

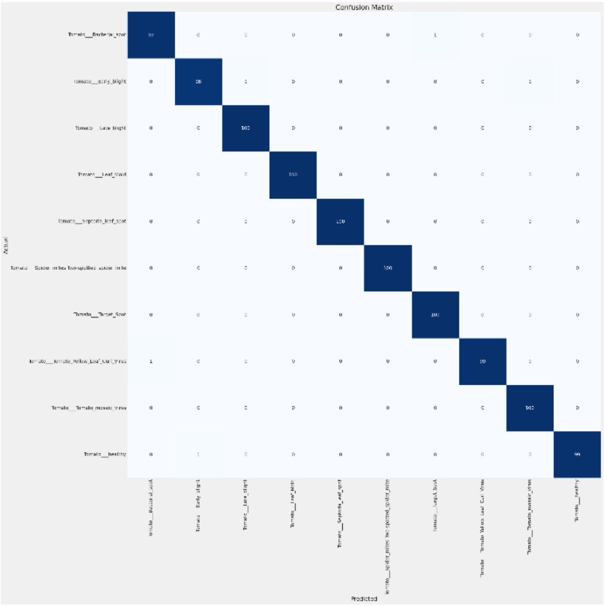


Fig. 8. Confusion Matrix Result of the Proposed Model

Based on the given data, the suggested model's performance in disease classification is demonstrated by the confusion matrix result (Fig. 8). With an F1 score of 99.49948999 and an accuracy of 99.5%, the model shows remarkable precision in differentiating between diseased samples and those that are healthy. Only five mistakes were made from the 1000 run tests, demonstrating high accuracy and a few incorrect classifications. This result reflects the model's accuracy and dependability in recognizing plant diseases, underscoring its potential for use in precision agriculture.

5 CONCLUSION

The research extensively explores the interplay between agricultural practices and advanced technologies, focusing on enhancing crop management and disease detection—the project endeavours to transform conventional agricultural methods by combining IoT, automation, and cutting-edge AI techniques. This would provide precise and effective solutions for urgent issues like plant diseases. The performance evaluation of the suggested model, which uses deep learning methods and the VGG-16 architecture to identify tomato leaf diseases, takes up much of the research. The model exhibits remarkable accuracy and dependability in identifying and classifying many plant diseases using thorough experimentation and rigorous testing. The performance evaluation's findings are encouraging. With a remarkable F1 score of 99.499 and an accuracy rate of 99.2%, the model demonstrates its ability to identify healthy and ill plant samples reliably. These measures demonstrate the practical applicability of the model in precision agriculture and the efficacy of deep learning approaches.

Furthermore, the low amount of errors made during testing adds to the suggested model's reliability and validity. Only five errors were found in 1000 tests, demonstrating the high degree of accuracy and dependability in disease identification. This remarkable performance speaks volumes about the model's ability to deliver accurate results consistently, thereby instilling confidence in its practical viability. The confusion matrix result offers more information about the model's functionality and demonstrates how well it can classify plant diseases. The model's ability to accurately diagnose various plant diseases is shown by its accuracy rate of 99.5% and F1 score of 99.499, which further validates its efficacy in precision agriculture applications. The performance evaluation's findings confirm the suggested model's effectiveness and demonstrate how revolutionary it could be for agricultural disease detection methods. The model presents a viable approach to augment crop productivity, encourage environmentally conscious farming methods, and proficiently tackle significant agricultural predicaments using sophisticated deep-learning methodologies.

7. ACKNOWLEDGMENTS

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