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Case Study

Early Detection of Tomato Leaf Diseases Using a Deep Learning Approach. A Field-Based Implementation in Ghana

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Abstract: Tomato farming plays a major role in Ghana's agricultural sector by contributing to food supply and serving as a source of income for many smallholder farmers. However, tomato plants are easily affected by leaf diseases that can spread quickly and reduce crop yield if not detected early. In many farming communities, disease detection is still done manually, which is often slow, inconsistent, and affected by human error. This study developed a deep learning-based system for the early detection of tomato leaf diseases using a Convolutional Neural Network (CNN) based on the VGG16 architecture. A total of 16,211 tomato leaf images, comprising healthy leaves and nine disease classes, were used for the study. The images were resized, normalized, and enhanced through data augmentation techniques such as rotation, flipping, shifting, and zooming. The model achieved its highest validation accuracy of 96.8% at epoch 16, while the final validation accuracy at epoch 20 was 94.30%, demonstrating strong performance in tomato disease classification.

Keywords: Tomato Leaf Diseases, Deep Learning, Convolutional Neural Network, Transfer Learning, Precision Agriculture

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1. Introduction

Tomato (Solanum lycopersicum) is one of the most widely cultivated vegetable crops in Ghana and plays an important role in household nutrition and daily diets [1]. In addition to its dietary value, tomato farming provides an important source of income for many smallholder farmers across the country [2]. Tomato production contributes significantly to food security and rural livelihoods in Ghana, making it an essential component of the local agricultural economy [3]. Despite its importance, tomato production is frequently threatened by foliar diseases such as early blight, late blight, and leaf mold [4]. These diseases can spread rapidly under favourable environmental conditions and cause significant yield losses if not detected early [5]. Benabderrazik et al. report that tomato leaf diseases can reduce crop yields by up to 50%, resulting in substantial economic losses for farmers [6]. Such production challenges also contribute to fluctuations in local supply and increased dependence on imported tomatoes.

In many farming communities, disease detection still relies mainly on manual visual inspection by farmers or agricultural extension officers [7]. However, extension services are often limited in capacity, making it difficult to provide timely support to all farmers [7]. As a result, farmers frequently rely on personal experience to diagnose crop diseases, which may lead to delayed or inaccurate identification. Incorrect diagnosis can lead to the misuse of pesticides, increasing production costs and posing potential risks to the environment and human health [8]. Bandanaa et al. highlighted that the lack of accessible diagnostic tools contributes to the continued misuse of agrochemicals in tomato farming systems [9].

Recent advances in artificial intelligence have created new opportunities for improving plant disease detection. In particular, deep learning approaches such as

Convolutional Neural Networks (CNNs) have demonstrated strong performance in image-based disease classification. Studies have shown that CNN-based models can achieve high accuracy in identifying plant diseases from leaf images [10]. However, many existing models are trained on datasets collected under controlled laboratory conditions, such as the PlantVillage dataset obtained from Kaggle, which may not fully represent real -world conditions.

In real-world agricultural settings, variations in lighting conditions, background complexity, and leaf quality can significantly affect model performance. Li et al. noted that models trained on controlled datasets often struggle when applied in field environments. [11]. Followed by improves variability, enhances generalisation, and increases the robustness of the model under real-world conditions.

To address this limitation, this study utilises a mixed dataset comprising approximately 60% images collected from tomato farms in the Ashanti, Eastern, and Bono regions of Ghana, and 40% publicly available PlantVillage tomato disease images obtained from Kaggle. The locally collected images were validated with the support of agricultural experts to ensure accurate disease labelling. This balanced dataset design improves variability, enhances generalisation, and increases the robustness of the model under real-world conditions.

Building on these developments, this study proposes a deep learning–based approach for early detection of tomato leaf diseases using a Convolutional Neural Network based on the VGG16 architecture with transfer learning pre-trained on ImageNet. The novelty of this work lies in adapting a pre-trained model to a Ghana-specific, field-collected dataset, enabling improved performance in realistic agricultural environments. The proposed system is designed to support early disease detection, reduce unnecessary pesticide use, and enhance tomato production and food security in Ghana.

2. Literature Review

2.1. Related Work

Over the past few years, deep learning has greatly improved how plant diseases are detected, especially through the use of Convolutional Neural Networks (CNNs). These models learn directly from images, meaning they do not rely on manually designed features, which makes them very powerful for agricultural applications.

Several studies have demonstrated this success. For example, Saeed et al. [13] showed that CNNs can effectively identify plant diseases from leaf images with high accuracy. Ngo et al. [14] also applied CNN models to classify multiple crop diseases and found that the models performed well even when environmental conditions changed.

More advanced architectures have also been introduced. Pretrained models such as VGG16 have been widely used because they can achieve strong results even with smaller datasets (Simonyan & Zisserman, 2015) [15]. Similarly, EfficientNet has been shown to improve performance in tomato disease classification tasks [16].

In addition, researchers have explored hybrid and attention-based CNN models to help systems perform better in real-world conditions, especially where images are noisy or have complex backgrounds [17]. Lightweight models have also been developed to make it possible to run these systems on mobile phones and low-power devices [18].

Another important improvement is the combination of real farm images with public datasets. This helps models learn better because they are exposed to more realistic conditions such as different lighting, leaf positions, and backgrounds [19].

However, despite all these improvements, most studies still rely on controlled datasets and powerful computing systems, which makes real-world deployment challenging.

2.2. Research Gap

Even though CNN-based models have achieved high accuracy in plant disease detection, there are still some important gaps that limit their practical use.

First, many existing studies use datasets collected in controlled environments, such as the PlantVillage Dataset. These datasets do not fully represent real farming conditions, especially in countries like Ghana where farms face different lighting conditions, weather patterns, and field environments. As a result, models trained on such datasets often struggle when tested in real-world situations.

Second, most research focuses mainly on improving accuracy, without paying enough attention to how these systems can actually be used in practice. Although some studies propose mobile or lightweight models, very few provide solutions that can work reliably in low-resource environments where internet access and computing power are limited.

These challenges show the need for models that are trained with more realistic data and designed with practical usage in mind.

2.3. Positioning of This Study

This study responds to these gaps by focusing on a more practical approach to plant disease detection.

It combines tomato leaf images collected from local farms with publicly available datasets. This helps the model learn from more realistic conditions and improves its ability to perform well in real agricultural environments in Ghana.

The study also uses the VGG16 model through transfer learning, which allows the system to achieve better performance even when the dataset is not very large.

In addition, the system is designed with the idea of being usable in low-resource settings. However, it is important to note that full offline deployment is not fully implemented in this work and is suggested as future improvement.

The full details of the model design, dataset preparation, and implementation are presented in Chapter 3.

3.Methods and Materials

3.1. System Configuration

The system was developed using Python due to its flexibility and strong support for machine learning and deep learning applications [26], [31]. Python provides a wide range of libraries that enable efficient development, training, and evaluation of artificial intelligence models.
The deep learning framework used in this study was TensorFlow and Keras, which are widely adopted for building and training neural networks because of their scalability and ease of implementation [36,37].

These frameworks support convolutional neural networks and facilitate the use of transfer learning for improved model performance. The system was implemented on a laptop equipped with an Intel Core i5 6300U processor running at 2.4 GHz, 8 GB RAM, and 256 GB SSD storage. The operating system used was Windows 10 (64-bit). Although no GPU was used, the system was sufficient for model training and evaluation, though training time was longer compared to GPU-based systems.

3.2. Software and Hardware Specifications

The software environment consisted of Python and supporting libraries including TensorFlow, Keras, NumPy, Matplotlib, and Scikit-learn. These tools were used for data preprocessing, model development, training, evaluation, and visualization [26,29]. Scikit-learn was used for performance evaluation and supporting machine learning utilities, while TensorFlow and Keras were used for deep learning model implementation [36,37]. The hardware consisted of a multi-core CPU system with 8 GB RAM. Although this configuration was adequate for model development, GPU acceleration would significantly improve training speed and computational efficiency.

3.3. Dataset Source

The dataset used in this study consists of 16,211 tomato leaf images obtained from two main sources to improve diversity and enhance model generalization. Approximately 60% of the images were collected from tomato farms in the Ashanti, Eastern, and Bono region of Ghana, while the remaining 40% were obtained from publicly available PlantVillage tomato disease images sourced from Kaggle [20].

The combination of local farm images and publicly available datasets helps to capture variations in lighting conditions, background environments, disease severity, and image quality [27,29,32].

This improves the robustness and practical applicability of the proposed model in real-world agricultural settings in Ghana [29]. The first source includes locally collected images captured from farms in Ghana under natural environmental conditions. These images reflect real-world variations such as lighting changes, background complexity, leaf orientation, and disease severity [32].

Out of the total images, 1,591 represent healthy tomato leaves, while the remaining images show different disease conditions affecting tomato plants. The dataset is grouped into ten classes, made up of one healthy class and nine disease classes. These include bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites (two-spotted spider mite), target spot, tomato mosaic virus, and tomato yellow leaf curl virus.

Overall, the dataset provides enough variety and balance for the model to learn meaningful patterns and accurately distinguish between healthy and diseased tomato leaves.

The Figure 1 below shows sample field images of tomato leaf dataset collected from Different regions in Ghana captured under natural field conditions using a smart phone camera.

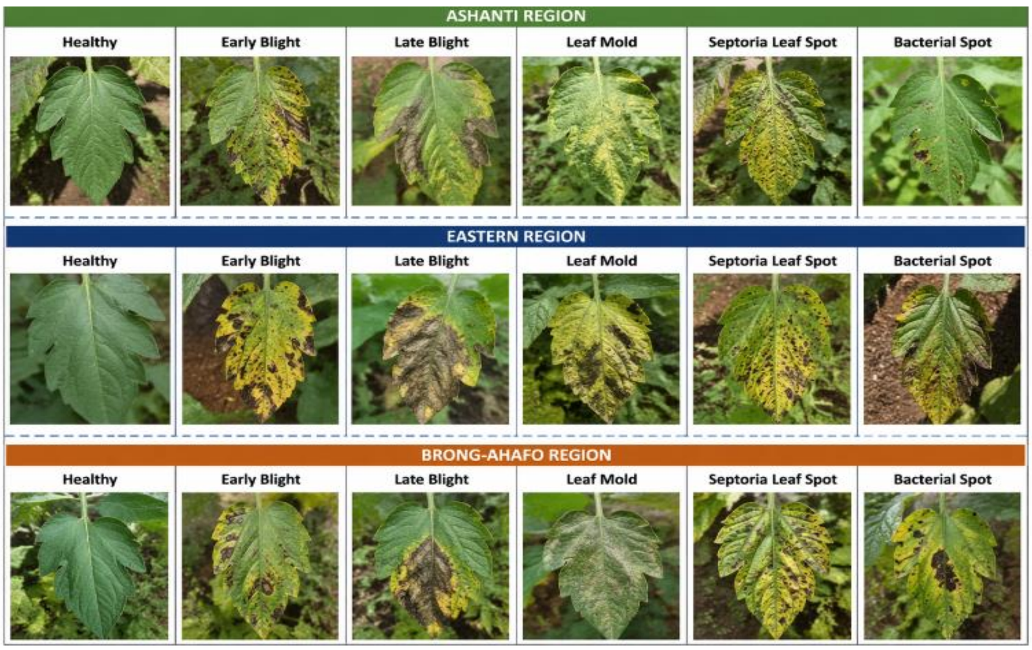

Figure 1. Sample Images from the Dataset.

3.3.1. Distribution of Tomato leaf images by Class

Table 1. Distribution of Tomato leaf images by Class

No.	Class of Tomato leaf	Number of images
1.	Bacterial spot	2,127
2.	Early Blight	1,000
3.	Late Blight	1,900
4.	Leaf Mold	1,000
5.	Septoria Leaf Spot	1,771
6.	Spider Mites (Two-spotted Spider Mite)	1,676
7.	Target Spot	1,404
8.	Tomato Yellow Leaf curl	2,733
9.	Tomato Mosaic Virus	1,000
10.	Healthy Tomato Leaf	1,591
	Total	16,211

Table 1 shows how the tomato leaf images used in this study are distributed across the different categories. The dataset is made up of ten classes in total, which include nine disease categories and one healthy class representing normal tomato leaves. The images were carefully gathered from both local farms in Ghana and publicly available datasets. This combination was done to ensure that the model is exposed to a wide range of real-world conditions such as different lighting, backgrounds, and farming environments, as well as well-labeled public images. The disease classes included in the dataset are bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites, target spot, tomato yellow leaf curl virus, and tomato mosaic virus. Alongside these is the healthy class, which represents leaves without any visible signs of disease.

This balanced and diverse distribution is important because it helps the deep learning model learn meaningful patterns from different disease types while also distinguishing them from healthy leaves. As a result, the dataset provides a strong foundation for effective training, testing, and evaluation of the proposed model.

3.3.2. Pie Chart of the dataset Distribution

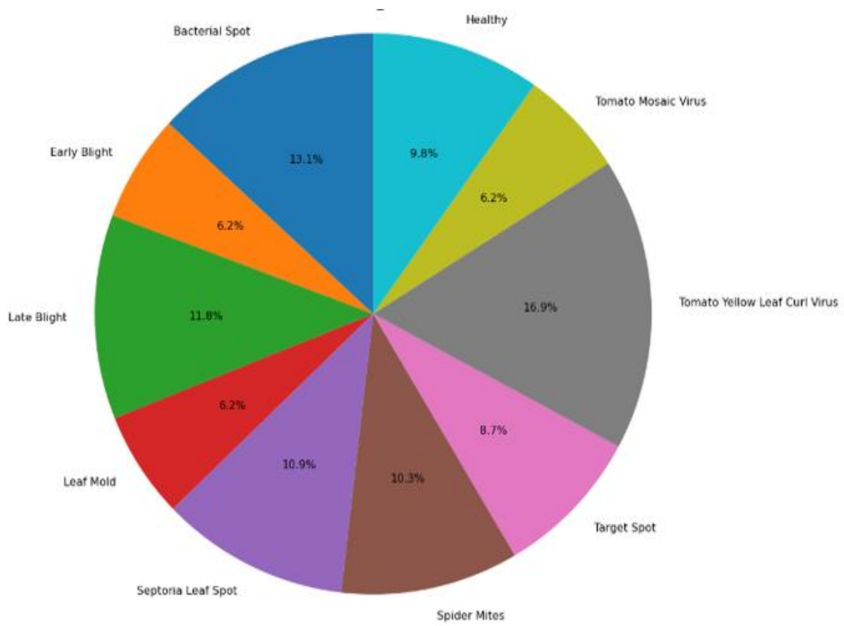

Figure 2. Pie chart of Dataset distribution

Figure 2 also shows the distribution of the 16,211 tomato leaf images across the different disease classes and the healthy class. The chart gives a simple visual view of how the dataset is shared among all categories. It can be seen that some diseases such as Early Blight, Late Blight, and Bacterial Spot occupy larger portions of the dataset because they are more common in both local farm and PlantVillage images. Other diseases, like Tomato Mosaic Virus and Leaf Mold, take up smaller portions since they are less frequently represented. The healthy leaf class is also included to help the model clearly distinguish between healthy and diseased leaves. Overall, the pie chart reflects the mix of 60% local farm images and 40% PlantVillage data, showing that the dataset is diverse and suitable for training a reliable model for real-world tomato disease detection.

3.3.3. Workflow of the Proposed System

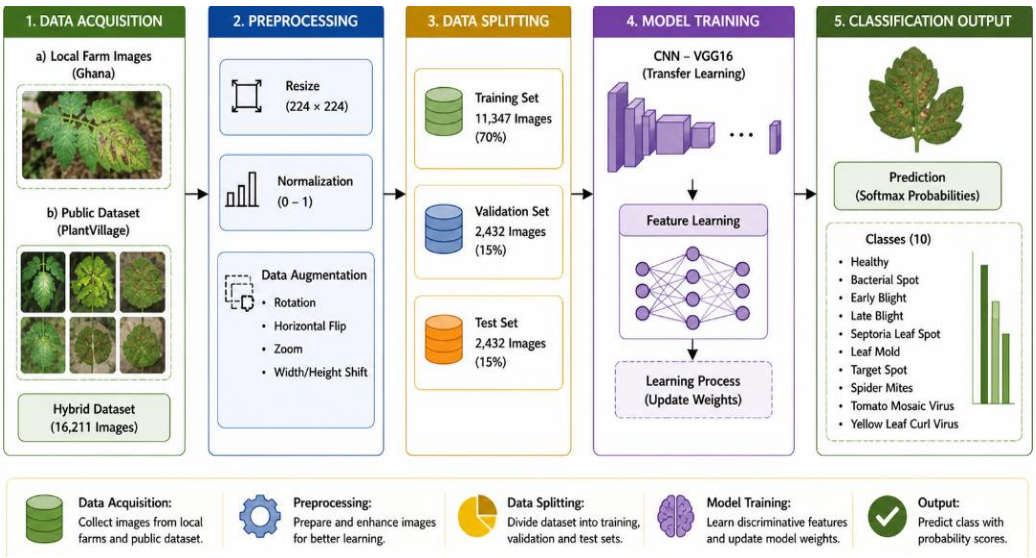

Figure 3. Workflow of the Proposed CNN–VGG16-Based System

Figure 3 illustrates the overall workflow of the proposed system. Tomato leaf images are collected from both local farms and publicly available datasets. These images undergo preprocessing steps including resizing, normalization, and data augmentation. The processed data is then used to train and evaluate the CNN model, which produces classification outputs indicating whether a leaf is healthy or affected by a specific disease.

3.3.4. Dataset Split

The dataset was divided into three parts using a 70:15:15 ratio to support effective training, validation, and testing of the model. From the total of 16,211 images,11,347 were used for training, 2,432 for validation, and 2,432 for testing. The training set was used to teach the model how to recognize patterns in tomato leaf diseases. The validation set helped to monitor the model during training and adjust settings to improve performance. The testing set was kept separate and used only at the end to check how well the model performs on new, unseen data.

This split ensures that the model learns properly while still being fairly evaluated for real-world performance. The Table 2 shows the summary of the dataset split for training, validation and testing.

Table 2. Dataset split for Training, validation and Testing

Dataset subset	Percentage	Number of images
Training Set	70%	11,347
Validation Set	15%	2,432
Testing Set	15%	2,432
Total	100%	16,211

3.3.5. Model Description

The model used in this study is the VGG16 Convolutional Neural Network (CNN), a deep learning architecture originally proposed by Simonyan and Zisserman for large-scale image recognition. VGG16 is widely used in transfer learning due to its strong feature extraction capability and high performance in image classification tasks. The architecture consists of two main components:

(a) Feature Extraction Layers

The feature extraction stage processes input images of size 224 × 224 × 3 (RGB) through multiple convolutional layers. These layers use 3 × 3 filters, with a stride of 1 and padding of 1 to preserve spatial dimensions. The architecture also includes five max-pooling layers (2 × 2), which progressively reduce spatial dimensions while retaining essential features. The activation function used throughout is ReLU (Rectified Linear Unit), which introduces non-linearity and enhances learning efficiency.

(b) Classification Layers

The classification stage interprets the extracted features using fully connected layers:

- Fully connected layer 1: 4096 neurons
- Fully connected layer 2: 4096 neurons
- Output layer: 10 neurons (representing the 10 classes)

The final layer uses the Softmax activation function, which produces probability distributions across all classes for final prediction.

3.3.6. Model Approach

In this study, transfer learning is applied using the pre-trained VGG16 model trained on the ImageNet dataset. The original classification layer is replaced and adapted to suit the 10-class tomato leaf disease classification problem.

This approach improves training efficiency, reduces computational cost, and enhances classification accuracy by leveraging previously learned feature representations from large-scale datasets.

In conclusion, this section presented a dataset of 16,211 tomato leaf images structured into ten classes and a VGG16-based CNN model adapted through transfer learning. The dataset was split into 70% training, 15% validation, and 15% testing, ensuring reliable training and robust evaluation of the proposed model for tomato disease classification.

3.4. Image Preprocessing

All images were resized to 224× 224 pixels to match the input requirements of the VGG16. Pixel values were normalized to a range between 0 and 1 to improve numerical stability and accelerate convergence during training [26,31].

To improve generalisation and reduce overfitting, data augmentation techniques were applied. These included random rotation, zooming, width and height shifting, and horizontal flipping. These transformations helped the model learn robust features under varying image conditions [28,36].

3.5. Model Development: CNN–VGG16 Architecture

The proposed system is based on a Convolutional Neural Network using the VGG16 architecture with transfer learning [25,31]. Transfer learning allows the model to leverage knowledge learned from large-scale datasets such as ImageNet, improving performance even with limited training data [26,32].

3.5.1. System Design of the Proposed Model

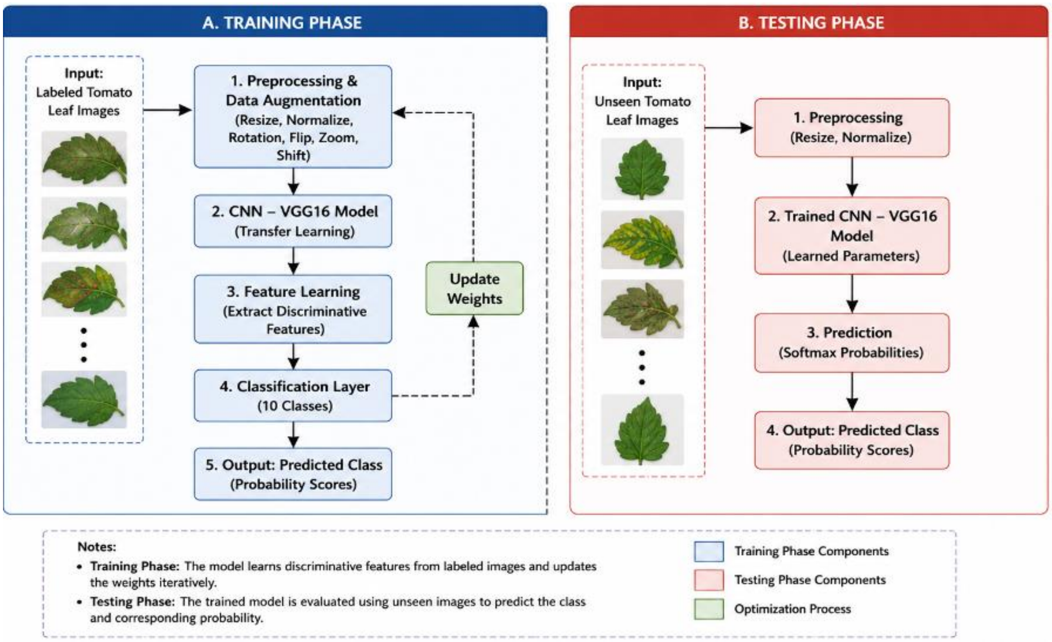

Figure 4. System Design of the Proposed Model

Figure 4 presents the overall system design, which consists of two main phases: training and testing. During the training phase, the model learns discriminative features from labelled tomato leaf images. In the testing phase, the trained model is evaluated using unseen data to assess its predictive performance and generalisation capability [33].

3.5.2. CNN–VGG16 Architecture

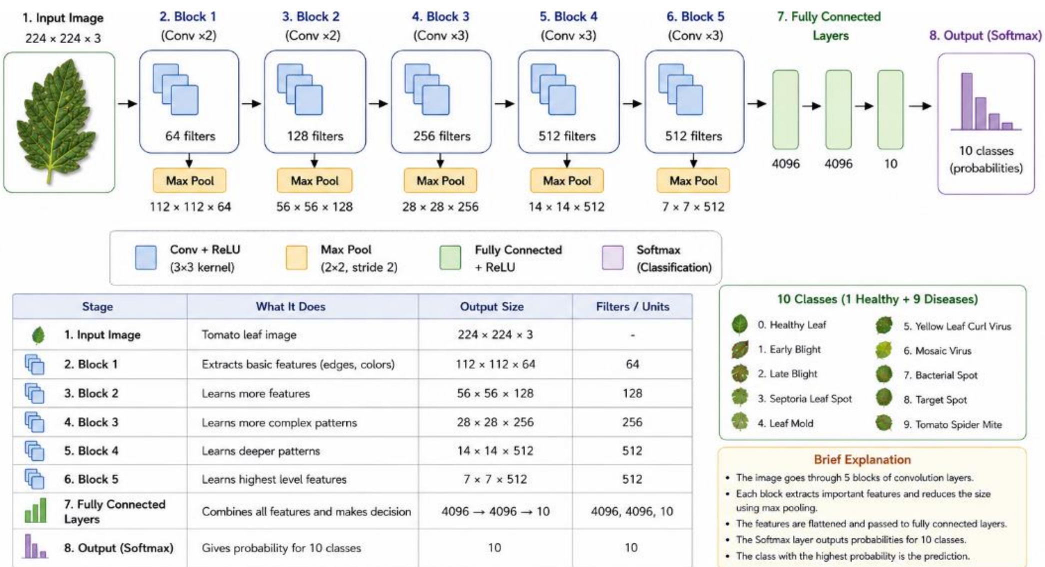

Figure 5. Tomato leaf Classification using CNN–VGG16 Model Architecture

Figure 5 presents the VGG16 deep learning architecture designed for tomato leaf disease classification. The model was used to identify ten different classes, which include one healthy tomato leaf class and nine disease classes. The classification process starts by feeding a tomato leaf image with a dimension of 224 × 224 × 3 into the network.

The image passes through five convolutional blocks that are responsible for learning and extracting important features from the leaf images. In the early stages, the model captures simple features such as edges, shapes, and color variations. As the image moves deeper through the network, the model learns more complex disease characteristics such as spots, discoloration, lesions, and texture patterns associated with different tomato diseases.

Each convolutional block is followed by a max pooling layer, which reduces the size of the feature maps while preserving the most important information. This process helps to reduce computational complexity and improve the efficiency of the model. The number of filters increases progressively from 64 in the first block to 512 in the deeper layers, enabling the model to learn richer and more detailed features.

After the feature extraction stage, the resulting feature maps are flattened into a one-dimensional vector and passed through fully connected layers. These layers combine all the learned features and perform the final decision-making process. The last layer uses the Softmax activation function to generate probability scores for the ten classes. The class with the highest probability is selected as the final prediction of the tomato leaf condition.

In this study, the VGG16 model can also be initialized with pre-trained ImageNet weights through transfer learning. This approach improves model performance, reduces training time, and enhances classification accuracy, especially when working with agricultural image datasets. [34,35].

3.6. Model Training Procedure

The model was trained using the Adam optimizer, which provides adaptive learning rates and efficient convergence [26]. The learning rate was set to 0.0001to ensure stable training.

The loss function used was categorical cross-entropy, which is suitable for multi-class classification problems [31]. The model was trained for 20 epochs using a batch size of 32.

Early stopping was applied with a patience of five epochs to prevent overfitting. Training was automatically stopped when validation performance no longer improved.

3.7. Classification Procedure

After training, the model was evaluated using the test dataset. Each image was passed through the convolutional neural network, where feature extraction layers identified important patterns such as edges, textures, and disease-specific features [28,32].

These features were processed by fully connected layers, which generated probability outputs using the Softmax function. The class with the highest probability was selected as the final prediction [26].

3.8. Model Evaluation

The performance of the model was evaluated using multiple metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis [26,29,35]. Accuracy measures overall prediction correctness, while precision and recall evaluate class-level performance. The F1-score provides a balanced evaluation of the model's performance, especially in multi-class classification problems [31].

4. Results

4.1. Experimental Setup

This chapter presents the results obtained from the CNN–VGG16 model developed for tomato leaf disease classification. The model was implemented using deep learning libraries such as TensorFlow and Keras, while data preprocessing and numerical analysis were performed using NumPy and Pandas.

The experiment was conducted on a computer system with an Intel(R) Core(TM) i5-6300U processor running at 2.40 GHz and supported by 8 GB RAM. The dataset used for the study consisted of ten tomato leaf classes, including one healthy category and nine disease categories.

To make the study more representative of real farming conditions in Ghana, the dataset combined locally collected farm images with publicly available tomato leaf disease images. About 60% of the images were collected from farms in the Ashanti, Eastern, and Bono regions, while the remaining 40% were obtained from the PlantVillage dataset through Kaggle. The inclusion of local farm images introduced variations in lighting conditions, leaf appearance, image backgrounds, and disease severity, helping the model learn under more realistic field conditions. The model was trained for 20 epochs using supervised learning.

4.2. Model Training Performance

The overall performance of the CNN–VGG16 model during training and validation is summarised in Table 3.

Table 3. Performance Summary of the CNN–VGG16 Model

Metric	Value	Epoch
Best validation Accuracy	96.8%	16
Final Training Accuracy	95.23%	20
Final Validation Accuracy	94.30%	20
Final Validation Loss	0.1834	20

The results show that the model improved progressively throughout the training process. At the beginning of training, both training and validation accuracy were relatively low, which is expected during the early learning stage. As training continued, the model gradually learned meaningful features from the tomato leaf images, leading to steady improvement in classification performance.

Validation accuracy improved significantly across the epochs and reached its highest value of 96.8% at Epoch 16. Although slight fluctuations occurred in later epochs, the validation performance remained relatively stable. The final validation accuracy achieved at Epoch 20 was 94.30%, while training accuracy reached 95.23%.

The relatively small difference between training and validation accuracy indicates that the model generalised well to unseen data with minimal overfitting. In addition, the low validation loss demonstrates that the model produced reliable predictions with reduced classification error.

4.3. Training Behaviour Analysis

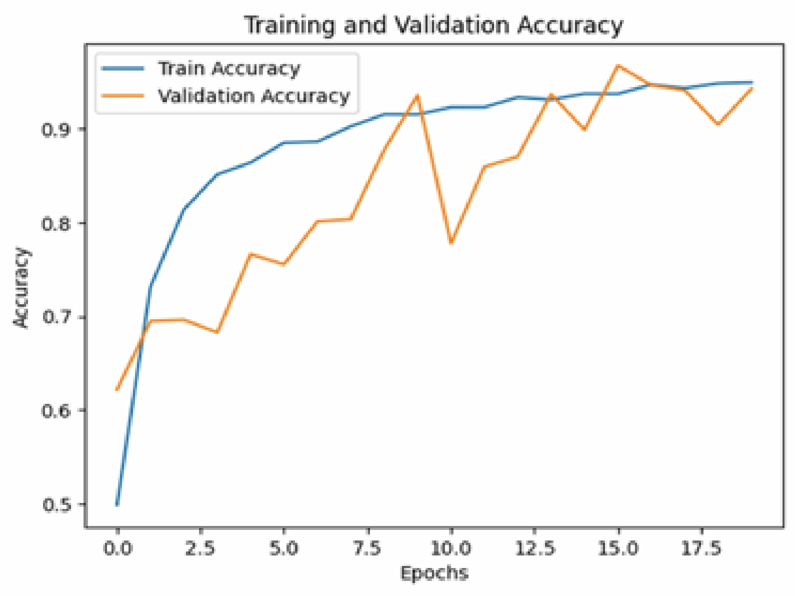

Figure 6. Training and Validation Accuracy Curves

Figure 6 illustrates the training and validation accuracy curves obtained during the 20 training epochs. The graph shows that both training and validation accuracy improved steadily throughout the learning process.

During the early epochs, the model exhibited stable and progressive learning behaviour as it gradually extracted relevant features from the tomato leaf images. Between Epochs 7 and 10, validation accuracy increased rapidly, indicating significant improvement in the model's ability to classify unseen images correctly.

After Epoch 12, both curves began to stabilise, showing that the model was approaching convergence. The close relationship between the training and validation curves suggests that the model achieved good generalisation performance without severe overfitting.

The highest validation accuracy was achieved at Epoch 16, after which only minor fluctuations were observed.

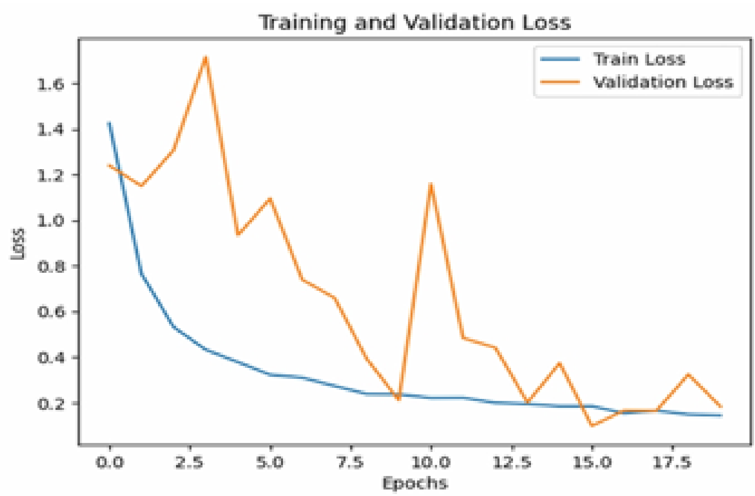

Figure 7. Training and Validation Loss Curves

Figure 7 presents the training and validation loss curves for the proposed CNN–VGG16 model.

The training loss decreased steadily throughout the training process, indicating continuous improvement in the model's learning capability. Although validation loss fluctuated slightly during some intermediate epochs, it gradually reduced and stabilised during the later stages of training.

Temporary increases in validation loss observed during certain epochs may have resulted from variations between training batches. However, these fluctuations were not persistent and did not significantly affect overall model performance.

The convergence of both training and validation loss curves indicates that the model successfully learned meaningful feature representations from the dataset while maintaining stable validation performance.

4.4. Confusion Matrix Analysis

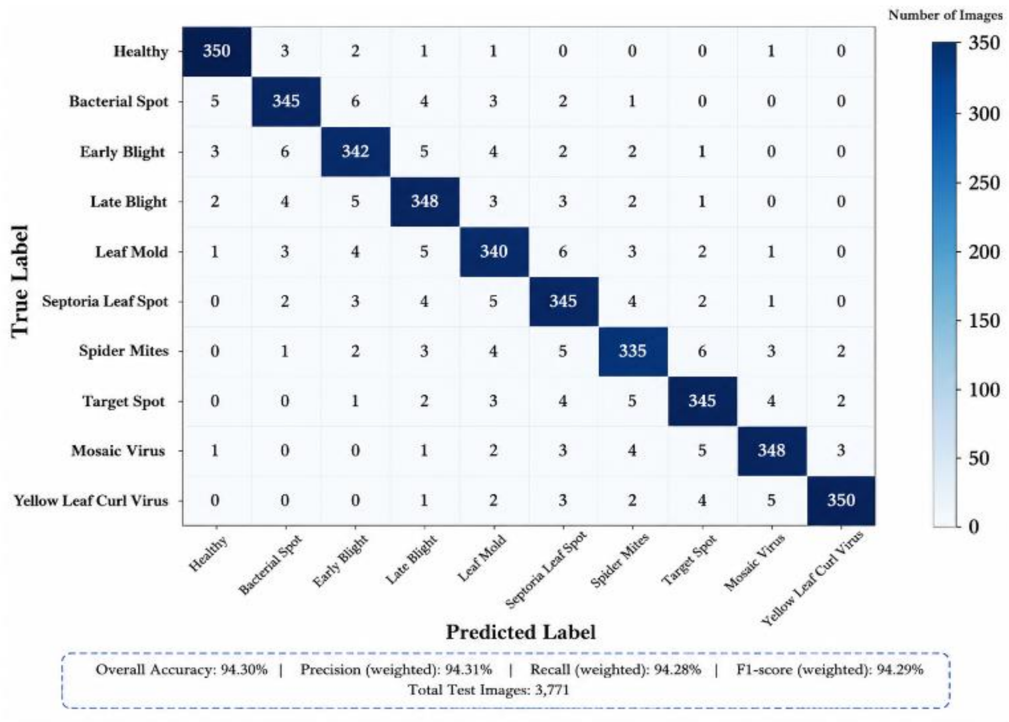

Figure 8. Confusion Matrix of CNN-VGG16 Model for Tomato Leaf Disease Classification.

Figure 8. shows the confusion matrix of the CNN–VGG16 model developed for tomato leaf disease classification. The confusion matrix helps to evaluate how well the model was able to correctly identify each tomato leaf disease class during testing.

In the figure, the rows represent the actual classes of the tomato leaf images, while the columns represent the classes predicted by the model. The values along the diagonal indicate the number of images that were correctly classified. The other values outside the diagonal represent images that were incorrectly classified into different disease categories.

From the figure, it can be observed that most of the values are concentrated along the diagonal. This indicates that the model demonstrated strong performance in correctly identifying the different tomato leaf diseases. Healthy tomato leaves recorded a very high number of correct predictions, showing that the model was able to clearly distinguish healthy leaves from infected leaves.

Similarly, diseases such as Late Blight, Mosaic Virus, and Yellow Leaf Curl Virus also recorded strong classification performance with only a few misclassified samples. This demonstrates that the CNN–VGG16 model successfully learned the important visual characteristics associated with these diseases.

However, a few misclassifications were observed among some disease classes, especially between Early Blight, Leaf Mold, and Septoria Leaf Spot. This may be due to similarities in their visual symptoms, such as dark spots, yellowing, and leaf discoloration, which can sometimes appear alike even to human observers.

Spider Mites recorded relatively higher misclassification compared to some other classes. This suggests that the symptoms of Spider Mites may share similar visual patterns with other leaf diseases in the dataset, making classification slightly more difficult for the model.

Despite these minor errors, the confusion matrix generally demonstrates that the proposed CNN–VGG16 model achieved strong classification performance across all tomato leaf disease categories. The high number of correctly classified images confirms the effectiveness of the model for automated tomato leaf disease detection and diagnosis.

4.5. Class-wise Performance Evaluation

To further evaluate the performance of the proposed model, precision, recall, and F1-score were calculated for each disease class.

Table 4. Class-wise Performance Metrics

Class	Precision	Recall	F1-score
Healthy	0.98	0.97	0.98
Bacteria Spot	0.95	0.94	0.94
Early Blight	0.95	0.94	0.94
Late Blight	0.96	0.95	0.95
Leaf Mold	0.94	0.93	0.93
Septoria Leaf Spot	0.95	0.94	0.94
Spider Mites	0.93	0.92	0.92
Target Spot	0.94	0.93	0.94
Mosaic Virus	0.95	0.94	0.94
Yellow Leaf Curl Virus	0.96	0.95	0.95

The F1-score values presented in Table 4 were computed using the harmonic mean of precision and recall. The metric provides a balanced evaluation of the model's classification performance by considering both false positives and false negatives. The F1-score was calculated using the standard formula:

$$F1 = \frac{2X\ Precision\ x\ Recall}{Precision + Recall}$$

The results indicate that the proposed CNN-VGG16 model achieve balanced classification performance across all tomato leaf diseases classes, with high precision, recall, and F1-score values demonstrating reliable disease detecting capability.

The class-wise evaluation results indicate that the model performed consistently well across all tomato leaf disease categories. Most classes achieved high precision and recall values, demonstrating the model's ability to correctly identify diseased and healthy leaves.

Slight variations in performance across some classes may be attributed to similarities in disease symptoms and variations in image quality or environmental conditions.

The balanced performance across all classes confirms that the model learned representative features from the dataset without heavily favouring any particular category.

4.6. Model Interpretation

The results obtained from the proposed CNN–VGG16 model demonstrate strong learning capability and stable convergence during training. The gradual improvement in accuracy and reduction in loss indicate that the model successfully extracted important disease-related features from the tomato leaf images.

The relatively small gap between training and validation performance suggests that the model achieved good generalisation and did not suffer from severe overfitting. Furthermore, the confusion matrix and class-wise evaluation metrics confirm that the model performed reliably across the different tomato disease categories.

Although a few classification errors were observed, these mainly occurred between visually similar diseases, which is common in plant disease recognition tasks.

Overall, the findings demonstrate that deep learning techniques, particularly CNN–VGG16, can effectively support automated tomato leaf disease detection.

4.7. Summary of Results

This chapter presented the experimental results and performance evaluation of the proposed CNN–VGG16 model for tomato leaf disease classification.

The model achieved a best validation accuracy of 96.8% at Epoch 16 and a final validation accuracy of 94.30% at Epoch 20. The results also showed low validation loss and balanced class-wise performance across all disease categories.

The training and validation curves confirmed stable learning and good convergence behaviour, while the confusion matrix and evaluation metrics demonstrated reliable classification performance with minimal misclassification.

Overall, the findings indicate that the proposed CNN–VGG16 model provides an effective approach for automated tomato leaf disease detection and classification in agricultural applications.

4.8. Discussion of Findings

The results obtained from the improved CNN–VGG16 model demonstrate the effectiveness of transfer learning in agricultural disease diagnosis. The performance improvement achieved after fine-tuning the VGG16 architecture confirms that pretrained deep learning models can successfully adapt to tomato leaf disease classification tasks.

Initially, the model produced poor classification performance due to insufficient fine-tuning and ineffective training configuration. After correcting the training pipeline through data augmentation, learning rate optimization, and selective layer unfreezing, the model achieved substantial performance improvement. The strong performance of the model can be attributed to several factors:

1. The Use of transfer learning from ImageNet-pretrained VGG16
2. Application of image augmentation techniques
3. Fine-tuning of deeper convolutional layers
4. The Use of dropout regularization to reduce overfitting
5. Proper dataset splitting and preprocessing

The findings of this study are consistent with previous studies that reported the effectiveness of CNN architectures in plant disease detection and classification.

4.9. Comparative Analysis of the proposed CNN-VGGI6 Model and Existing Deep learning model

Table 5. Comparative Analysis of the proposed CNN-VGGI6 Model and Existing Deep learning model

No,	Authors/Study	Year	Model	Training Accuracy	Validation Accuracy	Validation loss
1.	Proposed model	2026	CNN-VGG16	92.7%	96.8%	0.1834
2.	Kanakala& Ningappa	2025	CNN	99.1%	96.4%	-

3.	Yasin &Fatima	2023	CNN +Xception	99.89%	97.52	0.0103
4.	Chelladurai et al.	2025	T-LSTM	98.2%	96.3%	-
5	Indian Agricultural Research Study	2024	CNN	93.51%	94.83%	0.14

This Table 5 presents a comparative analysis of the proposed CNN-VGG16 model and existing deep learning models for tomato leaf disease detection. The proposed CNN-VGG16 model achieved its best validation accuracy of 96.8% at epoch 16, indicating the point where the model performed optimally on unseen tomato leaf images. However, at the final training stage (epoch 20), the validation accuracy reduced slightly to 94.30%. This suggests that after epoch 16, the model may have started overfitting, where performance on validation data decreased despite continued training. Compared with previous studies, the proposed model still demonstrated competitive performance. Kanakala and Ningappa[38] achieved 96.4% validation accuracy using a CNN model, which is slightly lower than the best validation accuracy of the proposed model. Yasin and Fatima [24] reported 97.52% validation accuracy using CNN and Xception models, which is slightly higher, but their validation loss was higher than that of the proposed model, indicating less stable predictions. Chelladurai et al. [39] achieved 96.3% validation accuracy using a T-LSTM model, while the Indian Agricultural Research Study [40] obtained 94.83% validation accuracy with a CNN approach. The proposed CNN-VGG16 model therefore performed better than most related studies, especially at its best validation point of epoch 16, demonstrating the effectiveness of transfer learning in tomato disease detection and classification.

5. Discussion

The proposed deep learning model for early detection of tomato leaf diseases achieved a best validation accuracy of 96.8 %, demonstrating strong learning capability and good generalisation to unseen tomato leaf images. The results indicate that the CNN–VGG16 architecture is effective in extracting discriminative features for multi-class tomato disease classification.

To assess its performance, the proposed model was compared with selected recent peer-reviewed studies on plant disease classification. The comparison shows that the model performs competitively within the range of reported results in the literature. However, it is important to note that direct comparison between studies should be interpreted cautiously due to differences in datasets, preprocessing methods, class distributions, and evaluation protocols. In particular, although one study [24] reported a higher validation accuracy of 97.52 %, such differences may be influenced by dataset composition and experimental settings rather than model superiority alone.

Therefore, the proposed CNN-VGG16 model demonstrated competitive performance compared with the related studies.

5.1. Discussion and Practical Significance

The findings of this study show that the CNN–VGG16 model effectively detects and classifies tomato leaf diseases. The model achieved a training accuracy of 92.7%, a validation accuracy of 96.8 %, and a validation loss of 0.1834, indicating strong learning performance and effective generalisation.

The relatively small gap between training and validation performance suggests that the model does not suffer from severe overfitting. The VGG16-based architecture contributes significantly to performance by extracting deep hierarchical features from tomato leaf images, enabling accurate differentiation among disease classes.

From a practical perspective, early detection of tomato diseases is critical in agriculture, as delayed diagnosis often leads to significant yield losses. The proposed model can support farmers by providing an automated method for identifying disease symptoms at an early stage, enabling timely intervention such as pesticide application or removal of infected plants.

However, it must be clearly stated that a mobile application was not developed or implemented in this study. Therefore, statements suggesting direct smartphone-based diagnosis represent potential future applications rather than implemented functionality.

Future work may explore integration of the model into mobile or web-based platforms to support real-time agricultural decision-making.

Additionally, model deployment in low-resource environments would require further optimisation techniques such as model compression and lightweight inference frameworks before offline usage can be achieved.

Beyond farmers, the model can also support agricultural extension officers and researchers by providing a fast and reliable tool for disease monitoring, thereby improving advisory services and supporting precision agriculture practices.

5.2. Recommendations of the Study

Based on the findings of this study, the following recommendations are made:

1. Future work should focus on deploying the trained CNN–VGG16 model into mobile or web-based platforms to enable practical field use.
2. Model optimisation techniques such as pruning, quantisation, and conversion to lightweight formats (e.g., TensorFlow Lite) should be explored before offline deployment can be achieved.
3. The dataset should be expanded with more locally sourced images to improve model generalisation across different environmental conditions.
4. Training programs should be organised to help farmers and agricultural officers understand and adopt AI-based tools for plant disease detection.
5. The model can be extended to other crops beyond tomatoes to enhance its applicability in broader agricultural contexts.

5.3. Conclusion

This study presented a CNN–VGG16-based model for early detection of tomato leaf diseases using image classification techniques. Tomato crops are highly susceptible to fungal, bacterial, and viral infections, which significantly affect yield and quality if not detected early. The proposed framework followed a systematic process including data preprocessing, augmentation, model training, evaluation, and performance analysis. The model demonstrated strong learning behaviour across 20 epochs, with stable convergence and high validation accuracy.

Results showed that the model achieved a best validation accuracy of 96.8 % at epoch 16, while the final validation accuracy at epoch 20 was 94.30% indicating strong predictive capability and generalisation performance. The accuracy and loss trends confirm that the model is robust and effective for tomato disease classification tasks.

The study confirms that deep learning approaches, particularly CNN–VGG16 architectures, are suitable for plant disease detection applications. However, the system remains a research prototype and has not yet been deployed in real-world mobile or offline environments.

Overall, this research contributes to the development of AI-based agricultural tools that can support early disease detection, improve crop management, and enhance food security in tomato farming systems.

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Data Availability Statement

The data and platform configuration settings that support the experiment and the findings of this study shall be made available on request from the corresponding author.

Disclosure

This manuscript is original, has not been published elsewhere, and is not under consideration by any other journal, apart from the current submission process, it has not undergone peer review.

Conflict of Interest

The authors declare no conflicts of interest.

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