



Tomato Leaf Disease Classification Using a Mobile-Integrated Deep Learning Framework Based on Custom CNN and ResNet50 Models

Olayiwola C. Adesoba^{1*}, Waliu O. Apena¹, Folasade M. Dahunsi¹, Ayodele M. Ajayi²

¹Department of Computer Engineering, Federal University of Technology Akure, Nigeria

²Department of Crop, Soil and Pest Management, Federal University of Technology Akure, Nigeria

*Corresponding author email: ocadesoba@futa.edu.ng

KEYWORDS

Tomato diseases
Deep learning
TDD-Net
Mobile diagnosis
Precision agriculture

ABSTRACT

Tomato leaf diseases pose a significant threat to crop productivity and require timely diagnosis to minimize yield losses and improve disease management. This study developed and validated a mobile-integrated deep learning framework for automated tomato leaf disease classification using a custom convolutional neural network (TDD-Net) and a fine-tuned ResNet50 model. A heterogeneous dataset comprising 15,549 publicly available and field-acquired tomato leaf images representing bacterial spot, early blight, grey leaf spot, late blight, and healthy leaves was used for model development. Both models were trained under identical optimization settings and evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). The proposed TDD-Net achieved superior performance, attaining a validation accuracy of 98.94%, precision of 0.9882, recall of 0.9863, F1-score of 0.9871, and an AUC of 0.9944, outperforming the fine-tuned ResNet50 across all evaluation metrics. The trained TDD-Net model was subsequently integrated into a FlutterFlow-based mobile application with Firebase support to enable real-time disease diagnosis using smartphone images. The results show that a task-specific convolutional neural network provides highly accurate tomato leaf disease classification while supporting practical deployment through an accessible mobile decision-support system for precision agriculture.

Received 30 June 2026; Revised 13 July 2026; Accepted 30 July 2026; Published 01 October 2026

1.0 INTRODUCTION

Tomato (*Solanum lycopersicum*) is one of the most extensively cultivated vegetable crops worldwide and constitutes an important component of human nutrition, agricultural trade, and food security [1]. Owing to its high nutritional value, versatility in food processing, and economic importance, tomato production has expanded steadily across both developed and developing countries [2]. According to the Food and Agriculture Organization (FAO), global tomato production exceeds 190 million tonnes annually, making it one of the most valuable horticultural commodities worldwide [3]. Besides its contribution to household nutrition through vitamins, antioxidants,

minerals, and dietary fibre, tomato cultivation represents an important source of income for millions of smallholder and commercial farmers. Consequently, maintaining healthy tomato production systems is fundamental to sustainable agriculture, rural livelihoods, and global food supply [4], [5].

Despite its economic significance, tomato cultivation remains highly susceptible to numerous diseases caused by fungi, bacteria, viruses, and environmental stressors. Among the most destructive foliar diseases are bacterial spot, early blight, late blight, and grey leaf spot, each capable of causing severe yield reduction if not detected and managed promptly [6], [7]. Disease outbreaks frequently reduce both crop quantity and market quality, resulting in substantial economic losses through decreased productivity, increased production costs, and excessive pesticide application [8]. In severe epidemics, late blight alone has been reported to destroy entire tomato fields within a relatively short period under favourable environmental conditions [9], [10]. The growing frequency of disease outbreaks, coupled with climate variability and expanding agricultural production, has further increased the need for reliable and timely disease monitoring systems [11].

Early identification of plant diseases remains one of the most effective strategies for minimizing crop losses and improving disease management. Conventional diagnosis is primarily based on visual examination of symptomatic leaves by experienced farmers, agricultural extension personnel, or plant pathologists [12], [13]. Although this approach has been practiced successfully for decades, it is often influenced by the observer's experience and the visual similarity among disease symptoms [14]. Several tomato diseases exhibit overlapping lesion characteristics, chlorosis patterns, and necrotic regions that are difficult to distinguish during the early stages of infection [15]. Furthermore, access to plant pathology experts remains limited in many rural farming communities, particularly within developing countries where extension services are inadequate [16]. These constraints frequently delay disease identification, resulting in inappropriate pesticide application, increased production costs, environmental contamination, and avoidable yield losses [17].

Recent advances in artificial intelligence (AI) have created new opportunities for improving agricultural decision support through automated image analysis. Within precision agriculture, machine learning and deep learning techniques have increasingly been adopted for crop monitoring, disease diagnosis, yield prediction, weed identification, pest detection, and resource optimization [18], [19]. Among these approaches, deep convolutional neural networks (CNNs) have sustained remarkable success in image recognition because of their ability to automatically learn hierarchical visual features directly from raw images without relying on manually engineered descriptors [20]. Their capacity to extract discriminative representations has made CNNs the dominant approach for plant disease classification across numerous crop species [21].

The increasing availability of publicly accessible plant image datasets, advances in graphical processing units (GPUs), and improvements in deep learning frameworks have accelerated research in automated plant disease diagnosis [22], [23]. Early studies showed that deep CNNs could successfully classify healthy and diseased plant leaves with considerably higher accuracy than traditional machine learning methods based on handcrafted features. Subsequent investigations expanded these capabilities through transfer learning, attention mechanisms, residual learning, lightweight convolutional architectures, ensemble models, and hybrid deep learning frameworks [24]. More recently, researchers have explored transformer-based architectures and explainable artificial intelligence techniques to improve both predictive performance and model interpretability.

Several recent investigations have reported encouraging performance for tomato leaf disease classification. Transfer learning models based on ResNet, DenseNet, EfficientNet, MobileNet, Inception, and Vision Transformer architectures have achieved high classification accuracy under benchmark conditions [25], [26]. Similarly, lightweight CNNs have showed considerable potential for deployment on resource-constrained devices such as smartphones and embedded agricultural systems. Other studies have integrated attention mechanisms and feature-fusion strategies to improve recognition of visually similar disease symptoms, while hybrid architectures have combined deep feature extraction with optimized classification layers to enhance predictive performance [27],

[28], [29], [30]. Collectively, these developments support the considerable progress achieved in applying deep learning to plant disease diagnosis.

Nevertheless, a careful examination of the recent literature reveals several important limitations that continue to restrict practical deployment. First, a substantial proportion of published studies rely almost exclusively on the PlantVillage dataset or similarly curated image collections acquired under controlled laboratory conditions. While these datasets have played a crucial role in advancing algorithm development, their uniform backgrounds, controlled illumination, and limited environmental variability differ considerably from images encountered during routine agricultural practice. Consequently, models developed using highly controlled datasets may experience reduced generalization when deployed under natural field conditions characterized by complex backgrounds, varying illumination, occlusion, and differences in image acquisition devices.

Second, although many studies emphasize maximizing classification accuracy, comparatively fewer investigations consider the complete deployment pipeline required for practical agricultural applications. In numerous cases, research concludes with offline performance evaluation without extending the trained model into an operational mobile platform capable of supporting farmers during routine crop monitoring. This disconnect between algorithm development and field implementation limits the practical impact of many otherwise promising disease-classification models.

Third, despite the widespread popularity of transfer learning, relatively limited attention has been devoted to examining whether carefully designed task-specific convolutional architectures can outperform deeper pretrained models for heterogeneous tomato disease datasets. Transfer learning has become the default approach in many agricultural image-classification studies because pretrained networks provide strong feature extraction capabilities. However, their performance depends strongly on dataset characteristics, domain similarity, optimization strategy, and the extent of model fine-tuning. Consequently, deeper architectures do not necessarily guarantee superior performance for every agricultural classification task.

These observations reveal an important research gap. There remains a need for an integrated tomato disease diagnosis framework that combines heterogeneous image acquisition, robust deep learning classification, comparative evaluation against established transfer-learning models, and practical mobile deployment within a unified system. Such a framework would provide stronger evidence of real-world applicability than studies focusing exclusively on benchmark classification accuracy.

To address this gap, the present study develops a mobile-integrated deep learning framework for tomato leaf disease classification using two convolution-based models: a custom-designed convolutional neural network (TDD-Net) and a fine-tuned ResNet50 architecture. Unlike many previous studies that rely solely on publicly available benchmark datasets, the proposed framework utilizes a heterogeneous image collection comprising both field-acquired and publicly available tomato leaf images representing bacterial spot, early blight, grey leaf spot, late blight, and healthy leaves. Both models are trained under identical optimization conditions and evaluated using multiple performance indicators, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. Beyond model development, the best-performing classifier is deployed within a FlutterFlow-based mobile application integrated with Firebase and cloud-hosted inference to facilitate practical disease diagnosis using smartphone-acquired images.

Rather than focusing exclusively on improving classification accuracy, this work contributes an application-oriented framework that bridges deep learning research and practical agricultural deployment. By integrating heterogeneous image acquisition, task-specific CNN development, comparative evaluation against a widely adopted transfer-learning baseline, and mobile implementation within a single workflow, the study advances the development of intelligent decision-support systems capable of improving early tomato disease diagnosis in resource-constrained agricultural environments.

2.0 METHODOLOGY

2.1 Overall Research Framework

This study adopted a deep learning-based system development methodology to design, validate, and deploy a mobile-integrated framework for automated tomato leaf disease classification. The research workflow comprised six sequential phases: dataset acquisition, image preprocessing, deep learning model development, model training and validation, comparative performance evaluation, and mobile application deployment. The framework was designed to evaluate the effectiveness of a custom convolutional neural network (TDD-Net) relative to a fine-tuned ResNet50 architecture while simultaneously demonstrating practical deployment through a smartphone-based disease diagnosis application.

The methodological workflow began with the acquisition of tomato leaf images from both field surveys and publicly available repositories. Following image preprocessing and dataset preparation, the two deep learning models were trained using identical optimization settings to ensure a fair comparative evaluation. Model performance was subsequently assessed using multiple classification metrics before the best-performing model was integrated into a cloud-connected mobile application for real-time disease diagnosis. The overall workflow of the proposed framework is illustrated in Figure 1.

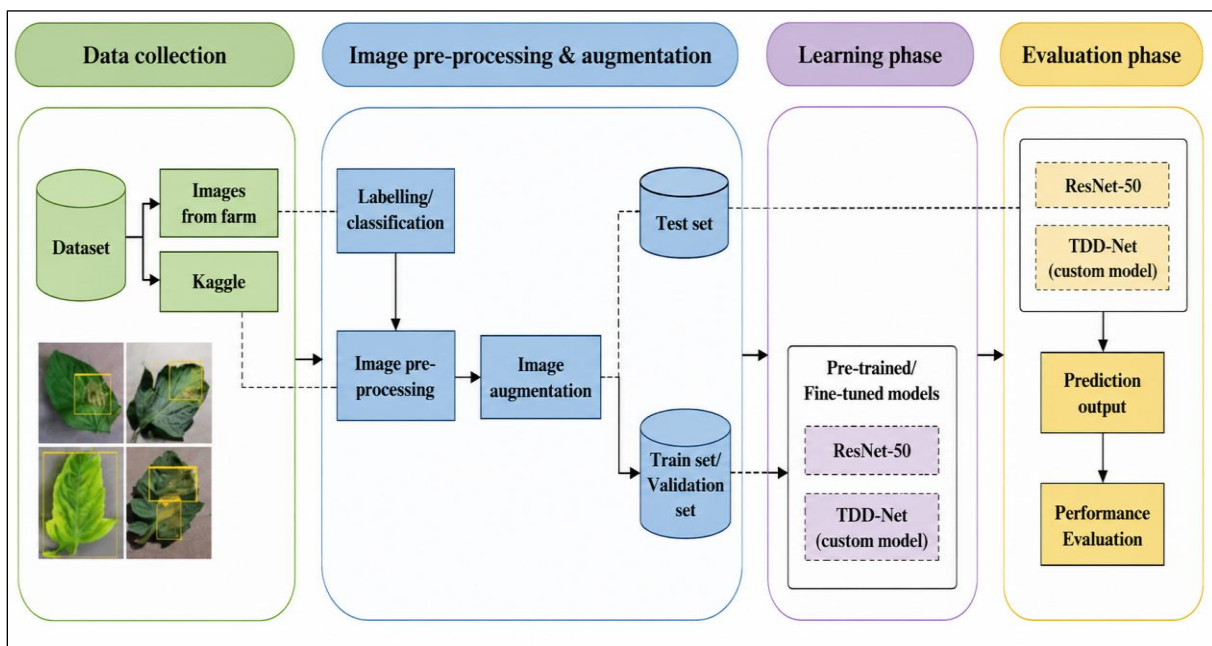


Figure 1: Overall framework of the proposed tomato leaf disease classification system

2.2 Dataset Acquisition

The dataset used in this study consisted of tomato leaf images representing five disease categories: bacterial spot, early blight, grey leaf spot, late blight, and healthy tomato leaves. To improve image diversity and enhance the robustness of model training, the dataset was compiled from two complementary sources.

The first source comprised images captured directly from tomato farms using smartphone cameras under natural field conditions. Field acquisition was intended to expose the models to realistic agricultural environments characterized by varying illumination, background complexity,

viewing angles, and symptom severity. Such variability improves the practical relevance of the developed classification system by reducing dependence on highly controlled laboratory images.

The second source consisted of publicly available tomato leaf images obtained from the Kaggle platform. These benchmark images complemented the field dataset by increasing sample diversity and improving class representation. The combination of locally acquired and publicly available images was intended to improve the model's capacity to generalize across different imaging conditions while reducing dataset bias associated with a single acquisition source.

To ensure the reliability of the dataset, all field-acquired images were manually annotated according to the visible disease symptoms exhibited on the tomato leaves. The annotation process was carried out by a plant pathologist, who verified the disease category assigned to each image before it was included in the dataset. This expert verification helped minimise the risk of incorrect labels arising from the visual similarity of certain disease symptoms and provided a reliable reference for supervised model training. By combining expert-validated field images with publicly available benchmark data, the resulting dataset captures a wider range of disease presentations and imaging conditions, thereby supporting the development of a classification model with improved robustness and practical applicability.

Following dataset compilation, a total of 15,549 images were obtained. The dataset included 3,117 bacterial spot images, 3,175 early blight images, 3,037 grey leaf spot images, 3,192 healthy leaf images, and 3,028 late blight images. The relatively balanced distribution of disease classes reduced the likelihood of model bias toward any particular category during training. The dataset composition is summarized in Table 1.

Following preprocessing, the dataset was randomly partitioned into training, validation, and testing subsets using an 80:10:10 ratio. Specifically, 80% of the images were used for model training, 10% for validation during model optimization, and the remaining 10% for independent performance evaluation. This partitioning ensured that model development, hyperparameter tuning, and final performance assessment were conducted using mutually exclusive image sets.

Table 1: Distribution of tomato leaf images used for model development

Class	Number of images (Field-sourced)	Number of images (Kaggle-sourced)	Total Amount (Per Class)
Bacterial Spot	2,117	1,000	3,117
Early blight	2,175	1,000	3,175
Grey leaf spot	2,037	1,000	3,037
Healthy	2,192	1,000	3,192
Late Blight	2,028	1,000	3,028
Total	10,549	5,000	15,549

2.3 Image Preprocessing

Prior to model development, all images underwent preprocessing to ensure uniformity and compatibility with the convolutional neural network architectures. Images were resized to 224×224 pixels with three RGB colour channels, corresponding to the input dimensions required by ResNet50 and facilitating consistent input across both models.

Image normalization was performed during preprocessing to improve numerical stability during optimization. During training, data augmentation was performed using random horizontal flipping, rotation, zooming, translation, and brightness adjustment to increase image variability and improve model robustness against changes commonly encountered under field conditions. Augmentation

exposed the models to realistic image transformations while preserving disease-specific visual characteristics, thereby improving robustness to variations commonly encountered under field conditions.

The preprocessing pipeline further ensured that all images were standardized prior to feature extraction, thereby minimizing inconsistencies arising from differences in camera resolution and image dimensions.

2.4 Development of the Deep Learning Models

Two convolution-based image classification models were investigated in this study: a fine-tuned ResNet50 model and a custom-designed convolutional neural network designated as Tomato Disease Detection Network (TDD-Net).

2.4.1 Fine-Tuned ResNet50

ResNet50 served as the transfer-learning baseline for performance comparison. The model was selected because it is one of the most widely adopted deep convolutional neural networks for transfer learning in plant disease classification and has consistently confirmed competitive performance in agricultural image analysis. The architecture consists of fifty layers interconnected through residual learning blocks that facilitate gradient propagation during deep network optimization. Transfer learning enables pretrained feature representations learned from the ImageNet dataset to be adapted for tomato disease classification through fine-tuning of the upper network layers.

2.4.2 Proposed TDD-Net Architecture

To investigate whether a task-specific architecture could provide superior performance, a custom convolutional neural network referred to as TDD-Net was developed. The network was designed specifically for tomato leaf disease classification by combining multiple convolutional layers with batch normalization, max-pooling operations, global average pooling, fully connected layers, dropout regularization, and a Softmax output layer. The architecture incorporated L2 kernel regularization and dropout layers to minimize overfitting while preserving generalization performance. Compared with deeper transfer-learning models, TDD-Net was designed to learn disease-specific feature representations directly from the prepared dataset while maintaining computational efficiency suitable for eventual mobile deployment. The architectures of both models are presented in Figure 2.

The architectural design of TDD-Net was guided by the need to achieve an effective balance between classification performance and computational efficiency. Rather than increasing network depth, the proposed model progressively extracts hierarchical features associated with tomato leaf diseases, including lesion texture, colour variation, and edge characteristics, while maintaining a relatively lightweight structure suitable for mobile deployment. Batch normalization improves training stability, whereas dropout and L2 regularization enhance generalization by reducing overfitting. Consequently, the proposed architecture was designed to provide robust disease classification without the computational overhead commonly associated with deeper generic convolutional neural networks.

The novelty of the proposed TDD-Net lies not only in its architectural design but also in its integration within a complete disease diagnosis framework tailored to practical agricultural use. Unlike many existing studies that primarily adapt generic pretrained models for tomato leaf disease classification, TDD-Net was developed specifically to learn discriminative visual patterns associated with tomato pathology while maintaining a computationally efficient architecture suitable for mobile deployment. The proposed framework further distinguishes itself by combining heterogeneous field-acquired and publicly available images to improve robustness under varying imaging conditions, evaluating the model against a widely adopted transfer-learning baseline under identical

experimental settings, and translating the best-performing classifier into a functional mobile application for real-time disease diagnosis. Collectively, these complementary components extend the contribution of the study beyond the development of a standalone classification model by demonstrating an end-to-end approach that bridges algorithm development and practical implementation.

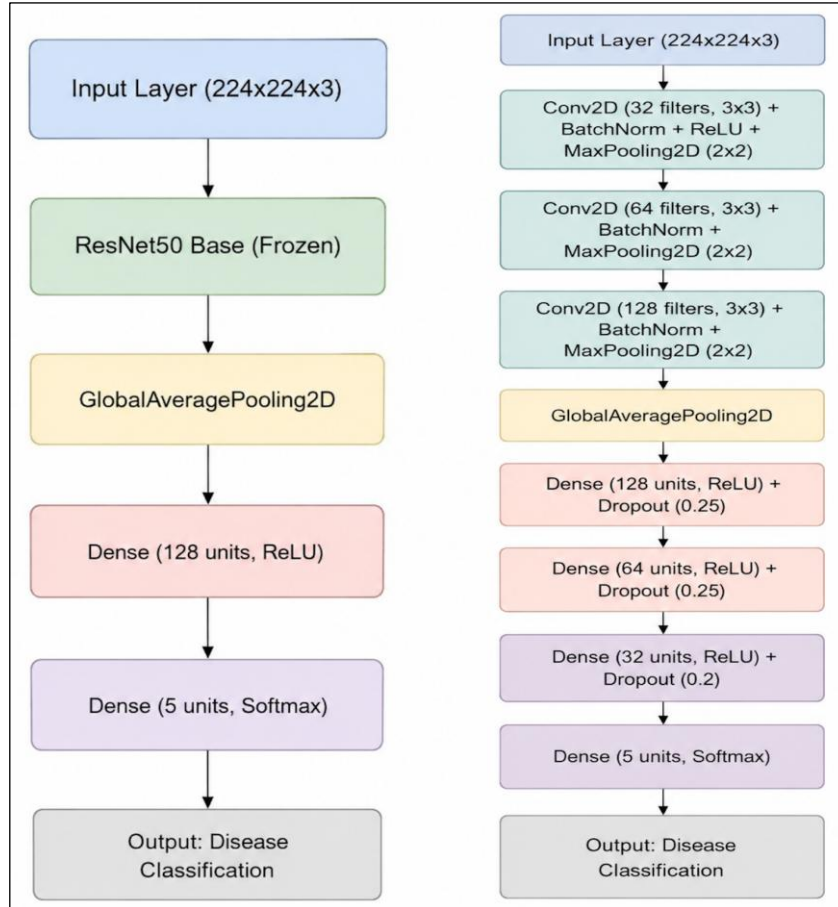


Figure 2: Architectures of ResNet50 and the proposed TDD-Net

2.5 Model Training Strategy

To ensure an unbiased comparison, both models were trained using identical optimization settings. Both models were trained for a maximum of 35 epochs using a batch size of 32. Early stopping was employed to terminate training automatically if validation performance ceased to improve, thereby preventing unnecessary computation and reducing the likelihood of overfitting.

Training was performed using the RMSprop optimizer with an initial learning rate of 1×10^{-3} , rho value of 0.85, and epsilon value of 1×10^{-6} . Multi-class classification was performed using categorical cross-entropy loss with label smoothing of 0.1, which was introduced to improve model generalization and reduce prediction overconfidence.

Training stability was further enhanced through three callback mechanisms. The ModelCheckpoint callback retained the model exhibiting the lowest validation loss. EarlyStopping monitored validation loss and terminated training after fifteen epochs without improvement while restoring the optimal model weights. Additionally, ReduceLROnPlateau dynamically adjusted the learning rate whenever validation performance plateaued, thereby improving optimization efficiency and convergence stability.

The selected training parameters were chosen to provide a balance between learning efficiency, computational cost, and model generalization. An input image size of 224×224 pixels was adopted to ensure compatibility with the ResNet50 architecture while maintaining sufficient visual detail for disease feature extraction. A batch size of 32 was selected to achieve stable gradient estimation without imposing excessive memory requirements during training. RMSprop was employed because of its adaptive learning capability, which has been shown to perform effectively for convolutional neural networks in image classification tasks. The initial learning rate of 1×10^{-3} provided stable convergence, while label smoothing was incorporated to reduce prediction overconfidence and improve generalization. Early stopping and adaptive learning-rate reduction were further used to prevent unnecessary training once validation performance plateaued and to improve convergence during later stages of optimization. Together, these training choices were intended to promote fair model comparison while minimizing overfitting and enhancing the robustness of the learned representations.

2.6 Performance Evaluation

Model performance was evaluated using multiple quantitative performance indicators to provide a comprehensive assessment of classification effectiveness. Overall classification accuracy was computed as the proportion of correctly classified samples relative to the total number of validation images. Precision was used to evaluate the reliability of positive predictions, whereas recall measured the model's ability to correctly identify disease-positive samples. The harmonic balance between precision and recall was quantified using the F1-score.

The discriminatory capability of each classifier was further assessed using the Area Under the Receiver Operating Characteristic Curve (AUC). Receiver operating characteristic curves were generated to evaluate model performance across different decision thresholds, thereby providing additional insight beyond overall accuracy.

To further assess learning behaviour during optimization, epoch-wise training and validation curves were monitored for accuracy, precision, AUC, and loss throughout model training.

2.7 Mobile Application Development

Following model validation, the trained classifier was integrated into a mobile application to facilitate practical disease diagnosis. The application was developed using FlutterFlow, while Firebase provided user authentication and cloud database management. The trained deep learning model was deployed through a cloud-hosted inference service to enable prediction using images uploaded from smartphones.

The mobile application allows users to register, authenticate, upload tomato leaf images, receive disease predictions, access supplementary disease information, and review previous diagnostic records. This deployment strategy transforms the trained deep learning model into a practical decision-support tool suitable for use by farmers, agricultural extension officers, and researchers.

3.0 RESULTS AND DISCUSSION

3.1 Model Validation Performance

Both models converged under identical training conditions; however, their validation performance differed considerably. The proposed TDD-Net consistently outperformed the fine-tuned ResNet50 across all evaluation metrics. Specifically, TDD-Net achieved a validation accuracy of 98.94%, with a precision of 0.9882, recall of 0.9863, F1-score of 0.9871, and an AUC of 0.9944. These results demonstrate the excellent ability of the proposed architecture to learn highly discriminative

representations for the five tomato leaf disease classes while maintaining balanced predictive performance.

Although the fine-tuned ResNet50 also learned meaningful disease representations, its performance was comparatively lower. Training accuracy increased steadily from approximately 42% to 72%, indicating stable convergence throughout the learning process. Validation accuracy likewise improved despite minor fluctuations, reaching a maximum of 79.80% at the final epoch. The relatively small gap between the training and validation curves suggests moderate overfitting while still demonstrating satisfactory generalization to unseen samples. Overall, the fine-tuned ResNet50 achieved a precision of 0.7926, recall of 0.7980, F1-score of 0.7948, and an AUC of 0.7919, indicating reliable classification performance but lower predictive capability than the proposed TDD-Net. The superior accuracy, precision, F1-score, and AUC achieved by TDD-Net prove that the proposed architecture was better suited to the characteristics of the tomato leaf dataset than the fine-tuned ResNet50. Although pretrained deep learning models are widely recognized as powerful feature extractors, the findings of this study indicate that a task-specific convolutional neural network can achieve outstanding performance for the tomato leaf disease classification task investigated. The quantitative performance of both models is summarized in Table 2.

Table 2: Performance comparison of TDD-Net and fine-tuned ResNet50

Model	Accuracy (%)	Precision	Recall	F1-score	AUC
TDD-Net (Proposed)	98.94	0.9882	0.9863	0.9871	0.9944
Fine-tuned ResNet50	79.80	0.7926	0.7980	0.7948	0.7919

As shown in Table 2, the proposed TDD-Net consistently outperformed the fine-tuned ResNet50 across all evaluation metrics, demonstrating excellent classification accuracy together with high precision, recall, F1-score, and AUC values.

The stronger performance of TDD-Net is likely due to its architecture being specifically designed for tomato leaf disease classification rather than relying on generic visual features learned from large-scale image datasets. The network progressively learned discriminative disease characteristics, including lesion patterns, colour variations, and texture features, while the combined use of batch normalization, dropout, and L2 regularization improved generalization and reduced overfitting. Although the fine-tuned ResNet50 benefited from pretrained feature representations, its greater architectural depth may have introduced unnecessary complexity for this classification task, resulting in slightly lower predictive performance.

This performance advantage can be further explained by TDD-Net's ability to learn disease-specific feature representations directly from tomato leaf images rather than relying on generic visual features transferred from large-scale natural image datasets. Although ResNet50 benefits from ImageNet pretraining, many of its learned filters are optimized for broad object recognition tasks and may not effectively capture the subtle lesion textures, chlorotic regions, necrotic spots, and colour variations that distinguish tomato leaf diseases. In contrast, TDD-Net progressively extracts hierarchical features tailored to the visual characteristics of tomato pathology, enabling more effective discrimination among visually similar disease classes. Furthermore, its relatively lightweight architecture reduces unnecessary model complexity, improving optimization efficiency while minimizing the risk of overfitting. The combined use of batch normalization, dropout, and L2 regularization further contributed to stable training and enhanced generalization across heterogeneous field-acquired and publicly available images. Since both models were trained under identical preprocessing, augmentation, optimization, and evaluation settings, the observed performance advantage can reasonably be attributed to the architectural suitability of TDD-Net for the tomato leaf disease classification task.

The consistently high precision, recall, and F1-score indicate that the proposed TDD-Net maintained balanced classification performance across all disease categories, suggesting that no single class disproportionately influenced the overall accuracy.

3.2 Learning Behaviour of the Models

The learning behaviour of both models was further examined using the training and validation accuracy and loss curves presented in Figure 3. As shown in Figure 3(a), the training and validation accuracy of TDD-Net increased steadily throughout the training process, indicating effective feature learning and stable convergence. Likewise, the corresponding loss curves in Figure 3(b) exhibited a consistent downward trend with only minor fluctuations, suggesting that the model learned discriminative representations while maintaining good generalization.

The learning curves of the fine-tuned ResNet50 are presented in Figures 3(c) and 3(d). Similar to TDD-Net, the model confirmed stable convergence during training. However, its validation accuracy remained consistently, though only slightly, lower than that of TDD-Net, and the validation loss showed greater fluctuations during the later training epochs. These observations suggest that while both models learned meaningful feature representations, the proposed TDD-Net exhibited more stable optimization and superior generalization to unseen validation samples.

Overall, the learning curves support the quantitative results presented in Table 2, demonstrating that both models converged successfully, with TDD-Net maintaining a consistent performance advantage throughout the training process.

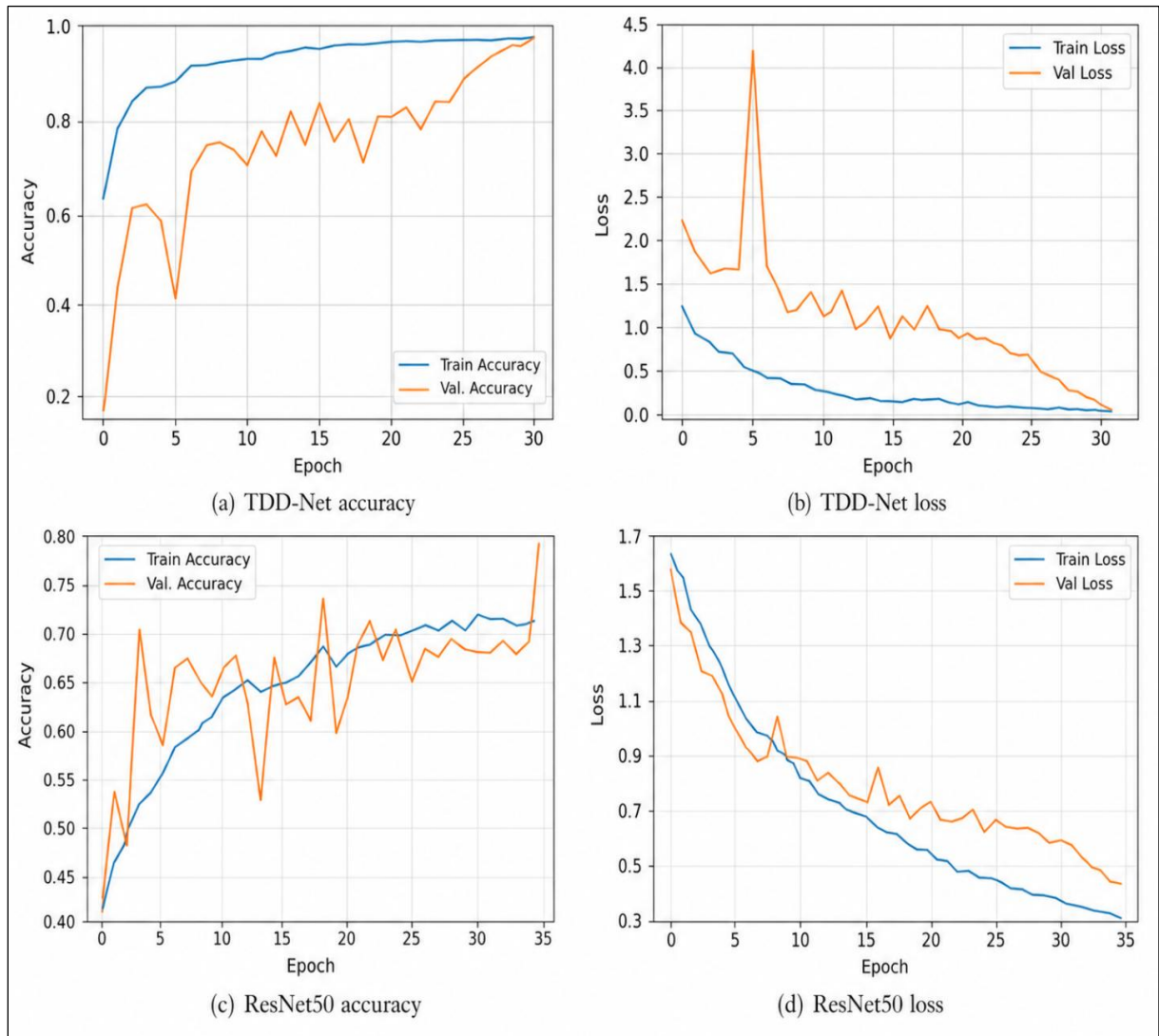


Figure 3: Training and validation learning curves for (a) TDD-Net accuracy, (b) TDD-Net loss, (c) ResNet50 accuracy, and (d) ResNet50 loss.

3.3 Mobile Application Implementation

To establish the practical applicability of the proposed framework, the trained TDD-Net model was integrated into a mobile application developed using FlutterFlow and Firebase. The application provides a complete workflow for tomato leaf disease diagnosis, including user registration and authentication, image upload, disease prediction, disease information, and prediction history. This implementation extends the study beyond model development by providing a functional platform capable of supporting real-time disease diagnosis in practical agricultural settings.

Representative screenshots of the developed application are presented in Figures 4 and 5, illustrating the major interfaces, including the homepage, image upload interface, prediction output, and disease information page.

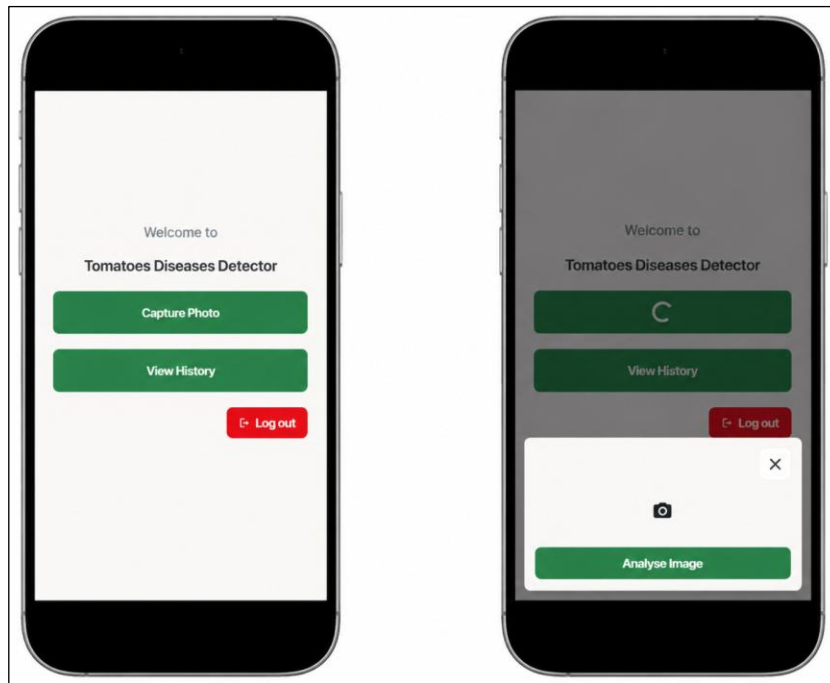


Figure 4: Home page and the upload image interfaces

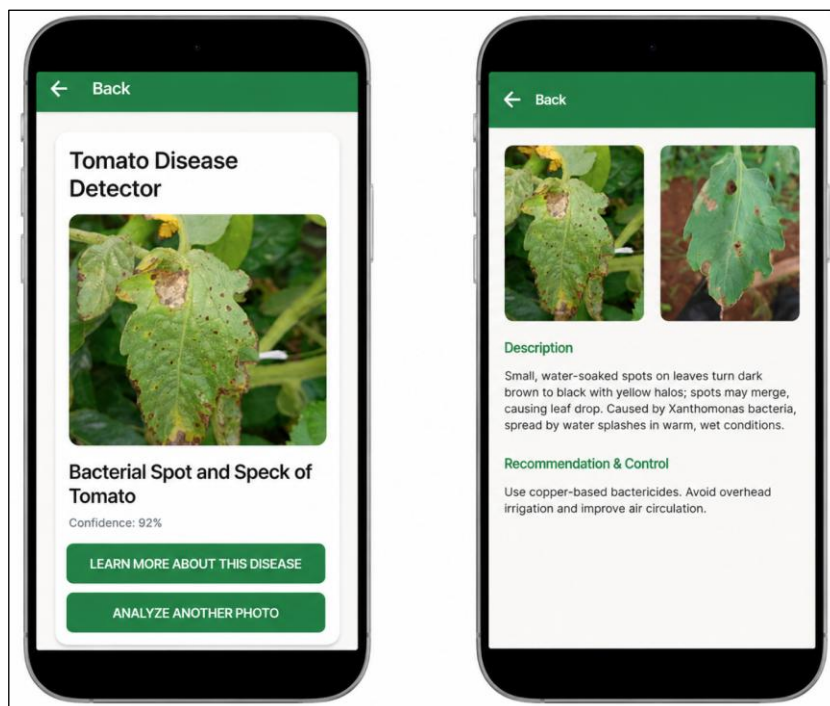


Figure 5: Prediction output and disease information interfaces

3.4 Comparison with previous studies

The proposed framework was compared with representative studies on tomato leaf disease classification, as presented in Table 3. The comparison indicates that classification performance varies across studies owing to differences in datasets, disease classes, model architectures, and

evaluation protocols. Several recent studies have reported classification accuracies approaching or exceeding 98% using different deep learning architectures and benchmark datasets. The proposed TDD-Net achieved a validation accuracy of 98.94%, demonstrating performance that is comparable with these cutting-edge approaches. Beyond achieving competitive classification performance, the proposed framework further distinguishes itself through the integration of a custom deep learning model into a FlutterFlow-based mobile application, thereby providing an end-to-end diagnostic system suitable for practical agricultural applications.

Table 3: Comparison of the proposed framework with representative tomato leaf disease classification studies

Study	Model	Dataset	Accuracy (%)	Deployment	Key Contribution
[12]	Optimized Capsule Network	PlantVillage	96.39	No	Capsule-network-based tomato leaf disease classification
[20]	TrioConvTomatoNet-BiLSTM	Public + field images	98.83	No	Lightweight CNN for real-time complex-background classification
[22]	ResNet50-MobileNetV2 Ensemble	PlantVillage	99.91	No	Ensemble transfer learning for improved tomato disease classification
[26]	Adaptive Ensemble Model	Tomato leaf dataset	98.70	No	Adaptive ensemble learning with exponential moving average fusion
This study	TDD-Net	Public + field-acquired images	98.94	Yes	Custom CNN integrated into a FlutterFlow-Firebase mobile application for real-time tomato leaf disease diagnosis

The comparison presented in Table 3 shows that both the proposed TDD-Net and the selected leading models are capable of achieving effective tomato leaf disease classification. Overall, the proposed TDD-Net achieved classification performance comparable with several recent tomato leaf disease classification models while additionally providing a complete mobile deployment framework.

Compared with the representative studies summarized in Table 3, the proposed framework places greater emphasis on practical deployment by integrating the classification model into a FlutterFlow-Firebase mobile application that supports image acquisition, real-time disease diagnosis, disease information retrieval, and prediction history management within a unified platform. This end-to-end implementation validates the feasibility of translating a deep learning model into a practical decision-support tool for intelligent crop health monitoring and extends the contribution of the study beyond offline model evaluation.

The findings of the present study are broadly consistent with recent advances in deep learning-based plant disease classification, which have demonstrated that carefully designed convolutional neural networks can achieve high diagnostic accuracy for tomato leaf diseases. While some previous studies reported slightly higher classification accuracies, many of those models were developed and evaluated primarily using benchmark datasets acquired under controlled imaging conditions. In contrast, the proposed framework was trained and validated using a heterogeneous dataset that combined publicly available images with field-acquired samples exhibiting variations in background, illumination, viewing angle, and symptom presentation. These more challenging imaging conditions provide a closer representation of practical agricultural environments and may explain the small differences in reported classification performance. Consequently, the competitive accuracy achieved by TDD-Net, together with its successful integration into a mobile application, demonstrates that the

proposed framework offers a practical balance between predictive performance and real-world applicability, extending its potential value beyond laboratory-based image classification studies.

Despite these contributions, several limitations should be acknowledged. The current framework is limited to the classification of five tomato leaf disease classes and therefore cannot reliably identify additional diseases, nutrient deficiencies, or abiotic stress conditions beyond the trained categories. Furthermore, although the dataset combined publicly available and field-acquired images, additional validation using larger datasets collected across different geographical regions, growing seasons, and imaging devices would further establish the robustness and generalizability of the proposed framework. Future work should also investigate disease severity estimation, explainable artificial intelligence techniques to improve model interpretability, and offline inference capabilities to enhance usability in environments with limited internet connectivity.

4.0 CONCLUSION

This study developed and validated a mobile-integrated deep learning framework for tomato leaf disease classification and demonstrated the effectiveness of the proposed TDD-Net architecture compared with a fine-tuned ResNet50 model under identical training and evaluation conditions. Using a heterogeneous dataset comprising 15,549 tomato leaf images across five disease classes, TDD-Net achieved a validation accuracy of 98.94%, together with a precision of 0.9882, recall of 0.9863, F1-score of 0.9871, and an AUC of 0.9944, confirming its ability to accurately distinguish between healthy and diseased tomato leaves. To demonstrate its practical applicability, the trained model was integrated into a FlutterFlow-based mobile application supported by Firebase and cloud-hosted inference, enabling real-time disease diagnosis using smartphone-acquired images. These findings indicate that a carefully designed task-specific convolutional neural network can provide an effective balance between classification accuracy and practical deployment for intelligent crop health monitoring. The proposed framework therefore offers a practical decision-support tool that can assist farmers and agricultural extension officers in identifying tomato leaf diseases at an early stage, facilitating more informed crop management decisions, reducing avoidable yield losses, and encouraging more precise use of plant protection measures, particularly in resource-constrained agricultural settings. Although the framework demonstrated strong performance, the present study was limited to five tomato leaf disease classes, and further evaluation using larger datasets collected across different geographical regions, growing seasons, environmental conditions, and smartphone devices would provide additional evidence of its robustness and generalizability. Future research will focus on extending the framework to include additional diseases, incorporating disease severity assessment and explainable artificial intelligence techniques, supporting offline edge-based inference for areas with limited internet connectivity, and integrating the system with IoT-enabled smart farming platforms for continuous crop health monitoring.

Author Contribution

Olayiwola C. Adesoba: Conceptualization, methodology, investigation, visualisation, writing and editing. Waliu O. Apena: Conceptualization, supervision, and validation. Folasade M. Dahunsi: Conceptualization, supervision, methodology, and validation. Ayodele M. Ajayi: Investigation and data analysis, and supervision.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Not Applicable.

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