Bima Journal of Science and Technology, Vol. 8(4A) Dec, 2024 ISSN: 2536-6041

DOI: 10.56892/bima.v8i4.1155

Real-Time Tomato Leaf Disease Classification Using Efficientnet and UAV

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ABSTRACT

Tomato leaf diseases significantly hinder agricultural productivity, resulting in considerable yield losses when not detected and managed in a timely manner. Traditional disease detection methods, often reliant on manual inspection, are time-intensive, prone to errors, and unsuitable for large-scale monitoring. This study addresses these limitations by developing a real-time tomato leaf disease classification system leveraging a Tello drone integrated with a deep learning model based on EfficientNet-B5 and a Streamlit interface. The model was trained on the PlantVillage dataset, encompassing 9 distinct tomato leaf diseases and a healthy class, with data augmentation techniques applied to improve its generalization capacity. While similar models achieve high accuracy in controlled environments (99.8%), the novelty of this work lies in its adaptation for real-time field deployment, where the system achieved an accuracy of 96%. This research bridges the gap between laboratory-based deep learning systems and practical agricultural applications by enabling the drone to capture images dynamically, analyze them in real-time, and provide immediate feedback. The proposed system offers a scalable, efficient, and precise solution for early disease detection, emphasizing its transformative potential for precision agriculture and sustainable farming practices.

Keywords: EfficientNet-B5, Deep learning, Tello drone, Real-time classification, Tomato leaf disease detection.

INTRODUCTION

Agriculture plays a vital role in global food security and economic stability. With the world population projected to reach 9.7 billion by 2050 (United Nations, 2019), the demand for efficient and sustainable agricultural practices has become increasingly critical. Tomatoes, a significant vegetable crop with global production reaching 180 million tonnes in 2019 (FAO, 2021), face numerous challenges, particularly susceptibility to various diseases that can significantly impact crop yield and quality.

Tomato plants are prone to diseases such as bacterial spot, early blight, late blight, leaf mold, and viral infections like tomato yellow leaf curl virus (TYLCV) (Jones et al., 2014). These diseases contribute to substantial economic losses, with estimates suggesting up to 30% of global tomato production is lost annually due to various pathogens (Savary et al., 2019). Early detection and accurate diagnosis of these diseases are crucial for implementing timely interventions and minimizing crop losses.

Traditional disease detection methods in tomato plants have relied on visual inspection by trained agronomists or farmers. However, this approach is time-consuming, labor-intensive, and often subjective, leading to potential delays in disease identification and management). The increasing scale of agricultural operations further renders manual

DOI: 10.56892/bima.v8i4.1155

inspection of large fields impractical and economically unfeasible.

Recent years have seen the integration of artificial intelligence (AI), specifically deep learning techniques, with computer vision showing tremendous potential in automating and improving the accuracy of plant disease detection (Ferentinos, 2018). Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks, including the identification of plant diseases from leaf images (Mohanty et al., 2016).

In this study, we build upon the work of Bhandari et al. (2023), who developed an advanced deep learning model for tomato leaf disease classification using EfficientNet architecture. Our research extends their foundation by integrating their model with drone technology and a real-time user interface, addressing the critical need for large-scale, in-field disease monitoring.

Key innovations of this research include:

1. **Drone Integration:** Employing a Tello drone as an aerial platform for image capture, enabling efficient coverage of large agricultural areas.
2. **Real-time Processing:** Optimizing the EfficientNet model for on-board processing, enabling real-time classification of tomato leaf diseases during drone flight.
3. **User Interface Development:** Creating a Streamlit-based web application that provides a user-friendly interface for drone control, real-time video streaming, and disease classification visualization.
4. **Field-ready System:** Transforming the lab-based model into a system capable of operating in varied environmental conditions, making it directly applicable to real-world agricultural scenarios.

In this research, we represent a significant step forward in the practical application of AI in agriculture, bridging the gap between advanced machine learning models and real-world farming needs. The outcomes of this study have the potential to significantly impact agricultural practices, improving crop yields, reducing losses, and ultimately contributing to more sustainable and efficient food production systems.

LITERATURE REVIEW

This review examines the current state of research in tomato leaf disease detection using deep learning techniques and the integration of drone technology in agricultural monitoring. The literature reveals significant advancements in both areas, setting the stage for their convergence in real-time, field-ready disease detection systems.

Recent years have seen remarkable progress in applying deep learning to plant disease detection, particularly for tomato leaf diseases. Convolutional Neural Networks (CNNs) have emerged as the predominant architecture for this task, demonstrating high accuracy and efficiency.

Bhandari et al. (2023) introduced "BotanicX-AI," an explainable deep learning framework for tomato leaf disease identification. Using transfer learning with EfficientNetB5 and integrating explainable AI techniques, their model achieved impressive accuracies: 99.84% for training, 98.28% for validation, and 99.07% for testing. This study highlights the potential of EfficientNet architectures and the importance of model interpretability in agricultural applications.

Other notable contributions include Zhang et al. (2020), who enhanced the Faster RCNN model for tomato leaf disease detection, achieving 98.54% mean average precision. Durmus et al. (2017) compared AlexNet and SqueezeNet architectures, finding that while

DOI: 10.56892/bima.v8i4.1155

AlexNet achieved slightly higher accuracy (95.65% vs. 94.3%), SqueezeNet's smaller model size and faster inference time made it more suitable for real-time applications.

Geetharamani and Pandian (2019) introduced a nine-layer deep convolutional neural network for plant leaf disease identification, achieving 96.46% accuracy on a dataset that included various plant species. While outperforming other state-of-the-art CNNs, the model was limited to a specific set of diseases. Future work suggested real-time implementation in field conditions.

Barbedo (2019) used deep learning to identify plant diseases from individual lesions, achieving an average accuracy of 87.9% across 79 diseases affecting 14 plant species, including tomatoes. The approach showed potential for early-stage detection but was limited to visible symptoms and struggled with similar-looking diseases. Future work suggested detecting diseases before symptoms appear.

In a related study, Prajwala et al. (2018) demonstrated the feasibility of using a LeNet-based CNN for detecting tomato leaf diseases, achieving an accuracy of 94-95% on the PlantVillage dataset. This approach highlights the potential of lightweight architectures for plant disease detection with minimal computational requirements, aligning with the goals of real-time systems.

The integration of drone technology with deep learning has opened new avenues for agricultural monitoring and disease detection. Several studies have demonstrated the potential of this combination for improving crop management and disease control.

Shi et al. (2022) presented CropdocNet, a model for automated potato late blight disease detection using hyperspectral imagery from UAVs. Their approach, which considers spectral-spatial hierarchical features of crop diseases, achieved high accuracies of 98.09% for training and 95.75% for testing datasets.

Abdulridha et al. (2020) investigated the identification of tomato diseases using UAV-based hyperspectral imaging and machine learning techniques. Their study highlighted the effectiveness of specific vegetation indices like MTVI 1 and RDVI in distinguishing between diseases.

Kerkech et al. (2018) demonstrated the effectiveness of combining deep learning with UAV imagery for vine disease detection, achieving an accuracy of 96.5%. This study underscores the potential of integrating deep learning models with drone-captured imagery for disease detection in various crops.

Vardhan and Swetha (2023) introduced a method for plant disease detection using CNNs integrated with a prototype drone for live field monitoring. Their approach utilized a dataset of various plant diseases and demonstrated that CNNs outperformed other technologies in categorizing and detecting crop diseases, even under challenging imaging conditions.

Shahi et al. (2023) conducted a comprehensive review of advancements in crop disease detection using UAVs and deep learning. Analyzing 55 publications, they highlighted the critical role of UAV platforms and sensors in enhancing detection accuracy. The study found that deep learning-based methods consistently achieved the highest accuracy in crop disease estimation, underscoring their effectiveness in UAV-based applications.

Table 1 summarizes the key findings from the reviewed literature, providing an overview of the methodologies, models, and technologies employed in related studies.

Table 1: Summary of Key Studies.

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Year	Authors	Methods	Dataset	Key Findings	Accuracy
2023	Bhandari et al.	Efficient NetB5, Explainable AI	11,000 images, 10 classes	XAI techniques enhance interpretability	99.8%
2022	Shi et al.	CropdocNet (Deep Learning)	UAV hyperspectral imagery	Effective for potato late blight detection	95.75%
2020	Zhang et al.	Improved Faster RCNN	Lab dataset	Enhanced feature extraction and detection speed	98.54%
2020	Abdulridha et al.	UAV hyperspectral imaging, ML	Lab and field data	MTVI1, RDVI effective for disease distinction	High Accuracy
2018	Kerkech et al.	Deep learning with UAV imagery	UAV images of vine diseases	Effective for vine disease detection	96.5%
2017	Durmus et al.	AlexNet,SqueezeNet	54,309 images, 10 classes	SqueezeNet more suitable for real-time applications	94.3%

The literature review reveals a significant gap in the integration of advanced disease classification algorithms with drone-based imaging techniques into a cohesive system for real-time, in-field disease detection. The proposed research aims to address this gap by:

1. Integrating EfficientNet with drone technology for real-time tomato leaf disease classification.
2. Optimizing the model for drone hardware to enable on-the-fly disease detection.
3. Incorporating a Streamlit interface for real-time classification visualization.
4. Focusing specifically on tomato diseases for improved accuracy and tailored insights.
5. Developing a field-ready system capable of operating in real-world conditions.

By addressing these aspects, this research has the potential to make a significant contribution to precision agriculture and plant disease detection, bridging the gap between laboratory models and practical field applications.

MATERIALS AND METHODS

A. Research Design

We adopt a quantitative research approach, utilizing deep learning techniques for image classification. An experimental methodology was employed to develop and test a deep learning model specifically designed for real-time disease classification in tomato leaves.

B. Dataset Acquisition and Preprocessing

The dataset used in this study comprises images of tomato leaves, categorized into 10 distinct classes: nine representing various diseases and one representing healthy leaves. These images were sourced from the PlantVillage dataset available on Kaggle (Hughes & Salathé, 2015). To optimize computational resources while maintaining a balanced representation of all classes, a subset of 4,000 images was selected, with 400 images per class. This selection ensures that the model is trained on a diverse and representative set of data, enhancing its ability to generalize to new, unseen images. Figure 1 presents a sample image from each

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class, illustrating the visual diversity within the dataset.

Figure 1: Sample Images of Tomato Leaf Diseases and Healthy Leaf from the PlantVillage Dataset.

Before feeding the images into the model, several preprocessing steps were necessary to ensure consistency and enhance the model's learning process. The images were resized to 456 × 450 pixels using bicubic interpolation (Keys, 1981), a method that preserves image quality during resizing. Following resizing, the pixel values were normalized to a [0, 1] range, facilitating faster convergence during training. Additionally, data augmentation techniques were applied to artificially expand the dataset and prevent overfitting. These techniques included horizontal flipping, random rotation, zooming, and shifting. The augmentation process can be mathematically represented as follows:

$$T(I) = S(R(F(I)) \quad \text{---------------} \ (1)$$

where:

- I is the input image
- F is the flipping operation
- R is the rotation operation
- S is the scaling (zoom and shift) operation

The preprocessed dataset was divided into three distinct subsets to support different stages of model development: training, validation, and testing. Specifically, 70% of the dataset, comprising 2,800 images, was allocated for training the model. Another 20% of the dataset, or 800 images, was set aside for validation, which helped fine-tune the model and reduce the risk of overfitting. The remaining 10%, consisting of 400 images, was reserved for testing the model's performance on unseen data. Figure 2 illustrates the entire data processing workflow, from acquisition to the final dataset division, emphasizing the structured

DOI: 10.56892/bima.v8i4.1155

approach taken to prepare the data for model development.

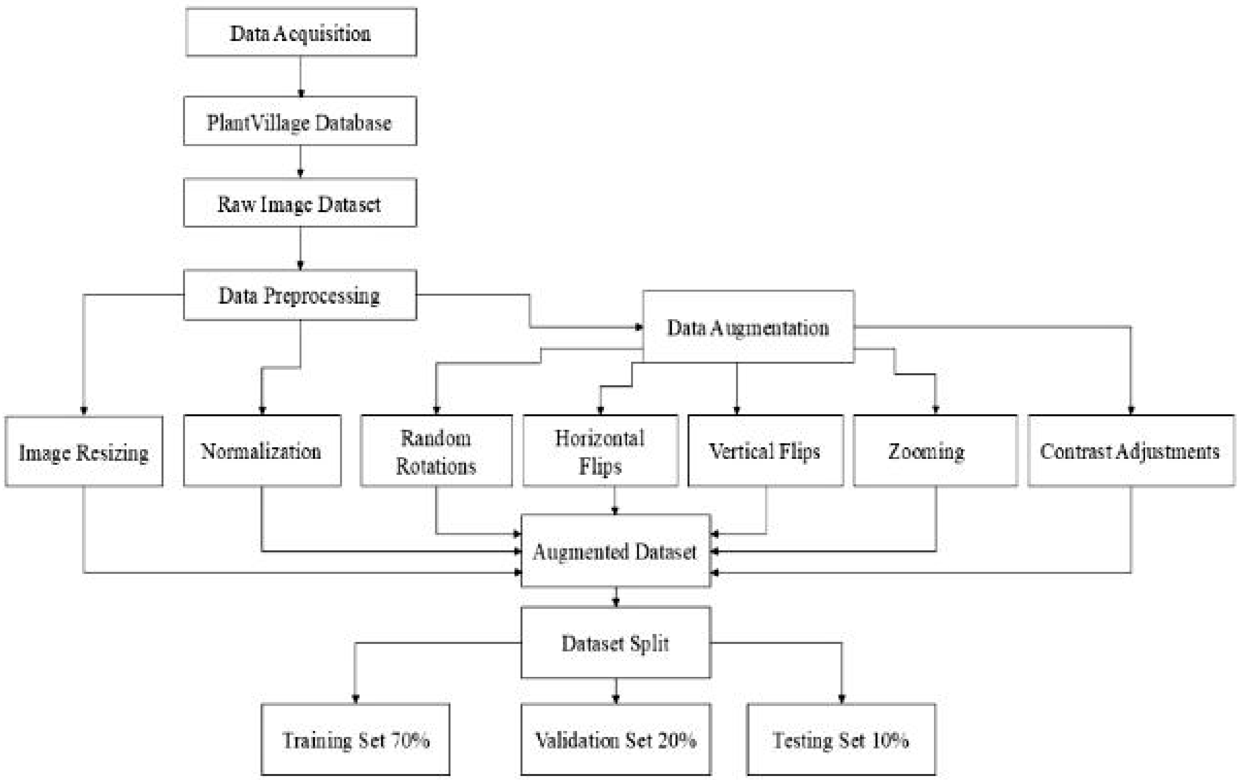

Figure 2: Data Processing Workflow from Acquisition to Final Dataset Division.

C. Model Architecture

The EfficientNetB5 architecture was selected as the base model for this study due to its proven balance of accuracy and computational efficiency. Part of the EfficientNet family, EfficientNetB5 is known for its scalable architecture, which achieves high accuracy with fewer parameters compared to other convolutional neural networks (CNNs) (Tan & Le, 2019).

The adaptation of the EfficientNetB5 model to meet the specific needs of this study. The pretrained layers from EfficientNetB5, initially trained on the ImageNet dataset, were retained, and several additional layers were added to enhance performance for the classification task. These layers included Global Average Pooling (GAP) to reduce feature map dimensionality, Batch Normalization to stabilize learning, a Dense layer, a Dropout layer to prevent overfitting, and an Output Dense layer with softmax activation for classifying images into one of the 10 classes. The adapted model can be mathematically expressed as:

$$y = softmax\,(W2\,.\,ReLU\,\left(BN\left(W1\,.\,GAP\,\left(CNN\,(x)\right) + b1\right)\right) + b2) \quad \text{--------------------- (2)}$$

(Tan & Le, 2019).

where:

x is the input image

CNN represents the EfficientNet

B5 convolutional layers

GAP is Global Average Pooling

BN is Batch Normalization

$W1, W2, b1, b2$ are learnable parameters

Various regularization techniques were implemented to enhance the model's generalization capabilities and prevent overfitting. Specifically, L2 Kernel Regularization was applied with a regularization parameter $\lambda = 0.016$ to the kernel weights. Additionally, L1 Activity and Bias Regularization were employed, using a regularization parameter $\lambda = 0.06$ for both activity and bias. To further reduce overfitting, a dropout rate of 0.5 was utilized, which randomly deactivated half of the neurons during training.

D. Model Training

The training process, which utilized the Adam optimizer due to its suitability for deep learning tasks, thanks to its adaptive learning rate. The optimizer was configured with a learning rate of 0.001 and beta parameters $\beta_1 = 0.9, \beta_2 = 0.999$ (Kingma & Ba, 2014). The model was trained using the categorical cross-entropy loss function, which is standard for multi-class classification problems. The loss function is defined as:

$$L = - \sum_{i=1}^{C} yi\,(\hat{y}i) \quad \text{------------ (3)}$$

where:

C is the number of classes

yi is the true label

$\hat{y}i$ is the predicted probability

The training was conducted with a batch size of 11 over 20 epochs. Early stopping and callback functions were employed to halt training when the validation loss failed to improve for five consecutive epochs, thereby preventing overfitting.

A learning rate schedule was implemented using the ReduceLROnPlateau callback. This function reduces the learning rate by 0.5 when the validation loss plateaus, allowing the model to fine-tune its weights as training progresses. Additionally, the EarlyStopping callback was used to stop training early if the validation loss did not improve over a set number of epochs, preventing overfitting and conserving computational resources.

E. Real-Time Processing and Drone Control Using Streamlit

In this section, we provide an overview of Streamlit, which serves as the interface for controlling the Tello drone and displaying real-time classification of tomato leaf diseases. Streamlit offers a user-friendly platform that allows users to interact with both the drone and the deep learning model simultaneously. (Teixeira & Woloszyn, 2022).

The Tello drone is integrated into the Streamlit application using the *tello-py* library, enabling control of the drone's movements and image capture through Python commands (Rausch, 2023). The communication between the drone and the model involves several key steps:

i **Drone Initialization and Command Execution:** The drone is initialized and connected via a Wi-Fi interface. Streamlit sends commands to the drone, such as takeoff, landing, and movement, through Python functions mapped to buttons on the user interface.

ii **Live Streaming and Image Capture:** The drone's camera provides a live video stream that is displayed in real-time on the Streamlit interface. Frames from the video stream are periodically captured using the *capture_frame()* function, then resized and

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preprocessed to meet the input requirements of the deep learning model.

iii **Image Classification and Result Display:** The preprocessed images are passed to the model using the *predict_disease(image)* function, which processes the images through the deep learning model and returns the predicted class of tomato leaf disease. The prediction results are then displayed on the Streamlit interface, providing immediate feedback to the user.

The communication flow, as illustrated in Figure 3, begins with the drone capturing an image, followed by preprocessing, model prediction using *predict_disease(image),* and the real-time display of the classification result on the Streamlit interface.

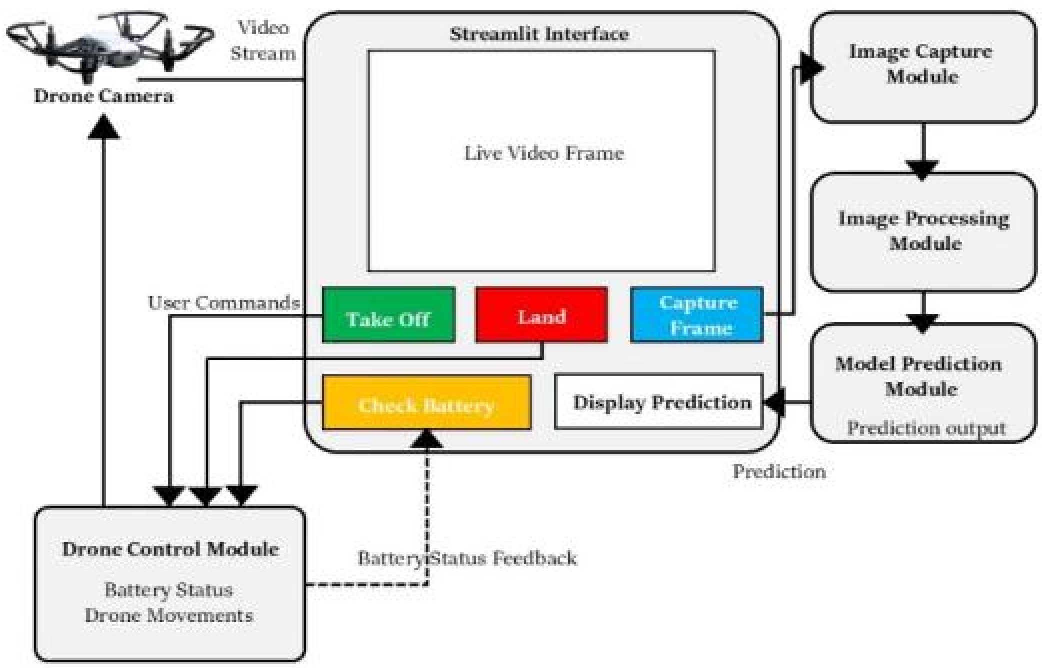

Figure 3: Real-Time Image Processing Workflow.

We also provide a comprehensive overview of the system, detailing the interaction between data preparation, model development, drone integration, and the Streamlit interface for real-time tomato leaf disease classification. Figure 4 illustrates the entire workflow of the system.

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DOI: 10.56892/bima.v8i4.1155

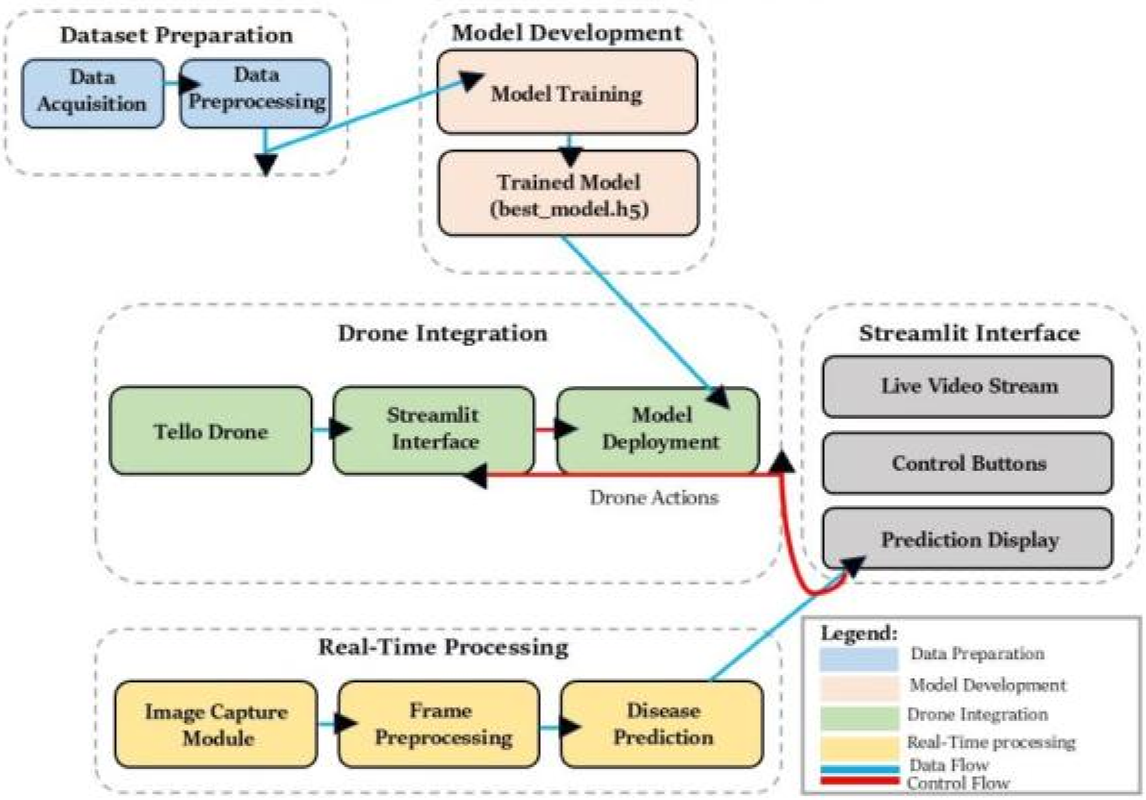

Figure 4: Complete System Workflow.

F. Mathematical Representation of the System

The mathematical representation of the system is presented, focusing on the original model and the enhancements introduced through drone integration and real-time classification.

1. **Existing Model Y :** The base model, EfficientNetB5, trained on the PlantVillage dataset, is represented by $Y = f(D, \theta)$. ---------- (4)
   Where f is the model function, D is the dataset (images of tomato leaves with diseases), and θ represents the learned parameters.
2. **Novel Contribution X:** The research's main contribution, denoted by $X = g(I, S, T)$, -------- (5)
   It involves integrating drone technology and real-time classification using a Streamlit interface. Here, g represents the integration function, I is the input images captured by the drone, S is the Streamlit interface for real-time processing, and T includes transformation processes like image preprocessing.
3. **Final System Output Z :** The final output: $Z = h(Y, X) = h\big(f(D, \theta), g(I, S, T)\big)$ ----------- (6)
   It combines the original model Y with the novel enhancements X, resulting in the system's overall output.

G. Evaluation Metrics

The performance of the model in detecting tomato leaf diseases was evaluated using several key metrics: Accuracy, Precision, Recall, F1-score, Support, and Confusion Matrix. These metrics are essential for assessing the effectiveness of a classification model, particularly in multi-class scenarios (Sokolova & Lapalme, 2009).

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1. Accuracy is the ratio of correctly predicted instances to the total instances and is calculated as:

   $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ --------- } (7)$$

   where TP (True Positives) are correctly predicted positive instances, TN (True Negatives) are correctly predicted negative instances, FP (False Positives) are incorrectly predicted positive instances, and FN (False Negatives) are incorrectly predicted negative instances.

2. Precision measures the accuracy of positive predictions and is defined as:

   $$Precision = \frac{TP}{TP+FP} \text{ ---------- } (8)$$

   High precision indicates a low false positive rate, which is crucial in scenarios where the cost of a false positive is high (Powers, 2020).

3. F1-score is the harmonic mean of Precision and Recall, offering a balanced measure of both and is calculated as:

   $$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \text{ -------- } (9)$$

   This metric is especially useful for imbalanced datasets (Sasaki, 2007).

4. Confusion Matrix is a table used to evaluate classification performance by showing the number of correct and incorrect predictions for each class. For multi-class classification, it is represented as an $n \times n$ matrix, where n is the number of classes, and the element at position (i, j) represents the number of observations known to be in class i but predicted to be in class j

   These metrics collectively provide a comprehensive assessment of the model's performance in multi-class classification tasks.

RESULTS AND DISCUSSIONS

The tomato leaf disease classification model, trained on a dataset from the PlantVillage database focusing on 9 distinct tomato leaf diseases and one healthy class, demonstrated robust performance. Leveraging data augmentation techniques such as random rotations, flips, zooming, and contrast adjustments, the model achieved a training accuracy of 98% and a validation accuracy of 96%. These results indicate effective learning of features during training and good generalization to unseen data.

The model's performance on the test set yielded an accuracy of 96%, further confirming its reliability. Figure 5 presents the confusion matrix for the test set, illustrating the classification performance across different disease categories. Figure 6 provides a detailed breakdown of precision, recall, and F1-score for each class, offering insights into the model's effectiveness in distinguishing between various tomato leaf conditions. A key innovation of this study is the integration of the trained model with a Tello drone and Streamlit interface, creating a novel real-time disease classification system. This integration required specific hardware and software components to ensure smooth operation. The hardware requirements included a Tello Drone, a computer with a minimum of 4GB RAM, and a stable Wi-Fi connection. On the software side, the system utilized Python 3.8, Streamlit, TensorFlow, OpenCV, and the Tello SDK.

Figure 7 showcases the Streamlit interface developed for disease classification. The interface features several functional buttons: a battery check button to ensure sufficient power for flight (with a 15% threshold for takeoff), a takeoff button to launch the drone, a streaming button to initiate real-time

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image capture and disease prediction, and a land button for safe drone retrieval.

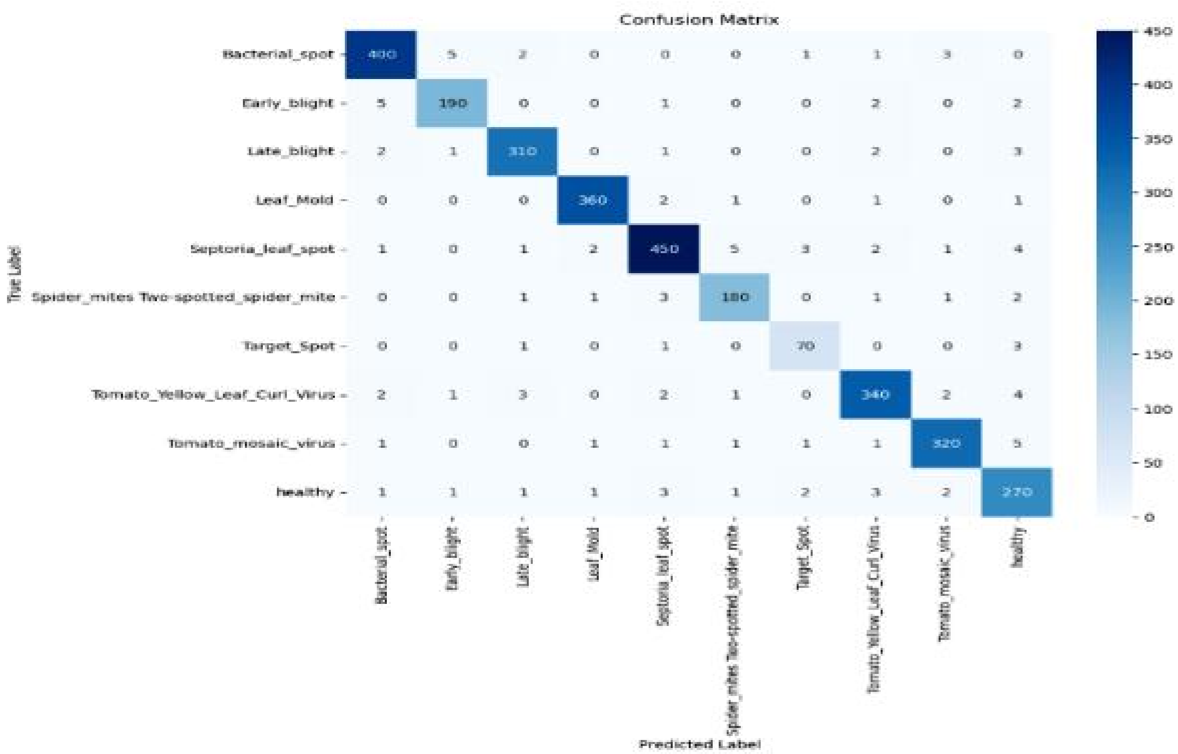

Figure 5: Confusion Matrix for Test Set.

	precision	recall	f1-score	support
Tomato___bacterial_spot	0.95	0.94	0.94	426
Tomato___early_blight	0.96	0.95	0.95	200
Tomato___healthy	0.96	0.97	0.96	319
Tomato___late_blight	0.98	0.94	0.96	382
Tomato___leaf_curl	0.94	0.95	0.94	472
Tomato___leaf_mold	0.93	0.94	0.94	191
Tomato___mosaic_virus	0.92	0.93	0.93	75
Tomato___septoria_leaf_spot	0.93	0.96	0.95	355
Tomato___spider_mites	0.96	0.95	0.95	336
Tomato___target_spot	0.94	0.96	0.95	281
accuracy			0.95	3637
macro avg	0.95	0.95	0.95	3637
weighted avg	0.95	0.95	0.95	3637

Figure 6: Precision, Recall, and F1-Score for Each Class.

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Figure 7: Streamlit Interface for Disease Classification.

To contextualize the performance of our drone-integrated model, we conducted a comparative analysis with other well-known architectures. Table 2 summarizes this comparison, highlighting the accuracy metrics of various models, including our proposed system.

Table 2: Analysis of Different Models Comparative

Model	Accuracy %	Reference
Deep Learning-based Detector	83.06	Fuentes et al., 2017
SqueezeNet	94.3	Durmus et al., 2017
AlexNet	95.65	Durmus et al., 2017
CNN-RNN Classifier	94.0	David et al., 2021
EfficientNetB5	99.07	Bhandari et al., 2023
Proposed Model with Drone	96.0	*This Study*

Figure 8 provides a visual representation of the accuracy metrics detailed in Table 2.

While our model's accuracy (96%) is slightly lower than the highest reported accuracy (99.8% by Bhandari et al., 2023), it's important to note that our system offers the significant advantage of real-time, drone-based disease detection. This practical feature represents a substantial advancement in agricultural applications, potentially outweighing the marginal difference in accuracy.

Qualitative Evaluation

The qualitative evaluation of our tomato leaf disease classification system was conducted through comprehensive field testing at a tomato farm in Garin Malam Ari, Kumo, Akko Local Government Area of Gombe State. This location was chosen due to the prevalence of a locally significant disease known as "Cutan Kuturta" (identified as early blight), as well as other common tomato diseases.

Our system demonstrated high efficacy in detecting key tomato diseases. It accurately identified early blight, locally referred to as "Cutan Kuturta," caused by Alternaria solani.

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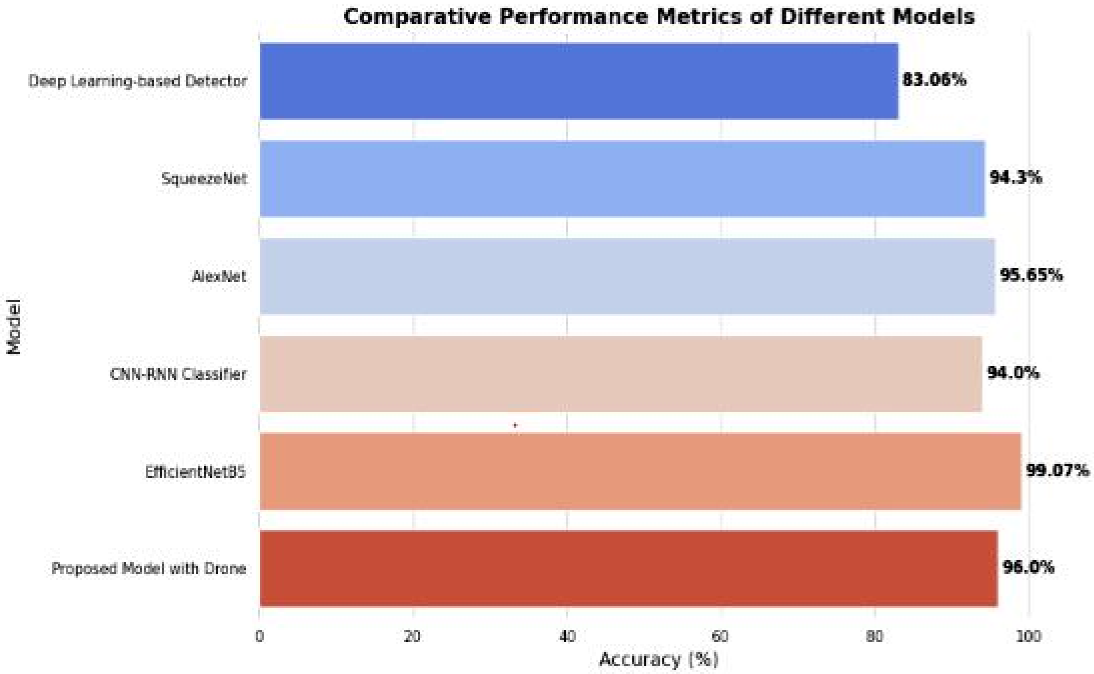

Figure 8: Comparative Performance Metrics of Different Models.

This disease is marked by dark, concentric rings on leaves and can lead to significant yield losses if not managed promptly (Jones et al., 2014). The drone-based system successfully detected this disease in real-time by analyzing the distinctive lesions on the leaves, as shown in Figure 9. Additionally, the system effectively identified Tomato Yellow Leaf Curl Virus (TYLCV), a significant disease transmitted by the whitefly Bemisia tabaci. TYLCV causes stunted growth, yellowing of leaves, and reduced fruit yield (Barbedo, 2016). Figure 10 also illustrates the system's capability to detect TYLCV by recognizing the characteristic yellowing and curling of leaves in real-time.

Figure 9: Drone-captured image showing early blight on tomato plants.

Bima Journal of Science and Technology, Vol. 8(4A) Dec, 2024 ISSN: 2536-6041

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Figure 10: Drone-captured image showing Yellow Leaf Curl Virus on tomato plants.

The system also proved effective in identifying late blight, caused by Phytophthora infestans. This devastating disease is characterized by large, water-soaked lesions on leaves and stems (Jones et al., 2014). Our model accurately detected these symptoms in real-time, as evidenced by Figure 11, which shows a drone-captured image of late blight on tomato plants. Equally important to disease detection is the accurate identification of healthy plants. Our system consistently recognized healthy tomato plants, characterized by vibrant green leaves, uniform growth patterns, and absence of spots, lesions, or discolorations (Barbedo, 2016). Figure 12 presents an image captured by the drone showing healthy tomato plants with no visible disease symptoms.

CONCLUSION

This study highlights significant advancements in tomato leaf disease classification through the integration of drone technology and deep learning models. The use of the Tello drone, combined with a Streamlit interface, offers a novel and effective approach for real-time disease detection in agricultural settings.

Figure 11: Drone-captured image showing Late blight on tomato plants.

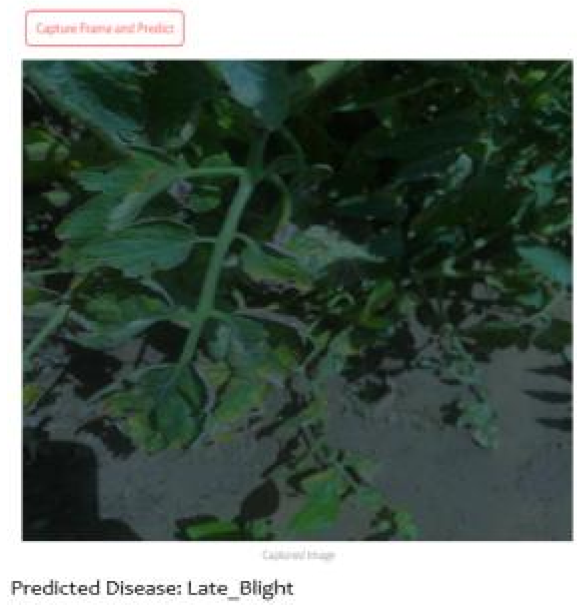

Figure 12: Drone-captured image showing Late blight and Healthy Leaf on tomato plants.

While the standalone model's accuracy of 96% is slightly lower than some top-tier models reported in the literature (Bhandari et al., 2023), the drone-integrated system's real-world applicability provides substantial

DOI: 10.56892/bima.v8i4.1155

advantages. It enables immediate, on-site disease detection and classification, facilitating timely interventions and potentially reducing crop losses.

Field tests in Garin Malam Ari demonstrated the system's effectiveness in detecting early blight, late blight, TYLCV, and septoria leaf spot, as well as healthy plants, showcasing its practical utility for farmers. However, challenges such as the drone's performance in windy conditions and limited battery life were noted. Future improvements could focus on more wind-resistant drones, extended battery life, and GPS-based systems for targeted pesticide application.

In conclusion, this study establishes a new benchmark for real-time agricultural monitoring by combining high-accuracy deep learning models with drone technology. Despite areas for improvement in model accuracy and operational efficiency, the system represents a significant advancement in effective and timely plant disease management.

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