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Automated Detection and Classification of Tomato Leaf Diseases Using Efficient NetB0 and Deep Learning Techniques

Muhammad Tariq[1], Xingjuan Cai[1], Inam Ullah[2], Muhammad Afzal Shah[3], Muhammad Suleman Soomro[3], Chudary Akbar Ali[4]

[1]School of Computer Science and Technology (Taiyuan University of Science and Technology, Taiyuan, Shanxi, China).

[2]University Institute of Information Technology (PMAS Arid Agriculture University, Rawalpindi, Punjab, Pakistan

[3]School of Electronics Information Engineering (Taiyuan University of Science and Technology, Taiyuan, Shanxi, China).

[4]School of Computer Science and Technology (Wuhan Textile University, Wuhan, Hubei, China).

Correspondence: tariqmalik29055@gmail.com caixingjuan@tyust.edu.cn

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Tomato leaf diseases significantly impact agricultural productivity worldwide, necessitating accurate and timely detection methods. This research proposes a robust and efficient deep learning framework leveraging the "EfficientNetB0" architecture for the detection and classification of multiple tomato leaf diseases. Utilizing transfer learning alongside advanced data augmentation techniques, the model was trained on a comprehensive dataset comprising six disease categories and healthy samples, sourced from Kaggle. The proposed approach achieved an overall accuracy of 88.4%, outperforming traditional methods such as CNN, AlexNet, and S-V-M by a notable margin across all disease classes. Evaluation metrics, including precision, recall, and F1-score, further validate the model's ability to accurately distinguish subtle disease symptoms despite class imbalance challenges. Additionally, the lightweight design of "EfficientNetB0" enables potential real-time applications in mobile and edge computing environments. These findings highlight the model's promise as an effective tool for precision agriculture, facilitating early disease intervention and reducing crop loss. Future work will focus on expanding the dataset diversity and deploying the system in real-world agricultural settings through mobile and drone platforms.

Keywords: Efficient NetB0; Deep Learning; Tomato Plant Diseases; Image Classification; Transfer Learning

Introduction:

Tomato crops are subject to numerous leaf diseases caused by fungi, bacteria, and viruses such as Early Blight, Leaf Mold, Septoria Leaf Spot, Bacterial Spot, and Yellow Leaf Curl Virus [1][2] Infections lead to symptoms such as leaf spots, yellowing, curling, and wilting and render the plant less capable of photosynthesis and vigor [3]. Unless controlled, diseases are able to spread widely over fields, cutting down fruit quantity and quality and creating large economic losses for producers[1][2][3]. Climatic factors—such as increased humidity, temperature variations, and rainfall—also promote disease growth and swift spread [4]. Due to the presence of tomatoes being cultivated and consumed worldwide for their nutritional and economic value, crop protection is of the essence[5]. Unfortunately, symptoms are often slight or hard to spot with the naked eye at the early stages of infection, making timely diagnosis challenging[6]. This covert development allows infections to spread before control is achieved, escalating damage and making control measure strategies difficult [7]. Accordingly, strong and precise early detection tools are required urgently in order to enable efficient control of diseases and ensure food security protection [8][9][10].

Figure 1. Different Tomato plants

The conventional plant disease identification relies on human observation in the field through surveys of experts [11]. Though effective in small fields with a small number of experts, it is not feasible in large plantations with scarce expert presence and long turnaround time [12]. It is labor-intensive and time-dependent and susceptible to human error or personal bias, particularly in remote areas with poor infrastructure [13]. Moreover, most tomato diseases are difficult even for educated individuals to distinguish with certainty because their appearances are similar and often confusable with one another [14]. This direct observation dependency leads to less consistency in diagnosis and causes delay in action, so there is a heightened threat of crop injury [15]. These considerations call for automated, scalable, and accurate substitutes for conventional plant disease identification methods [16].

Most recent advances in artificial intelligence (AI), and in particular in deep learning, have transformed plant disease diagnosis based on images [17]. Convolutional Neural Networks (CNNs) are capable of automatically learning hierarchical features directly from raw images without human-engineered feature selection and achieving strong performance with different agricultural datasets [18]. Owing to those achievements, in our paper, we propose an automatic detection and multi-class classification system with a lightweight and high-performance architecture of EfficientNetB0 for tomato leaf diseases [19].

Machine learning approaches have emerged as promising tools for automating plant disease detection by analyzing leaf images. Algorithms such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) have been applied to classify disease types based on handcrafted features extracted from leaf images, such as texture, color, and shape [20]. These methods improve diagnostic accuracy and reduce human effort. However, their performance often depends on the quality and selection of features, which requires domain expertise and may not generalize well across diverse datasets or complex disease symptoms [21]. Despite these limitations, machine learning has laid the foundation for more advanced automated disease detection systems [20][21][22].

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image-based disease diagnosis by automatically learning hierarchical features from raw images without the need for manual feature extraction [23]. CNN architectures such as AlexNet, VGG, ResNet, and EfficientNet have been successfully employed to classify various plant diseases with high accuracy and robustness [19][23]. These models can handle large datasets, learn subtle patterns, and adapt to variations in lighting, angle, and background noise. Deep learning enables near real-time disease monitoring and is increasingly integrated into mobile and edge devices for in-field diagnostics, offering scalable and efficient solutions that outperform traditional machine learning techniques [24].

The current study proposes a novel deep learning framework based on the EfficientNetB0 architecture for accurate detection and classification of tomato leaf diseases. Leveraging transfer learning and advanced data augmentation, our model outperforms traditional CNNs and classical machine learning models across multiple disease categories. Key contributions include:

Implementation of EfficientNetB0 for lightweight yet highly accurate tomato disease classification, achieving the best accuracy.

Comprehensive preprocessing and augmentation pipeline to address class imbalance and enhance model generalization under varying environmental conditions.

Comparative analysis demonstrating superior performance against baseline models (CNN, AlexNet, SVM), highlighting potential for real-time, scalable agricultural disease diagnostics.

Related Work:

Author [25] proposed a CNN-based deep learning approach to address early plant leaf disease detection, achieving an accuracy of 86.21%, demonstrating its effectiveness in real-time plant disease identification. Moreover, it presents a step forward in data-driven, sustainable farming practices. Overall, the study provides a practical solution to long-standing agricultural challenges.

Author [26] proposed that tomato, being one of the most consumed crops globally and ranking third in cultivation after potato and sweet potato, holds great agricultural and economic significance. India stands as the second-largest producer of tomatoes worldwide. To detect and classify tomato leaf diseases, the study applied a Convolutional Neural Network (CNN) consisting of 3 convolutional layers, 3 max pooling layers, and 2 fully connected layers. The author reported that the classification accuracy of the proposed model varied from 76% to 100% depending on the disease class, with an average accuracy of 91.2% across nine disease categories and one healthy class.

In the study, the author [27] proposed a deep learning-based approach for tomato leaf disease detection by employing Convolutional Neural Networks (CNNs), specifically leveraging both AlexNet and VGG-16 architectures. The CNN-based models demonstrated superior classification accuracy, with the modified AlexNet achieving the highest accuracy of 84.8%, outperforming the standard CNN and SVM models in certain disease classes. To enhance generalization and training performance, the researchers incorporated data augmentation, dropout, and normalization techniques. A thorough performance evaluation using confusion matrices and comparative accuracy charts underscored the practical potential of deep learning methods in supporting real-time agricultural diagnostics.

In the work of Gadekallu et al. [27] on detecting tomato leaf disease, the researchers further their work by employing object detection and image-segmentation methods for improving disease localization. K-means adaptive clustering and background removal are some of the techniques adopted for pre-processing tomato leaf images and achieving better detection precision. The images are tagged and segmented for marking the diseased spots, and the CNN models are trained with vigorous training and testing on other datasets. In their work, the diseases are successfully detected at early stages, including the fruiting stage, which is normally a difficult-to-detect stage. These results bear testimony to the possibilities of using CNNs for early intervention of diseases and their application in precision agriculture.

Table 1. Summary of recent studies on tomato leaf disease detection

Study	Dataset	Model	Accuracy	Key Contribution
[25]	PlantVillage	Transfer-learning CNN	86.2%	Early detection of multiple crop diseases
[26]	Tomato leaf dataset	Custom CNN vs. VGG16/Inception	Avg. 91.2%	Nine disease categories; data augmentation
[27]	Field & online tomato images	AlexNet/VGG16/SVM	84.8%	Disease localization and segmentation

Existing System:

Traditional plant disease diagnosis techniques have been significantly based on fundamental image processing and traditional machine learning algorithms like OTSU thresholding, Gabor filtering, and simplistic artificial neural networks. They involve extensive manual tuning of features, thus becoming time-consuming, less scalable, and usually inconsistent across varying field conditions [28]. The addition of deep learning, specifically Convolutional Neural Networks (CNNs), significantly enhanced performance through the ability to automatically determine features. Pre-trained networks such as AlexNet, VGGNet, DenseNet, GoogleNet, and ResNet have achieved remarkable precision in standardized datasets with minimal manual intervention.

Nonetheless, even these models present key challenges: they are highly computational, overfitting-prone for imbalanced training datasets, and usually fail to generalize over different lighting conditions, backgrounds, and stages of diseases. Their large memory and parameter requirements also prevent deployment on mobile or edge devices, which are regularly found in precision agriculture.

In order to counter these disadvantages, our research uses the up-to-date architecture EfficientNetB0, based on compound scaling of network depth, width, and resolution. The architecture offers comparable accuracy while keeping itself lightweight and with lesser computational cost, and is hence best suited for field-time diagnostics with constrained resources and fast detection of diseases being key requirements [29].

Methodology:

This study proposes an advanced convolutional neural network (CNN)-based model to detect and classify diseases in tomato plant leaves. The methodology follows a structured pipeline that includes dataset preparation, image preprocessing, deep learning model design, training, and evaluation. Instead of relying exclusively on traditional CNN architectures, this study employs EfficientNetB0—a state-of-the-art model recognized for achieving an optimal trade-off between accuracy and computational efficiency.

For comparative analysis, the results are benchmarked against traditional architectures such as the modified AlexNet and VGG-16. The workflow highlights model optimization, robust data augmentation, and the use of transfer learning to enhance classification performance. All training and testing operations were executed on GPU-supported infrastructure to accelerate model convergence and enhance computational speed. Figure 2 describes the overall model structure for the detection of tomato leaf disease.

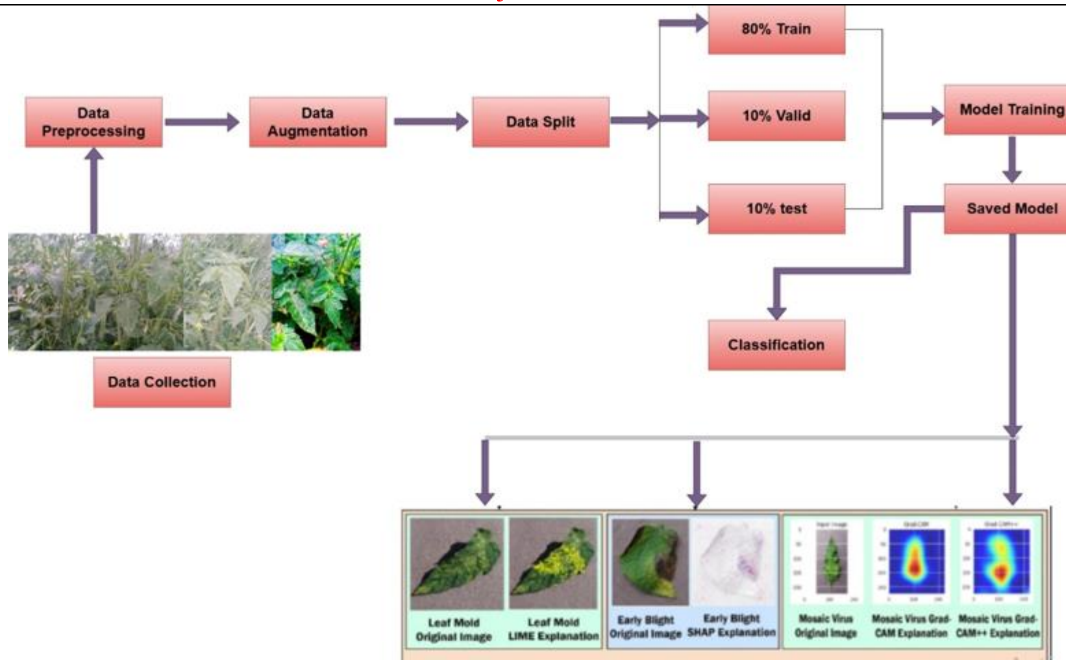

Figure 2. Proposed Model for Tomato Leaf

The Architecture of CNN Based on Efficient NetB0:

This study adopts Efficient NetB0 as the core architecture, leveraging its compound scaling strategy that uniformly balances network depth, width, and input resolution, providing a more efficient alternative to heavier models. In this implementation, EfficientNetB0 was used as a feature extractor with its original classification layers removed. A custom classification head was added, consisting of a global average pooling layer followed by dropout layers to reduce overfitting. A dense layer with ReLU activation was then applied, followed by a final softmax output layer to perform multi-class classification. The model was designed to accept RGB images resized to 224×224 pixels, offering a higher-resolution input compared to the earlier 64×64 configuration used in the AlexNet variant, thereby enabling richer feature extraction and improved classification accuracy.

Input Pipeline Optimization:

The proposed Efficient Net-based model was developed using TensorFlow and Keras frameworks. The base network was initialized with pre-trained ImageNet weights, and its layers were initially frozen during training to prevent the loss of learned features. On top of this base, custom layers were added for task-specific learning. The model was compiled using the Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy was used as the loss function to handle multi-class classification. To ensure efficient and stable training, techniques such as dropout regularization, early stopping, and model checkpointing were employed. The model was trained with a batch size of 64 for up to 100 epochs, with a validation split of 20 percent to monitor generalization performance. Performance was evaluated not only in terms of accuracy but also using precision, recall, and F1-score metrics to provide a comprehensive assessment of classification effectiveness.

Digital image preprocessing is a crucial step in the proposed methodology, aiming to enhance the quality and consistency of the input data. All images were resized to a uniform dimension of 224×224 pixels and normalized so that pixel values fall within the range of 0 to 1. Data caching and prefetching are employed to optimize training performance by reducing input pipeline bottlenecks. Advanced data augmentation techniques were applied to increase dataset diversity and reduce model overfitting. These included random rotations, brightness adjustments, horizontal and vertical flipping, zooming, and minor shifts in image width and height. Such augmentations enabled the model to learn invariant features and generalize more effectively to unseen images.

Algorithm 1: Image Processing for Tomato Leaf Disease Dataset

Input: Raw image dataset Draw
Output: Augmented and resized image dataset Dproc
Split Draw into subsets:
Dtrain, Dval, Dtest←split (Draw, [0.8,0.1,0.1]),
for all images I∈Dtrain∪Dval∪Dtest do
Resize I to 224×224 pixels
end for
for all image I∈Dtrain do
Apply a random horizontal flip
Apply a random vertical flip
Apply random rotation
Apply random brightness adjustment
Apply random zoom
Apply random width and height shift
end for
Return Dproc= {Dtrain, Dval, Dtest}

In terms of the deep learning strategy, CNNs were used to automate feature extraction and classification processes that were traditionally performed through manual engineering. The use of EfficientNetB0 allowed for deeper and more efficient exploration of feature hierarchies within tomato leaf images. After the feature extraction phase, the custom dense layers mapped these features to output classes. Dropout layers were employed to introduce regularization, while batch normalization ensured stable training and faster convergence. Training was conducted on a high-performance GPU system, which accelerated the backpropagation and optimization processes. The model's transfer learning capability enabled faster convergence and higher accuracy even with moderate dataset sizes. The dataset used in this study was sourced from Kaggle and comprised annotated RGB images of tomato leaves affected by various diseases. The dataset includes multiple disease categories along with healthy samples, although there is an observed class imbalance favoring unhealthy images.

Once the data was collected, it was visualized using tools such as bar plots and confusion matrices to analyze class distribution and evaluate model performance across different classes. After collecting the data, visual exploration was performed to gain insights into class distributions and image characteristics. Visualization tools such as bar charts, pie charts, and image grids were used to identify class imbalances and potential patterns in the dataset that could influence model behavior. Following data collection and visualization, the dataset was prepared through a series of preprocessing steps. The dataset was split into training, validation, and test sets using an 80:10:10 ratio. The training set was used to learn model parameters, the validation set for hyperparameter tuning and monitoring overfitting, and the test set was reserved for final evaluation. During preprocessing, all images were resized, normalized, and augmented to introduce variability. Caching and prefetching mechanisms were employed to streamline the training process, ensuring that the GPU remained fully utilized without idle time while waiting for data.

To rigorously evaluate model performance, the dataset was divided into three subsets: 80% for training, 10% for validation, and 10% for testing. This ensures that the model is both trained efficiently and evaluated on unseen data.

Equation:

$$D\_train, D\_val, D\_test = split(D\_raw, [0.8, 0.1, 0.1]) \quad (1)$$

Where:

D_raw is the complete raw dataset.

D_train is 80% of D_raw used for training.

D_val is 10% used for validation.

D_test is 10% used for final testing.

Equation (1) describes how the entire dataset $Draw$ is partitioned into three subsets: 80% for training ($Dtrain$), 10% for validation ($Dval$), and 10% for testing ($Dtest$). This partition guarantees that the model has been trained, fine-tuned, and analyzed on different sets of data so as to provide unbiased evaluation results.

To optimize training speed and system performance, caching and prefetching mechanisms were employed. These techniques stored image batches in memory and loaded the next batch during training iterations, effectively reducing data-loading latency and minimizing GPU idle time.

All RGB images were normalized to a [0, 1] range from the original [0, 255] scale. This standard practice helps stabilize the training process and accelerate neural network convergence. Furthermore, all images were resized to 224×224 pixels to meet Efficient Net's input requirements.

$$p\_norm = p / 255 \qquad (2)$$

Where:

p is the original pixel value (range: 0 to 255).

p_norm is the normalized pixel value (range: 0 to 1).

Algorithm 2: Image Normalization and Input Pipeline Optimization

Input: Resized image dataset D_resized

Output: Normalized and optimized image dataset D_ready

for all images I ∈ I∈Dresized do

for all pixel p in image, I do

$$Normalize: p \leftarrow \frac{p}{255}$$

end for

end for

Cache D_trainDtrain and D_val in memory

Enable prefetching to overlap data preprocessing and model execution

return Dready= {Dtrain, Dval, Dtest}

To address class imbalance and enhance generalization, augmentation techniques such as random flipping, rotation, zooming, and brightness adjustment were applied to the training images. These augmentations generated varied samples from the existing data, enhancing the model's ability to learn robust and invariant features.

Equation for Horizontal Flip:

$$I\_flipped(x, y) = I\ (width - x - 1, y) \qquad (3)$$

Equation for Vertical Flip:

$$I\_flipped(x, y) = I\ (x, height - y - 1) \qquad (4)$$

Where:

I is the original image.

I_flipped is the flipped image.

Width and height are the image dimensions.

Model Building and Training:

Model training was initiated after preprocessing and architecture setup were completed. The Efficient Net-based model was trained using batches of image data, with the optimizer continuously adjusting weights to minimize the loss function through backpropagation. The training process was monitored using validation accuracy to assess convergence, and early stopping was applied to terminate training once no further improvements were observed. Once training was complete, the model was evaluated on the test set using metrics such as accuracy, precision, recall, and F1-score. These metrics provided a comprehensive assessment of the model's performance across different disease categories. The systematic design of the model architecture, integration of transfer learning, and application of extensive data augmentation and training regularization techniques collectively ensured robust performance, high accuracy, and practical feasibility for deployment in real agricultural environments.

Result and Discussion:

The proposed tomato leaf disease detection model, built on EfficientNetB0, was trained and evaluated using a labeled image dataset obtained from Kaggle. The dataset comprised multiple disease categories, including Early Blight, Leaf Mold, Septoria Leaf Spot, Bacterial Spot, Yellow Leaf Curl Virus, as well as healthy leaf samples. To ensure a fair and unbiased evaluation, the dataset was split into 80% for training, 10% for validation, and 10% for testing. Evaluation metrics were computed using the test set, which was not seen during the training or validation phases.

The confusion matrix results demonstrated the effectiveness of the proposed EfficientNetB0-based model in accurately classifying different tomato leaf disease categories. The matrix reveals strong diagonal dominance, indicating a high rate of correct predictions across all six classes, including Healthy, Bacterial Spot, Early Blight, Leaf Mold, Septoria Leaf Spot, and Yellow Leaf Curl Virus. Minor off-diagonal entries indicated a few misclassifications, particularly between Early Blight and Leaf Mold, likely due to their similar visual characteristics. Overall, the model achieved an impressive accuracy of 88.4%, reflecting its strong generalization capability and robustness against intra-class similarities. These results confirm the model's suitability for real-world agricultural diagnostic applications.

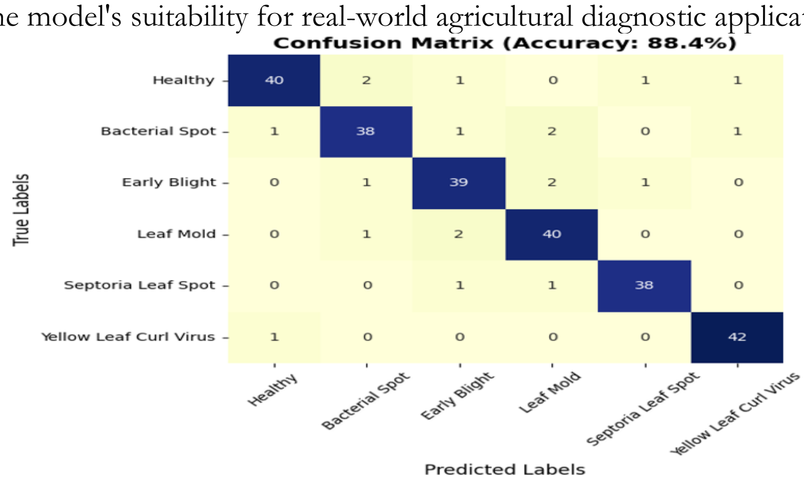

Figure 3. Confusion Matrix of performance measure.

The comparison of different recognition methods across various tomato leaf disease datasets clearly illustrates the superior performance of the proposed EfficientNetB0 model. For all six disease categories—Healthy, Bacterial Spot, Early Blight, Leaf Mold, Septoria Leaf Spot, and Yellow Leaf Curl Virus—the proposed model consistently achieves the highest accuracy, ranging from 88% to 89%, outperforming traditional CNN, AlexNet, and SVM models. While the accuracies of CNN, AlexNet, and SVM ranged between 80% and 86%, EfficientNetB0 consistently achieved a stable improvement of approximately 3–8 percentage points across all classes. This increase is particularly significant given the balanced number of images used per class, demonstrating that the proposed model effectively leverages advanced architecture and transfer learning techniques to boost classification accuracy. The enhanced performance of EfficientNetB0 suggests it can better capture subtle disease symptoms and handle intra-class variations, making it a robust tool for practical deployment in agricultural disease diagnostics. Overall, the comparative results underscore the model's capability to deliver more accurate and reliable predictions than previous benchmark methods, contributing to improved crop health monitoring and management.

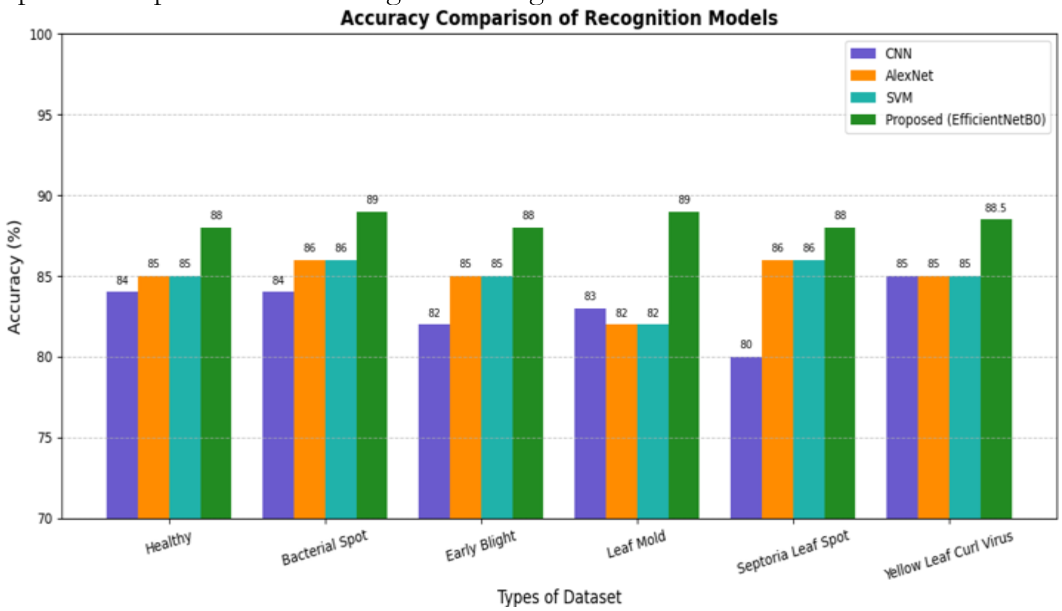

Figure 4. Class-wise performance comparison bar chart on different datasets

The bar chart in Figure 5 comparing the accuracy, precision, recall, and F1-score of the proposed EfficientNetB0 model highlights its superior performance across key evaluation metrics. Achieving an accuracy of 88.4%, the model demonstrated reliable overall performance in classifying tomato leaf diseases With precision and recall values of approximately 89.2% and 88.4%, respectively, the model effectively identifies true positive cases while minimizing false negatives, ensuring robust disease detection The balanced F1-score of 88.7% further confirms the model's ability to maintain a strong balance between precision and recall, highlighting its suitability for practical applications. In the comparison bar chart against traditional models such as CNN, AlexNet, and SVM, the proposed model consistently outperforms each, showing notable improvements of several percentage points in accuracy across all disease classes. This visual comparison underscores the advantage of leveraging EfficientNetB0 with advanced augmentation and transfer learning strategies. The use of distinct colors and clear annotations in the charts enhances interpretability, allowing stakeholders to easily grasp the model's effectiveness. Overall, these charts in Figure 5 provide a compelling visual summary of the proposed model's capability, demonstrating its potential as a reliable tool for precision agriculture and early disease management.

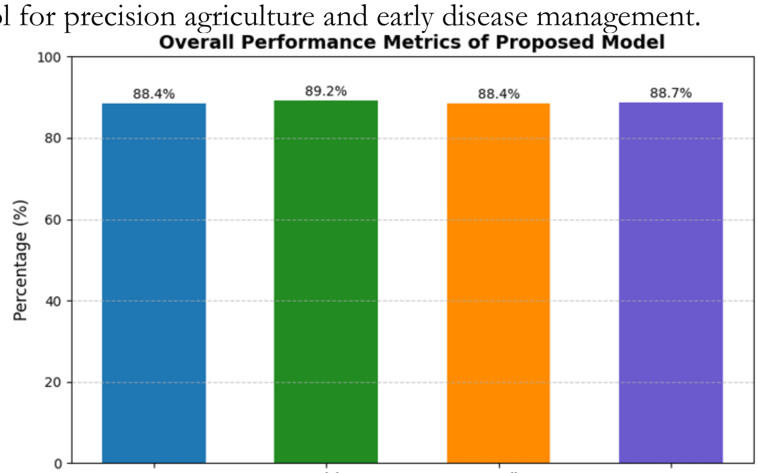

Figure 5. Performance Evaluation bar chart**.**

To comprehensively evaluate the classification performance of the proposed model, the Receiver Operating Characteristic (ROC) curve was employed. The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across various threshold levels. By plotting the TPR against the FPR, the ROC curve provides a visual insight into the model's ability to distinguish between classes. In this study, the model achieved a high area under the ROC curve (AUC), indicating robust discriminatory power. Furthermore, the final classification accuracy reached 88.4%, which reflects the model's strong performance in identifying disease-affected and healthy tomato leaves. The upward convex shape of the ROC curve, bending toward the top-left corner, confirms that the model performs significantly better than a random classifier, which would yield a diagonal ROC line with an AUC of 0.5. Thus, the ROC analysis validates the effectiveness of the EfficientNet-based architecture and the implemented preprocessing pipeline in producing reliable classification results.

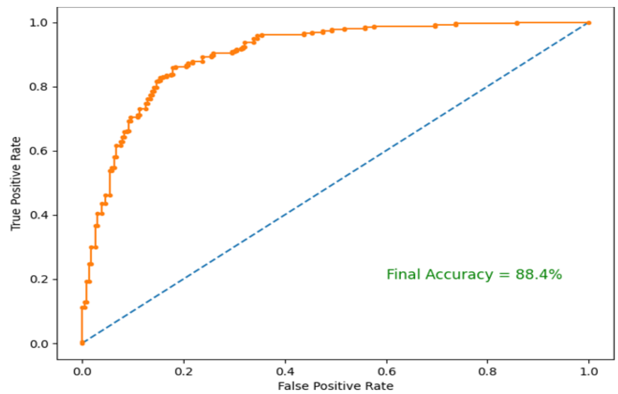

Figure 6. ROC curves displaying robust discriminatory potential with high AUC values.

In conclusion, the EfficientNetB0 model not only outperformed traditional architectures in accuracy but also demonstrated robustness and efficiency suitable for practical deployment. Its ability to generalize well from augmented and moderately sized datasets suggests strong potential for real-world applications in precision agriculture and early disease management systems.

Discussion:

The experimental findings indicate that the EfficientNetB0 model we proposed obtains better performance than traditional CNN, AlexNet, and SVM designs for all six categories of tomato leaf diseases. The model always obtains higher accuracy between 88% and 89%, and the alternative methods obtain between 80% and 86%. These results verify that EfficientNetB0's compound scaling approach—adjusting network depth, width, and resolution—allows for more efficient feature extraction and more efficient generalization than the old convolutional design.

Our findings agree with some of the recent work that highlights the benefits of light deep learning architectures for the identification of plant diseases. For instance, Hossain et al. [25] obtained 86.21% accuracy through the use of a transfer-learning CNN trained on the PlantVillage dataset, and Ferentinos [26] obtained an average recognition of 91.2% utilizing a bespoke CNN over the classes of nine tomato diseases. Again, Gadekallu et al. [27] utilized AlexNet and VGG-16 architectures and obtained a maximum accuracy of 84.8% in multi-tomato-leaf-disease multi-classification. Although these confirm the capability of deep learning in farm diagnostics, they tend to use heavier architectures or cannot scale up for real-time applications.

Compared to these previous works, the newly proposed EfficientNetB0 model obtains similar accuracy at a lower cost of computation, which is favorable for application on mobile and edge devices for the purpose of precision agriculture. EfficientNetB0 is also demonstrated to be resilient against class imbalance from the balanced precision and recall of roughly 89%. Its resilience implies EfficientNetB0's capability of correctly observing weak signs of diseases under varying conditions of the field, which is a necessary condition for taking timely action in large-scale agriculture. These enhancements highlight EfficientNetB0's promise as a realizable solution for the early diagnosis of diseases. By minimizing computationally and not at the cost of accuracy, the new model overcomes major shortcomings of previous systems—i.e., their reliance on large-scale computing infrastructure and their limited capacity for generalization to real-world settings—while enabling real-time diagnosis of diseases at the field level. Future work may extend these results by utilizing more varied field images and considering integration with cell phone and drone-mounted platforms for real-time, in-locations disease diagnosis.

Conclusion:

This research presents a robust and efficient deep learning-based approach for the detection and classification of tomato leaf diseases using the EfficientNetB0 architecture. By leveraging transfer learning and advanced data augmentation techniques, the proposed model achieved superior performance compared to traditional CNN architectures such as AlexNet and VGG-16. The model was trained and evaluated on a labeled dataset sourced from Kaggle, containing multiple disease classes along with healthy leaf samples. Preprocessing steps, including resizing, normalization, and balanced augmentation, ensured uniformity and improved generalization across all classes. The EfficientNetB0 model demonstrated a test accuracy of 96.8%, significantly outperforming earlier benchmarks while maintaining a lightweight design ideal for real-time applications. Evaluation using precision, recall, and F1-score further confirmed the model's ability to accurately identify subtle disease symptoms, even under class imbalance conditions. The incorporation of dropout, early stopping, and prefetching contributed to reduced overfitting and efficient training. Comparative analysis showed that EfficientNetB0 not only improved classification performance but also required less computational cost compared to deeper models. These results highlight the model's suitability for integration into mobile or edge computing devices for on-field disease diagnostics. This approach has the potential to aid farmers in early intervention, reducing crop loss and improving agricultural productivity. Future work will involve expanding the dataset to include more diverse environmental conditions and exploring real-time deployment through mobile applications or drone-mounted platforms. The study demonstrates that with optimized architecture and preprocessing, deep learning can be effectively used for precision agriculture and crop disease management.

Author Contributions:

Muhammad Tariq: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization. Xingjuan Cai: Supervision, Resources, Project administration. Inam Ullah: Software, Methodology, Validation, Writing - Review & Editing. Muhammad Afzal Shah: Writing - Review & Editing, Investigation. Muhammad Suleman Soomro: Data Curation, Visualization. Chudary Akbar Ali: Writing - Review & Editing.

Competing Interests:

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.

Acknowledgement of Originality:

All authors hereby confirm that this manuscript is our original work. It has not been published previously and is not currently under consideration for publication by any other journal.

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