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COMPARATIVE STUDY ANALYSIS TOMATO LEAF DISEASES USING DEEP LEARNING MODELS CONVOLUTIONAL NEURAL NETWORK

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Abstract— *Diseases that significantly impact tomato foliage contribute to decreased agricultural productivity and reduced crop quality, thus requiring accurate and efficient detection methods. This study aims to evaluate the effectiveness of three Convolutional Neural Network (CNN) architectures, namely EfficientNetB0, InceptionV3, and MobileNetV2, in classifying tomato leaf diseases using images. The dataset used in this study consists of 4,804 tomato leaf images sourced from field observations as well as publicly available datasets from Kaggle and Mendeley. In this dataset, five disease categories are recognized: Bacterial Spot (1,116 images), Early Blight (1,158 images), Late Blight (1,063 images), Septoria Leaf Spot (1,137 images), and Mosaic Virus (330 images). This study uses an experimental approach that includes image pre-processing, dataset splitting (70% for training and 30% for testing), transfer learning-based models, and performance evaluation using metrics such as accuracy, precision, memory, F1 score, and error matrix. The results show that EfficientNetB0 achieved the highest accuracy of 74.6%, followed by MobileNetV2 at 73.21% and InceptionV3 at 68.91%. Furthermore, MobileNetV2 demonstrated excellent computational efficiency, having the fewest parameters and the fastest inference time. Further Grad-CAM analysis confirmed that EfficientNetB0 primarily focused on disease-related tomato leaf regions during its prediction process. These findings indicate that EfficientNetB0 offers the best overall classification performance, while MobileNetV2 achieves a favorable balance between prediction accuracy and computational efficiency, making it suitable for resource-constrained agricultural applications.*

Keywords: *Comparative Study, Deep Learning, EfficientNetB0, InceptionV3,* MobileNetV2.

Intisari— *Penyakit yang berdampak signifikan pada dedaunan tomat berkontribusi pada penurunan produktivitas pertanian dan penurunan kualitas tanaman, sehingga membutuhkan metode deteksi yang akurat dan efisien. Studi ini bertujuan untuk mengevaluasi efektivitas tiga arsitektur Convolutional Neural Network (CNN), yaitu EfficientNetB0, InceptionV3, dan MobileNetV2, dalam mengklasifikasikan penyakit daun tomat menggunakan gambar. Dataset yang digunakan dalam studi ini terdiri dari 4.804 gambar daun tomat yang bersumber dari pengamatan lapangan serta dataset yang tersedia secara publik dari Kaggle dan Mendeley. Dalam dataset ini, lima kategori penyakit dikenali: Bercak Bakteri (1.116 gambar), Hawar Dini (1.158 gambar), Hawar Akhir (1.063 gambar), Bercak Daun Septoria (1.137 gambar), dan Virus Mosaik (330 gambar). Studi ini menggunakan pendekatan eksperimental yang mencakup pra-pemrosesan gambar, pembagian dataset (70% untuk pelatihan dan 30% untuk pengujian), model berbasis transfer learning, dan evaluasi kinerja menggunakan metrik seperti akurasi, presisi, memori, skor F1, dan matriks kesalahan. Hasil penelitian menunjukkan bahwa EfficientNetB0 mencapai akurasi tertinggi sebesar 74,6%, diikuti oleh MobileNetV2 sebesar 73,21% dan InceptionV3 sebesar 68,91%. Lebih lanjut, MobileNetV2 menunjukkan efisiensi komputasi yang sangat baik, dengan parameter paling sedikit dan waktu inferensi tercepat. Analisis Grad-CAM lebih lanjut mengkonfirmasi bahwa EfficientNetB0 terutama berfokus pada area daun tomat yang terkait dengan penyakit selama proses prediksinya. Temuan ini menunjukkan bahwa EfficientNetB0* *menawarkan kinerja klasifikasi keseluruhan terbaik, sementara MobileNetV2 mencapai keseimbangan yang menguntungkan antara akurasi prediksi dan efisiensi komputasi, sehingga cocok untuk aplikasi pertanian dengan keterbatasan sumber daya.*

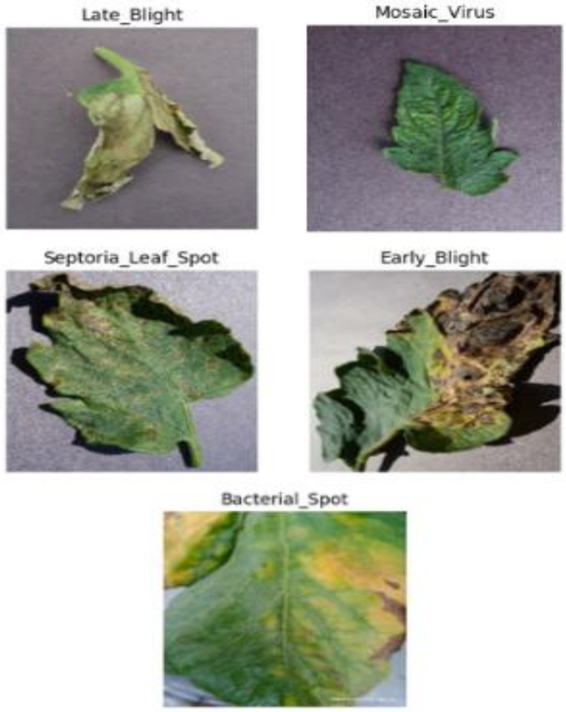
***Kata Kunci**: Studi Komparatif, Deep Learning, EfficientNetB0, InceptionV3, MobileNetV2.*

INTRODUCTION

Plant pathologies constitute a critical factor that leads to diminished agricultural output worldwide [1]. The incursion of pathogenic entities, encompassing bacteria, fungi, and viruses, possesses the capacity to perturb critical physiological processes in plants, including photosynthesis, vegetative growth, and reproductive functions, thereby directly influencing both the quality and quantity of agricultural outputs [2]. In the domain of horticultural commodities, losses stemming from pathogen afflictions not only influence the volume of production but also profoundly affect the economic sustainability of agronomists and the agricultural industry at large [3], [4]. One of the agronomic commodities that is vulnerable to pathogen incursion is the cultivation of tomatoes (Solanum Lycopersicum), which is categorized among the crops of considerable consumption and production importance in numerous nations [5], [6], [7].

In Solanum Lycopersicum, various foliar diseases including Bacterial Spot, Early Blight, Septoria Leaf Spot, Late Blight, and Mosaic Virus exhibit distinct phenotypic manifestations on the adaxial and abaxial surfaces of the leaves [8]. Bacterial Spot is defined by the presence of diminutive brown lesions encircled by a yellowish halo, whereas Early Blight is identified by brown lesions exhibiting a concentric circular arrangement. In contrast, Septoria Leaf Spot is characterized by the emergence of small grayish lesions with darker peripheries that propagate across the foliar surface, while Late Blight manifests through irregular brown lesions that progress to extensive necrotic tissue. Furthermore, viral infections, exemplified by Mosaic Virus, are distinguished by the alteration of leaf pigmentation to a dark green mosaic configuration, which is further associated with morphological deformations of the leaf.

These pathological symptoms are capable of inflicting persistent damage to foliar tissue, diminishing the effective photosynthetic area of the leaf, and facilitating the dissemination of infection throughout other regions of the plant [9]. Consequently, pathologies that impact foliar structures hold significant importance due to the critical role of leaves in the processes of photosynthesis and the comprehensive metabolism of plants [10]. Should leaf disease outbreaks remain unrecognized and inadequately addressed in a timely manner, they have the potential to escalate significantly, particularly in humid environments, leading to considerable reductions in agricultural yield [11], [12].



Source : (Research Result, 2026)

Figure 1. Tomato Leaf Disease

The development of artificial intelligence technology has led to a remarkable transformation in plant disease detection systems [13]. At present, scholars are thoroughly employing computer vision, machine learning, and deep learning techniques to supplant conventional identification methodologies that depend on human visual assessment [14], [15]. In the preliminary stage, computational methods including Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor were employed utilizing features that were manually derived, encompassing attributes such as foliar pigmentation, surface texture, and morphological shape [16]. Nonetheless, this methodology encounters obstacles when addressing intricate fluctuations in situational

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parameters and additionally necessitates elaborate pre-processing protocols [17], [18].

With the exponential growth in computational capabilities and the proliferation of plant image datasets, the Convolutional Neural Network (CNN) methodology has ascended as a preeminent approach, as it possesses the ability to independently execute feature extraction and attain markedly enhanced classification accuracy outcomes in comparison to conventional methods [19], [20]. For instance, prior investigations employing the EfficientNet architectural framework for the classification of tomato leaf ailments demonstrated an accuracy surpassing 99% on datasets comprising leaf images, thereby suggesting that deep learning methodologies are exceptionally proficient in autonomously recognizing a diverse array of plant pathologies.

In the domain of agricultural research pertaining to tomato cultivation, a multitude of investigations have employed convolutional neural network (CNN) architectures alongside transfer learning methodologies to detect various phytopathologies utilizing datasets such as PlantVillage in conjunction with field-based imagery. Notable models, including InceptionV3 and Inception ResNet, have exhibited accuracies nearing 99.22% in the differentiation between healthy and diseased tomato foliage [21], in the interim, advanced models derived from MobileNet and an array of alternative network architectures have been developed to enhance computational efficiency while maintaining classification precision. Prior investigations have demonstrated that the MobileNet architecture attains an accuracy of up to 97% in the classification of tomato leaf diseases and achieves a remarkable 99.45% in other plant disease datasets, thereby establishing the model as one of the lightweight frameworks that is proficient in the classification of plant disease imagery. [22], [23].

The classification of leaves employing a deep learning methodology predominantly employs a Convolutional Neural Network (CNN) architecture, which possesses the capability to autonomously extract image characteristics via convolutional layers, pooling layers, and fully connected layers [24]. In contrast to conventional methodologies necessitating manual feature engineering, Convolutional Neural Networks (CNNs) possess the capability to autonomously discern textural patterns, color discrepancies, morphological structures, and the hierarchical organization of foliar damage from visual data [17], [25]. The classification procedure commences with preliminary processing phases including resizing, normalization, and data augmentation, aimed at enhancing the model's capacity for generalization [26].

In order to enhance both accuracy and operational efficiency, numerous research endeavors have implemented transfer learning techniques through the employment of pre-trained models including InceptionV3, ResNet, MobileNet, and EfficientNet [21], [27], [28]. Moreover, the advancement of an architectural framework that employs attention mechanisms and bilinear pooling significantly enhances the model's acuity in discerning nuanced distinctions among various disease categories [29]. The efficacy of the model is subsequently assessed utilizing various metrics, including accuracy, confusion matrix, recall, and F1-score, to guarantee consistent and thorough classification performance.

In the interim, MobileNetV2, InceptionV3, and a multitude of variants of Convolutional Neural Network (CNN) architectures demonstrated remarkable efficacy in the classification of diseases affecting tomato foliage [30]. MobileNetV2 is recognized for its streamlined architecture and operational efficacy on mobile platforms. Nevertheless, its restricted capacity for feature representation may lead to a decline in performance when confronted with intricate variations in field imagery or heterogeneous data distribution [26]. InceptionV3 exhibits enhanced and more accurate capabilities for feature extraction. Nonetheless, its architectural intricacy escalates computational requirements and training duration, rendering it less appropriate for real-time applications or devices with limited resources [21].

As an advancement over prior models, EfficientNetB0 has emerged as one of the most prevalent architectures in the classification of leaf diseases, attributable to its capability to attain a harmonious equilibrium between precision and computational efficacy. EfficientNetB0 employs the concept of compound scaling, which systematically augments the depth, width, and resolution of the input, thereby yielding exceptional performance with a comparatively modest number of parameters in contrast to traditional convolutional neural networks (CNN).

According to research conducted by Ferga et al [31], the application of EfficientNetB0 in the classification of tomato leaf images has been shown to yield precise feature extraction while concurrently upholding a remarkable level of performance stability, culminating in an overall accuracy rate of 89%. These advantageous characteristics render EfficientNetB0 exceptionally versatile in adapting to variations in leaf texture and disease manifestations that present subtle visual discrepancies. Moreover, its optimized architectural framework promotes an expedited training process and necessitates a reduced memory footprint in comparison to more complex models such as Inception or ResNet. In light of these properties, EfficientNetB0 emerges as a significant candidate for evaluation and comparison within this research, which aspires to establish an optimal model for tomato leaf disease classification with respect to accuracy, efficiency, and adaptability to field data.

Although a plethora of scholarly investigations have elucidated promising outcomes in the classification of tomato leaf diseases via deep learning techniques, a conclusive understanding pertaining to which Convolutional Neural Network (CNN) architecture optimally reconciles classification precision, computational efficiency, model complexity, and applicability remains elusive. Prior research has indicated that models predicated on EfficientNet frequently attain enhanced classification accuracy through the implementation of integrated scaling methodologies, whereas MobileNetV2 exhibits diminished computational requirements and is particularly advantageous in settings where resources are constrained.

Conversely, InceptionV3 displays adeptness in the extraction of multi-scale features but generally necessitates more substantial computational resources. Notwithstanding this, these architectures are predominantly assessed in isolation, employing disparate datasets, preprocessing techniques, and experimental paradigms, thereby precluding a straightforward comparative evaluation. As a result, uncertainty persists regarding which architecture is most appropriately aligned with the classification of tomato leaf diseases when scrutinized under uniform experimental conditions. Additionally, the visual resemblances among specific tomato leaf ailments, such as Bacterial Spot, Early Blight, and Late Blight, may differentially influence model performance, contingent upon the feature extraction characteristics inherent to each architecture.

Therefore, EfficientNetB0, InceptionV3, and MobileNETv2 have been selected owing to their embodiment of varied deep learning design philosophies and distinct performance metrics, thereby enabling a comprehensive assessment of predictive accuracy, computational efficiency, and model complexity. These findings are anticipated to yield practical insights for the judicious selection and implementation of models within tomato leaf disease diagnostic frameworks and precision agriculture methodologies.

Therefore, this research endeavors to perform a comparative examination of three deep learning frameworks, specifically EfficientNetB0, InceptionV3, and MobileNetV2, in the classification of tomato leaf diseases utilizing image data. The assessment methodology incorporates performance metrics including accuracy, recall, F1 score, and confusion matrix analysis to comprehensively evaluate the models' proficiency in differentiating among the distinct categories of tomato leaf diseases. This comparative approach is paramount as each architecture possesses distinctive characteristics concerning parameter complexity, computational demands, and feature extraction efficacy [30].

Prior investigations have demonstrated that alterations in network architecture can significantly influence performance stability, particularly in datasets distinguished by variations in field imagery and uneven class distribution [27], [32]. Consequently, the comparative examination not only underscores the paramount accuracy metric but also considers the efficacy of training, the duration of inference, and the model's capacity to generalize to unseen data. The outcomes of this comparative investigation are anticipated to yield suggestions for optimal architectures that attain a harmonious equilibrium between classification efficacy and implementation efficiency within a deep learning-based tomato leaf disease detection framework.

MATERIALS AND METHODS

This study was performed using a quantitative methodology through an experimental framework to showcase the efficacy of three deep learning models in identifying tomato leaf diseases from images. The quantitative approach was chosen as this research aimed to evaluate the models' performance, encompassing metrics such as accuracy, precision, recall, and F1-score. In parallel, the experimental framework was executed via a series of tests carried out on three Convolutional Neural Network (CNN) architectures: EfficientNetB0, InceptionV3, and MobileNetV2, all utilizing the same dataset, which facilitated an unbiased analysis of the comparative results.

The phases of the research encompass recognizing the problem, conducting a literature review, gathering datasets from both the field and public repositories, preprocessing the data, sharing training and test datasets, modeling, training, evaluating, and performing comparative analysis to

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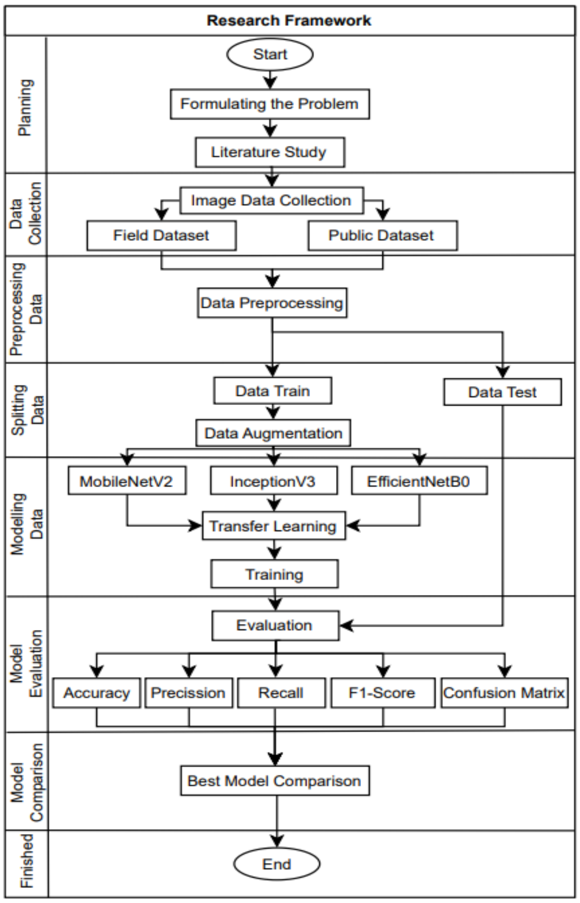
identify the optimal model. The complete research process is illustrated in Figure 2.



Source : (Research Result, 2026)

Figure 2. Research Framework

Dataset Collection

The datasets employed in the present investigation are derived from two distinct origins: an empirical dataset and a publicly accessible dataset. The empirical dataset was obtained through the direct acquisition of images of tomato foliage within the agricultural region of Gunung Manik Village, situated in the Talaga District of Majalengka Regency. The imagery was procured utilizing a Samsung A15 mobile phone camera during daylight hours, under natural illumination, while incorporating a variety of shooting angles, distances, and backgrounds.

Furthermore, supplementary datasets were acquired from publicly accessible repositories such as Kaggle and Mendeley Data to augment the volume of data and enhance the generalization capabilities of the model. Subsequently, all data were amalgamated and classified into five distinct disease categories: Bacterial Spot, Early Blight, Septoria Leaf Spot, Late Blight, and Mosaic Virus. Following the data integration procedure, the comprehensive dataset utilized comprised 4,804 images. The collection comprises 1,116 images showcasing Bacterial Spot, 1,158 images depicting Early Blight, 1,063 images representing Late Blight, 1,137 images illustrating Septoria Leaf Spot, and 330 images of Mosaic Virus. This distribution mirrors the fluctuations in disease occurrence observed in the field and documented in publicly available datasets. The variety of disease types, accompanied by differing sample sizes, is intended to enhance the model's ability to generalize across various disease characteristics and imaging conditions.

Table 1. Tomato Leaf Disease Dataset

Disease Class	Number of Images
Bacterial Spot	1.116
Early Blight	1.158
Late Blight	1.063
Septoria Leaf Spot	1.137
Mosaic Virus	330

Source : (Research Result, 2026)

Preprocessing Data

In the initial phase of data preprocessing, the images undergo a resizing transformation to dimensions of 224 x 224 pixels, followed by normalization via the preprocess_input function. This normalization process is designed to synchronize the distribution of pixel values with that of the pre-trained ImageNet model, consequently enhancing the efficacy of the model's performance.

In a general context, the normalization operation can be articulated as a transformation:

$$X' = f(X) \tag{1}$$

where X represents the initial pixel value and X' signifies the pixel value derived from the transformation process. The function $f(X)$ modifies the pixel values in accordance with the distinctive attributes inherent to each model architecture. This stage is designed to enhance the uniformity of the input data and to facilitate the convergence of the model during the training phase [33].

Table 2. Data Preparation

Parameter	Data Train	Data Test
Target Size	224 × 224	224 × 224
Color Mode	RGB	RGB
Subset	Training	Testing
Batch Size	32	32
Proportion	0.70	0.30
Label Mode	Categorical	Categorical
Random Seed	42	42

Source : (Research Result, 2026)

Splitting Data

Subsequent to the preprocessing stage, the dataset was partitioned into two principal subsets, specifically 70% designated for training purposes and 30% allocated for testing, which were extracted from a synthesis of field data and publicly available data sources, including Kaggle and Mendeley Data (comprising 4,804 image datasets).

The distribution of data occurs automatically via a mechanism that employs pre-defined random numbers (seed = 42), thereby guaranteeing that the resultant data distribution remains consistent and reproducible, which is a standard approach to ensure replicability in machine learning experiments [34]. From a mathematical perspective, the distribution of the dataset can be articulated as:

$$D = D_{train} \cup D_{test}, D_{train} \cap D_{test} = \emptyset \quad (2)$$

where D represents the comprehensive dataset, *D_train* denotes the training subset, and *D_test* signifies the testing subset [35].

The dataset was divided into 70% for training and 30% for testing to provide ample samples for model training while preserving distinct subsets for performance evaluation. This research was designed as a comparative analysis of EfficientNetB0, InceptionV3, and MobileNetV2 under consistent experimental conditions, instead of concentrating on hyperparameter optimization. As a result, all models were trained utilizing the same preprocessing techniques, training parameters, and dataset distribution. The main objective was to assess the comparative performance of various CNN architectures on the same datasets, rather than trying to enhance the performance of a single model through extensive parameter tuning. Although employing a dedicated validation set is generally advisable, the training-test split approach applied in this study was considered sufficient for comparative analysis. Future studies might integrate different subsets for training, validation, and testing to further enhance the evaluation of model generalization.

Data Augmentation

Augmentation techniques are employed to enhance the variability of a training dataset without altering the original data directly. This approach aims to mitigate overfitting, bolster model robustness, and improve deep learning models' ability to generalize across different object perspectives, orientations, and scales. In image classification tasks, data augmentation has become a prevalent approach to boost the diversity of training samples and enhance model performance in cases of limited datasets [36]. In this research, augmentation was executed through a range of image transformations, including random rotation, horizontal flipping, zooming within a ±20% range, and random image displacement.

The rotational transformation is implemented through the utilization of the following mathematical equation:

$$I'(x, y) = I\ (x\ cos\ cos\ \theta - y\ sin\ sin\ \theta, x\ sin\ sin\ \theta + y\ cos\ cos\ \theta \quad (3)$$

where *I'(x,y)* represents the resultant image following the application of the rotation transformation, *I(x,y)* denotes the initial image, and θ signifies the angle of rotation [36].

Modeling Data

In the data modeling phase, tomato leaf disease classification was performed using three Convolutional Neural Network (CNN) architectures: EfficientNetB0, InceptionV3, and MobileNetV2. These three models employ a transfer learning approach, utilizing pre-trained weights obtained from ImageNet to improve feature performance and learning efficiency, particularly when the available dataset size is limited [35]. Each architecture was adjusted at the final layer (fully connected layer) to accommodate the number of classes in the research dataset, with a softmax activation function formulated as:

$$yi = \frac{e^{zi}}{\sum_j^n = 1\ e^{zj}} \quad (4)$$

where yi signifies the likelihood of the i-th classification, zi represents the output generated by the neuron, and n indicates the aggregate number of classifications. The training protocol is executed utilizing training datasets that uphold a uniform configuration throughout each model, thereby guaranteeing that performance evaluations are impartial and solely dictated by the inherent attributes of each CNN architecture [33].

EfficientNetB0 employs a compound scaling methodology to achieve an equilibrium among network depth, width, and resolution [37]. The architectural design comprises several MBConv (Mobile Inverted Bottleneck Convolution) modules, which enable effective feature extraction while utilizing a comparatively limited quantity of parameters.

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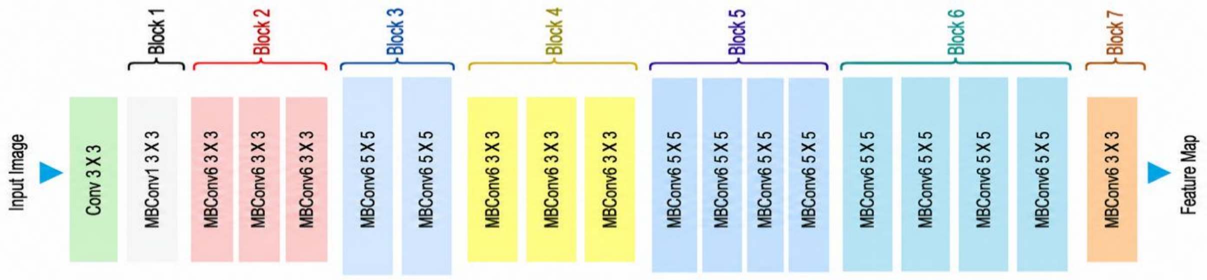
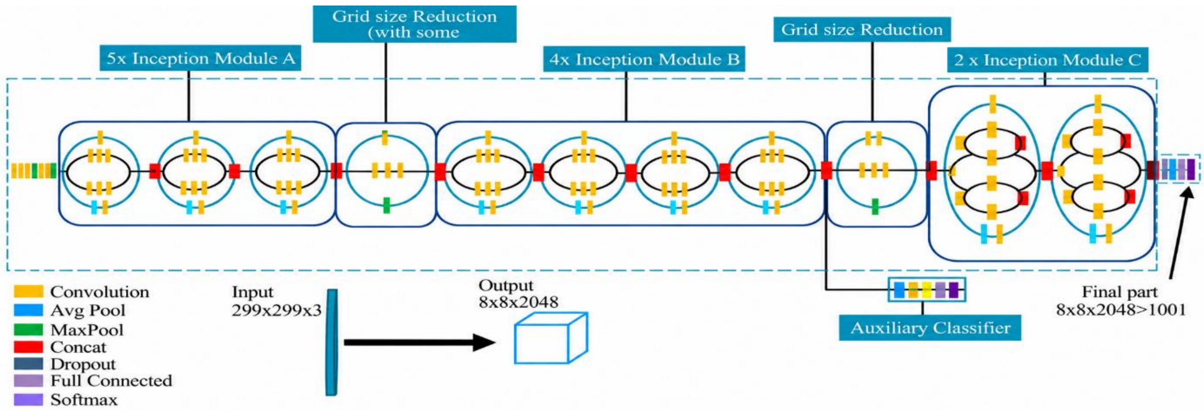


Source : (Alirezazadeh et al., 2023)

Figure 3. EfficientNetB0 architecture

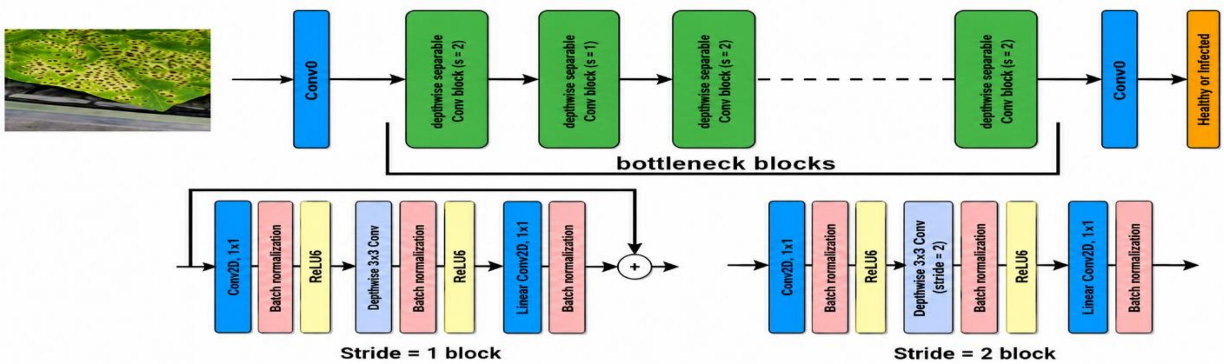
InceptionV3 employs the principle of the Inception Module, which amalgamates various convolutional filters of differing dimensions within a singular layer. This architecture facilitates the model's ability to concurrently extract features across multiple scales. InceptionV3 improves computational efficiency by breaking larger convolutions into smaller convolution processes, which reduces the number of parameters and computational requirements while maintaining powerful feature representation capabilities [39].



Source : (Shoaib et al, 2022)

Figure 4. InceptionV3 Architecture

MobileNetV2 was conceived as a streamlined architecture that employs depthwise separable convolution in conjunction with an inverted residual bottleneck. This approach enables a decrease in both the parameter count and computational demands without sacrificing the model's capacity to extract significant features. This architecture greatly minimizes the parameters and computational expenses while preserving efficient feature extraction capabilities, rendering MobileNetV2 ideal for environments with limited resources [40].



Source : [Shahoveisi et al., 2023]

Figure 5. MobileNetV2 architecture

Upon establishing the architecture of the model designated for implementation, the subsequent phase necessitates the compilation of the model utilizing the particular parameters that were employed throughout the training process.

Table 3. Parameter Compile

Parameter Compile	Value
Loss Function	categorical_crossentropy
Optimizer	Adam
Metrics	accuracy
Learning Rate	0.0001
Batch Size	32

Source: (Research Results, 2026)

Training Model

During the training phase, each model is subjected to training utilizing the dataset from a singular epoch to discern feature patterns inherent in tomato leaf imagery. Throughout each epoch, the model computes accuracy and loss metrics, which function as evaluative measures of advancement in the learning paradigm. An enhancement in accuracy, alongside a concomitant decrease in loss, signifies that the model is systematically refining its capacity to adeptly recognize patterns across various classifications [42]

The training process for all CNN architectures was carried out over a duration of 25 epochs. During the initial phases of training (epochs 1-10), each model demonstrated a notable rise in accuracy accompanied by a substantial decline in loss values. Following epochs 15-20, the accuracy rate began to decline, whereas the loss value experienced only a minimal reduction. As training neared the final epoch, the accuracy and loss curves approached a plateau, signifying that the models had arrived at a relatively stable learning condition. By epoch 25, EfficientNetB0 achieved an accuracy of 74.6% with a loss of approximately 0.76, MobileNetv2 reached an accuracy of 73.21% with a loss around 0.78, and InceptionV3 recorded an accuracy of 68.91% with a loss of about 0.86. These outcomes suggest that the models are nearing convergence within the allocated training period. Therefore, epoch 25 is deemed a suitable stopping point, as further training is unlikely to result in substantial performance enhancements, while also incurring increased computational expenses and the heightened risk of overfitting.

Model Evaluation

Upon the conclusion of the training procedure, the efficacy of each model was assessed utilizing testing data that had not been incorporated during the training stage. The performance of the models was quantified through various metrics including accuracy, precision, recall, and the F1-score. Furthermore, a confusion matrix was employed to identify instances of misclassification across each disease category. The outcomes of this assessment were instrumental in evaluating the proficiency of each model in the classification of tomato leaf diseases.

Best Model Evaluation

The most robust model comparison was executed by scrutinizing the evaluative outcomes of three distinct convolutional neural network architectures: EfficientNetB0, InceptionV3, and MobileNetV2. This comparative analysis was undertaken by evaluating metrics such as accuracy, precision, recall, and F1-score, in conjunction with the consistency of the validation results. The superior model was identified based on the maximum accuracy metric, which was further substantiated by an equilibrium of precision, recall, and F1-score. The findings from this comparative analysis served as a foundation for formulating recommendations regarding the optimal CNN architecture for implementation within an image-based system for the identification of tomato leaf diseases.

RESULTS AND DISCUSSION

This research investigated three distinct Convolutional Neural Network (CNN) architectures—EfficientNetB0, InceptionV3, and MobileNetV2—with the objective of classifying tomato leaf diseases. The assessment was undertaken employing a variety of metrics, which included accuracy, precision, recall, F1-score, and a confusion matrix. Initially, the training performance of each model was scrutinized through a learning curve that delineates the evolution of accuracy and loss values throughout the training phase. This visualization is pivotal in assessing the model's convergence rate, the uniformity of the learning process, as well as indications of overfitting and underfitting prior to comprehensive evaluation via the confusion matrix and additional classification metrics.

The findings of this study should also be interpreted considering the distribution of the dataset utilized. While the dataset comprises 4,804 images, the sample sizes among the disease categories are uneven. The Mosaic Virus has a mere 330 images, whereas Bacterial Spot, Early Blight, Late Blight, and Septoria Leaf Spot each have upwards of 1,000 images. This imbalance among the classes can affect the learning process and the efficacy of classification, especially for categories

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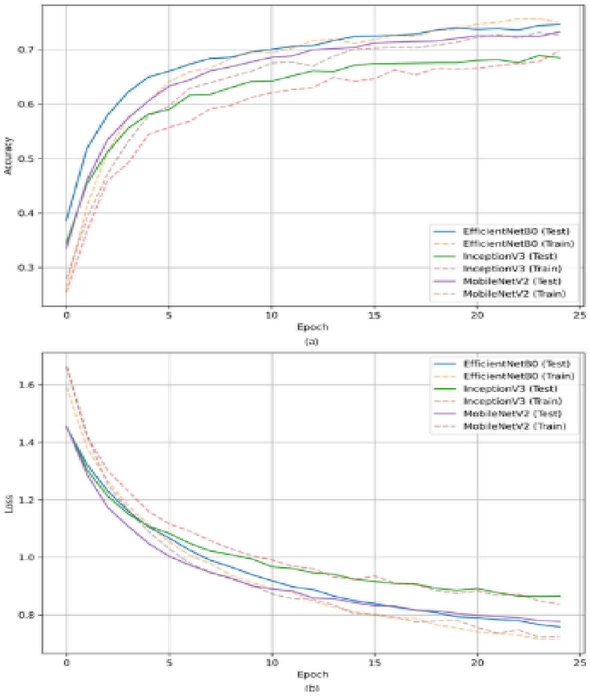
deemed to be underrepresented. As a result, some instances of misclassification observed during model evaluation may be partly attributed to the unequal distribution of training samples across the disease classes.



Source : (Research Result, 2026)
Figure 6. (a) Accuracy vs Epoch (b) Loss vs Epoch

Figure 6 illustrates a comparative analysis of the training efficacy among three distinct deep learning architectures, specifically EfficientNetB0, InceptionV3, and MobileNetV2, predicated on the accuracy and loss metrics over a span of 25 epochs. In general, all three models exhibit a progressive enhancement in accuracy alongside a concurrent reduction in loss as the epoch count escalates, thereby suggesting that the models proficiently assimilate image patterns pertinent to tomato leaf diseases.

In the accuracy chart, EfficientNetB0 achieved the highest validation accuracy of 74.6%, succeeded by MobileNetV2 with an accuracy of 73.21%, and InceptionV3, which recorded an accuracy of 68.91%. EfficientNetB0 demonstrated a consistent enhancement in performance throughout the training process, suggesting that the compound scaling methodology effectively enhances feature extraction capabilities by optimizing the balance among network depth, layer width, and input resolution. MobileNetV2 also exhibited commendable performance, notwithstanding its utilization of a more lightweight architecture, thereby reflecting considerable computational efficiency through the implementation of the depthwise separable convolution technique. Conversely, InceptionV3 attained the lowest accuracy and displayed a comparatively slower improvement trajectory relative to the other two models, suggesting that its generalization capability has not been fully refined within the context of this research dataset.

In the loss graph, the comprehensive model demonstrates an effective optimization trajectory, characterized by a reduction in loss throughout the training phase. EfficientNetB0 attained the minimal loss value at the conclusion of the epoch, approximately 0.76, succeeded by MobileNetV2 at roughly 0.79, and InceptionV3 at around 0.85. Reduced loss values signify that the model's predictions are increasingly aligning with the actual labels.

In general, the three models demonstrated distinct learning attributes throughout the training phase. In order to achieve a more thorough understanding of their efficacy, each model was subsequently assessed through final accuracy metrics, classification statistics, and a confusion matrix to evaluate their proficiency in accurately identifying each category of tomato leaf disease with greater precision.

EfficientNetB0

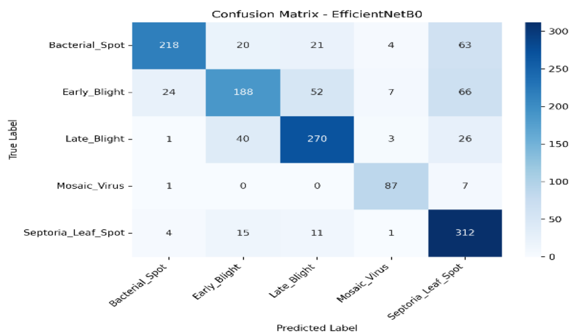
As the model exhibiting the greatest accuracy during the training phase, EfficientNetB0 was subjected to an extensive analysis employing classification metrics to evaluate its proficiency in discerning each category of tomato leaf diseases. The findings derived from the assessment of the EfficientNetB0 model are illustrated in Table 4 and Figure 7.

Table 5. EfficientNetB0 Model Results

	Precision	Recall	F1-score	Support
Bacterial_Spot	0,87	0,66	0,75	326
Early_Blight	0,71	0,55	0,62	337
Late_Blight	0,76	0,79	0,77	340
Mosaic_Virus	0,85	0,91	0,88	95
Septoria_Leaf_Spot	0,65	0,90	0,76	343
Accuracy	0,74	0,74	0,74	0,74
Macro avg	0,77	0,76	0,76	1441
Weighted avg	0,75	0,74	0,74	1441

Source : (Research Result, 2026)

According to the data presented in Table 4, the EfficientNetB0 model attained an accuracy of 0.74 (74%), in conjunction with a macro average precision of 0.77 and a macro average recall of 0.76, signifying commendable classification efficacy and a relatively equitable distribution among the various classes. The Mosaic Virus category exhibited the most favorable performance, showcasing a precision of 0.85, a recall of 0.91, and an F1-score of 0.88, suggesting that the model was highly proficient in identifying the visual attributes characteristic of the disease, whereas the Septoria Leaf Spot category also demonstrated robust results with a recall of 0.90 and an F1-score of 0.76. In contrast, the Early Blight category recorded the lowest recall at 0.55 and an F1-score of 0.62, although its precision of 0.71 reveals that a considerable portion of the actual data was still misclassified owing to the resemblance of leaf spot patterns to those of other disease categories.



Source : (Research Result, 2026)

Figure 7. Confusion Matrix Results of EfficientNetB0

According to Figure 7, the confusion matrix illustrates that EfficientNetB0 demonstrates superior proficiency in accurately categorizing the Septoria Leaf Spot class, achieving 312 correct identifications, followed by the Late Blight class with 270 correct identifications, the Bacterial Spot class with 218 correct identifications, the Early Blight class with 188 correct identifications, and finally the Mosaic Virus class with 87 correct identifications. These findings signify a commendable capacity to discern distinct visual patterns. Nevertheless, the model encountered challenges in correctly classifying the Early Blight class, which is frequently misidentified as Septoria Leaf Spot or Late Blight, as well as in the Bacterial Spot class, which recorded 63 instances of predictions erroneously categorized as Septoria Leaf Spot. In summation, EfficientNetB0 exhibits considerable effectiveness in the classification of tomato leaf diseases; however, it continues to encounter difficulties in differentiating between classes that exhibit analogous leaf spot characteristics.

InceptionV3

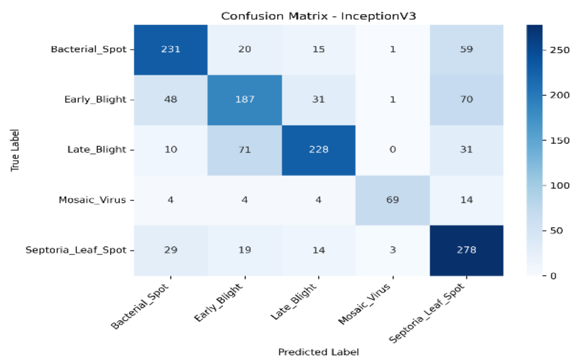
The InceptionV3 model, which was subjected to analysis within the parameters of this investigation, was assessed for its capacity to discern various diseases afflicting tomato leaves, predicated on its architecture, which emphasizes multi-scale feature extraction. The findings pertaining to the performance of the InceptionV3 model are presented in Table 5 and illustrated in Figure 8.

Table 6. InceptionV3 Model Results

	Precision	Recall	F1-score	Support
Bacterial_Spot	0,71	0,70	0,71	326
Early_Blight	0,62	0,55	0,58	337
Late_Blight	0,78	0,67	0,72	340
Mosaic_Virus	0,93	0,72	0,81	95
Septoria_Leaf_Spot	0,61	0,81	0,69	343
accuracy	0,68	0,68	0,68	0,68
macro avg	0,73	0,69	0,70	1441
weighted avg	0,69	0,68	0,68	1441

Source : (Research Result, 2026)

According to the data presented in Table 5, the InceptionV3 model attained an accuracy of 0.68 (68%), along with a macro average precision of 0.73, a macro average recall of 0.69, and an F1-score of 0.70, signifying a commendable classification performance that demonstrates relative consistency across the various classes. The most superior performance was observed in the Mosaic Virus category, which exhibited a precision of 0.93, a recall of 0.72, and an F1-score of 0.81, suggesting that the model is highly adept at accurately identifying this particular class. The Late Blight class also demonstrated satisfactory outcomes with an F1-score of 0.72, whereas the Bacterial Spot category yielded consistent results with an F1-score of 0.72. Conversely, the Early Blight category recorded the lowest F1-score of 0.58, succeeded by the Septoria Leaf Spot with an F1-score of 0.69, indicating that the model continues to encounter difficulties in differentiating between several classes that possess similar leaf spot characteristics.



Source : (Research Result, 2026)

Figure 8. InceptionV3 Confusion matrix results

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According to Figure 8, the confusion matrix illustrates that the InceptionV3 model demonstrates superior performance in accurately identifying the Bacterial Spot and Septoria Leaf Spot categories, achieving a total of 278 correct classifications for each respective category, followed by the Bacterial Spot class with 231 classifications, the Late Blight class with 228 classifications, the Early Blight class with 187 classifications, and the Mosaic Virus class with 69 classifications. Nevertheless, the model encountered challenges related to misclassification within the Early Blight category, which was often erroneously identified as the Septoria Leaf Spot class with 70 misclassified entries, and the Bacterial Spot class with 48 misclassified entries, in addition to the Late Blight class with 71 misclassified entries. Furthermore, the Mosaic Virus category was also inaccurately classified as the Septoria Leaf Spot class with 14 misidentified entries. In conclusion, although InceptionV3 exhibited a relatively balanced classification performance overall, it still fell short of optimally distinguishing between leaf spot disease categories that share similar attributes.

MobileNetV2

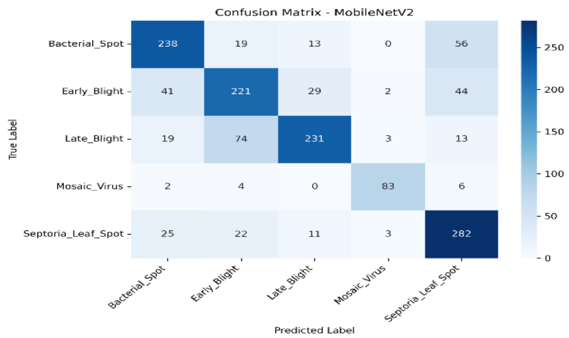
As a framework characterized by a streamlined and effective architectural design, MobileNetV2 was subjected to scrutiny in order to evaluate its proficiency in detecting diseases affecting tomato foliage while minimizing computational intricacies. The outcomes of the assessment pertaining to the MobileNetV2 model are presented in Table 6 and illustrated in Figure 9.

Table 7. MobileNetV2 Model Results

	Precision	Recall	F1-score	Support
Bacterial_Spot	0,72	0,73	0,73	326
Early_Blight	0,65	0,65	0,65	337
Late_Blight	0,81	0,67	0,74	340
Mosaic_Virus	0,91	0,87	0,89	95
Septoria_Leaf_Spot	0,70	0,82	0,75	343
Accuracy	0,73	0,73	0,73	0,73
Macro avg	0,76	0,75	0,75	1441
Weighted avg	0,73	0,73	0,73	1441

Source : (Research Result, 2026)

According to the data presented in Table 6, the MobileNetV2 architecture attained an accuracy rate of 0.73 (73%) accompanied by a macro average precision of 0.76 and a macro average recall of 0.75, which signifies a commendable classification proficiency and a relatively equitable performance across various classes. The most exemplary performance was observed in the Mosaic Virus category, achieving a precision of 0.91, a recall of 0.87, and an F1-score of 0.89, while the Septoria Leaf Spot and Late Blight classifications also demonstrated acceptable outcomes, reflected in their F1 scores of 0.75 and 0.74, respectively. In contrast, the Early Blight classification recorded the least favorable performance, with an F1-score of 0.65, whereas the Bacterial Spot category secured an F1-score of 0.73. Collectively, MobileNetV2 displayed a competitive performance characterized by commendable computational efficiency and accuracy that is comparable to that of EfficientNetB0.



Source : (Research Result, 2026)
Figure 9. Confusion Matrix Results of MobileNetV2

According to Figure 9, the confusion matrix indicates that MobileNetV2 demonstrates superior performance in the Septoria Leaf Spot classification with 282 accurate predictions, followed closely by Bacterial Spot with 238, Late Blight with 231, Early Blight with 221, and Mosaic Virus with 83. Nonetheless, the model encountered instances of misclassification; for instance, within the Late Blight category, there was a notable frequency of confusion with Early Blight, accounting for 74 instances. In summary, MobileNetV2 exhibits a more equitable prediction distribution relative to alternative models, thereby suggesting an impressive capacity for generalization despite its comparatively lightweight architecture.

Comparative Analysis of the Best Models

According to the assessment findings, the three models exhibited varying levels of efficacy in the classification of tomato leaf diseases. Presented subsequently is a comparative analysis of the accuracy metrics for the three models, as illustrated in Table 8.

Table 8. Model Comparison Results

Model	*Accuracy*
EfficientNetB0	74,6 %
MobileNetV2	73,21 %
InceptionV3	68,91 %

Source : (Research Result, 2026)

The EfficientNetB0 architecture attained a remarkable accuracy of 74.6%, closely followed by MobileNetV2, which recorded an accuracy of 73.21%, and InceptionV3, which achieved an accuracy of 68.91%. This outcome signifies that EfficientNetB0 exhibits a greater proficiency in the extraction of image features in comparison to the other two architectures, a conclusion that is substantiated by a compound scaling methodology that effectively harmonizes network depth, layer width, and input resolution.

The MobileNetV2 architecture attained a level of accuracy indicative of performance that is highly competitive, approaching that of EfficientNetB0. This finding illustrates that an efficient architecture utilizing depthwise separable convolutions can achieve elevated classification efficacy while necessitating diminished computational resources. Consequently, MobileNetV2 could be deemed appropriate for deployment in environments characterized by limited resources or within mobile computing frameworks. Meanwhile, InceptionV3 exhibited the least accuracy in comparison to the other two models. This suggests that the Inception Module architecture did not yield optimal performance on the research dataset employed, especially in differentiating between disease classes that possess analogous characteristics. Overall, EfficientNetB0 emerges as the most effective model in this investigation owing to its exceptional accuracy, whereas MobileNetV2 functions as a feasible alternative when evaluating computational efficiency.

The findings from this research largely correspond with earlier investigations regarding the classification of tomato leaf diseases using deep learning techniques. Saeed et al. [21] illustrated that CNN models employing transfer learning, such as InceptionV3, achieved remarkable classification accuracy, while Nguyen et al. [23] demonstrated that MobileNet-based architectures can sustain competitive performance with lower computational requirements. In a similar vein, this study showed that MobileNetV2 attained an accuracy of 73.21% while showcasing the greatest computational efficiency among the models assessed. Additionally, prior studies have indicated that the EfficientNet architecture strikes a favorable balance between feature extraction capability and computational efficiency through its integrated scaling methodologies [31]. This observation is further supported by the outcomes of this research, where EfficientNetB0 reached the highest classification accuracy of 74.6%, highlighting its exceptional ability to identify disease-related features under consistent experimental conditions.

Nonetheless, the classification accuracy achieved in this research falls short of that reported in numerous previous studies, where results frequently surpassed 90% [21], [23], [31]. This discrepancy may be attributed to the use of a more varied dataset that includes field-captured images alongside publicly available photographs, resulting in greater variability in lighting, background complexity, image quality, and manifestations of disease symptoms. Moreover, class imbalance, especially the limited number of Mosaic Virus images, may have influenced the training model and contributed to certain misclassification occurrences. These findings underscore the significant impact of architectural variation on prediction performance and computational efficiency, with EfficientNetB0 achieving the highest accuracy, MobileNetV2 offering an ideal balance between accuracy and resource consumption, and InceptionV3 demonstrating comparatively lower performance. As a result, this study provides valuable insights for selecting CNN architectures in the classification of tomato leaf diseases, tailored to meet the specific demands of precision agriculture applications.

While classification accuracy serves as the main gauge of predictive performance, computational efficiency holds equal significance, particularly in real-world scenarios where resources are limited. Consequently, additional comparisons were conducted, taking into account the overall number of model parameters and the average inference time per image, to offer a more thorough evaluation of the three CNN architectures.

Table 9. Performance and Computational Efficiency Comparison of CNN Models

Model	*Total Parameters*	*Inference Time (ms/image)*
EfficientNetB0	4,055,976	320.73
MobileNetV2	2,264,389	259.68
InceptionV3	21,813,029	363.52

Source : (Research Result, 2026)

In addition to evaluating classification, we also investigated computational efficiency by examining the overall number of model parameters and the average inference time for each image, as outlined in Table 9. The findings indicate that MobileNETv2 demonstrates the highest computational efficiency among the evaluated architectures, utilizing merely 2,264,389 parameters and an average inference time of 259.68 ms per image. Conversely, InceptionV3 shows the greatest model complexity with 21,813,029

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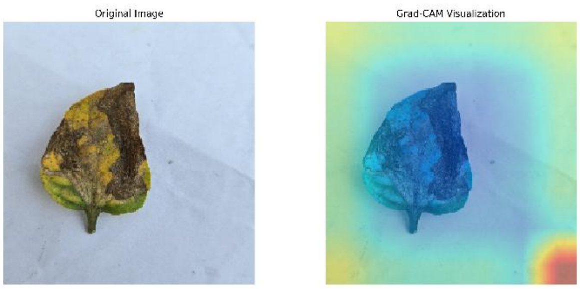
parameters and records the slowest inference speed at 363.52 ms per image. EfficientNetB0 requires 4,055,976 parameters and reaches an inference time of 320.73 ms per image while attaining the highest classification accuracy of 74.60%.

These findings reveal a trade-off between predictive performance and computational efficiency. While EfficientNetB0 provides impressive classification accuracy, MobileNETv2 strikes a more advantageous balance between precision and resource demands owing to its considerably smaller model size and quicker inference speed. Therefore, MobileNetv2 may be more appropriate for deployment on resource-limited platforms, such as mobile devices and edge computing systems, whereas EfficientNetB0 may be favored when the primary objective is to optimize classification performance.

Explainable Artificial Intelligence (XAI) Analysis

While the quantitative evaluation metrics demonstrate that EfficientNetB0 excels in classification performance among the assessed CNN architectures, these metrics alone do not sufficiently illuminate the rationale behind the model's predictions. In practical agricultural applications, comprehending how the model arrives at its conclusions is essential for enhancing transparency, interpretability, and user confidence. Therefore, an analysis utilizing Explainable Artificial Intelligence (XAI) was conducted employing Gradient-Weighted Class Activation Mapping (Grad-CAM), a widely-used visualization technique for elucidating convolutional neural network predictions. Explainable Artificial Intelligence (AI) aims to reduce the unclear aspects of deep learning models by providing transparent and comprehensible explanations of the mechanisms behind predictions, thus fostering transparency and confidence in AI-driven decision-making [43].



Source : (Research Result, 2026)
Figure 10. Grad-CAM Visualization of EfficientNetB0 for Tomato Leaf Disease Classification

Figure 10 displays a Grad-CAM visualization produced by the EfficientNetB0 model. Grad-CAM is a post-hoc interpretation technique that leverages gradient information from the last convolutional layer to create class activation maps, which emphasize the areas of an image that are critical for classification outcomes [43]. The emphasized areas indicate that the model mainly focuses on disease-related signs found on tomato leaves, such as lesion patterns, color changes, and infected regions, while also taking into account pertinent contextual elements around the affected areas.

Such visualizations illustrate that EfficientNetB0 adeptly identifies important visual features associated with the disease and utilizes these aspects during the prediction phase. The concentration of activation regions on symptomatic leaf areas suggests that the decision-making model is guided by biologically pertinent features, rather than irrelevant background elements. Moreover, the incorporation of Grad-CAM improves the model's transparency by providing visual proof of the decision-making process, enabling users to achieve a better understanding and validation of the classification outcomes. This interpretation boosts confidence in the model and reinforces its potential as a dependable decision-support tool for the automated diagnosis of tomato leaf diseases.

CONCLUSION

This research assessed the effectiveness of three Convolutional Neural Network (CNN) architectures—EfficientNetB0, InceptionV3, and MobileNetv2—for the classification of tomato leaf diseases utilizing a combined dataset comprising both field-acquired images and publicly accessible resources. The experimental findings indicated that EfficientNetB0 attained the highest accuracy of 74.6%, followed by MobileNetv2 at 73.21%, and InceptionV3 at 68.91%. These outcomes demonstrate that EfficientNetB0 stands out in its feature extraction capabilities among the evaluated architectures, while MobileNetv2 offers competitive predictive performance along with enhanced computational efficiency, making it particularly advantageous for deployment in resource-limited environments. Moreover, Grad-CAM analysis confirmed that EfficientNetB0 predominantly focuses on the regions of tomato leaves related to disease, thereby enhancing the clarity and interpretability of the classification process. Nonetheless, this study encounters certain limitations. Firstly, a portion of the field dataset was obtained from a specific geographic area, which may restrict the generalizability of the results to other agricultural contexts. Secondly, the dataset encompasses only five disease categories and exhibits class cohesion, especially in the Mosaic Virus category, which has significantly fewer samples compared to other classes. Thirdly, various disease categories, such as Bacterial Spot, Early Blight, and Late Blight, display similar visual symptoms, resulting in misclassification challenges across all models. Future research should consider the integration of Vision Transformer (ViT)-based architectures, semi-supervised learning techniques to utilize larger unlabeled field datasets, and innovative data balancing strategies to enhance data classification. Furthermore, future inquiries could explore the implementation of lightweight disease classification models on Edge AI platforms and mobile devices to enable real-time disease monitoring and support precision agriculture efforts..

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