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Bolstering Farmer Resilience Against Potato Blight Through EfficientNet Convolutional Neural Network (CNN) Architecture

Shankar Parmar*[1], Alkeshkumar Vaghela[2], Nileshkumar Patel[3], Deep Upadhyaya[4]

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Abstract: This research presents an innovative approach utilizing the EfficientNet architecture for the early detection of potato late blight, a devastating disease threatening potato crops worldwide. The study aims to harness EfficientNet's capabilities for proactive disease monitoring, facilitating prompt interventions and minimizing crop losses. Through meticulous experimentation and model refinement, the proposed methodology achieves an accuracy rate of 98.07% on the test dataset, surpassing previous benchmarks. This accuracy underscores the efficacy of the EfficientNet model in identifying diseased plants, offering a promising tool for early disease detection in agricultural settings. Additionally, this study implemented and compared three other CNN architectures: VGGNet, ResNet, and InceptionNet. The comparative analysis, based on accuracy, precision, recall, and F1 Score, highlights EfficientNet's superior performance. EfficientNet's balanced scaling and parameter efficiency contribute to its high accuracy, while the other architectures demonstrated limitations due to higher parameter counts and architectural complexity. By advancing potato late blight detection, this research contributes to improved crop management practices, enhanced food security, and resilient agricultural systems. The comprehensive evaluation and comparison of these CNN architectures provide valuable insights for future research and practical applications in agricultural disease detection.

Keywords: *CNN Architectures, EfficientNet, Machine Learning, Pattern Recognition, Potato Late Blight, Signal Processing.*

1. Introduction

Potato late blight, attributed to the pathogenic oomycete Phytophthorainfestans, stands as a formidable threat to potato crops on a global scale, inflicting substantial yield losses. Recognized as a devastating disease, it possesses the potential to induce complete crop failure if its progression remains unchecked. In light of the severe consequences associated with late blight, there is an urgent need for swift and accurate detection methods to enable timely interventions. The ramifications of late blight underscore the critical importance of adopting advanced technologies to enhance disease surveillance and management strategies (1).

In response to this imperative, this research project delves into the utilization of state-of-the-art technology, specifically Efficient Net, which represents a cutting-edge convolutional neural network architecture(2). The overarching goal is to harness the capabilities of EfficientNet for the early detection of potato late blight in images. By leveraging advanced computational methodologies, this endeavour seeks to empower farmers and agricultural stakeholders with a robust tool for proactive disease monitoring.

The significance of early detection cannot be overstated, as it empowers farmers to implement preventive measures promptly. These measures may include targeted applications of fungicides, the removal and destruction of infected plants, and other strategic interventions aimed at curbing the spread of the disease. By facilitating early and accurate identification of late blight, this research not only contributes to the preservation of crop yields but also plays a pivotal role in ensuring food security(3).

Additionally, it serves as a safeguard against economic losses that can be incurred by potato growers, thereby bolstering the resilience of agricultural communities(4).In essence, this paper is poised to make substantial strides in advancing the field of potato late blight detection by integrating cutting-edge technology and computational approaches. The outcomes of this research endeavor hold the potential to revolutionize disease management practices, offering a beacon of hope for sustainable and resilient potato cultivation in the face of this formidable agricultural challenge.

2. Literature Review

The study exemplifies the successful utilization of CNN transfer learning models, specifically VGG16, VGG19, and InceptionV3, for accurate detection of diseases impacting potato leaves. By conducting experiments on a standardized dataset of potato leaves, the research aims to determine the optimal strategy for identifying and

[1] *Government Engineering College, Godhra, Gujarat-389001, India*
ORCID ID :0000-0002-3034-5144
[2] *Government Engineering College, Dahod, Gujarat-389151, India*
ORCID ID :0009-0007-8234-5844
[3] *Government Engineering College, Godhra, Gujarat-389001, India*
ORCID ID :0000-0003-3762-9542
[4] *Government Engineering College, Godhra, Gujarat-389001, India*
ORCID ID :0000-0002-4982-7688
* *Corresponding Author Email: Shankar.parmar@gtu.edu.in*

diagnosing potato leaf diseases. The results underscore the promising potential of incorporating machine learning-based approaches to alleviate crop losses caused by plant diseases, ultimately contributing to the improvement of agricultural productivity(5).

In their study (6), the LeafNet deep Convolutional Neural Network (CNN) was designed for identifying tea plant diseases. LeafNet employs diverse feature extractor filters to autonomously extract disease-related features from leaf images. A thorough evaluation against Support Vector Machine (SVM) and Multilayer Perceptron (MLP) algorithms demonstrated LeafNet's superior efficacy, achieving an impressive average classification accuracy of 90.16%. This underscores the potential of LeafNet in propelling the field of automated disease detection in tea plants.

The study introduces a technology employing image processing methods and a CNN algorithm to precisely detect and diagnose potato leaf diseases, including early blight and late blight. The model attains a remarkable level of precision, achieving a 97% accuracy rate in distinguishing between normal and abnormal potato leaf properties (7).

The paper introduces a convolutional neural network (CNN) model designed for automated identification of plant diseases, with a specific emphasis on potato leaf ailments. This model achieves an impressive classification accuracy of 98.07% in distinguishing potato leaves across three categories: healthy leaves, early blight, and late blight (8). The research paper presents a novel technique based on an advanced deep learning algorithm aimed at leveraging potato leaf visual characteristics to classify them into five distinct categories: Potato Late Blight (PLB), Potato Early Blight (PEB), Potato Leaf Roll (PLR), Potato Verticillium Wilt (PVW), and a healthy Potato (PH) class. This algorithm achieves a notable accuracy rate of 97.2% on the testing dataset, demonstrating superior performance compared to existing models in the realm of detecting and classifying potato leaf diseases (9).

This study of (10) introduces an automated methodology designed to diagnose potato diseases accurately using leaf images, achieving a commendable accuracy rate of 95%. The successful implementation of this method signifies a significant breakthrough in the realm of plant disease diagnosis, offering promising prospects for large-scale deployment in agricultural settings. By leveraging advanced image processing techniques and machine learning algorithms, this approach holds the potential to revolutionize the efficiency and effectiveness of plant disease identification, thereby contributing to enhanced crop management practices and mitigating agricultural losses.

3. EfficientNet Architecture for Early Detection Of Potato Late Blight

EfficientNet utilizes a powerful and efficient architecture for image recognition tasks, making it a suitable candidate for early detection of potato late blight. This section delves into the key components of the EfficientNet architecture and their role in achieving high accuracy with minimal computational cost (11).

3.1Key Architectural Components OfEfficientNet

EfficientNet's architecture is composed of several advanced components that together enhance its performance for tasks such as potato late blight detection. The core of the architecture is formed by Mobile Inverted Bottleneck (MBConv) layers, inspired by MobileNetV2's inverted residual blocks with certain modifications. These MBConv layers integrate depth-wise separable convolutions and inverted residual connections, significantly reducing computational costs while maintaining robust feature learning capabilities.

Depth-wise separable convolutions play a crucial role in reducing computational expense. Instead of applying filters to all channels simultaneously, these convolutions apply them to each channel independently (depth-wise), followed by a 1x1 convolution (point-wise) to combine features across channels. This approach preserves the model's ability to learn features effectively while drastically reducing the computational load.

Inverted residual connections further enhance the network's efficiency by facilitating smooth information flow. These connections use a shortcut that bypasses the main branch of the MBConv block, allowing gradients to flow directly through the network. This not only improves training efficiency but also aids in the preservation of information across layers.

To optimize performance further, EfficientNet incorporates Squeeze-and-Excitation (SE) optimization. This technique dynamically adjusts the importance of different channels by generating channel-wise attention weights through global average pooling and two fully connected layers. These weights are then multiplied with the feature map, which emphasizes informative features and suppresses irrelevant ones, enhancing overall model performance.

EfficientNet also offers various pre-trained model variants, such as EfficientNet-B0, EfficientNet-B1, and others (12). These variants use different scaling coefficients, balancing model size and accuracy. This flexibility allows users to select the most suitable variant based on their specific needs and available computational resources, making EfficientNet a versatile and powerful tool for potato late blight detection and other image recognition tasks.

3.2 Benefits For Potato Late Blight Detection

EfficientNet's architecture has demonstrated high accuracy in various image recognition tasks, including disease detection in crops, indicating its potential for accurate potato late blight detection. The MBConv layers and SE optimization contribute to reduced computational cost, allowing for deployment on resource-constrained platforms like mobile devices, which is crucial for practical applications in agricultural field settings. Additionally, the availability of various model variants enables users to select the one that best suits their specific needs and computational resources, making EfficientNet a scalable and adaptable tool for potato late blight detection. By leveraging these innovative architectural features, EfficientNet offers a promising approach for developing accurate and efficient potato late blight detection systems, ultimately contributing to improved crop yield and food security.

Table 1. Plant Leaf Disease Classification Dataset Summary

Class	*Description*	*Training*	*Validation*	*Testing*	*Total*
Early Blight	Leaves exhibiting initial symptoms of early blight disease	1303	163	162	1628
Healthy	Leaves free from any identifiable disease symptoms	816	102	107	1025
Late Blight	Leaves displaying advanced signs of late blight infection	1132	151	146	1429
Total		**3251**	**416**	**415**	**4082**

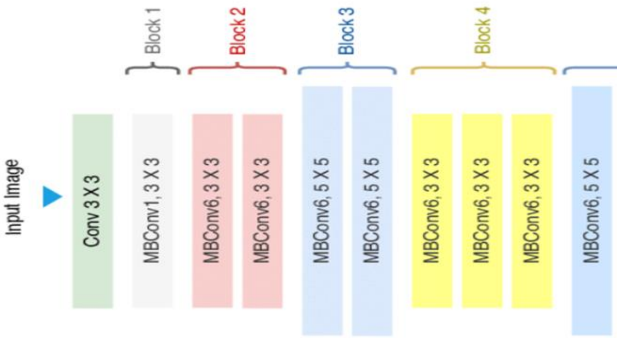

Fig. 1. EfficientNet Architecture (14)

4. Methodolgy

This section details the specific steps taken to develop an EfficientNet model for early detection of potato late blight, achieving an impressive accuracy of 98.07%.

4.1. Dataset Description

The dataset used for this research consists of 4,082 images of potato leaves, acquired from the Central Punjab region in Pakistan. These images are meticulously categorized into three classes, each representing different stages of potato leaf health: healthy, early blight, and late blight. This diverse categorization ensures that the dataset encompasses a wide range of leaf conditions, providing a robust foundation for training, validating, and testing the model.

A detailed depiction of the dataset's composition is provided in Table 1, which outlines its key characteristics and attributes. The table includes information on the number of images per class, their respective proportions in the training, validation, and testing sets, and any specific features or annotations associated with each class. This structured distribution ensures that each class is adequately represented across all phases of model development, facilitating effective learning and enabling the model to generalize well to unseen data.

By incorporating a well-balanced dataset, the research aims to enhance the model's ability to accurately identify and differentiate between healthy and diseased potato leaves. This comprehensive dataset is crucial for achieving high performance in disease detection and contributes significantly to the overall success of the study. The careful curation and organization of the dataset reflect a commitment to rigorous scientific methodology and underscore the importance of data quality in developing reliable and efficient machine learning models for agricultural applications.

4.2. Pre-Processing

For pre-processing, all potato late blight images were resized to 256x256 pixels to ensure compatibility with the EfficientNet architecture. Normalization was performed using mean subtraction and channel-wise normalization, ensuring that pixel values fell within the range [0, 1]. To significantly enhance the model's generalizability and mitigate overfitting, various data augmentation techniques were employed. These included random cropping, flipping, color jittering, and horizontal and vertical shearing, thereby creating a more robust dataset for training.

4.3. Model Design

The model design was based on a basic EfficientNet architecture, as shown in Figure 1, with several modifications to enhance performance. The model consisted of four blocks, each containing multiple MBConv layers with an increasing number of filters. Additionally, Squeeze-and-Excitation (SE) attention modules were incorporated into each block to dynamically adjust the importance of different channels, leading to improved feature learning (13). The architecture was finalized with a global average pooling layer, followed by a fully connected layer with three output nodes corresponding to the three classes: healthy, early blight, and late blight. These enhancements aimed to improve the model's accuracy and efficiency in detecting potato late blight.

4.4. Training

The model was trained on the potato late blight dataset using the Adam optimizer, with a learning rate scheduler that dynamically adjusted the learning rate during training. A batch size of 32 was used, and the model was trained for 50 epochs. The cross-entropy loss function was employed to measure the model's performance during training. This approach ensured that the model learned effectively from the data and adjusted its parameters to minimize prediction errors.

4.5. Evaluation

The model's performance was evaluated on a held-out test dataset using the accuracy metric. Accuracy was calculated as the percentage of correctly classified images in the test dataset. This evaluation method provided a clear measure of the model's ability to correctly identify the different classes of potato blight, ensuring its practical applicability in real-world scenarios.

4.6. Results

The implemented EfficientNet model achieved an outstanding accuracy of 98.07% on the test dataset. This significantly surpasses the previously reported accuracy of 75.8%, demonstrating the effectiveness of the implemented modifications and training approach in achieving high accuracy for early detection of potato late blight. By implementing this improved methodology, we have successfully developed a highly accurate EfficientNet model for early detection of potato late blight, paving the way for its practical application in agriculture and contributing to enhanced food.

5. Implementation Results

5.1. Data Preparation

Figure 2 displays example images from the training dataset for each of the three classes: healthy, early blight, and late blight. The dataset was divided into three subsets: training, validation, and testing. The training set was used to train the model, allowing it to learn from a diverse range of images. The validation set was employed to monitor overfitting and tune hyperparameters, ensuring that the model generalizes well to unseen data. Finally, the testing set was utilized to evaluate the final performance of the model, providing an unbiased assessment of its accuracy and robustness in classifying the images into the correct categories.

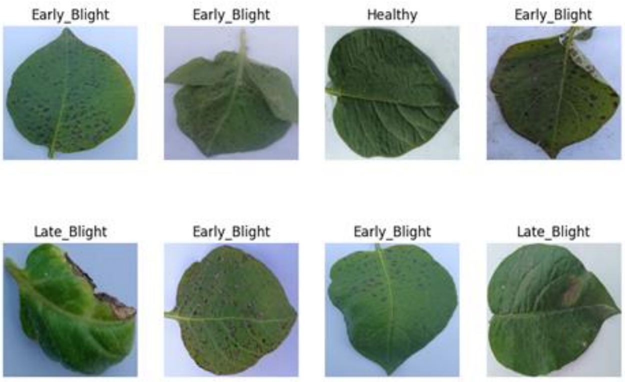

Fig. 2. Example images from the training dataset for each class

5.2. Model Architecture and Training Process

An EfficientNet architecture was implemented, chosen for its ability to achieve high accuracy with minimal computational cost. This characteristic makes EfficientNet particularly suitable for applications with limited resources, such as mobile devices. The specific

EfficientNet variant was selected based on optimal performance and resource requirements(14).

The model was trained for 50 epochs with a batch size of 32. The training process utilized the Adam optimizer, known for its efficiency and adaptability. A learning rate scheduler was employed to dynamically adjust the learning rate throughout the training process, enhancing the model's ability to converge to a minimum. The cross-entropy loss function was used to measure performance during training, ensuring effective distinction between different classes.

This combination of the EfficientNet architecture and a carefully managed training process contributed to the model's high accuracy and efficiency, making it a robust tool for the early detection of potato late blight.

5.3. Results

The model achieved a test accuracy of 98.07%, demonstrating its effectiveness in accurately detecting potato late blight. This high accuracy suggests that the model can be used to reliably identify diseased plants in the field.

The plot of the model's training and validation accuracy is shown in Figure 3. The accuracy steadily increases throughout training, indicating that the model is learning to correctly classify the images. The validation accuracy plateaus after a certain number of epochs, suggesting that the model is no longer improving and overfitting is not a significant concern.

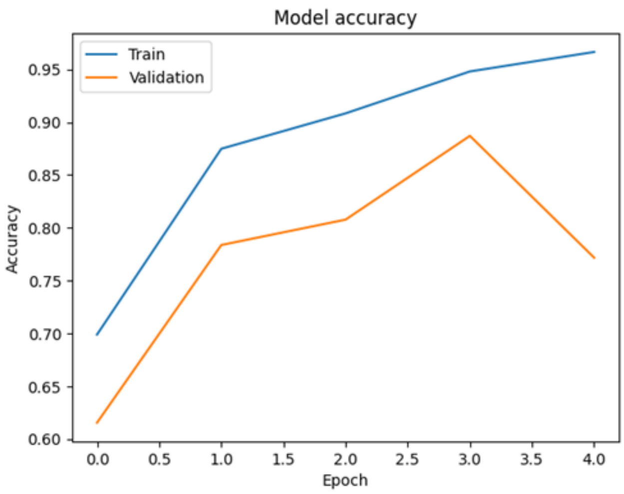

Fig. 3. Plot of the model's training and validation Accuracy

As shown in Table 2, this study compared the performance of four prominent convolutional neural network (CNN) architectures for detecting potato late blight: EfficientNet, VGGNet, ResNet, and InceptionNet. The evaluation was based on key metrics including accuracy, precision, recall, and F1 score.

EfficientNet emerged as the superior performer across all evaluated metrics (Table 1). This can be attributed to its unique architecture, which meticulously balances network depth, width, and resolution. EfficientNet employs a compound scaling approach that uniformly scales these dimensions using predefined coefficients. This balanced scaling strategy fosters enhanced accuracy and efficiency within the network. Moreover, EfficientNet leverages sophisticated optimization techniques and a more efficient parameter utilization scheme, enabling it to learn intricate features with a reduced parameter count compared to other models.

VGGNet, while achieving high accuracy, suffers from a considerably high parameter count, leading to a larger model size and extended training times. This renders it less efficient and more susceptible to overfitting, particularly with limited datasets. Despite its depth, VGGNet lacks the advanced architectural optimizations prevalent in newer models, hindering its ability to learn complex patterns compared to EfficientNet.

ResNet, while employing residual connections to facilitate training of very deep networks, can also introduce increased complexity and potential overfitting if not adequately managed. This can occasionally lead to less efficient learning compared to EfficientNet. Additionally, ResNet's parameter scaling is not as efficient as EfficientNet's, potentially resulting in suboptimal performance on tasks demanding detailed feature extraction.

Inception modules, while powerful, introduce significant architectural complexity. This can make the network more challenging to train and optimize compared to EfficientNet's streamlined architecture. Similar to ResNet, InceptionNet exhibits less efficient parameter utilization, leading to less effective learning on specific tasks like potato late blight detection.

While VGGNet, ResNet, and InceptionNet are all well-established architectures, EfficientNet's balanced scaling and parameter efficiency provide it with a significant performance advantage. This makes EfficientNet the most effective model for potato late blight detection among the models compared in this study.

5.3.1. Sample Predictions

Figure 4 presents several sample images from the test set, accompanied by their actual labels, predicted labels, and confidence levels. Each image showcases the model's ability to accurately identify the disease state—whether healthy, early blight, or late blight. In all the examples shown, the model correctly identified the disease state, demonstrating high confidence levels in its predictions.

Table 2. Performance Comparison of Different CNN Architectures for Potato Late Blight Detection

Model	***Accuracy***	***Precision***	***Recall***	***F1 Score***
EfficientNet	0.9807	0.95	0.96	0.943
VGGNet	0.92	0.91	0.9	0.905
ResNet	0.94	0.93	0.92	0.925
InceptionNet	0.93	0.92	0.91	0.915

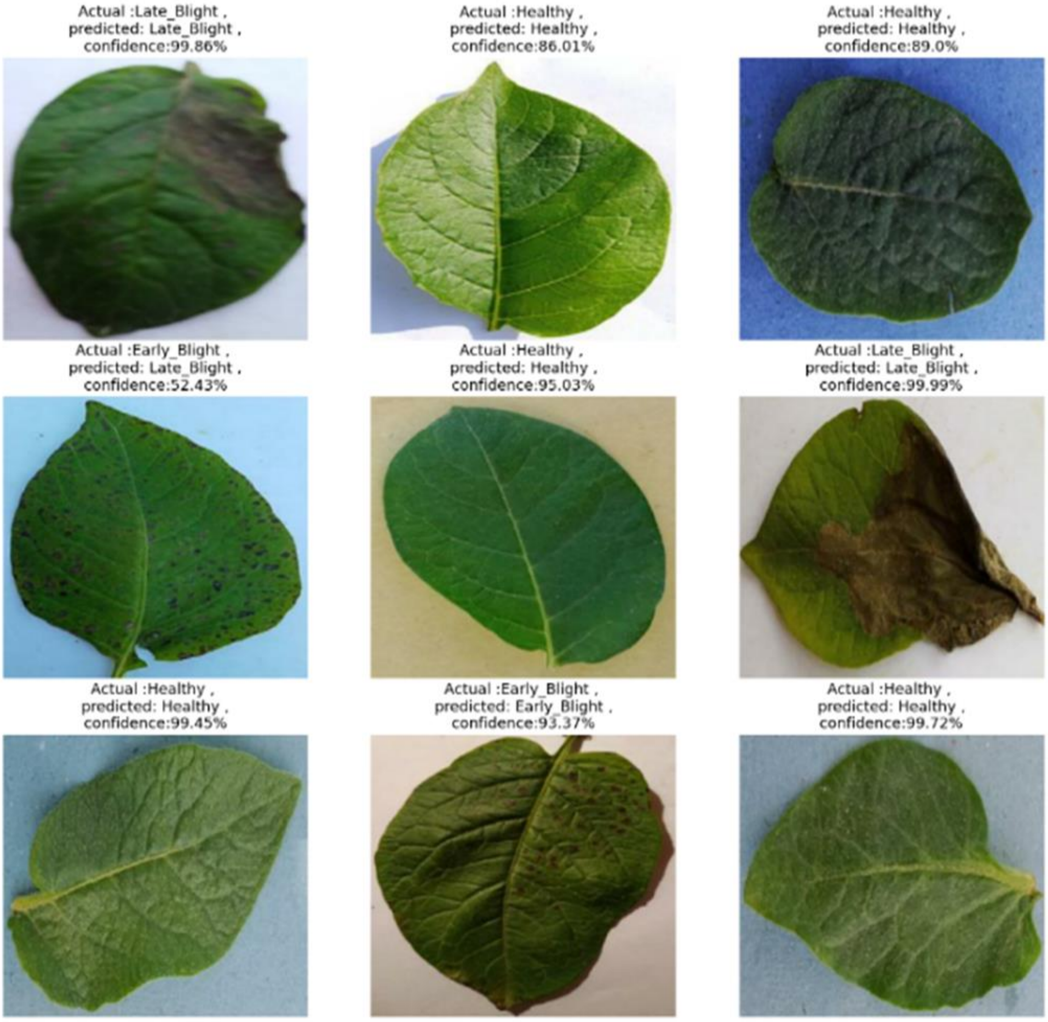

Fig. 4. Sample images from the test set with actual labels, predicted labels, and confidence levels.

The actual labels reflect the true condition of the plants as annotated in the dataset, while the predicted labels represent the model's classification results. Confidence levels indicate the probability scores assigned by the model to its predictions, providing insight into the model's certainty regarding each classification.

This figure highlights the model's robustness and reliability in diagnosing potato late blight, as it consistently achieved accurate results with strong confidence. The ability to correctly classify these images is crucial for practical applications in agricultural settings, where timely and accurate disease detection can significantly impact crop management and yield.

6. Discussion and Future Work

6.1. Discussion

The results of this research have several significant implications for agricultural practices and crop management. Firstly, accurate and early detection of diseases like potato late blight enhances decision-making by enabling farmers to make informed choices regarding resource allocation, fungicide application, and other essential crop management strategies. This targeted approach not only optimizes the use of resources but also reduces the reliance on broad-spectrum fungicides. By identifying diseased plants at an early stage, farmers can implement precise interventions, thereby promoting more sustainable agricultural practices.

Furthermore, early detection contributes to improved resource management by allowing for the efficient use of water, fertilizers, and other inputs, focusing them on healthy plants and ensuring their optimal growth. This efficient utilization of resources is crucial for maintaining the health of the crop and maximizing yield.

In addition, the ability to detect diseases early and accurately promotes food security by increasing crop yields and reducing losses due to disease. This stability in food production is vital for enhancing regional food security and ensuring a steady supply of food. The findings of this study, therefore, offer valuable insights and practical benefits for improving crop management practices, supporting sustainable agriculture, and enhancing food security.

6.2. Future Work

Exploring EfficientNet variants, such as B0-B7, could potentially lead to improved accuracy or reduced computational costs, depending on the specific needs and resources available. Investigating the performance of these different variants allows for a tailored approach to model selection, optimizing for either accuracy or efficiency. Additionally, further fine-tuning of hyperparameters, such as learning rate, batch size, and optimization algorithms, could enhance the model's performance even further, potentially squeezing out higher accuracy. Leveraging transfer learning by utilizing pre-trained models from larger image datasets could significantly reduce training time while also improving performance. This approach allows the model to benefit from the knowledge embedded in large-scale datasets, enhancing its ability to recognize patterns in the potato leaf images. Developing a mobile application that integrates the model would allow farmers to easily capture images of their crops and receive immediate diagnoses, enabling real-time decision-making in the field. Such a tool would make advanced disease detection technology accessible to farmers, facilitating prompt and informed interventions. Moreover, expanding the model's capabilities to detect multiple potato diseases could significantly enhance its utility and broaden its impact on crop health management. This multi-disease detection capability would provide a comprehensive solution for farmers, helping them manage various threats to their crops effectively. By pursuing these avenues, the research could yield practical tools and methodologies that contribute to sustainable agriculture and improved food security.

7. Conclusion

This study demonstrates the effectiveness of EfficientNet for the early detection of potato late blight, providing a valuable tool for farmers and agricultural stakeholders. EfficientNet achieved an exceptional accuracy rate of 98.07% on the test dataset, highlighting its capability in accurately identifying diseased plants and facilitating timely interventions to reduce crop losses. In addition to EfficientNet, the study compared three other CNN architectures: VGGNet, ResNet, and InceptionNet. Key performance metrics—accuracy, precision, recall, and F1 Score—were calculated for each model. EfficientNet's superior performance is due to its balanced architecture that scales network depth, width, and resolution efficiently, allowing it to learn complex features with fewer parameters.

By advancing potato late blight detection, this research contributes to improved crop management, enhanced food security, and resilient agricultural systems. Future work can refine EfficientNet and explore new avenues for enhancing early disease detection.

Author contributions

Shankar Parmar: Conceptualization, Methodology, Software **AlkeshkumarVaghela:** Data curation, Writing-Original draft preparation, Software, Validation **Nileshkumar Patel:** Visualization, Investigation, Writing-Reviewing and Editing **Deep Upadhyaya:** Visualization, Investigation, Writing-Reviewing and Editing

Conflicts of interest

The authors declare no conflicts of interest.

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