

Deep Learning-Based Detection of Potato Leaf Diseases Using ResNet-50 with Mobile Application Deployment

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Abstract

Plant diseases significantly reduce agricultural productivity, especially in developing regions with limited access to early detection tools. This research presents a deep learning-based approach for detecting potato leaf diseases, focusing on Early blight, Late blight, and healthy conditions. A modified ResNet-50 architecture was employed and trained using a publicly available potato leaf image dataset. Preprocessing steps included data augmentation and normalization to enhance model generalization. The model achieved a high accuracy of 99.31%, with precision, recall, and F1-score all exceeding 99%, indicating excellent classification performance. This study introduces a novel approach that improves classification performance through an optimized deep learning architecture, achieving higher accuracy compared to existing models. In addition to enhancing predictive capability, the study also addresses the practical need for accessibility by integrating the trained model into an Android-based mobile application. The application allows users to upload or capture leaf images and receive real-time predictions. The interface was designed for simplicity and usability in field conditions, making it accessible to farmers and agricultural workers. The findings demonstrate that combining deep learning with mobile technology can offer an effective and scalable solution for early disease detection in agriculture. Future work may explore cross-crop adaptability and lightweight model optimization for real-time performance on low-resource devices.

Keywords : *Deep learning, Potato leaf disease, ResNet-50, Mobile application, Image classification, Precision agriculture.*

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1. INTRODUCTION

Agricultural productivity is critical for global food security and economic stability [1]. Plant diseases significantly threaten crop yields, causing an estimated 20–40% reduction in annual production worldwide[2]. In particular, potato (*Solanum tuberosum*) is a staple crop grown and consumed by millions globally – especially in developing countries[3]. Potato yields are frequently devastated by foliar diseases such as late blight (caused by *Phytophthora infestans*) and early blight (*Alternaria* spp.), which can destroy entire fields within days under conducive conditions[4], [5]. These outbreaks lead to substantial economic losses for farmers and exacerbate food insecurity in vulnerable regions [6], [7]. Effective management of potato diseases is therefore a high priority in agriculture [8]

Traditionally, farmers and agronomists rely on manual visual inspection of potato plants to identify disease symptoms in the field. Such conventional methods are labor-intensive, subjective, and error-prone [9], [10]. Early symptoms of different diseases often appear similar, making accurate diagnosis challenging without expert knowledge or laboratory tests[11]. For example, early blight and late blight both cause leaf lesions that are hard to distinguish at initial stages, leading to frequent misdiagnosis[12]. Furthermore, manual scouting is impractical for large potato farms, and its effectiveness is limited by human fatigue and inconsistency [6], [7]. Missed or late detections allow diseases to spread unabated, compounding yield losses. These limitations highlight the need for

automated, rapid, and accurate plant disease detection solutions that can scale to monitor vast crop areas [13], [14]. In recent years, technological advances in sensors and imaging, coupled with artificial intelligence (AI), offer promising avenues to meet this need [15]. In particular, deep learning techniques in computer vision have emerged as powerful tools for detecting plant diseases from leaf images with high precision, potentially overcoming the shortcomings of human-based monitoring [16].

Early applications of AI for plant disease detection utilized classical machine learning algorithms on hand-crafted image features. For instance, techniques like k-nearest neighbors (k-NN), support vector machines (SVM), and random forests were used to classify diseased vs. healthy leaves [10]. In one study, image segmentation was applied to isolate potato leaf lesions, and an SVM classifier then achieved about 91% accuracy in distinguishing disease classes [9]. Similarly, Iqbal and Talukder (2020) developed an image processing pipeline combining color segmentation and machine learning to identify potato blight, reporting ~97% accuracy with a Random Forest classifier [12]. While these conventional approaches showed the potential of automation, they required manual feature engineering and struggled with complex, variable inputs [10]. By 2020, direct deep learning approaches began to appear. For example, Tiwari et al. (2020) applied a deep CNN model on Potato Leaf Disease images, demonstrating the viability of end-to-end learning with high accuracy [17]. Consequently, over the past few years there has been an explosion of research employing deep learning for plant disease detection across a range of crops.

Convolutional Neural Networks (CNNs), in particular, have become the de facto standard for plant disease image classification [18]. Dozens of studies since 2020 have demonstrated near-expert or superior accuracy in identifying plant leaf diseases using CNN-based models. For example, Sholihati et al. (2020) applied the VGG16 and VGG19 CNN architectures to classify four common potato leaf diseases (including late blight and early blight), achieving around 91–93% average accuracy [11]. Soon after, researchers began exploring deeper and more advanced CNN architectures. Ngugi et al. (2021) evaluated several pretrained networks and found DenseNet-201 with a remarkable 99.7% accuracy on a potato leaf disease dataset [16]. Likewise, Lakshmanarao et al. (2021) reported 98.3% accuracy in a potato/tomato/pepper disease classification task using a custom ConvNet [19]. Numerous other studies on the open PlantVillage dataset (a benchmark collection of crop disease images) have yielded very high performance (~98–99% accuracy) for potato disease identification using CNNs [20][21]. For instance, a modified EfficientNet-V2 CNN with an attention module achieved 99.7% accuracy on PlantVillage potato leaf images [22], and a standard ResNet-50 CNN attained ~98.3% on the same dataset [21]. Such consistently high results on curated datasets underscore the efficacy of deep learning in capturing the visual patterns of plant diseases.

The state-of-the-art in potato leaf disease recognition now boasts very high accuracy on curated image datasets. Multiple studies report classification accuracies in the 95–99% range for detecting diseases like late blight from clear images of potato leaves [5][23]. For example, a recent deep CNN model by Shaheed et al. (2023) – called EfficientRMT-Net (combining ResNet-50 and a Vision Transformer) – achieved about 99.1% accuracy on the PlantVillage potato disease images [24]. Likewise, Arshad et al. (2023) introduced a hybrid CNN-based framework (PLDPNet) that attained 98.6% accuracy (with an F1-score of 96.3%) on a similar lab-controlled dataset [25]. Even fine-tuned conventional networks can perform excellently: Chakraborty et al. (2022) showed that a VGG16 model, after fine-tuning, could distinguish late blight vs. early blight on potato leaves with 97.9% accuracy [25]. These figures approach perfect classification under experimental conditions, suggesting that deep learning can effectively recognize even subtle differences in disease symptoms.

A review of current literature indicates that deep learning has emerged as a powerful tool for the detection of potato leaf diseases. For instance, Khalifa et al. developed a multi-level CNN model that demonstrated effective recognition of potato diseases, yielding high accuracy rates [8]. More et al.

reported an impressive 98% accuracy using their tailored deep learning model, underscoring the reliability of CNNs in categorizing different disease classes within potato leaves [26], [27]. Additionally, Hamza et al. acknowledged the superior performance of deep learning systems compared to traditional methods, with accuracies often exceeding 90% in various studies [28]. Despite these advancements, researchers note challenges, particularly related to hyperparameter optimization, which can complicate model training [29].

The impetus for conducting this research arises from the intersection of a growing demand for efficient agricultural practices and the limitations of existing detection methods. Previous studies have established a solid foundation by showcasing state-of-the-art models with remarkable accuracy; however, there remains a significant gap in both practical implementation and model reliability under real-world agricultural scenarios [30]. While many studies have reported very high accuracies on curated datasets, these results do not necessarily generalize well to field conditions where environmental variability, noise, and complex disease symptoms are present. This research aims to bridge these gaps by developing a robust and user-friendly deep learning framework that not only achieves high accuracy but is also scalable and accessible for diverse agricultural settings, enabling farmers to integrate the solution into their everyday practices for timely and accurate disease detection to minimize crop loss.

The purpose of this research is to explore the efficacy of advanced deep learning techniques in recognizing potato leaf diseases and to develop a solution that achieves high accuracy while being scalable and accessible to various agricultural settings. The specific research questions focus on how different deep learning architectures can be optimized to enhance detection performance and operational usability in agricultural environments. The innovative aspect of this study lies in its commitment to providing practical applications for deep learning technologies to transform agricultural disease management, with previous models achieving accuracies of over 90% [26][27]. This study introduces a novel approach that improves classification performance through an optimized deep learning architecture, achieving higher accuracy compared to existing models. In addition to enhancing predictive capability, the study also addresses the practical need for accessibility by integrating the trained model into an Android-based mobile application. This integration enables real-time disease diagnosis directly from leaf images, thereby increasing the model’s usability and relevance for end-users such as farmers and agricultural practitioners in resource-limited environments.

2. METHOD

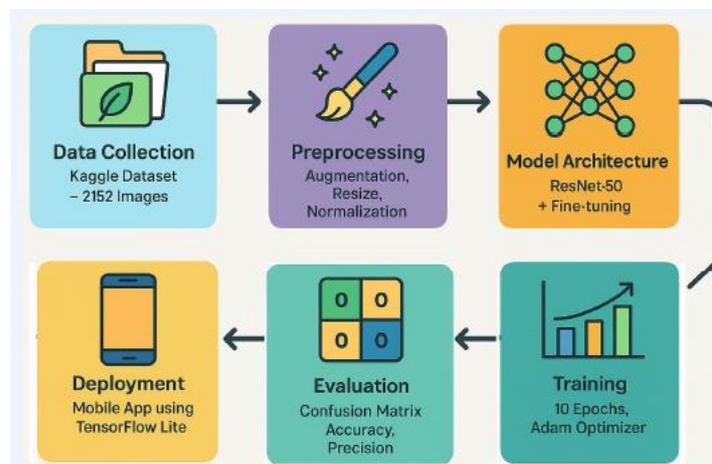


Figure 1. Method

The utilization of deep learning techniques in agricultural practices, specifically for identifying potato leaf diseases, has gained considerable traction due to advancements in computational methods

and imaging technologies. An accurate and timely diagnosis of diseases like late blight can significantly enhance efficacy in crop management. As shown in Figure 1, This research method outlines the systematic approach for developing a deep learning model tailored for potato leaf disease detection, integrating image acquisition, data preprocessing, model training, and validation.

2.1. Data Collection

Gathering a comprehensive dataset is pivotal for training robust deep learning algorithms. High-quality images of potato leaves exhibiting various disease symptoms should be obtained from multiple sources, including field trials and public datasets such as Plant Village [31]. Unmanned Aerial Vehicles (UAVs) equipped with hyperspectral cameras can be employed for this purpose, allowing the capture of detailed imagery that reflects various light spectra, enhancing the model's capacity to differentiate between healthy and diseased leaves [30]. The dataset used in this study consists of a total of 2,152 images, which were obtained from a publicly available source on Kaggle.

2.2. Preprocessing

Data preprocessing forms the backbone of effective deep learning applications. Steps typically involve enhancing image quality through normalization, resizing, and augmentation techniques to increase dataset diversity, which helps in reducing overfitting. It is also crucial to segment images to focus on leaf regions, using methods such as thresholding and edge detection [32], [33]. Image processing techniques will utilize Convolutional Neural Networks (CNNs) to extract critical features automatically, mitigating reliance on manual feature selection that is often error-prone [34].

2.3. Model Architecture

An appropriate model architecture is fundamental to achieving high performance on tasks involving plant disease classification. Recent studies have explored various architectures, including traditional CNNs and hybrid models that combine CNNs with other neural network types such as Vision Transformers (ViTs) and attention mechanisms [35], [36]. The implementation of an ensemble learning approach, combining multiple models, can enhance classification accuracy by leveraging the strengths of different architectures [37]. Moreover, fine-tuning pre-trained models on datasets can yield efficient results, especially when training data is limited. The model employed in this study is based on the ResNet-50 architecture, a deep convolutional neural network that has been widely utilized in image classification due to its residual learning framework and ability to mitigate the vanishing gradient problem. To adapt the pre-trained ResNet-50 model to the specific task of potato leaf disease classification, this study performed transfer learning by retaining the convolutional base while replacing the original fully connected (FC) classification head. Specifically, the final FC layer, originally configured for 1,000 ImageNet classes, was removed and replaced with a custom sequential block consisting of a dropout layer with a rate of 0.01 to prevent overfitting, followed by a linear (fully connected) layer with an output dimension of three, corresponding to the three target classes: Early blight, Late blight, and Healthy. This modification enables the model to focus on learning task-specific features while leveraging the generalized representations learned from large-scale image data. The modified classification head was fine-tuned on our labeled dataset using the Adam optimizer and cross-entropy loss function, allowing the model to adapt effectively to domain-specific features present in potato leaf images.

2.4. Training

Once the model architecture is finalized, the next phase involves training the model utilizing labeled datasets. Techniques like transfer learning can be utilized in conjunction with optimization algorithms such as Adam or Stochastic Gradient Descent (SGD) to minimize loss function effectively

and improve convergence rates [38], [39]. Utilizing techniques such as cross-validation ensures that the model remains generalizable across unseen data and aids in assessing model performance metrics such as accuracy, precision, recall, and F1 score [40], [41].

In this study, the model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. Cross-entropy was used as the loss function to optimize multi-class classification. A dropout rate of 0.01 was applied in the modified classification head to mitigate overfitting. The training was conducted for 10 epochs. The number of epochs was determined based on preliminary experiments, where the validation loss and accuracy stabilized after approximately the eighth epoch, indicating convergence. Extending the training beyond 10 epochs did not yield significant performance gains and increased the risk of overfitting. Therefore, 10 epochs were chosen to balance performance and training efficiency.

2.5. Evaluation

Post-training, the model should undergo rigorous evaluation using separate validation datasets. Various performance metrics should be employed to evaluate the effectiveness of the classification results. Confusion matrices, ROC curves, and precision-recall analysis can help identify misclassification trends, guiding model refinements [42], [43]. The deployment phase should include a feedback loop to continuously update the model as more data becomes available and to adapt to any changes in disease pathology or appearance due to environmental factors.

The use of evaluation metrics is essential to determine the classification capability of the trained model. The evaluation metrics employed in this study include accuracy, precision, recall, and F1-score. Accuracy represents the ratio of correctly predicted classes to the total number of evaluated data (1). Precision is the proportion of correctly predicted positive cases among all predicted positives (2). Recall, or sensitivity, measures the ability to correctly identify positive cases among all actual positives (3). Here, TP, FP, TN, and FN denote the number of cases classified as true positive, false positive, true negative, and false negative, respectively. According to Apoorva Gupta, higher recall corresponds to higher sensitivity, which is crucial for early disease detection and for reducing false negatives in machine learning predictions. The F1-score is defined as the harmonic mean of recall and precision (4) [44].

$$Accuracy = (TP + TN) / (TP+TN+FP+FN) \tag{1}$$

$$Precision = TP / (TP + FP) \tag{2}$$

$$Recall = TP / (TP + FN) \tag{3}$$

$$F1\ Score = 2 * (Precision \times Recall) / (Precision + Recall) \tag{4}$$

2.6. Deployment

The deployment of the trained model into real agricultural settings can be facilitated through mobile applications that provide farmers with diagnostic tools via smartphone cameras. This implementation can afford farmers real-time insights into crop health, enabling timely intervention to mitigate disease spread [45]. Coupling the model with machine learning techniques allows for predictive analytics, informing farmers of optimal disease management practices and enhancing overall agricultural productivity and sustainability [46].

3. RESULT AND DISCUSSION

3.1. Data Collection

The figure 2 depicts a comparative visual analysis of potato leaf conditions, categorized into three distinct groups: healthy leaves, early blight-infected leaves, and late blight-infected leaves. The top row illustrates early blight symptoms, characterized by brown lesions with concentric rings and yellowing edges, indicative of the disease's progression. The middle row showcases late blight infection,

marked by dark, water-soaked spots that often spread rapidly, leading to necrosis and wilting. In contrast, the bottom row presents healthy potato leaves, exhibiting vibrant green coloration and intact structures without any visible signs of damage or discoloration. This visual representation is crucial for understanding the morphological differences between healthy and diseased leaves, which can be leveraged in deep learning-based detection systems to automate and enhance the accuracy of plant disease identification.

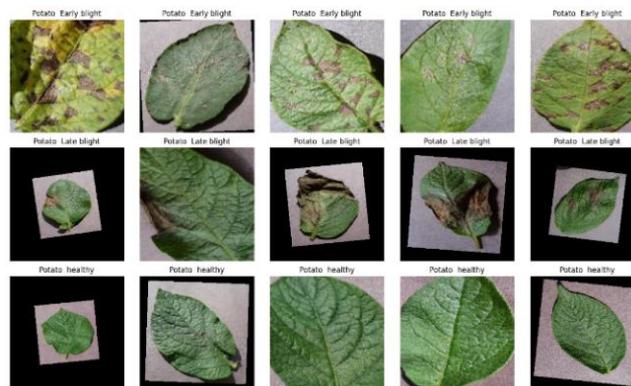


Figure 2. Grid of potato leaf image

3.2. Preprocessing

In the preprocessing phase, label encoding was first applied to convert categorical disease labels into numerical format using the `LabelEncoder()` function, ensuring compatibility with machine learning algorithms. Following this, a stratified data splitting approach was employed to preserve the original class distribution across the training, validation, and test subsets. The dataset was initially partitioned into 70% training data and 30% temporary data using `train_test_split()` with stratification. Subsequently, the temporary data was further divided into validation (10%) and test sets (20%) by allocating 67% of the temporary subset to testing, aligning with the evaluation protocol commonly adopted in prior studies. This ensured an effective and balanced distribution of samples for model learning and evaluation. For data augmentation, the training set was subjected to a series of transformations using the `transforms.Compose()` pipeline, including resizing to 224×224 pixels, random affine transformations (with rotation up to 10 degrees, shear of 0.3, and scaling between 0.5 and 1.5), and horizontal flipping. These augmentations are crucial for enhancing the model's ability to generalize by simulating natural variability in leaf orientation, scale, and perspective. In contrast, the validation and test sets were only resized and converted to tensors to maintain consistency during evaluation. This preprocessing strategy was fundamental in improving the robustness and performance of the deep learning model by expanding data diversity during training while preserving evaluation integrity.

3.3. Model Architecture

In the model selection and architectural design phase, the ResNet-50 architecture was adopted as the backbone model due to its proven performance and depth in handling complex image classification tasks. The model was initialized with pretrained weights from the ImageNet dataset, allowing the network to leverage rich, generalized feature representations from a large-scale visual corpus. This transfer learning approach significantly reduces training time and enhances convergence by providing a well-initialized starting point. The model was subsequently transferred to the designated computational device (GPU or CPU) using `model.to(device)` to ensure efficient execution. To adapt the architecture to the specific classification task involving multiple disease categories, the original fully connected (FC) layer of ResNet-50 was replaced with a new sequential block comprising a Dropout layer (with a dropout

rate of 0.01) and a Linear layer configured to match the number of target classes. This modification allows for better generalization by reducing overfitting while maintaining the network's representational power. The revised FC layer was also allocated to the appropriate device for seamless integration. For the optimization process, the CrossEntropyLoss function was utilized as the loss criterion, which is well-suited for multi-class classification tasks, while the Adam optimizer was employed with a learning rate of 0.001 to ensure adaptive and efficient parameter updates. Finally, the model architecture was summarized using the torchsummary utility to verify the integrity and configuration of the network, particularly for an input image size of $3 \times 224 \times 224$, which aligns with the preprocessing pipeline. This architectural setup establishes a solid foundation for effective and scalable deep learning-based disease classification.

Model selection and architecture play imperative roles in the successful application of deep learning techniques, particularly in areas leveraging transfer learning, such as image classification tasks. ResNet-50, a model characterized by its innovative residual learning framework, has demonstrated significant effectiveness in several applications. This discussion synthesizes findings from various studies that highlight the advantages of using ResNet-50 in transfer learning scenarios and elucidates the model selection process pertinent to this architecture.

Transfer learning hinges on the ability to repurpose pre-trained models to enhance performance on different, yet related, tasks. ResNet-50, pretrained on the ImageNet dataset, has been widely adopted due to its capacity to extract hierarchical features effectively from images, facilitating high accuracy even when annotations are limited [47], [48]. It is particularly beneficial in fields such as medical imaging and agriculture, where labeled data can be scarce. For instance, in the prediction of hemorrhagic strokes using CT images, a ResNet-based model effectively categorized images by utilizing the foundational features learned during its pre-training. Similarly, in agricultural pest detection, ResNet-50 attained an impressive classification accuracy through fine-tuning, underscoring its adaptability and effectiveness within transfer learning frameworks [49].

The architecture of ResNet-50 incorporates skip connections that mitigate the vanishing gradient problem, which can hinder training in deep networks. This characteristic supports robustness in various tasks and datasets. However, empirical evaluations indicate that its performance can vary, necessitating comparative studies among different architectures such as VGG and DenseNet. Research comparing these architectures has highlighted that ResNet consistently outperforms its counterparts in several scenarios, particularly when fine-tuning techniques are applied [50], [51].

Model selection is often influenced by dataset characteristics and specific use cases. In scenarios where datasets are limited, techniques such as fine-tuning—where certain layers of the pre-trained model are adjusted while others remain fixed—have proven beneficial. A hybrid approach, tuning only some layers or applying a slower learning rate to the initial layers, has also shown to enhance performance across various datasets [51], [52]. These methods reflect the nuanced strategies researchers employ to harness the underlying potential of ResNet-50 while adapting to the requirements of their specific tasks.

Furthermore, the emergence of hybrid models that integrate transfer learning with attention mechanisms or other enhancements indicates the growing complexity of applied approaches, which aim to optimize the performance of classification tasks [53]. The adaptability of ResNet-50 facilitates this integration, allowing researchers to tailor models not just for task generalization but also for enhanced interpretability.

3.4. Training

The training process was conducted for 10 epochs, meaning the entire dataset was passed through the model ten times during the learning phase. In each epoch, the model first learned from the training data by adjusting its internal parameters based on the differences between its predictions and the actual

labels. After each training cycle, the model's performance was evaluated using a separate validation dataset to assess how well it could generalize to new, unseen data. The model continued to train until all 10 epochs were completed, and the results, including training and validation accuracy and loss values, were recorded after each epoch. This approach allowed the researchers to monitor whether the model was improving over time and to ensure it was not only memorizing the training data but also performing well on validation samples.



Figure 3. The Training Process of ResNet-50

Figure 3 illustrates the training and validation progress over 10 epochs. As shown, the model demonstrated steady improvements in both training and validation performance across the epochs. In the initial epoch, the training accuracy was recorded at 92.43% with a relatively high validation loss and a validation accuracy of 61.97%, indicating that the model had not yet effectively generalized to unseen data. However, as training progressed, significant improvements were observed. By the second epoch, validation accuracy sharply increased to 98.12% with a substantial drop in validation loss, suggesting that the model quickly learned discriminative features. Minor fluctuations in validation performance in subsequent epochs (e.g., epoch 3 and 6) likely reflect the model's sensitivity to certain batch variations or sample complexities, yet the overall trend remained positive. By epoch 9, the model achieved a perfect validation accuracy of 100%, with training and validation losses reduced to 0.0256 and 0.0046, respectively. These results indicate that the model effectively converged within the predefined training cycle. The decision to fix the number of epochs at ten was sufficient, as performance plateaued and stabilized towards the final epochs. These findings confirm that the model was capable of learning complex patterns from the potato leaf images while maintaining strong generalization to the validation set.

3.5. Evaluation

Figure 4 presents a comparison between training loss and validation loss across the 10 training epochs. The graph demonstrates a sharp decrease in validation loss during the early phase of training, particularly between the first and second epochs, indicating a rapid improvement in the model's ability to generalize to unseen data. Although minor fluctuations are observed in subsequent epochs—most notably at epochs 2, 4, and 5—both loss curves show an overall downward trend. This suggests that the model was continuously refining its predictions while avoiding significant overfitting. From epoch 6 onward, both training and validation losses remained consistently low, converging near zero by epoch 9. The alignment between the two curves in the final epochs reflects stable learning and high generalization capability. These results further validate the effectiveness of the chosen model

architecture and training strategy, indicating that the model was able to learn relevant features without overfitting to the training data.

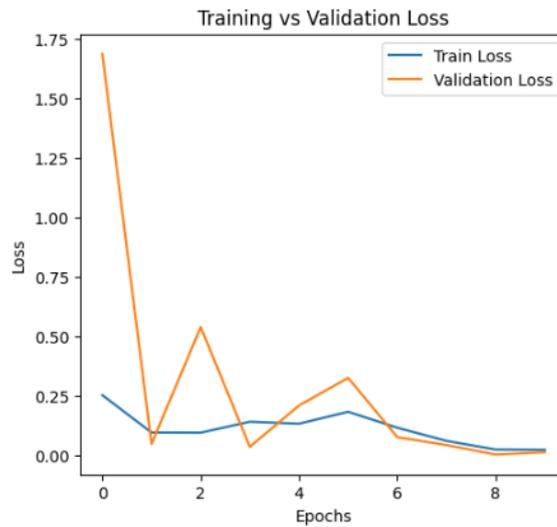


Figure 4. Training Validation Loss

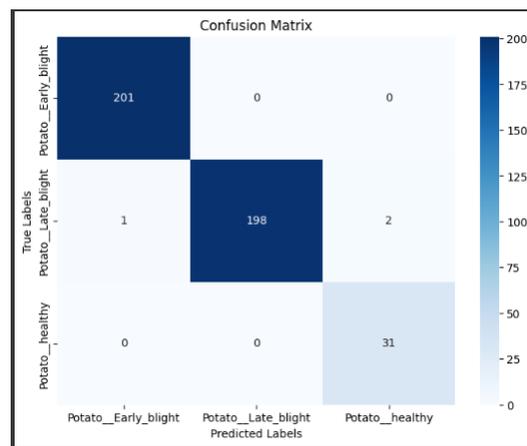


Figure 5. Confusion Matrix

Figure 5 displays the confusion matrix summarizing the classification performance of the trained model on the test dataset, covering three classes: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. The results indicate strong overall predictive performance, with the model correctly classifying 201 samples of Early blight, 198 samples of Late blight, and 31 samples of Healthy leaves. Misclassifications were minimal, with only one Late blight sample incorrectly predicted as Early blight and two misclassified as Healthy. No misclassification occurred between Early blight and Healthy classes, demonstrating the model’s robustness in distinguishing disease-infected leaves from healthy ones. The high values along the diagonal of the matrix reflect the model’s ability to learn discriminative features among the three classes effectively. These results confirm the model’s high accuracy and generalization capability, making it suitable for real-world applications in automated plant disease diagnosis.

The model's performance on the test dataset is further supported by quantitative evaluation metrics. As shown in Figure 5, the confusion matrix reveals strong class-wise predictive accuracy, with most samples correctly classified into their respective categories. This is reflected in the overall test

accuracy of 99.31%, indicating that the model made correct predictions in nearly all test cases. In addition, the model achieved a precision of 99.34%, demonstrating its ability to produce highly reliable predictions with minimal false positives. The recall score of 99.31% confirms that the model successfully identified nearly all relevant instances, with very few false negatives. Moreover, the F1-score of 99.31%, which balances precision and recall, highlights the model's excellent overall classification performance. These metrics collectively indicate that the trained model is highly effective in distinguishing between Early blight, Late blight, and Healthy potato leaves, and is therefore well-suited for deployment in practical plant disease detection systems, particularly in real-time field applications.

3.6. Deployment



Figure 6. Interface of Application for Scanning Potato Leaves

Upon completion of the training process, the model's learned parameters were serialized and saved using the `torch.save()` function. This file contains the trained weights of the modified ResNet-50 architecture and serves as the final model checkpoint for deployment purposes. Saving the model in this format enables its portability and reusability across platforms without requiring retraining.

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To facilitate real-world usage, the trained model was integrated into a mobile application designed for Android devices. As shown in Figure 6, the application interface allows users—such as farmers or agricultural field officers—to either upload or capture a live image of a potato leaf using the device's camera. Once an image is selected, the system invokes the trained model to perform on-device inference, providing a real-time classification result (e.g., healthy, Early blight, or Late blight), which is displayed under the Prediction Result section. The lightweight nature of the model, combined with its flexible deployment options such as Flask for online server-based inference or TensorFlow Lite conversion for offline on-device processing, ensures that predictions can be delivered efficiently with minimal latency. These deployment strategies allow the system to adapt to varying field conditions, whether operating with stable internet connectivity or in remote agricultural areas with limited or no network access. This integration demonstrates the practical applicability of the proposed deep learning solution for field-based disease diagnosis, supporting timely intervention and precision agriculture.

The proposed model achieved a high classification accuracy of 99.31%, demonstrating superior performance compared to previous studies in the domain of potato disease detection. For instance, Khalifa et al. [8] reported an accuracy of 98.00% using deep learning techniques for potato leaf disease classification, while Oppenheim et al. [26] obtained 96.00% accuracy in detecting potato tuber diseases through image-based deep learning approaches. While both studies successfully leveraged deep learning for agricultural disease detection, neither integrated their models into a practical, real-time mobile application.

3.7. Discussion

The experimental results demonstrated that the modified ResNet-50 architecture achieved a classification accuracy of 99.31%, with precision, recall, and F1-score all exceeding 99%. These findings confirm that the model is highly reliable in distinguishing potato leaf conditions, including healthy, early blight, and late blight. The near-perfect evaluation metrics indicate that the proposed deep learning framework successfully captured subtle visual variations in disease symptoms, thereby validating its robustness and suitability for automated plant disease detection. Such performance is particularly relevant in the agricultural domain, where accurate and timely diagnosis is critical to preventing large-scale yield losses.

In comparison with existing studies, the proposed approach performs at least on par with, and in some cases superior to, previously reported results. Earlier works employing CNN-based models such as VGG, DenseNet, or custom architectures generally reported classification accuracies ranging from 95% to 99%. By surpassing this benchmark across all major evaluation metrics, the present study establishes the modified ResNet-50 as a state-of-the-art solution. Beyond model accuracy, this research contributes an additional novelty by integrating the trained model into an Android-based mobile application. This implementation enables real-time, on-device disease diagnosis, thus bridging the gap between academic research and practical applications. The mobile deployment underscores the potential of AI-based solutions to be directly adopted by farmers and agricultural practitioners, providing a portable and farmer-friendly diagnostic tool that does not require advanced technical expertise.

Nevertheless, several limitations merit attention. The model was trained and evaluated on a publicly available dataset that, while comprehensive, is relatively curated and does not fully represent the variability of real-world agricultural environments. Factors such as inconsistent lighting, occlusion, mixed disease symptoms, and environmental noise may affect the model's generalizability in field conditions. High accuracy on benchmark datasets does not necessarily guarantee equivalent performance in uncontrolled environments. Future research should therefore emphasize validation with diverse, real-world datasets and further investigate lightweight optimization techniques to enhance model efficiency on low-resource devices. Despite these limitations, the present study demonstrates that combining advanced deep learning with mobile technology provides a scalable, effective, and accessible framework for early detection of potato leaf diseases, contributing to improved disease management and sustainable agricultural productivity.

4. CONCLUSION

In conclusion, this study successfully developed and evaluated a deep learning-based classification framework for detecting potato leaf diseases using a modified ResNet-50 architecture. The proposed model achieved an accuracy of 99.31%, with precision, recall, and F1-score each exceeding 99% on the test dataset, thereby confirming its effectiveness in discriminating between Early blight, Late blight, and healthy leaves. These results are competitive with, and in several cases superior to, those reported in prior studies that employed CNN-based models such as VGG, DenseNet, and custom architectures, which typically reported accuracies within the range of 95–99%. The consistent

outperformance across all evaluation metrics highlights the robustness of the optimized ResNet-50 approach for plant disease recognition.

Beyond classification accuracy, the research contributes practical value by deploying the trained model into an Android-based mobile application. This implementation enables real-time image-based disease diagnosis directly from users' smartphones, offering a portable and farmer-friendly solution for precision agriculture. Such integration addresses a frequently noted gap in the literature, namely the transition from high-performing laboratory models to field-ready diagnostic tools. The scalability and accessibility of the mobile application demonstrate its potential to support timely disease management in remote and resource-limited agricultural areas, thereby reducing crop losses and improving food security.

From a broader perspective, the findings of this study carry important implications for the field of informatics. The demonstrated ability of optimized deep learning models to not only achieve state-of-the-art classification performance but also to be embedded into mobile platforms underscores the transformative role of artificial intelligence in applied domains. This work exemplifies how advancements in computer vision and deep learning architectures can be translated into tangible, high-impact solutions for real-world challenges. The urgency of such integration lies in bridging the gap between theoretical AI development and its operational deployment in critical sectors like agriculture. Future research should extend this framework towards cross-species generalization, multi-disease detection, and lightweight model optimization for edge devices, while incorporating diverse environmental conditions and disease stages to further strengthen robustness. By doing so, the study contributes both to the advancement of agricultural informatics and to the ongoing discourse on the scalability and societal impact of artificial intelligence.

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