Customized Convolutional Neural Networks for Plant Disease Detection on Leaf Images

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Abstract

Ensuring agricultural productivity and food security depends on effectively detecting and classifying plant leaf diseases. In this study, we present a tailored Convolutional Neural Network (CNN) approach specifically designed to identify plant leaf diseases. Our methodology is based on a carefully curated dataset that includes 29 distinct disease classes. By using transfer learning and fine-tuning techniques, we carefully optimize the CNN architecture to suit the unique characteristics of the dataset, resulting in improved accuracy and robustness. Through extensive experimentation and evaluation, we demonstrate the effectiveness of our approach in accurately diagnosing plant leaf diseases across multiple classes. Our model achieves impressive performance, with a notable accuracy of 96.53% and a minimal loss of 0.1. Outperforming existing methods on a range of evaluation metrics, we emphasize the superiority of our customized CNN approach through comprehensive comparative analyses. This study represents a significant advancement in computer vision techniques for agriculture by providing a reliable and efficient solution for automated plant disease diagnosis. The proposed methodology holds great promise for practical implementation in agricultural systems, enabling early disease detection and management to reduce crop losses and promote sustainable agricultural practices.

Keywords: Deep Learning; CNN; Plant diseases; Leaf Images; Detection.

1. Introduction

Plant diseases represent a major threat to global food security [1], [2], leading to significant yield losses and imposing heavy economic burdens on agricultural industries worldwide. Timely and accurate detection of these diseases is critical for implementing effective intervention strategies to prevent extensive crop damage. Recent advancements in computer vision and machine learning have shown great promise in automating the detection and diagnosis of plant diseases through the analysis of leaf images [3], [4]. Convolutional Neural Networks $(CNNs)$ have proven to be highly effective for image classification tasks [5], [6], including the detection of plant diseases. However, achieving optimal performance in this area involves addressing several challenges, such as dataset heterogeneity, class imbalance, and symptom variability across different plant species. Moreover, existing CNN architectures often require customization to effectively manage the specific characteristics of plant disease datasets [29]. In this paper, we introduce a customized CNN approach designed specifically for identifying plant leaf diseases. Our study utilizes a modified dataset encompassing 29 distinct disease classes, representing a wide variety of plant species and pathologies. Our contribution has two primary objectives: first, to develop a robust and precise model capable of accurately distinguishing between multiple disease classes; and second, to address the limitations of existing CNN architectures by tailoring the model

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to better accommodate the unique characteristics of the plant disease dataset. By utilizing transfer learning and fine-tuning techniques, we optimize the CNN architecture to adapt to the unique features of the dataset, thereby improving both accuracy and robustness. Through extensive experimentation and evaluation, we showcase the effectiveness of our approach in accurately diagnosing plant leaf diseases across multiple classes. Furthermore, we conduct comprehensive comparative analyses to highlight the advantages of our customized CNN approach over traditional methods. Overall, our study aims to advance computer vision techniques in agriculture by offering a reliable and efficient solution for automated plant disease diagnosis. By tackling the challenges associated with plant disease classification, our customized CNN approach shows significant potential for practical implementation in agricultural systems. This can facilitate early disease detection and management, helping to mitigate crop losses and promote sustainable agricultural practices. We begin with an Introduction section that delineates the motivation, objectives, and primary contributions of our study. Subsequently, the Problem Statement section delineates the challenges in plant disease detection and articulates the specific aims of our research. In the Related Works section, we scrutinize existing methodologies, elucidating how our approach advances the field. The Methodology section elaborates on the specialized dataset, the design of the customized CNN architecture, the training process, and techniques for hyperparameter tuning. The Results and Discussion section presents the performance metrics of our model, deliberates on its generalization and scalability, and confronts the challenges of deploying deep learning models on diverse datasets, including issues pertaining to interpretability and transparency. Finally, the Conclusion and Future Works section recapitulates our findings and delineates potential avenues for further research and practical implementations.

2. Problem Statment

In the fields of agriculture and forestry, detecting plant diseases is vital for ensuring healthy crop production and forest management [26]. However, traditional methods of disease detection have significant disadvantages [27]. They rely on manual inspection and semi-automated processes, which are costly, time-consuming, prone to error, and lack precision and specificity [28]. Furthermore, these methods are not exhaustive and struggle to predict disease outbreaks accurately, resulting in delayed responses and potential agricultural losses (figure 1). The current detection methods involve visual inspection and manual data collection, which are labor-intensive, time-consuming, and prone to human error. These methods do not provide real-time results and often fail to accurately predict disease outbreaks, leading to delayed responses and significant agricultural losses. Given these drawbacks, there is an urgent need for an advanced solution that can overcome these limitations. The proposed solution should be automated, cost-effective, provide real-time results, be precise, and offer accurate predictions with a low error rate. Additionally, it should be exhaustive in its analysis, covering a wide range of potential diseases and environmental stressors. Artificial Intelligence (AI) presents a promising alternative to traditional detection methods. By using AI technologies, it is possible to develop systems that meet these criteria, thereby enhancing disease detection and management in agriculture and forestry. AI can process large amounts of data quickly and accurately, providing real-time insights and predictions that enable proactive measures to protect plant health against various threats. In conclusion, transitioning to AI-based detection methods can address the critical shortcomings of traditional approaches, offering a comprehensive and efficient solution for managing plant diseases and adapting to environmental changes.

3. Background of the study

3.1. Deep learning theory

The concept of Deep Learning (DL) was introduced in a seminal paper by Hinton et al., published in Science in 2006 [8]. Deep learning involves the use of neural networks for data analysis and

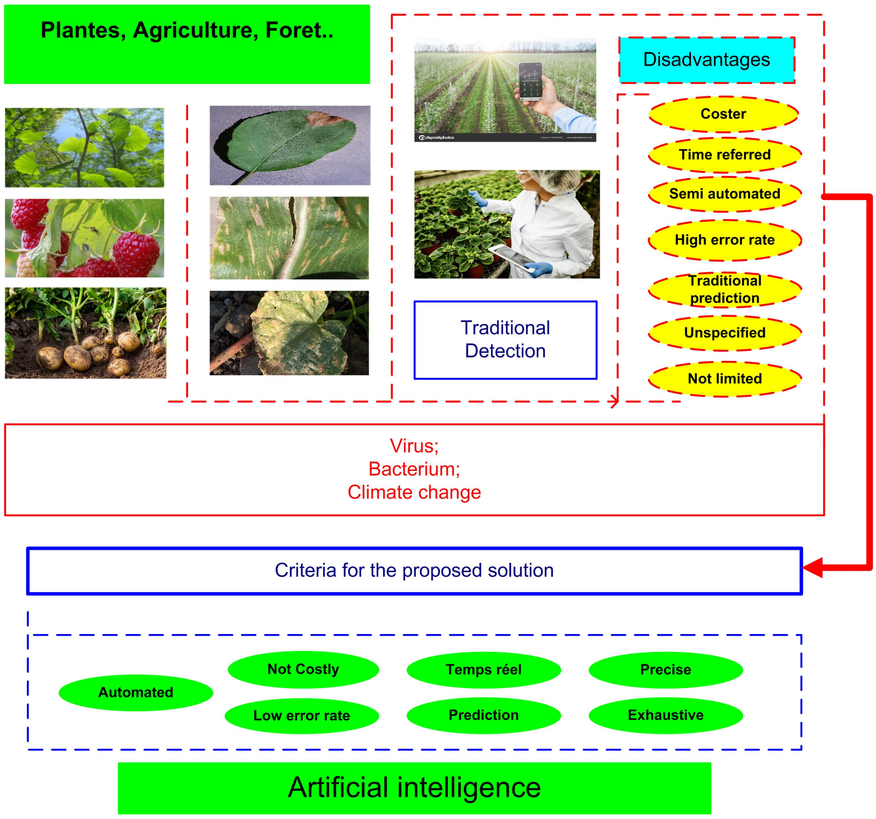

Figure 1: Limitations of traditional plant disease detection methods and the impact of artificial intelligence

feature learning [9]. In this approach, multiple hidden layers are used to extract features from the data. Each hidden layer acts as a perceptron, extracting low-level features that are then combined to form more abstract, high-level features. This approach effectively addresses the issue of local minima. Unlike traditional algorithms that rely on manually designed features, deep learning automates feature extraction, which has generated significant interest among researchers. It has been successfully applied in various domains, including computer vision [10], pattern recognition [11], speech recognition, natural language processing, and recommendation systems. Conventional methods for image classification and recognition rely on manually designed features, which only capture basic features and struggle to extract deep, complex information from images. Deep learning overcomes this limitation by directly learning from raw images, obtaining multi-level feature information that ranges from low-level to high-level semantic features [12]. Traditional algorithms for detecting plant diseases and pests primarily rely on manually designed features, which is a challenging and experience-dependent process that cannot automatically learn from images. On the other hand, deep learning models, with their multiple layers, possess robust autonomous learning and feature representation capabilities, allowing for automatic feature extraction in image classification and recognition tasks. This makes deep learning highly promising in the field of plant disease and pest image recognition[32]. Currently, several well-known deep neural network models have been developed within the realm of deep learning, including deep belief networks (DBN), deep Boltzmann machines (DBM), stacked de-noising autoencoders (SDAE), and deep CNNs. These models offer significant advantages over traditional manual feature extraction methods by automating feature extraction from high-dimensional feature spaces in image recognition tasks [21]. As the volume of training data increases and computational power improves, the representational power of deep neural networks continues to grow. The rise of deep learning is transforming both industry and academia, with deep neural network models consistently outperforming traditional approaches. Among these models, deep convolutional neural networks have become the most popular framework in recent years.

3.2. Convolutional neural network

Convolutional Neural Networks (CNNs) are a type of deep learning model [22] that is particularly well-suited for image classification tasks, such as detecting leaf diseases. The architecture of a CNN consists of multiple layers, including fully connected layers, max pooling, and normalization layers. The initial layer is the input layer, followed by convolutional layers, which apply various 2D filters to the image to extract features [23]. These features are then downsampled through pooling layers, creating a more compact representation. Fully connected (FC) layers, which are considered learnable features, process these extracted features to learn and optimize weights [24]. These FC layers are also crucial for making classifications, such as recognizing different plant diseases. The CNN [30],[31]learning process begins with training, using labeled images as input. Once trained, the model can accurately identify different types of diseases.

4. Related Works

We'll examine various studies that have utilized machine learning and deep learning methods for plant disease detection. Throughout this review, we'll focus on their methodologies, findings, and pinpoint the gaps our approach seeks to address. So, In the literature we detect several works related to our study. We illustrate some of them as follows:

- Xu et al. [7] tackled the task of identifying corn leaf diseases (healthy, leaf blight, rust) in intricate field settings with a scarcity of data. They introduced a CNN model leveraging VGG16 and transfer learning. By utilizing weight parameters pre-trained on ImageNet, they attained an average recognition accuracy of 95.33%.
- In (Hatuwal, B., and Thapa, D. (2020)) [15], the authors aimed to tackle significant crop losses in developing nations like Nepal, stemming from the delayed identification of plant diseases. They proposed a method to classify and predict plant diseases utilizing machine learning models, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest Classifier (RFC), and CNN. The study utilized Haralick texture features such as contrast, correlation, entropy, and inverse difference moments for SVM, KNN, and RFC models, while CNNs were directly fed with images. Their findings revealed that CNN achieved the highest accuracy at 97.89%, surpassing RFC (87.43%), SVM (78.61%), and KNN (76.96%) across sixteen distinct image categories. These results underscore the superior efficacy of CNNs in plant disease classification.
- In (Roy, A., and Patel, D. (2024))[16], the authors tackled the prevalent issue of leaf diseases in agriculture through disease classification employing deep learning techniques. They evaluated the performance of VGG-16, VGG-19, InceptionV3, and DenseNet-121 architectures, providing a comparative analysis. DenseNet-121 achieved the highest accuracy at 91.75%. The study encompassed training a dataset containing 13 different diseases, accompanied by an analysis based on validation accuracy, loss, and the number of epochs. This research underscored DenseNet-121's superiority over other deep learning models, affirming its efficacy in accurately classifying leaf diseases.
- The work by (Lingwal et al. (2023)) [17] addresses the critical need for early detection and classification of plant diseases to prevent their spread and minimize crop damage. By using deep learning techniques, specifically CNNs, the study focuses on classifying tomato leaf diseases using the PlantVillage dataset. This dataset includes nearly 16,000 leaf images, which were divided into training, test, and validation sets with ratios of 70%, 20%, and 10%, respectively[17]. The research compares a custom-developed CNN model with four transfer learning models: DenseNet121, ResNet50, Inception-V3, and VGG-16. Performance evaluations based on accuracy and cross-entropy loss indicated that both VGG-16 and the custom CNN model achieved impressive results, with validation accuracies of 90% and 83% on the test set, respectively[17]. These findings underscore the effectiveness of CNNs, especially transfer learning approaches, in accurately classifying tomato leaf diseases, thereby providing a valuable tool for early disease detection in agriculture[17].

- The study by (Zheng et al. (2023)) [18]emphasizes the critical role of computer vision in detecting plant diseases, particularly the necessity for accurate pattern recognition. A CNN was trained using a dataset comprising 22,930 tomato leaf images. The baseline model achieved a training accuracy of 90% [18]. Comparative analysis of various architectures, including VGG16, MobileNet, and InceptionV3, revealed that MobileNet had the highest training accuracy of 91% and was the most efficient[18]. Despite MobileNet's superior performance, the proposed CNN architecture offers faster training due to its shallower design. This research lays the foundation for future efforts in developing lightweight, fast, and accurate algorithms for classifying plant diseases, ensuring their practical application in agriculture[18].

The summarized studies encompass a variety of crops and diseases, including those affecting corn, wheat, tomatoes, apples, and various fungal infections. They employ a range of methods, from traditional machine learning algorithms such as SVM, KNN, and RFC, to advanced deep learning architectures like VGG16, CNN, DenseNet-121, MobileNet, and SqueezeNet. The dataset sizes vary considerably, with image counts ranging from a few thousand to nearly 37,000. The reported accuracy metrics generally demonstrate high effectiveness in disease detection. Studies utilizing advanced deep learning methods like CNNs and DenseNets typically achieve higher accuracy levels, highlighting their efficacy in image-based plant disease detection. Table 1 summarizes these studies, including the accuracy metrics used for model evaluation.

Table 1
Summary of recent research works about the application of DL and ML for plant diseases detection, (where Cd: Coefficient of determination and maP: Mean average precision)

Reference	Object	Method	Dataset	Performance
Xu et al. (2020) [7]	Corn	VGG16	–	Accuracy=95.33%
Kiruthika et al. (2019)[14]	Leaf	ANN	6108 images	Accuracy=93.33%
Hatuwal and Lee (2020)[15]	Leaf	SVM KNN RFC CNN	36,958 images	Accuracy=78.61% Accuracy=76.96% Accuracy=87.43% Accuracy=97.89%
Roy et al. (2024)[16]	Leaf	DenseNet-121	–	Accuracy=91.75%
Lingwal et al. (2023) [17]	Tomato	VGG-16	16,000 images	Accuracy=90%
Zheng et al. (2023)[18]	Tomato	MobileNet	22,930 images	Accuracy=91%
Shin et al. (2021)[19]	Fungal	SqueezeNet-MOD2	11,600 images	Accuracy=92.61%
Zhong et al. (2020) [20]	Apple	DenseNet-121	2462 images	Accuracy=92.29%

5. Methodology

Our methodology (see in Figure2) is designed to ensure accurate classification of plant diseases through a systematic process. First, we curate a customized dataset and preprocess it, carefully splitting it into training and test sets. Data augmentation techniques are then applied to enhance the dataset, improving the model's robustness. We construct a CNN model with precision, selecting convolutional and pooling layers to effectively extract key features while maintaining efficiency and accuracy. The model is optimized to balance performance with minimized parameters. After constructing the model, it is rigorously trained using advanced optimization techniques, followed by performance evaluation on the test set to assess its effectiveness in real-world scenarios. The final model is deployed for swift and accurate plant disease prediction, providing a reliable tool for early crop health detection. Throughout

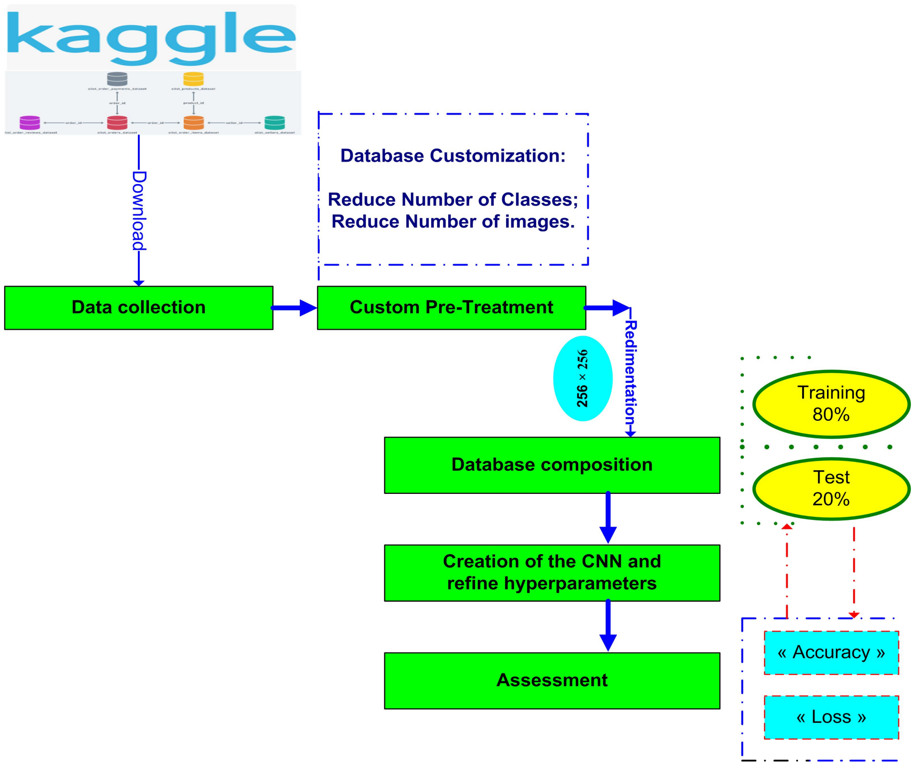

Figure 2: Overview of our methodology

the process, we carefully manage the dataset, model architecture, and parameter optimization to ensure precise and efficient disease classification.

5.1. Customized Dataset

The database contains a collection of plant leaf images, consisting of 39 different classes (figure 3). These classes include healthy leaves as well as leaves affected by various diseases or health issues. Each class represents a specific type of plant disease or health condition, such as apple scab, common corn rust, or tomato leaf mold. The dataset consists of a total of 61,486 images. After modifying and cleaning the database, we have created a new dataset with 29 different classes, representing various plant diseases and health states. The total number of images in the new dataset is now 31,573. To better manage our model training, we have divided this dataset into two parts: a training set and a test set. The training set contains 26,830 images, while the test set has 4,743 images (table 2). The purpose of modifying and

Table 2
Customized dataset

Number of classes	Training images	Testing images
29	26 830	4 743

cleaning the database is to personalize it for our needs. We have used an existing database that includes 16 types of plants and their associated diseases. This optimization helps to streamline processing on the server by avoiding the need to manage two separate processes.

5.2. CNN architecture

The CNN architecture, outlined in (table 3 and figure4), contains a total of eight layers. It starts with an input layer that accommodates images of dimensions 256x256 pixels with three color channels (RGB). The next three layers are Conv2D layers for feature extraction. The first Conv2D layer contains 32

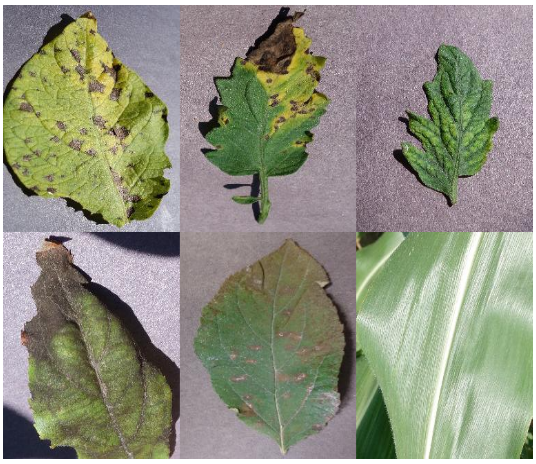

Figure 3: A selection of images depicting plant diseases for analysis

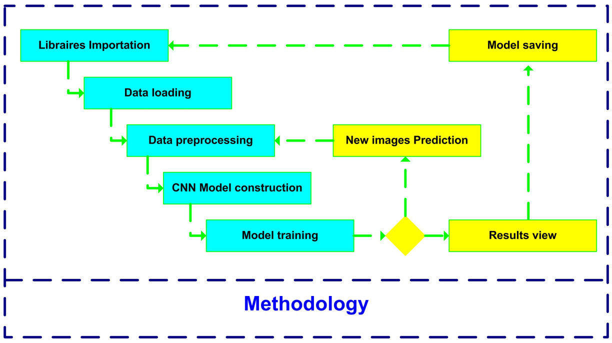

Figure 4: Illustration of the CNN Implementation Process for Image Classification

filters of size 5x5, followed by a Rectified Linear Unit (ReLU) activation function. This is followed by MaxPooling2D layers with pool sizes of 3x3 and 2x2 to downsample the spatial dimensions of the feature maps. The subsequent two Conv2D layers contain 32 and 64 filters of size 3x3, respectively, each with ReLU activation. These are followed by additional MaxPooling2D layers to further downsample the feature maps. The seventh layer flattens the resulting feature maps into a one-dimensional array. This is followed by two Dense layers with ReLU activation, containing 512 and 128 units, respectively. Dropout regularization is applied to the first Dense layer to mitigate overfitting. The final layer is the output layer, which contains 29 units with a Softmax activation function, facilitating multi-class classification by outputting class probabilities.

5.3. Hyperparameters configuration

The hyperparameters presented in the table 4 have been carefully selected and fine-tuned through a series of preliminary tests in order to optimize the performance of the model. These values were determined using a systematic approach.

- Image Dimensions: The image dimensions were chosen based on the typical size and aspect ratio of the input images in the dataset. We experimented with various dimensions and found that 256×256 pixels struck a good balance between capturing important features and computational efficiency.
- Batch Size: We tried different batch sizes and settled on 32 because it allowed for efficient training without excessive memory consumption or compromising model performance.
- Number of Classes: The number of classes in the dataset was predetermined based on the nature of the classification problem. In this case, there are 29 distinct classes representing different types of plant diseases.

Table 3
CNN Architecture Summary

Layer Type	Output Shape	Number of Parameters	Activation
Input (InputLayer)	(256, 256, 3)	0	-
Conv2D	(252, 252, 32)	2432	ReLU
MaxPooling2D	(84, 84, 32)	0	-
Conv2D	(82, 82, 32)	9248	ReLU
MaxPooling2D	(41, 41, 32)	0	-
Conv2D	(39, 39, 64)	18496	ReLU
MaxPooling2D	(19, 19, 64)	0	-
Flatten	(23104,)	0	-
Dense	(512,)	11829760	ReLU
Dropout	(512,)	0	-
Dense	(128,)	65664	ReLU
Dense	(29,)	3741	Softmax

- Number of Epochs: We trained the model for 13 epochs after determining that it achieved satisfactory performance within this timeframe. Increasing the number of epochs further did not yield significant improvements and posed a risk of overfitting.
- Optimizer and Learning Rate: After experimenting with different optimizers and learning rates, we chose the Adam optimizer with a learning rate of 0.001. Adam showed good convergence speed and model stability, while a learning rate of 0.001 struck a balance between fast convergence and avoiding overshooting the optimal solution.
- Data Augmentation: We applied data augmentation techniques such as rescaling, adjusting shear range and zoom range, and horizontal flipping to augment the training data. These techniques were selected to introduce variations in the training images, enhancing the model's ability to generalize to unseen data and improve overall performance.

These specific values were selected through an iterative process of experimentation and evaluation, ensuring optimal performance and generalization ability of the model.

Table 4
Hyperparameters Summary

Hyperparameter	Value
Image Dimensions	256x256 pixels, 3 channels (RGB)
Batch Size	32
Number of Classes	29
Number of Epochs	13
Optimizer	Adam
Learning Rate	0.001
Data Augmentation	- Rescaling: 1./255 - Shear Range: 0.2 - Zoom Range: 0.2 - Horizontal Flip: True

6. Results and discussion

6.1. Results

The customized CNN architecture applied to the customized dataset achieved an outstanding performance with an accuracy of 96.53% and a loss value of 0.1. These results indicate that the model is highly effective at classifying plant diseases, demonstrating both precision and reliability in its predictions.

The figure 5 illustrates the performance of our customized CNN model on the training and validation datasets.

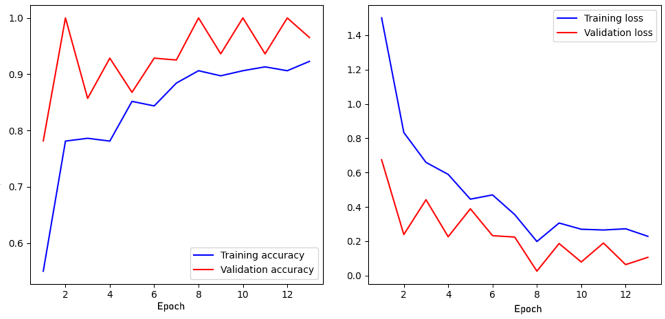

Figure 5: Training and Validation Performance of the Customized CNN Model

The confusion matrix (Figure 6) provides a detailed breakdown of the performance of our customized CNN model on the test dataset. Each cell in the matrix represents the number of predictions made by the model for each class, allowing us to see where the model performs well and where it might be making errors. The confusion matrix is a crucial tool for evaluating the performance of a classification model. By examining the diagonal and off-diagonal values, we can identify which classes the model predicts well and which ones it struggles with. This can guide further improvements in the model or dataset. It allows us to calculate these metrics for each class:

- Precision: It tells us how many of the predicted positive instances are actually correct.
- Recall: It indicates how many actual positive instances are correctly identified by the model.
- F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both.

By leveraging the insights from the confusion matrix, we can iteratively refine our model, making targeted adjustments to enhance its overall performance and reliability.

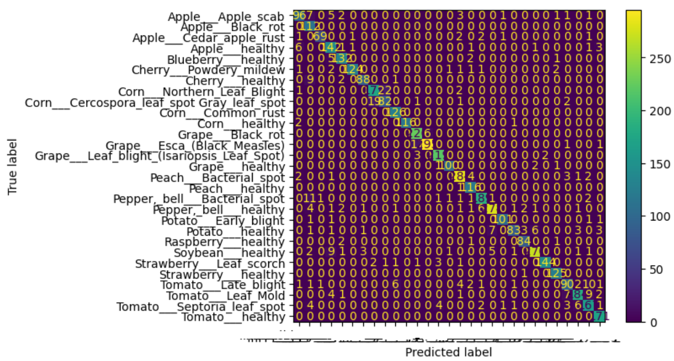

Figure 6: Confusion matrix

6.2. Discussion

In this study, we have developed a customized CNN architecture tailored for a specialized dataset containing images of various plant diseases. Our primary objective was to create a model capable of accurately identifying different plant diseases, making it a vital tool for agricultural management and disease control.

6.2.1. Model Performance

Our CNN model achieved an impressive accuracy of 96.53% and a loss value of 0.1 on the test dataset. These metrics underscore the model's ability to learn and recognize intricate patterns and features associated with each plant disease class effectively. The robustness of our model is further evidenced by the training and validation accuracy and loss graphs, as well as the confusion matrix, which illustrates the model's proficiency in correctly classifying the majority of plant disease images with minimal misclassifications.

6.2.2. Hyperparameter Tuning

Finding the ideal hyperparameters for training a deep learning model, such as the learning rate, batch size, and number of layers, can be a challenging and time-consuming task. It often requires extensive experimentation.

6.2.3. Interpretability and transparency

Interpretability and transparency are essential when deploying machine learning models, particularly in scenarios where understanding and justifying decisions is critical. Deep learning models like CNNs are often considered "black boxes" due to their complexity, making it hard to interpret their internal workings. This is a significant issue in fields like medical diagnosis or autonomous driving, where trust in the model's decisions is paramount. In our study, we tackled this challenge by creating a custom CNN architecture for plant disease classification. Unlike pre-trained models with many layers and parameters, our model is simpler, with fewer parameters, reducing complexity and enhancing interpretability. This streamlined design makes it easier to understand how features are processed and which ones are most influential in predictions. Additionally, the architecture incorporates domain-specific knowledge, which aligns the model's decisions with biological factors behind plant diseases, further increasing transparency.

6.2.4. Scalability and Adaptability

- Adaptation to New Data: A significant challenge is ensuring that the model can be easily adapted to new data and different contexts, such as new plant diseases or variations, without requiring extensive retraining.
- Model Scalability: The model should be able to handle a growing dataset and the addition of new classes without the need for extensive reengineering, while still maintaining its performance.

7. Conclusion

In this study, we have developed a customized Convolutional Neural Network for identifying plant diseases using a specialized dataset. The model achieved an impressive accuracy of 96.53% and a low loss value of 0.1, demonstrating its robustness and potential for practical agricultural applications. Moving forward, expanding the dataset to include more plant species and diseases, as well as images from different geographic regions, will improve the model's generalizability. Additionally, testing the model under real-world conditions and employing advanced hyperparameter tuning techniques can further enhance its performance. Exploring model pruning and quantization techniques can also help reduce computational requirements, allowing for deployment on mobile and low-power edge devices. To make the model accessible to farmers and agricultural professionals, it is crucial to integrate it with Internet of Things (IoT) devices for real-time monitoring. Furthermore, developing user-friendly mobile and web applications will facilitate the use of the model. These efforts will contribute to agricultural sustainability and food security. In conclusion, our customized CNN model holds great promise for plant disease detection. With ongoing development and refinement, it has the potential to become a crucial tool in global agriculture.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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