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AI-driven image classification for early detection of crop diseases

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Abstract

Crop diseases pose a significant threat to agricultural productivity and food security. Early detection is essential for effective disease management and timely intervention. However, the limitations of human vision often lead to delayed identification, typically after the disease has already caused considerable damage. To address this challenge, we present a custom-built Convolutional Neural Network (CNN) model designed to accelerate and improve the accuracy of plant disease detection. Our model was thoroughly trained and evaluated using a variety of datasets featuring apple, corn, and tomato crops, sourced primarily from platforms like Kaggle. Unlike conventional classification models that are often tailored to specific datasets, our model is designed to handle images taken under diverse lighting conditions, orientations, and resolutions, making it adaptable to a wide range of real-world farm environments. Through a structured training and validation process, our CNN consistently achieved testing accuracies of between 97% and 99% across all datasets. These results significantly outperform many existing CNN-based approaches to crop disease detection. The broader implications of this work are substantial for agriculture and crop management. By integrating our AI-powered detection system, we not only tackle immediate agricultural challenges but also contribute to addressing global concerns such as food insecurity and environmental sustainability. Early disease detection using our model aids in minimizing crop losses and optimizing resource usage, thereby supporting the growing demands of a rising global population and mitigating the effects of environmental stress on food systems. Nonetheless, it is important to recognize that, as a classification model, it may exhibit reduced accuracy when analyzing images that include unrelated visual elements. Overall, this research highlights the pivotal role that AI-based technologies can play in strengthening agricultural resilience and advancing global food security.

Keywords: Crop Disease Detection; Convolutional Neural Network (CNN); Deep Learning in Agriculture; Image Classification; Plant Village Dataset; Precision Agriculture

1 Introduction

Agriculture remains a foundational pillar of both the global economy and human society. Over the last two hundred years, the world's population has increased sevenfold, and projections indicate that an additional 2 to 3 billion people will be added within this century. With the global population expected to reach approximately 10 billion by 2050, agricultural output must rise by nearly 60% to meet the growing demand. Achieving this goal requires reducing losses caused by pests, diseases, and food waste. At present, pests and crop diseases contribute significantly to global yield losses, impacting 21.5% of wheat, 30.3% of rice, 22.6% of maize, 17.2% of potatoes, and 21.4% of soybeans [3].

One of the major hurdles in improving crop productivity is the timely detection of diseases. The causes of crop diseases are varied, ranging from climatic changes and nutritional deficiencies to pest infestations, making early and accurate diagnosis highly complex [4]. Traditionally, detecting plant diseases has relied on manual techniques such as visual inspections and microscopic analysis, which are labor-intensive and often prone to inconsistencies due to subjective human judgment. These methods are particularly impractical for large-scale farms or in regions where expert access is

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limited. The diagnosis process is not only time-consuming but can also become costly, especially when dealing with rare diseases [5]. Consequently, there is a growing need for more reliable and scalable alternatives [6]. Recent advancements have shifted attention toward automated disease detection methods using deep learning technologies. These AI-driven solutions have outperformed conventional techniques like molecular or serological testing by offering faster, more accessible, and cost-effective options. In contrast to expensive hyperspectral imaging systems, deep learning models can utilize standard digital cameras, making them suitable for widespread use in agricultural monitoring [6]. As a result, image-based automated disease identification is emerging as a practical solution to these longstanding challenges [5].

This automated approach involves applying advanced computational methods, particularly those derived from artificial intelligence (AI) and machine learning, to analyze digital images of crops and detect signs of disease. By training on a large and diverse set of images depicting both healthy and diseased plants, these algorithms learn to identify subtle visual cues associated with various conditions. Once trained, they can rapidly and accurately identify diseases in new images, enabling early intervention and more effective crop management. Among the most impactful AI techniques is deep learning, which has revolutionized fields such as image analysis and natural language processing. Within agriculture, deep learning has demonstrated significant promise, for instance, in predicting crop yields based on environmental and soil data [7], [8]. Convolutional Neural Networks (CNNs), a subset of deep learning designed for visual data, are particularly effective in this domain [9], [10]. These networks process image inputs through multiple layers that gradually extract increasingly complex features, from basic edges to full object recognition. This hierarchical processing structure makes CNNs especially suited for detecting early-stage crop diseases, where minor visual differences can indicate significant issues [11].

Numerous studies have validated the effectiveness of CNNs for crop disease detection [12]–[15]. However, common limitations persist. Many models are trained on narrowly focused datasets, which limits their ability to generalize across different crops, disease types, and environmental conditions. Additionally, the lack of high-quality, diverse images can restrict a model's performance in real-world settings, where variability is far greater than in controlled datasets. To address these limitations, our study introduces a CNN-based model enhanced with custom dense layers, designed for both accuracy and efficiency in detecting crop diseases. Unlike models that use extensive layers and prioritize depth, our approach uses a streamlined architecture, three primary convolutional layers, and two dense layers to deliver rapid performance suitable for practical farm use. Speed was a core design consideration to ensure timely alerts for farmers.

We trained and tested the model using three distinct datasets comprising images of apple, corn, and tomato leaves. These datasets included a combination of images collected from real-world farm locations in Gujarat, India, at different times of the day to introduce variation in lighting and background, alongside images from the publicly available Plant Village dataset [16]. Out of 16 farms, data from 12 were used for training, and the remaining four for testing. All labeled images were verified by an agricultural expert to ensure accuracy. The model demonstrated strong generalization capabilities when tested on unseen data, particularly the apple dataset from farms not included in the training, confirming its cross-environment adaptability. For each crop, the dataset was organized into three categories: healthy plants and two distinct disease types. The CNN model consistently achieved high classification accuracy across all categories. This research is guided by the hypothesis that a simplified yet powerful CNN can effectively identify multiple types of crop diseases, and our findings support this claim. Ultimately, this work aims to advance the field of precision agriculture by enabling earlier disease detection and improving overall crop health management.

1.1 CNN Architecture details

The Convolutional Neural Network (CNN) architecture and its training configuration were central to our image classification approach. Built using Keras' library, the model was designed with a sequential layer structure that methodically processes image inputs. The architecture began with a 2D convolutional layer containing 32 filters and a ReLU (Rectified Linear Unit) activation function, tasked with detecting basic image features such as edges. This was followed by a max-pooling layer, which reduces the spatial dimensions of the feature maps and introduces translation invariance, aiding in generalization.

Two additional convolutional layers were added, one with 64 filters and another with 128 filters, each paired with ReLU activations and max pooling. These deeper layers allow the network to capture increasingly complex visual patterns in the data. Next, a flattened layer was used to convert the multi-dimensional outputs into a 1D vector, making the data suitable for fully connected layers. This was followed by a dense layer with 128 units and a ReLU activation, responsible for learning abstract feature representations. The final output layer was a dense layer with a Soft Max activation function, which generated class probabilities for the three disease categories.

Each architectural decision, such as the number of filters and units, was the result of iterative experimentation and hyperparameter tuning, balancing model complexity with performance efficiency. Starting with 32 filters allowed for the detection of simple patterns, while scaling up to 64 and 128 enabled deeper feature extraction. The use of a dense layer with 128 units helped interpret complex relationships learned by the convolutional layers.

For training, the model was compiled using the Adam optimizer in combination with the categorical cross-entropy loss function, which is ideal for multi-class classification. Adam was selected due to its adaptive learning rate and effective handling of sparse gradients, which led to faster convergence and better results compared to other optimizers like Nadam and Adara. During training, AUC (Area Under the Curve) was monitored as a primary evaluation metric, followed by a rerun using accuracy. We also incorporated the Model Checkpoint callback, which automatically saved the best-performing model weights based on validation AUC/accuracy. This mechanism safeguards against overfitting, enabling the model to generalize well and recover optimal states when necessary.

1.2 Architecture of the Model

In this study, we developed and utilized a Convolutional Neural Network (CNN) for image classification and feature extraction, specifically applied to crop disease detection. To evaluate the model's performance and resilience, it underwent rigorous testing using datasets from Kaggle, focusing on tomato, corn, and apple crops. The effectiveness of our CNN model relied on several foundational techniques. For instance, the process of flattening helped transform complex image arrays into a simplified one-dimensional format, which allowed for more efficient data handling and better feature extraction across samples. Another essential method, batch normalization, standardizes intermediate outputs between layers, significantly improving both the training speed and stability.

Dense layers played a critical role in establishing complex interconnections between neurons, enhancing the model's ability to learn spatial hierarchies and accurately distinguish between healthy and diseased plant samples. Additionally, the use of activation functions introduced non-linearity into the model, enabling it to capture intricate relationships and patterns inherent in the dataset. This non-linearity was vital for effective generalization across various disease types. An important concept in training neural networks is the epoch; each epoch signifies one complete pass through the training dataset. During each epoch, the model updates its internal weights based on the loss function and selected optimization algorithm. While increasing the number of epochs can help the model learn deeper patterns, it also increases the risk of overfitting. Striking the right balance is key: in our experiments, six epochs were optimal for the tomato and apple datasets, as additional epochs led to decreases in AUC and accuracy. For corn, eight epochs were used, with AUC peaking at that point before declining. To further enhance model robustness, we introduced a checkpoint mechanism that monitored training performance and saved the optimal parameters at strategic intervals. This approach minimized overfitting and improved the model's ability to generalize to new, unseen data.

2 Materials and Methods

In this phase of the study, we utilized data from the Plant Village dataset, a widely recognized collection of agricultural imagery available on Kaggle, a leading platform for data science research and collaboration. The dataset includes high-resolution and standardized leaf images, each uniformly scaled to 256 × 256 pixels, ensuring consistency in model input. To enhance the model's predictive accuracy, we applied essential preprocessing steps. One of the most critical steps was data normalization, where pixel values were rescaled to a common range of [0, 1] [2, 4]. This process ensures that the model can generalize effectively by treating features on a consistent scale, allowing it to focus on meaningful visual patterns in diverse agricultural settings.

In addition, we incorporated data augmentation techniques to expand the diversity and robustness of the training dataset. Specifically, we applied zoom and flip transformations, which introduced variability in leaf orientation and scale. These augmentations significantly reduced the risk of overfitting by exposing the model to a broader set of visual representations. We observed substantial overfitting, particularly in the Apple dataset, where limited training data reduced the model's accuracy to 78%. However, the application of augmentation techniques helped address this issue by improving data diversity and supporting better generalization.

2.1 Testing and Results of the Apple Dataset

We categorized apple leaf images into three distinct classes: Healthy, Apple Scab, and Apple Cedar Rust (see Figure 1). While the first category comprises images of unaffected leaves, the other two represent disease conditions that commonly affect apple foliage. To train and evaluate our model, we divided the dataset into three subsets. Specifically, 80% of the total data,2040 images, was allocated for training. An additional 10% (255 images) was used for validation, and the remaining 10% (255 images) was reserved for testing.

2.1.1 *A detailed breakdown of image distribution per class is as follows*

- Training set: 1316 images of Healthy Apple Leaves, 504 of Apple Scab Leaves, and 220 of Apple Rust Leaves
- Validation set: 164 images (Healthy), 63 (Apple Scab), and 28 (Apple Rust)
- Testing set: 165 images (Healthy), 63 (Apple Scab), and 27 (Apple Rust)

This structured data partitioning, summarized in Table 1, was crucial to ensure balanced model training and reliable performance evaluation across all three apple leaf categories.

Figure 1 (Left) Healthy Apple Leaf, (Middle) Apple Scab, (Right) Apple Cedar Rust

Table 1 Apple Dataset Images for Classes in Training, Validation, And Testing

Apple Leaf Images	Apple Healthy	Apple Scab	Apple Rust	Total
Training	1316	504	220	2040
Validation	164	63	28	255
Testing	165	63	27	255

We utilized the categorical cross-entropy loss function, which is widely adopted for multi-class classification problems like ours. This function measures the degree of difference between the model's predicted class probabilities and the true class labels for each input image. By minimizing this loss during training, the model effectively learns to produce accurate predictions across the various disease classes in our dataset. To evaluate our model's performance, we relied on the AUC (Area Under the Curve) metric. While accuracy is a standard evaluation measure, AUC provides a more comprehensive assessment, especially useful when dealing with imbalanced datasets. It reflects the model's ability to distinguish between healthy and diseased samples over a full range of classification thresholds. By prioritizing AUC, we aimed to capture the subtleties of the classification task and improve the model's effectiveness in disease detection. During training, the model demonstrated strong learning behavior, reaching a training AUC of 0.978 after 6 epochs. A steady improvement in AUC was observed through the first four epochs, after which it stabilized.

The validation AUC similarly progressed well, peaking at 0.988 after 6 epochs. Notably, a minor dip occurred at epoch 2, likely due to early-stage noise or suboptimal weight adjustments. However, the model recovered and improved as training continued, identifying more refined patterns in the data. In the testing phase, the model achieved a peak AUC of 0.991, reflecting its high capability to generalize to unseen examples (Table 2). These results validate the robustness and discriminative power of the trained model, as illustrated in Figure 2.

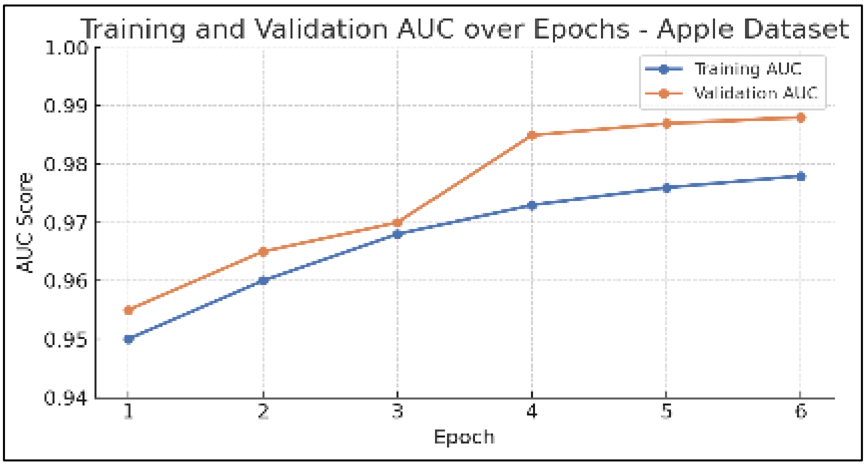

Figure 2 Training Area Under the Curve (AUC) and validation AUC of the Apple dataset model

Table 2 AUC Results for all classes

Leaf	Training AUC	Validation AUC	Testing AUC
Apple	0.978	0.988	0.991
Corn	0.988	0.999	0.996
Tomato	0.988	0.988	0.97

To gain a comprehensive understanding of the model's performance, we also assessed its accuracy alongside AUC. The model achieved a peak training accuracy of 0.927 after 6 epochs, reflecting consistent improvement throughout the learning phase. Simultaneously, validation accuracy reached its highest point,0.926, at epoch 5, indicating that the model was learning effectively from unseen data. However, a slight decline in validation accuracy was observed during epoch 6, suggesting the onset of overfitting. Despite this, the model performed strongly on the unseen test set, achieving a final test accuracy of 0.946, showcasing its generalization capability and robustness (Table 3).

2.2 Testing and Results of the Corn Dataset

We categorized corn leaf images from the Plant Village dataset into three distinct classes: Healthy, Corn Northern Blight, and Corn Common Rust (see Figure 3). The last two represent common diseases affecting corn foliage, while the healthy class contains images of uninfected leaves.

The dataset was divided into three subsets: 80% for training (2672 images), 10% for validation (333 images), and the remaining 10% for testing (334 images).

2.2.1 The class-wise distribution of images is as follows

- Training set: 930 images of Healthy Corn Leaves, 954 of Corn Northern Blight, and 788 of Corn Common Rust
- Validation set: 116 (Healthy), 119 (Corn Northern Blight), and 98 (Corn Common Rust)
- Testing set: 116 (Healthy), 119 (Corn Northern Blight), and 99 (Corn Common Rust)

These distributions, summarized in Table 4, helped maintain class balance throughout the training and evaluation phases.

Figure 3 (Left) Healthy Corn Leaf, (Middle) Corn common rust, (Right)

The model recorded its highest training AUC at 0.988 after 8 epochs, following a steady upward trajectory until epoch 4, after which it plateaued. Its validation AUC peaked impressively at 0.999 after just 6 epochs. In the testing phase, the model also demonstrated strong generalization performance with an AUC of 0.996 (Table 2). In terms of accuracy, the model reached its peak training accuracy of 0.987 at epoch 8, showing consistent improvement up to epoch 6. Likewise, validation accuracy reached a notable high of 0.996 by the 8th epoch. The model also performed exceptionally well on unseen data, achieving a testing accuracy of 0.996 (Table 3).

2.3 Testing and Results of the Tomato Dataset

The tomato leaf dataset from the Plant Village dataset was organized into three categories: Healthy, Tomato Early Blight, and Tomato Late Blight (Figure 4). The latter two are diseases that commonly affect tomato leaves, while the healthy class includes uninfected samples. The dataset was split as follows: 80% of the data (3600 images) was designated for training, 10% (450 images) for validation, and the remaining 10% (450 images) for testing.

2.3.1 A detailed distribution per class is outlined below

- Training set: 1273 images of Healthy Tomato Leaves, 800 of Tomato Early Blight, and 1527 of Tomato Late Blight
- Validation set: 159 (Healthy), 100 (Early Blight), 191 (Late Blight)
- Testing set: 159 (Healthy), 100 (Early Blight), 191 (Late Blight)

The model again exhibited strong AUC performance on this dataset. The peak training AUC reached 0.988 after 6 epochs, showing continuous gains until that point. The validation AUC followed a similar trend, also peaking at 6 epochs.

Table 3 Accuracy Results for all classes

Leaf	Training Accuracy	Validation Accuracy	Testing Accuracy
Apple	0.927	0.926	0.946
Corn	0.987	0.996	0.996
Tomato	0.885	0.888	0.882

Table 4 Corn dataset images for classes in training, validation, and testing

Corn Leaf Images	Corn Healthy	Corn Northern Blight	Corn Common Rust	Total
Training	930	954	788	2672
Validation	116	119	98	333
Testing	116	119	99	334

Figure 4 (Left) Healthy Tomato Leaf, (Middle) Tomato Early Blight, (Right) Tomato Late Blight

The model's validation AUC peaked at 0.967 after 6 epochs, demonstrating strong learning on unseen data. In the testing phase, the model sustained a robust performance with an AUC of 0.97 (Table 2), indicating its effectiveness in generalizing to new samples. In terms of accuracy, the model achieved a training accuracy of 0.885 at epoch 6, showing a steady and consistent upward trend throughout the learning process. Similarly, validation accuracy reached its maximum value of 0.888 at the same epoch.

When evaluated on the test set, the model delivered a solid testing accuracy of 0.882, highlighting its consistent and dependable performance across all phases of model evaluation (Table 3).

3 Result and Discussion

This study centers on the design and evaluation of a Convolutional Neural Network (CNN) model developed for image classification and feature extraction in agricultural applications. Using crop datasets obtained from Kaggle, we tested the model's performance across three key crops: apples, corn, and tomatoes. Our model was strengthened through the application of several core techniques, including data flattening, batch normalization, dense layers, activation functions, and a checkpoint mechanism. Performance assessment relied primarily on the AUC (Area Under the Curve) metric, which validated the model's ability to accurately differentiate between healthy and diseased plants, highlighting its potential for reliable disease detection in agricultural settings [17]. With the model framework established, a structured evaluation was conducted across each dataset. For the Apple dataset, which included categories like Healthy, Apple Scab, and Apple Cedar Rust, we applied an 80-10-10 split for training, validation, and testing. The model achieved strong results, particularly during the testing phase, where it effectively distinguished between healthy and infected apple leaves.

Moving to the corn dataset, which included Healthy, Corn Northern Blight, and Corn Common Rust, the model achieved impressive AUC scores in both training and validation phases, demonstrating its ability to learn subtle disease characteristics. Similarly, on the tomato dataset, which featured Healthy, Tomato Early Blight, and Tomato Late Blight, the model exhibited steady improvements and high classification accuracy. While these results are encouraging, it is essential to recognize several limitations. Factors such as inconsistent data collection, image quality, lighting conditions, and camera angles can introduce variability. The model's effectiveness may also decline when confronted with unseen diseases or variations absent from the training data. A key assumption of the methodology is that the labeled data is entirely accurate, an expectation that may not hold in real-world environments. Additionally, subtle visual differences between certain disease types can lead to misclassification, particularly when facing uncommon conditions or non-standard image inputs.

To mitigate these challenges, strategic solutions must be implemented. Enhancing the model's adaptability requires robust preprocessing techniques, such as image normalization and data augmentation, which help the model perform well under diverse conditions [18]. Integrating more varied datasets and capturing different lighting scenarios and perspectives can also improve generalization. Expanding the dataset with more diverse images, captured under varying lighting conditions and environmental settings, could significantly improve the model's generalization capabilities [19]. Continuously updating the training dataset with new disease instances or variations may enhance the model's flexibility when confronted with novel conditions [20].

To further strengthen the model's ability to detect unseen diseases, implementing transfer learning can be highly beneficial. This technique involves pre-training the model on a broad collection of plant diseases, followed by fine-tuning the specific target dataset to increase accuracy and adaptability [20]. However, in this study, we chose not to adopt transfer learning due to two key concerns. First, the domain adaptation challenge, where the source domain (pre-training data) may differ substantially from the target domain (crop disease images), could negatively affect performance. Second, the selection of an appropriate pre-trained model and the risk of overfitting during fine-tuning necessitated a more controlled approach for this initial phase.

Another promising avenue lies in exploring semi-supervised or weakly supervised learning methods, which reduce reliance on perfectly labeled data by utilizing a mix of labeled and unlabeled samples [21]. While these approaches improve the model's adaptability in real-world agricultural settings, they do present challenges, such as managing label noise and maintaining learning stability.

Future research could also benefit from replacing the current classification model with an object detection model, which would not only identify the presence of disease but also localize affected regions within the image. This would allow for multi-disease detection within a single sample and support targeted interventions, ultimately enhancing both accuracy and efficiency [22]. Another exciting opportunity involves the integration of drones (Unmanned Aerial Vehicles or UAVs) in agricultural monitoring. As highlighted in recent studies [23], UAVs equipped with high-resolution cameras can capture crop imagery from diverse altitudes and angles. Incorporating this aerial data into detection models provides a more dynamic, wide-coverage approach that improves both the timeliness and accuracy of disease identification [24]. Our developed CNN model exhibits significant scalability and practical utility. Its adaptable design allows it to extend beyond the originally tested crops, apple, corn, and tomato, supporting disease detection across a broader spectrum of agricultural environments. The potential integration of advanced technologies, including UAV-based imagery, positions this model for wider use in modern farming systems [23].

Ultimately, this research contributes to the transformation of agriculture through intelligent, data-driven technology. The model's reliable performance across multiple datasets illustrates its potential to reshape early disease detection, optimize resource allocation, and reduce yield losses, thereby advancing the goal of global food security [25]. By laying this foundation, the study supports the future development of sustainable tools for crop disease management and innovation in agricultural technology.

4 Conclusion

This research presents a customized Convolutional Neural Network (CNN) model designed for the early detection of crop diseases using digital images. By training and validating the model on diverse datasets of apple, corn, and tomato leaves, including images captured under varied lighting and environmental conditions, the CNN consistently achieved high accuracy and AUC values, demonstrating its robustness and generalizability. The model effectively distinguishes between healthy and diseased plant leaves, offering a rapid and reliable alternative to manual inspection methods that are time-consuming and prone to human error.

The integration of AI-driven classification models into agriculture holds transformative potential. This study contributes to precision agriculture by enabling timely interventions, minimizing crop losses, and optimizing resource use. While limitations remain, such as handling unseen disease variants or complex image backgrounds, future enhancements like transfer learning, object detection, and drone integration can further strengthen the model's applicability. Overall, this work underscores the vital role of deep learning in supporting sustainable agriculture and addressing global food security challenges.

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