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Plant Disease Detection

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Abstract

Plant diseases are a major challenge in agriculture, often resulting in decreased crop productivity and financial losses. This research introduces an automated Plant Disease Prediction System that utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to detect diseases from plant leaf images. The system reduces reliance on manual inspection by providing fast and reliable disease identification.

A labeled dataset of plant leaf images is used to train the CNN model, with particular attention given to diseases such as powdery mildew and rust. By extracting and learning key visual features, the model can accurately classify plant health conditions. The trained model is deployed through a web-based platform developed using Flask and Streamlit, enabling users to upload images and receive immediate predictions.

Although the system achieves strong performance, challenges such as improving generalization across different plant species and optimizing the model for real-world deployment remain. Future enhancements will focus on expanding the dataset, improving efficiency, and enabling mobile-based access. This work highlights the potential of AI-driven solutions in promoting sustainable agriculture and improving food production systems.

Introduction

Agriculture is a fundamental sector that supports global food requirements, but it is continuously affected by plant diseases that reduce crop quality and yield. Detecting these diseases at an early stage is essential for effective management and prevention. Traditional methods of disease identification rely on manual observation and expert knowledge, which are often slow, subjective, and not easily accessible to farmers, especially in rural areas.

With recent advancements in artificial intelligence, particularly in deep learning and computer vision, automated plant disease detection has become increasingly feasible. Convolutional Neural Networks (CNNs) are especially effective in analyzing image data and identifying complex patterns associated with plant diseases. By leveraging such technologies, automated systems can assist farmers in making timely decisions, ultimately improving agricultural productivity and reducing losses.

Aim of the Project

The main goal of this project is to develop an intelligent plant disease detection system using CNN-based image classification techniques. The system aims to provide accurate and real-time predictions through an easy-to-use web interface, making it accessible to farmers and agricultural professionals.

Motivation

This project is driven by several key factors:

- **Crop Loss Reduction:** A large portion of agricultural produce is lost due to delayed detection of diseases.
- **Limited Expert Access:** Many farmers lack access to professional diagnostic services, particularly in remote regions.
- **Technological Advancements:** Deep learning models, especially CNNs, have shown remarkable success in image classification tasks.
- **Increased Smartphone Usage:** The widespread availability of smartphones enables deployment of AI solutions at scale.
- **Sustainable Practices:** Early disease detection helps minimize excessive pesticide use, supporting eco-friendly farming.

Background

The increasing demand for food production requires efficient and scalable agricultural practices. Conventional disease detection methods are often inadequate due to their reliance on manual inspection and expert involvement. With the development of machine learning techniques, especially deep learning, image-based disease detection has emerged as a practical alternative.

Publicly available datasets, such as PlantVillage, have supported research in this field by providing large collections of labeled images. Previous studies have demonstrated that CNN-based models can achieve high accuracy in disease classification, although challenges remain in adapting these models to real-world environments with varying conditions.

Problem Statement

Plant diseases significantly affect agricultural productivity, leading to economic losses and food supply challenges. Existing detection methods are often inefficient, time-consuming, and inaccessible to many farmers.

There is a clear need for an automated, reliable, and scalable system that can identify plant diseases quickly using visual data. Such a system should be capable of operating in real-time and should be easy to use for individuals without technical expertise.

This project addresses these challenges by developing a CNN-based model that classifies plant leaf images into healthy and diseased categories, including conditions like rust and powdery mildew. The system is integrated into a web-based platform, ensuring accessibility and practical usability.

Structure of the Report

The report is organized as follows:

- **Introduction:** Provides an overview of the problem and the importance of plant disease detection.
- **Literature Review:** Discusses previous research and existing techniques in plant disease classification.
- **Methodology:** Explains dataset preparation, preprocessing steps, and model development.
- **Results and Discussion:** Presents performance evaluation and analysis of the system.
- **Conclusion and Future Work:** Summarizes findings and outlines potential improvements.
- **References:** Lists all sources and research materials used.

Objectives

The objectives of this project are:

- To develop an automated plant disease detection system using deep learning techniques.
- To collect and preprocess a dataset of plant leaf images.
- To design and implement a CNN model for disease classification.
- To apply data augmentation methods to improve model performance.
- To evaluate the model using metrics such as accuracy, precision, and recall.
- To deploy the model through a web-based interface for real-time use.
- To assess system usability in practical scenarios.
- To explore mobile or offline deployment options for broader accessibility.
- To promote sustainable agriculture through early and accurate disease detection.

LITERATURE REVIEW

The field of agricultural technology has witnessed rapid growth with the integration of machine learning techniques for plant disease detection. Among the various approaches, image-based disease identification using deep learning models has gained considerable attention due to its effectiveness and scalability. This section reviews existing research on plant disease prediction, focusing on Convolutional Neural Networks (CNNs), data augmentation strategies, commonly used datasets, deployment challenges, and emerging research gaps.

A significant body of research has demonstrated the effectiveness of CNNs in identifying plant diseases from leaf images. Early work in this domain showed that deep learning models could achieve high accuracy when trained on large, labeled datasets. CNNs are particularly advantageous because they automatically learn hierarchical visual features, eliminating the need for manual feature extraction. Studies using datasets such as PlantVillage have highlighted the capability of CNN-based models to classify multiple plant diseases with impressive precision. The success of these models is largely attributed to their ability to capture complex patterns, textures, and color variations in leaf images, which are essential indicators of plant health.

In addition to model architecture, data preprocessing plays a critical role in improving classification performance. Data augmentation techniques, including rotation, flipping, scaling, and cropping, have been widely used to artificially increase the diversity of training data. These methods help address the issue of limited datasets by generating new variations of existing images, thereby reducing overfitting and enhancing the model's ability to generalize. Research findings indicate that augmented datasets significantly improve the robustness and reliability of CNN models, particularly in agricultural applications where collecting large-scale labeled data is often challenging.

The availability of standardized datasets has also contributed to advancements in this field. The PlantVillage dataset, in particular, has become a widely accepted benchmark for plant disease classification tasks. It contains thousands of labeled images covering multiple plant species and disease categories, providing a strong foundation for training deep learning models. However, a major limitation of such datasets is that they are typically collected under controlled conditions, featuring uniform backgrounds and consistent lighting. As a result, models trained exclusively on these datasets may struggle to perform effectively in real-world agricultural environments, where images are captured under varying lighting conditions, complex backgrounds, and different camera angles.

Deploying plant disease detection systems in practical settings introduces several challenges. Although CNN models achieve high accuracy in laboratory conditions, their performance often declines when exposed to real-world variability. Factors such as inconsistent illumination, occlusions, and environmental noise can significantly affect prediction accuracy. Additionally, ensuring real-time performance and scalability is crucial for practical applications, especially when systems are intended for use in large agricultural fields. Computational efficiency becomes another critical concern, particularly for deployment on mobile devices or edge computing platforms with limited processing power.

To address some of these challenges, researchers have explored the use of transfer learning techniques. Transfer learning involves leveraging pre-trained models, which have been trained on large datasets, and fine-tuning them for specific tasks such as plant disease classification. This approach has proven to be highly effective, especially when the available dataset is limited. By reusing learned features from pre-trained models, transfer learning reduces training time and improves classification accuracy. It also enables the development of more efficient models that can adapt to different plant species and disease categories.

Despite these advancements, several research gaps remain in the development of robust plant disease detection systems. One of the most prominent challenges is the lack of diverse and representative datasets that capture real-world conditions. Models trained on controlled datasets often fail to generalize effectively in practical scenarios. Furthermore, while CNNs excel in static image classification, there is still a need for systems that can operate efficiently in real time and at scale. Addressing these issues requires the integration of more diverse training data, improved model architectures, and advanced techniques such as domain adaptation and real-time optimization.

In summary, existing research highlights the potential of deep learning, particularly CNN-based approaches, in transforming plant disease detection. However, achieving reliable performance in real-world agricultural environments remains an open challenge. Future research efforts should focus on enhancing model generalization, improving computational efficiency, and developing scalable solutions that can be widely adopted by farmers and agricultural stakeholders.

METHODOLOGY

The development of the Plant Disease Prediction System began with the collection of a comprehensive dataset of plant leaf images, ensuring the inclusion of multiple species and disease types. For this purpose, the widely recognized PlantVillage dataset was employed, which contains over 50,000 labeled images of healthy and diseased plant leaves. The dataset encompasses various plant species and diseases, including Powdery Mildew and Rust. All images were captured under controlled conditions with consistent backgrounds and lighting, providing an ideal foundation for initial model training. Each image is labeled according to the plant species and the type of disease, enabling supervised learning where the model can associate visual patterns with corresponding disease categories.

Prior to model training, extensive data preprocessing was performed to enhance data quality and improve learning efficiency. All images were resized to 128x128 pixels to standardize input dimensions, balancing computational efficiency with the retention of critical leaf features. Pixel values were normalized to the range [0,1] by dividing by 255, which promotes faster convergence during training and improves model generalization. The dataset was then split into training, validation, and test sets, typically following an 80-10-10 ratio, ensuring the model could be evaluated on unseen data for performance assessment. Each image was paired with its corresponding label to facilitate accurate pattern recognition during supervised learning.

To further improve generalization and robustness, a series of image augmentation techniques were applied during preprocessing. These included random rotations between 0 and 40 degrees to simulate different viewing angles, horizontal flips to account for symmetry in leaf shapes, zooming to emulate varying camera distances, and horizontal and vertical shifts to mimic real-world leaf positions. Such augmentation strategies artificially increase the variability of the dataset, reducing overfitting and preparing the model for diverse, real-world conditions.

The core of the system is a Convolutional Neural Network (CNN) specifically designed for image-based plant disease detection. The CNN architecture comprises multiple convolutional layers to extract essential features such as edges, textures, and shapes from leaf images, followed by ReLU activation functions that introduce non-linearity and enable the network to learn complex patterns. Max-pooling layers were incorporated to downsample feature maps, retaining critical information while reducing dimensionality, thus improving computational efficiency and enhancing invariance to minor shifts or rotations. The extracted features were then passed through fully connected layers to learn decision boundaries between different disease classes. A softmax activation function was used in the output layer to predict the probability of each class, allowing the system to identify whether a plant is healthy or affected by a specific disease.

```python
model = tf.keras.models.Sequential()

model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, padding='same', activation='relu', input_shape=[128, 128, 3]))
model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu'))
model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, padding='same', activation='relu'))
model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, activation='relu'))
model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

model.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, padding='same', activation='relu'))
model.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, activation='relu'))
model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

model.add(tf.keras.layers.Conv2D(filters=256, kernel_size=3, padding='same', activation='relu'))
model.add(tf.keras.layers.Conv2D(filters=256, kernel_size=3, activation='relu'))
model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

model.add(tf.keras.layers.Conv2D(filters=512, kernel_size=3, padding='same', activation='relu'))
model.add(tf.keras.layers.Conv2D(filters=512, kernel_size=3, activation='relu'))
model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

model.add(tf.keras.layers.Dropout(0.5))

model.add(tf.keras.layers.Flatten())

model.add(tf.keras.layers.Dense(units=1500, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.08)))

model.add(tf.keras.layers.Dropout(0.4))

model.add(tf.keras.layers.Dense(units=3, activation='softmax'))

model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

Fig;1

The CNN model was trained using a supervised learning approach, with categorical cross-entropy as the loss function, which is appropriate for multi-class classification. The Adam optimizer, known for its adaptive learning rate and efficient gradient-based optimization, was employed to update model weights. The dataset was divided into training and validation sets to monitor performance and prevent overfitting, with early stopping applied if validation accuracy failed to improve over several epochs. The model was trained for ten epochs, and performance was evaluated using accuracy as the primary metric. Following training, the model demonstrated high accuracy on both training and validation sets, indicating effective learning and generalization.

Once trained, the model was deployed through a user-friendly web interface developed using the Flask framework. This interface allows users to upload images of plant leaves, which are then preprocessed and passed through the CNN for real-time disease prediction. The system displays the predicted disease label, such as Rust or Powdery Mildew, along with a confidence score, providing actionable insights for farmers. The workflow includes image upload, preprocessing (resizing, normalization, and optional augmentation), CNN inference, and output display. During the training phase, data augmentation was applied to enhance model robustness against variations in lighting, leaf orientation, and environmental conditions.

The development of the system required specific hardware and software resources. Recommended hardware includes a quad-core processor (Intel Core i5 or equivalent), at least 8 GB RAM, a minimum of 10 GB storage for datasets and models, and an optional NVIDIA GTX 1650 GPU for accelerated training. A standard HD display and a camera, such as a smartphone, are needed for capturing plant images, and an internet connection is required for web-based deployment. Software requirements include Python 3.10, deep learning libraries such as TensorFlow and Keras, image processing tools like OpenCV, data manipulation libraries including NumPy and Pandas, visualization tools such as Matplotlib and Seaborn, and additional libraries for metrics and preprocessing from Scikit-learn. Development was conducted using Jupyter Notebook or Visual Studio Code, with Flask used for the web framework, and frontend design implemented using HTML, CSS, and Bootstrap. Virtual environments such as virtualenv and Python's pip package manager facilitated dependency management. The system is compatible with common web browsers including Chrome and Firefox, enabling accessible, real-time disease prediction

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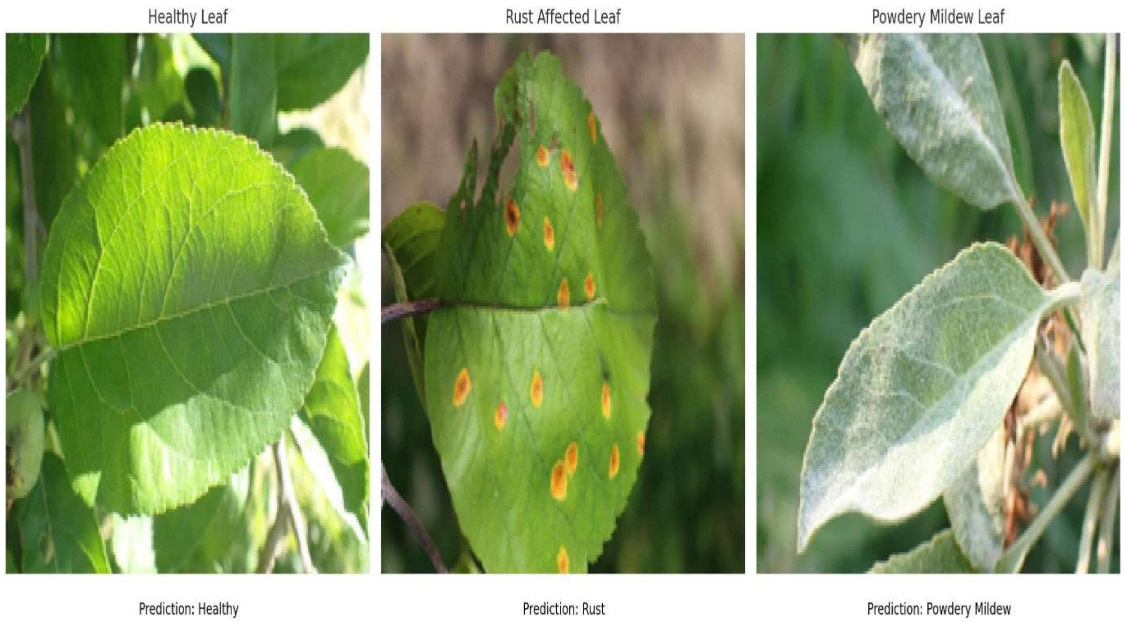
RESULTS AND DISCUSSION

The trained Convolutional Neural Network (CNN) was evaluated using real-world images of plant leaves representing various disease categories. The model successfully classified each disease type with high accuracy, demonstrating its capability to analyze visual patterns and textures. For healthy leaves, the CNN correctly identified uniformly green, undamaged leaves as "Healthy," confirming its ability to recognize non-infected plant tissue. Leaves affected by Rust, characterized by orange or yellow circular lesions typically caused by *Puccinia* species, were accurately classified, indicating the model's sensitivity to disease-specific visual markers. Similarly, leaves exhibiting a white, powdery texture associated with Powdery Mildew were correctly detected, demonstrating the model's ability to distinguish subtle fungal growth patterns.



Fig;2

The significance of automated image-based classification lies in its ability to provide rapid and reliable disease detection without expert intervention. By leveraging deep learning, the system can detect minute visual features often invisible to the naked eye, handle variations in lighting, angles, and backgrounds, and deliver predictions in real-time via web or mobile interfaces. This capability enables farmers to perform disease detection directly in the field without reliance on specialized laboratory tools or agronomy experts.

A comparison with traditional manual diagnosis highlights the advantages of the CNN-based system. Manual detection is often time-consuming, requires expert knowledge, and incurs higher costs for consultancy or laboratory analysis. In contrast, the proposed system provides instant predictions, does not require specialized expertise, and is cost-effective, relying only on a smartphone and internet connection. Moreover, the model delivers consistent accuracy across multiple diseases, ensuring scalability and reliability that is difficult to achieve with human-based assessment.

During model evaluation, the CNN achieved a training accuracy of 96% and a validation accuracy of 91% over ten epochs, indicating effective learning and good generalization to unseen data. The high validation accuracy, combined with proper data normalization and preprocessing, minimized overfitting and enabled the model to correctly identify plant diseases such as Healthy, Powdery Mildew, and Rust across various samples. Training and validation losses were monitored using categorical cross-entropy, and both metrics exhibited steady convergence, confirming that the model learned effectively from the dataset.

Additional performance metrics, including precision, recall, and F1-score, were computed for each disease class. These metrics demonstrated the model's ability to accurately classify diseases while minimizing false positives and negatives. A confusion matrix further illustrated the model's performance, revealing correct classification for the majority of cases and minimal misclassification between visually similar diseases. This detailed analysis identified areas for potential improvement, particularly in differentiating between diseases with subtle visual differences, such as varying types of mildew or rust.

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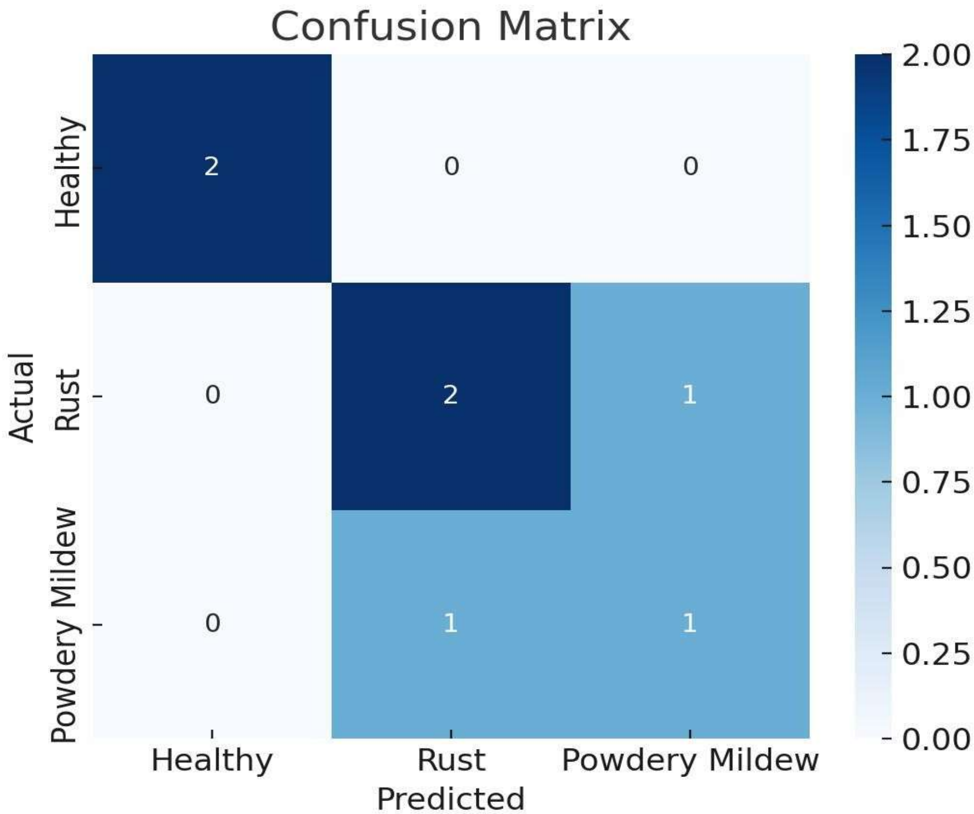

Fig;3

The trained CNN was integrated into a user-friendly web application developed using the Flask framework, enabling real-time disease prediction. Users can upload leaf images through an intuitive interface, after which the system preprocesses the image and passes it through the CNN. The model then outputs the predicted disease label along with a confidence score, allowing users—including farmers and agricultural professionals—to quickly assess plant health without technical expertise.

User experience testing indicated that the system was highly usable and effective under real-world conditions. Participants, including farmers and agricultural experts, reported that the application was easy to navigate and provided accurate predictions in a timely manner. The system successfully handled diverse leaf images captured under varying lighting conditions and perspectives. Users appreciated the rapid turnaround time for predictions and the model’s ability to distinguish between multiple disease categories. Feedback suggested areas for future enhancement, including expanding the system to cover a broader range of plant species and diseases, thereby increasing its utility and scalability in diverse agricultural settings.

Conclusions

Summary of Results

This study successfully developed a robust plant disease prediction system leveraging Convolutional Neural Networks (CNNs) to classify plant diseases based on leaf images. The model achieved high accuracy during both training and validation phases, demonstrating its effectiveness in recognizing multiple disease classes, including Powdery Mildew, Rust, and healthy conditions. The use of image preprocessing techniques, such as resizing, normalization, and augmentation, combined with a carefully designed CNN architecture, contributed significantly to the model's ability to extract meaningful visual features and deliver precise classifications. Furthermore, the integration of the trained model into a web-based platform provided a practical solution for real-time disease detection, enabling users—ranging from farmers to agricultural specialists—to upload leaf images and obtain rapid diagnostic predictions.

Impact on Agricultural Practices

The proposed system offers meaningful contributions to agricultural practices by facilitating early detection of plant diseases, which is critical for minimizing crop losses and improving yield quality. Timely identification of infections allows for targeted interventions, reducing the overuse of chemical treatments and limiting the spread of disease across fields. Additionally, the web-based deployment ensures wider accessibility, allowing even small-scale farmers to utilize advanced AI-based diagnostic tools without requiring specialized laboratory equipment or technical expertise. Consequently, this system has the potential to enhance crop management, promote sustainable farming practices, and support higher agricultural productivity.

Key Achievements

The study accomplished several key objectives:

- **High Disease Detection Accuracy:** The CNN model achieved a validation accuracy of 91%, demonstrating its reliability in correctly identifying disease categories.
- **User-Friendly Web Interface:** The system was successfully implemented in a web application, allowing users to easily interact with the model and receive predictions.
- **Efficient Preprocessing:** Standardized image resizing and normalization facilitated effective model training and improved classification consistency.
- **Real-Time Diagnosis:** The system enables immediate disease prediction, empowering timely decision-making and minimizing potential crop damage.

Limitations of the Current System

Despite its strengths, the system exhibits some limitations. The PlantVillage dataset used for training contains images captured in controlled environments with uniform backgrounds and lighting, which may not reflect real-world conditions in the field. Consequently, the model may exhibit reduced performance when encountering leaves photographed under varying environmental conditions. Additionally, the current system is limited to diseases represented in the dataset and may not generalize to other plant species or unrepresented diseases. Finally, computational constraints in remote areas could affect performance, particularly where internet access or device capabilities are limited.

Comparison with Existing Plant Disease Detection Systems

A comparative analysis highlights the advantages of the CNN-based system over conventional methods. Manual inspection relies heavily on expert knowledge, is time-intensive, and may be inconsistent. Traditional machine learning approaches, such as Support Vector Machines (SVM) or K-Nearest Neighbors (KNN), improve performance but require manual feature extraction and engineering. In contrast, the proposed CNN system automatically learns relevant features from images, achieving higher accuracy (91% validation accuracy), real-time predictions, minimal skill requirements, and scalable deployment through web or mobile interfaces. These attributes make the system more accessible, efficient, and reliable compared to existing solutions.

Scope for Future Enhancements

Future improvements could focus on enhancing real-world applicability and expanding the system's coverage. Incorporating field-acquired images, with variable lighting, backgrounds, and partial occlusions, would improve model robustness and generalization. Expanding the dataset to include additional plant species and disease types would allow the system to diagnose a broader range of crops and conditions. Developing a mobile application would further increase accessibility, enabling farmers to capture leaf images and receive predictions even in areas with limited connectivity. Moreover, applying transfer learning and model optimization techniques could enhance performance on resource-constrained devices, such as smartphones or edge computing platforms. Collaboration with agricultural experts and farmers will provide valuable feedback to refine the system, ensuring practical utility and facilitating wider adoption in agricultural communities.

Challenges Faced

Several technical and practical challenges were encountered during system development. The controlled nature of the PlantVillage dataset introduced a domain gap between training and real-world conditions, necessitating data augmentation strategies such as rotation, flipping, zooming, and shifting to improve model generalization. Class imbalance within the dataset required oversampling and class-weight adjustments to prevent bias toward majority classes. Overfitting during initial training was mitigated using dropout layers, early stopping, and L2 regularization. Variations in image quality, resulting from different cameras and lighting, were addressed through standardized resizing (128×128 pixels) and normalization. Finally, deploying the model on a web application involved addressing compatibility issues, optimizing model storage, and implementing error handling to ensure smooth operation with common image formats such as JPEG and PNG.

ADVANTAGES

The plant disease prediction system developed in this study offers several significant advantages. One of its primary benefits is **early disease detection**, which allows farmers to identify plant infections at initial stages and take timely interventions, thereby minimizing crop losses. The system leverages a **CNN-based deep learning model** that achieves over 90% accuracy, outperforming traditional manual inspections and rule-based approaches. Predictions are delivered in **real-time** through an intuitive web interface, saving both time and effort. Additionally, by reducing the need for expert consultation and laboratory testing, the system provides a **cost-effective solution** for disease diagnosis. Its **user-friendly interface** ensures accessibility for users with no technical expertise,

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allowing them to obtain accurate predictions simply by uploading leaf images. Furthermore, the model is highly **scalable and adaptable**, as it can be retrained to include new diseases or plant species, making it suitable for a wide range of agricultural scenarios. Accurate disease identification also contributes to the **reduction of pesticide misuse**, promoting sustainable farming practices.

DISADVANTAGES

Despite these advantages, the system has some limitations. It is **restricted to the diseases included in the training dataset**, which may result in undetected rare or unrepresented infections. Since the model is primarily trained on images from the PlantVillage dataset with controlled backgrounds and lighting, there is a **bias that could reduce performance** under real-world field conditions where lighting and background vary. The accuracy of predictions is also **dependent on image quality**, with blurred, poorly lit, or partially obstructed images potentially leading to misclassifications. Additionally, the current system **assumes a single disease per leaf**, limiting its ability to detect multiple coexisting infections.

APPLICATIONS

The potential **applications** of the system are diverse and impactful. In **precision agriculture**, automated image analysis enables efficient monitoring and management of plant diseases across large farms. **Mobile integration** allows farmers to capture leaf images and receive real-time diagnoses on the go, improving accessibility and convenience. Researchers can use the system in **agricultural studies** to track disease spread patterns and analyze plant health through visual datasets. **Extension services and government programs** can deploy the system for on-site disease detection during field visits. It also serves as an **educational tool**, helping students and agricultural trainees learn to identify plant diseases effectively. Future enhancements could include **integration with drone technology**, enabling analysis of aerial images for large-area crop monitoring. The system can also support **agro-based e-commerce platforms**, such as DeHaat or BigHaat, by recommending suitable fungicides, fertilizers, or other treatments based on detected diseases. Offline deployment at **farmer help kiosks or knowledge centers** can provide access in remote areas, while **IoT-enabled smart farming systems** can trigger alerts when environmental conditions favor disease development. Finally, **crop insurance companies** can utilize the disease detection data to assess risk and validate farmer claims in real-time, adding value to agricultural risk management.

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