



Plant Disease Detection using Deep Convolutional Neural Network

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KEYWORDS

Deep learning, Convolutional neural network (CNN), Transfer learning, Agriculture.

ABSTRACT

Plant health monitoring is essential for sustaining agricultural productivity, especially in regions where expert diagnosis is limited or delayed. Manual disease identification methods often lack consistency and may lead to late detection, increasing crop damage and financial loss. To address this issue, this project presents an automated plant disease recognition system developed using deep learning techniques applied to leaf images.

Initially, a custom-built Convolutional Neural Network was implemented to establish baseline classification performance. To further enhance recognition capability, a pretrained InceptionV3 architecture was integrated and fine-tuned using transfer learning strategies. The model was trained on a multi-class dataset containing various crop and disease categories to ensure robust learning across diverse leaf conditions.

Experimental evaluation demonstrates that the transfer learning approach achieves improved prediction stability and higher classification accuracy compared to the baseline model. In addition to disease identification, the system provides descriptive information and preventive recommendations, supporting practical agricultural decision-making. The overall framework confirms that deep learning-based solutions can offer scalable, efficient, and reliable assistance for modern crop health management.

INTRODUCTION

CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is a specialized deep learning model designed to analyze and interpret visual information. It processes images by learning

hierarchical feature representations through multiple interconnected layers. Instead of relying on manually engineered features, CNNs automatically identify important visual patterns such as edges, textures, color variations, and structural abnormalities. This capability

makes them highly effective for image classification tasks, including plant disease recognition from leaf images.

TRANSFER LEARNING

Transfer learning is a deep learning approach in which an already trained model is modified to address a new yet related problem. In plant disease identification, architectures such as InceptionV3 are fine-tuned using leaf image datasets to enhance accuracy when data availability is limited. This technique decreases training duration, strengthens feature learning, boosts classification efficiency, and supports improved generalization across diverse plant species and changing environmental conditions.

LITERATURE SURVEY

i. Saleem et al., 2019 – “Plant Disease Detection and Classification by Deep Learning”

<https://pmc.ncbi.nlm.nih.gov/articles/PMC6918394/>
ABSTRACT

This study reviews different deep learning approaches used for identifying plant diseases from leaf images. It highlights how convolutional neural networks (CNNs) and image processing techniques improve disease classification accuracy compared to traditional methods.

TECHNIQUES

- Convolutional Neural Networks (CNN)
- Image preprocessing and feature extraction
- Visualization techniques for disease patterns

FINDINGS

- Deep learning significantly improves detection accuracy
- CNN models outperform traditional machine learning methods

CONCLUSION

The study concludes that deep learning provides a strong foundation for automated plant disease detection, though challenges like dataset quality and generalization still exist.

ii. Eunice et al., 2022 – “Deep Learning-Based Leaf Disease Detection in Crops”

<https://www.mdpi.com/2073-4395/12/10/2395>

ABSTRACT

Agriculture plays a crucial role in ensuring food availability and supporting the growth of economies and

populations. However, plant diseases can severely impact crop yield and quality, leading to major economic losses and reduced biodiversity. Detecting these diseases at an early stage through reliable and automated methods is essential to improve agricultural productivity and maintain food quality.

With the rapid advancement of deep learning, significant progress has been made in image classification and object detection tasks. In this work, convolutional neural network (CNN)- based pre-trained models are utilized for effective plant disease detection. The study emphasizes fine-tuning the hyperparameters of widely used architectures, including DenseNet-121, ResNet-50, VGG-16, and Inception V4, to enhance performance.

Experiments were conducted on the widely used PlantVillage dataset, which contains 54,305 images representing 38 different classes of plant diseases. Model performance was assessed using evaluation metrics such as accuracy, sensitivity, specificity, and F1-score. A comparative analysis with existing state-of-the-art methods was also performed. The results demonstrate that the DenseNet-121 model achieved the highest performance, reaching an accuracy of 99.81%, thereby outperforming other models.

TECHNIQUES

- Transfer Learning
- Pre-trained models (ResNet, DenseNet, VGG, Inception)
- Hyperparameter tuning

FINDINGS

- Transfer learning reduces training time
- Pre-trained models achieve high accuracy even with limited data

CONCLUSION

Using pre-trained CNN models is efficient and effective for plant disease detection, especially when datasets are limited.

iii. Shoaib et al., 2023 – “Advancements in ML and DL for Plant Disease Detection”

<https://pmc.ncbi.nlm.nih.gov/articles/PMC10070872/>

ABSTRACT

Plants are essential for global food production, yet their growth is often affected by various environmental conditions that lead to diseases and reduced crop yield. Identifying these diseases manually is not only time-

intensive but also susceptible to human error, making it an unreliable approach for effective disease management and prevention.

The integration of advanced technologies such as Machine Learning (ML) and Deep Learning (DL) offers a promising solution by enabling faster and more accurate detection of plant diseases at early stages. This study reviews recent developments in the application of ML and DL techniques for plant disease identification, focusing on research conducted between 2015 and 2022. The findings from these studies highlight that such techniques significantly enhance both the accuracy and efficiency of disease detection systems.

In addition, the study examines key challenges associated with these approaches, including limited availability of quality datasets, variations in image conditions, and difficulties in distinguishing between healthy and infected plant samples. By analyzing these issues, the research provides useful insights for researchers, practitioners, and industry professionals. It also outlines possible strategies to address these limitations and offers a clear overview of the current progress, advantages, and constraints in this field, along with potential directions for future improvement.

TECHNIQUES

- Machine Learning (SVM, KNN)
- Deep Learning (CNN, DBN)
- Image-based feature extraction

FINDINGS

- Deep learning provides higher accuracy than traditional ML
- Dataset quality directly impacts performance

CONCLUSION

ML and DL techniques are effective, but more robust datasets and generalizable models are needed.

iv. Kim et al., 2024 – “ANFIS Fuzzy CNN Model for Leaf Disease Detection”

<https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2024.1465960/full>

ABSTRACT

Detection of leaf diseases plays a vital role in agriculture, as it has a direct influence on crop condition, productivity, and overall quality. Identifying diseases at an early stage helps limit their spread, reduces excessive use of chemical treatments, and lowers potential yield losses. This contributes not only to improved food

security but also promotes environmentally sustainable farming practices. Reliable detection systems enable farmers to make timely and informed decisions, resulting in healthier crops and better utilization of resources. With the growing demand for food and increasing environmental concerns, the development of advanced disease detection methods has become essential in modern agriculture.

This study introduces a novel method for detecting diseases in bell pepper leaves using a hybrid model that combines an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a Convolutional Neural Network (CNN), along with Local Binary Pattern (LBP) features for enhanced analysis. Experiments were conducted both with and without incorporating LBP features. The proposed model demonstrated strong performance even without LBP, achieving an accuracy of 0.8478, along with precision, recall, and F1 scores of 0.8959, 0.9045, and 0.8953, respectively. When LBP features were included, the model's performance improved significantly, with all evaluation metrics exceeding 99%.

Further comparison with existing advanced techniques confirmed the effectiveness and superiority of the proposed approach. To ensure consistency and reliability, cross-validation methods were applied during experimentation. Overall, the results indicate that the integration of fuzzy logic, deep learning, and texture-based features provides a highly accurate and efficient solution for plant disease detection, making it suitable for real-world agricultural applications.

TECHNIQUES

- CNN + ANFIS (Adaptive Neuro- Fuzzy Inference System)
- Local Binary Pattern (LBP)
- Feature extraction

FINDINGS

- Hybrid models outperform standard CNN
- LBP improves feature representation

CONCLUSION

Combining CNN with fuzzy logic enhances detection accuracy and provides better handling of complex patterns.

v. Krishna et al., 2025 – “Multi-Model Deep Learning for Plant Disease Detection”

<https://www.mdpi.com/2571-8800/8/1/4>

ABSTRACT

Plant diseases continue to pose a serious challenge to agricultural productivity, as they can spread quickly and cause major crop damage if not detected at an early stage. Achieving accurate disease identification in real-world conditions is difficult because many existing models are trained using controlled, laboratory-based images, which limits their ability to perform well in diverse environments. This study focuses on developing a robust detection system capable of identifying plant diseases under varying and unpredictable conditions, addressing the shortcomings of current approaches.

To achieve this, a combined dataset was created by merging the PlantDoc dataset with additional plant images collected from online sources. Several advanced convolutional neural network (CNN) architectures, including EfficientNet-B0, EfficientNet-B3, ResNet50, and DenseNet201, were implemented and fine-tuned for the task of leaf disease classification. An important aspect of this work is the use of enhanced data augmentation methods, such as introducing Gaussian noise, to improve the model's ability to generalize across different environments.

The experimental results showed differences in model performance depending on the dataset used. When both training and testing were conducted on the PlantDoc dataset, EfficientNet-B3 achieved an accuracy of 73.31%. In cross-dataset testing, where the model was trained on PlantDoc and evaluated on web-based images, the same model reached an accuracy of 76.77%. The highest performance was observed when both datasets were combined, resulting in an accuracy of 80.19%, indicating improved adaptability to diverse conditions. Additionally, high class-wise F1-scores, exceeding 90% for diseases such as apple rust and grape leaf infections, further validate the effectiveness of the proposed approach.

TECHNIQUES

- EfficientNet, ResNet, DenseNet
- Dataset combination (PlantDoc + web images)
- Model comparison

FINDINGS

- EfficientNet models perform best in accuracy
- Combining datasets improves generalization

CONCLUSION

Using multiple models and datasets leads to more reliable and scalable plant disease detection systems.

OBJECTIVE

The main objective of this project is to design an intelligent Plant Disease Detection System using Deep Learning methods to precisely recognize diseases from leaf images. The system is intended to support farmers, agricultural experts, and plant lovers in identifying plant diseases at an early phase to reduce crop damage and enhance productivity. This project emphasizes:

NEED FOR STUDY

Agriculture plays a vital role in sustaining national economies and ensuring consistent food availability for growing populations. The productivity and quality of crops are directly influenced by plant health. Unfortunately, various plant diseases significantly reduce yield, deteriorate crop quality, and lead to considerable financial strain on farmers. Detecting these diseases at an early stage is essential to prevent widespread damage and maintain stable agricultural output.

With rapid developments in artificial intelligence, especially in deep learning and image analysis, automated disease detection systems have become increasingly feasible. Advanced models can analyze visual patterns in leaf images, including texture irregularities, color changes, and lesion formations, to determine the presence of infection. Convolutional Neural Networks are particularly effective because they automatically learn discriminative features directly from image data without relying on handcrafted inputs.

There is a clear need to develop an intelligent plant disease detection solution that:

- Provides fast and dependable diagnosis
- Supports farmers in remote and underserved areas
- Reduces reliance on agricultural experts
- Enhances crop monitoring and management strategies
- Minimizes economic losses caused by delayed detection.

Therefore this project focuses on addressing a practical agricultural problem by combining deep learning methodologies with a user-friendly web application. The aim is to deliver a reliable, accessible and scalable system capable of assisting farmers in making timely and informed decisions.

EXISTING SYSTEM

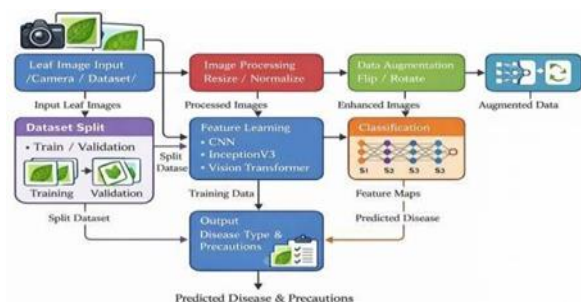
Prior to the emergence of deep learning– based techniques, plant disease identification was largely carried out through conventional and manual practices. Farmers mainly depended on visual examination of plant leaves to observe symptoms such as spots, color changes, or wilting. The assessment was made based on personal knowledge or by comparing with standard reference images. In doubtful situations, agricultural specialists were approached, and occasionally plant samples were forwarded for laboratory analysis. While laboratory analysis produced precise results, it required considerable time and involved high costs.

With the advancement of computer vision methods, conventional machine learning algorithms began to be applied for plant disease identification. These systems operated through a systematic pipeline in which images were preprocessed, and features such as color, texture, and edge details were manually derived. The obtained features were subsequently categorized using classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), or Random Forest. Nevertheless, these techniques depended heavily on manual feature design and often showed limited performance in complex backgrounds and changing illumination conditions.

Disadvantages

- Time-intensive manual examination
- Reliance on specialists
- Costly laboratory analysis
- Susceptible to human mistakes
- Needs manual feature engineering
- Restricted scalability
- Reduced effectiveness in complex scenes
- Unsuitable for real-time identification
- Decreased accuracy in multi-class categorization

SYSTEM ARCHITECTURE



MODULES

- Image Acquisition Module
- Image Preprocessing Module
- Data Augmentation Module
- Dataset Splitting Module
- Feature Learning Module
- Classification Module
- Output Module

1. Image Acquisition Module

The Image Acquisition Module is designed to gather plant leaf images that function as input for the system. Images can be captured through mobile phones, digital cameras, or sourced from a standard dataset. The resolution and clarity of the acquired images are essential for achieving precise disease identification. This module verifies that supported image formats such as JPG or PNG are accepted for subsequent processing.

2. Image Preprocessing Module

The Image Preprocessing Module conditions the input image before model evaluation. During this phase, images are resized to a fixed resolution (e.g., 224×224 pixels) to align with the model's input specifications. Pixel intensities are normalized to a consistent range to enhance training stability. Further preprocessing steps such as noise reduction or background adjustment may also be applied to improve image clarity and optimize feature extraction performance.

3. Data Augmentation Module

The Data Augmentation Module enhances the variability of the training dataset by applying transformations such as flipping, rotation, zooming, and shifting. This technique artificially enlarges the dataset and enables the model to learn robust and invariant features. Data augmentation minimizes overfitting and strengthens the model's capability to generalize to new, unseen images obtained under different environmental conditions.

4. Dataset Splitting Module

The Dataset Splitting Module partitions the dataset into training and validation sets. The training set is utilized to train the deep learning model, whereas the validation set is employed to assess its performance throughout training. This division enables tracking of model accuracy, identification of overfitting, and assurance of improved generalization performance.

5. Feature Learning Module

The Feature Learning Module serves as the central component of the system. It employs deep learning

architectures such as Convolutional Neural Networks (CNN) or InceptionV3 to automatically derive hierarchical and spatial representations from leaf images. In contrast to conventional machine learning methods, this module removes the need for manual feature design and captures significant patterns directly from raw image inputs.

6. Classification Module

In the Classification Module, the extracted features are passed through fully connected layers to predict the disease category. A Softmax activation function is used to compute probability scores for each class. The class with the highest probability is selected as the final prediction. This module ensures accurate multi-class disease classification.

7. Output Module

Within the Classification Module, the extracted representations are forwarded through fully connected layers to determine the disease label. A Softmax activation function is applied to calculate probability values for each class. The category with the highest probability is chosen as the final output. This module guarantees precise multi-class disease categorization.

PROPOSED SYSTEM

The proposed system adopts an automated plant disease identification framework utilizing deep learning methods such as Convolutional Neural Networks (CNN) and transfer learning with InceptionV3. In contrast to conventional techniques that depend on manual observation and handcrafted features, this system autonomously extracts significant features directly from leaf images.

The system operates through an organized workflow comprising image preprocessing, data augmentation, feature extraction, and classification stages. The trained model evaluates the input image and determines the disease category based on probability scores.

The final result presents the identified disease name together with the confidence score and recommended precautionary measures.

The system is implemented using a web-based platform that allows users to upload leaf images and obtain real-time disease predictions.

Advantages

- High precision enabled by deep learning - driven feature extraction
- Automatic recognition of intricate image patterns
- Minimized requirement for manual feature design
- Supports real-time disease identification
- Economical and scalable approach
- Reliable performance across varying lighting and background environments
- Efficient multi-class disease categorization
- Deployable on web platforms and adaptable to mobile applications

Hardware Requirements

- Processor : Intel Core i5 or higher
- RAM : 8 GB minimum
- GPU : Provides support for faster training
- Storage : Minimum 20 GB free disk space
- Input Device : Camera/Image dataset
- Output Device : Monitor / Display

Software Requirements:

- Operating System : Windows/Linux
- Language : Python 3.x
- IDE : Jupyter Notebook, VS Code
- Deep Learning

Frameworks : TensorFlow, Keras

- Libraries: NumPy, Pandas, OpenCV
- Models : CNN, InceptionV3, Vision Transformers
- Dataset : PlantVillage Dataset

TECHNIQUES USED IN THE PROJECT

Convolutional Neural Network (CNN)

In this project, a convolution-driven neural architecture was implemented to automatically extract visual disease patterns from plant leaf images. Rather than relying on manually designed descriptors such as color histograms or texture filters, the network learns relevant representations directly from raw pixel values through hierarchical processing.

Key Layers:

- Convolution Layer
- ReLU Activation
- Pooling Layer
- Fully Connected Layer
- Softmax Layer

Why CNN?

- Automatic spatial feature extraction
- Efficient handling of high-dimensional images
- Robust to noise
- Eliminates manual feature engineering

Input Representation:

Each leaf image is treated as a three-dimensional tensor:

$$X \in R^{H \times W \times C}$$

Where H and W denote spatial resolution and C represents the number of color channels. Prior to model training, images are resized to a fixed dimension and normalized to ensure numerical stability during optimization.

Spatial Feature Extraction Mechanism:

The primary operation within the network is convolution. A learnable kernel slides across the input tensor and performs element-wise multiplication followed by accumulation.

This can be expressed as:

$$F(i,j) = \sum_n \sum X(i+m,j+n)K(m,n) + b$$

Here, K represents the trainable kernel weights and b is the bias term. The resulting feature map F captures localized spatial structures such as discoloration patches, irregular textures, and boundary distortions associated with infected regions.

Through multiple stacked convolution layers, the network progressively transforms low-level pixel patterns into higher-level abstract disease signatures.

Non-Linear Transformation:

To enable the model to approximate complex mappings between input images and disease categories, a non-linear activation function is applied after each convolution operation. The activation used in this implementation is defined as:

$$g(x) = \max(0, x)$$

This transformation suppresses negative responses while preserving informative positive activations, promoting sparse representation and stable gradient flow during training.

Dimensionality Reduction and Invariance:

To reduce computational load and improve robustness to small spatial variations, pooling operations are introduced. In the case of maximum pooling, the

strongest activation within a predefined window is retained:

$$P = \max_{(u,v) \in R} F(u,v)$$

where R denotes the pooling region. This step decreases spatial resolution while maintaining dominant discriminative features.

Dense Mapping and Decision Formation:

After successive convolution and pooling stages, the multi-dimensional feature maps are flattened into a one-dimensional vector. This vector is processed by fully connected layers that perform weighted linear combinations:

$$z = Wx + b$$

where W contains trainable weights and x represents the flattened feature vector.

To obtain class-wise probabilities for disease prediction, a normalized exponential transformation is applied:

Here, N corresponds to the total number of disease categories. The class associated with the highest probability is selected as the predicted label.

Role of CNN in This Project:

Within the developed system, the convolution-based architecture serves as a baseline model for automated disease identification. It learns discriminative visual patterns such as:

- Small lesion clusters
- Chlorotic regions
- Texture disruptions
- Edge irregularities

The model eliminates dependency on handcrafted feature extraction and directly optimizes classification performance using backpropagation and gradient-based learning.

Transfer Learning using InceptionV3

In order to improve classification performance beyond the baseline CNN, a pretrained InceptionV3 architecture was incorporated into the system and adapted specifically for plant leaf disease recognition. Instead of constructing a deep model entirely from random initialization, the pretrained network was reused as a

feature extraction backbone and fine-tuned using the plant disease dataset.

Model Adaptation Strategy:

The convolutional base of InceptionV3 was retained to leverage its ability to capture complex spatial patterns. However, the final classification layers originally designed for large-scale object recognition were removed. These layers were replaced with task-specific dense layers configured to match the number of plant disease categories in this project.

Let the pretrained parameter set be denoted as:

θ_{pre}

During adaptation, selected layers were allowed to update their weights while earlier layers were kept fixed to preserve generalized visual representations. The updated parameter set can be expressed as:

$\theta = \theta_{pre} + \Delta\theta$

where $\Delta\theta$ represents adjustments learned from the plant disease training data.

This selective fine-tuning approach balances stability and adaptability, preventing excessive weight updates while allowing the model to specialize in identifying leaf-specific disease patterns.

Practical Impact on Feature Representation:

Through experimentation, it was observed that the pretrained architecture was capable of recognizing subtle disease characteristics such as:

- Irregular lesion boundaries
- Mild color intensity variations
- Early-stage infection patches
- Texture distortions not easily captured by shallow networks

Compared to the custom CNN, the adapted InceptionV3 model required fewer training epochs to stabilize and exhibited smoother validation accuracy trends.

Training Configuration in This Project:

To ensure stable convergence:

- The learning rate was reduced during fine-tuning
- Data augmentation was applied consistently
- Dropout layers were introduced to control overfitting
- Only higher-level layers were unfrozen for gradient updates

This configuration allowed the model to refine high-level disease representations while preserving foundational visual features.

Factorized Convolution

To enhance computational efficiency, InceptionV3 replaces larger convolution filters with smaller factorized operations. For example:

$n \times n \rightarrow 1 \times n + n \times 1$

This decomposition reduces the number of parameters and lowers computational cost while preserving representational power. As a result, the architecture achieves deeper feature extraction with improved efficiency.

Observed Performance Advantages:

When evaluated against the baseline CNN:

- Convergence was achieved faster
- Validation accuracy improved
- Overfitting was reduced
- Class-wise prediction consistency increased

The integration of pretrained weights enhanced the model's ability to generalize across varying lighting conditions and background variations in leaf images.

Role of Transfer Learning in This System:

Within the developed framework, transfer learning functions as a performance enhancement mechanism rather than a standalone model. It strengthens feature extraction depth and enables reliable multi-class disease prediction without requiring extremely large training datasets.

By adapting a pretrained architecture to the specific domain of plant pathology, the system achieves improved robustness and predictive confidence while maintaining computational efficiency.

Performance Evaluation Metrics

To evaluate the model, the following metrics are used:

Accuracy = $\frac{\{TP + TN\}}{\{TP + TN + FP + FN\}}$

Measures overall correctness of the model.

ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve plots:

TPR = $\frac{TP}{\{TP + FN\}}$

against

FPR = $\frac{FP}{\{FP + TN\}}$

The Area Under Curve (AUC) is:

$\int \{1 - TPR(FPR)\} d(FPR)$

AUC = \int

{0}

A higher AUC value indicates better discrimination capability.

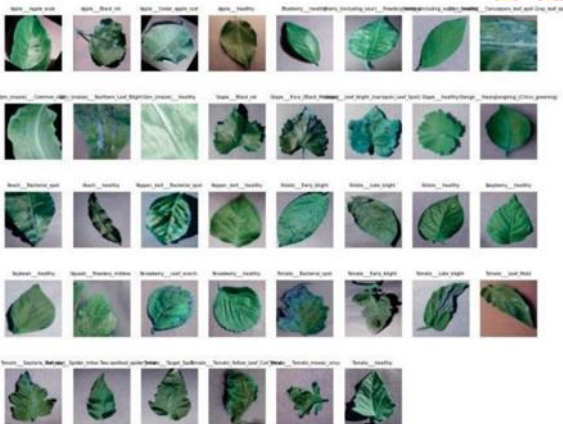
DATASET DESCRIPTION

Experimental Dataset Configuration:

The experimental dataset used in this project consists of labeled leaf images representing multiple crop types and disease categories. Each image corresponds to a single leaf sample classified either as healthy or affected by a specific infection. The dataset supports multi-class learning by covering several crop–disease combinations. For model development, the dataset was organized into structured directories where each folder represented one disease class. This structure enabled supervised training using categorical labels mapped directly to folder names. To ensure reliable evaluation, the dataset was divided into three subsets:

- Training set for weight optimization
- Validation set for monitoring generalization
- Testing set for final performance assessment

The split ratio was carefully selected to maintain class balance and avoid biased evaluation.



Data Preparation and Preprocessing Strategy:

All images were standardized before model training. Each image was resized to a fixed spatial resolution compatible with the neural network input layer. Pixel values were normalized to stabilize gradient updates during optimization. To improve model robustness, augmentation techniques were applied dynamically during training. These included:

- Random rotations
- Horizontal flips
- Slight zoom variations
- Minor spatial translations

This process increased effective data diversity and helped the model adapt to variations in orientation, lighting conditions, and background noise.

Observations from Dataset Usage:

During experimentation, it was observed that certain disease classes exhibited subtle visual differences, especially in early infection stages. Augmentation played a significant role in improving classification stability for such cases.

The dataset's variability in color distribution and texture patterns allowed the model to learn discriminative features that enhanced predictive accuracy across diverse plant types. Overall, the dataset proved suitable for training both the baseline CNN and the fine-tuned InceptionV3 architecture within a multi-class disease recognition framework.

CONCLUSION

This study developed an automated plant disease identification framework utilizing deep neural networks and transfer learning strategies. The implemented system eliminates the need for handcrafted feature extraction and enables direct learning from raw image inputs.

Comparative analysis confirmed that incorporating pretrained architectures improves predictive efficiency and generalization performance. The deployment of the system through a web-based interface enhances accessibility and supports real-time usage scenarios.

Overall, the work establishes that deep learning–driven solutions can significantly contribute to early-stage crop disease detection and intelligent agricultural management.

FUTURE ENHANCEMENT

Integration with IoT sensors can facilitate continuous monitoring of plant health conditions. Furthermore, future advancements may incorporate disease severity assessment, fertilizer suggestion modules, and multi-language support to enhance accessibility and farmer usability. These extensions would strengthen the system's practical relevance and overall scalability.

The incorporation of multilingual functionality and an intuitive mobile interface would enhance accessibility, particularly for farmers in rural and

non-English-speaking areas. Voice-enabled guidance and offline capabilities could further improve usability in regions with limited internet access. Additionally, integrating weather forecasting APIs and predictive modeling techniques can assist in forecasting possible disease outbreaks before they arise.

These improvements would substantially enhance the system's practical relevance, scalability, and real-world influence, evolving it from a basic disease identification tool into a comprehensive smart agriculture decision-support platform.

RESULT ANALYSIS

The developed plant disease detection framework was assessed by comparing the performance of a custom Convolutional Neural Network with a fine-tuned InceptionV3-based transfer learning model. Evaluation was conducted using multiple performance indicators to examine classification accuracy, stability, and generalization capability across unseen samples.

During the training phase, the transfer learning model reached convergence in fewer epochs than the baseline CNN. Accuracy progression showed smoother improvement trends, while validation performance remained consistently stable, indicating effective learning without significant fluctuation. This behavior suggests enhanced feature representation capability in the pretrained architecture.

Analysis of the confusion matrix indicated clearer differentiation between healthy and infected leaf categories when using the fine-tuned model. Misclassification instances were reduced, particularly among disease classes with visually similar symptoms. Receiver Operating Characteristic evaluation further demonstrated improved discrimination strength, reflected by higher AUC values for the transfer learning approach.

Overall findings confirm that leveraging pretrained convolutional features improves prediction reliability, enhances multi-class separation, and reduces overfitting tendencies, thereby strengthening the effectiveness of automated plant disease recognition systems.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

- [1] N. Vidgen, A. Hale, S. Guest, H. Margetts, and D. Broniatowski, "Learning from the Worst: Dynamically Generated Datasets to Improve Online Hate Detection," Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 1667–1678, 2020.
- [2] A. Risch and R. Krestel, "Aggression Identification Using Deep Learning and Data Augmentation," Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying, pp. 150–158, 2020.
- [3] Z. Waseem, T. Davidson, D. Warmley, and I. Weber, "Understanding Abuse: A Typology of Abusive Language Detection Subtasks," Proceedings of the Fourth Workshop on Online Abuse and Harms, pp. 1–13, 2021.
- [4] A. Mathew, P. Saha, S. Yimam, C. Biemann, P. Goyal, and A. Mukherjee, "HateXplain: A Benchmark Dataset for Explainable Hate Speech Detection," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 17, pp. 14867–14875, 2021.
- [5] S. Mozafari, M. Farahbakhsh, and N. Crespi, "A BERT-Based Transfer Learning Approach for Hate Speech Detection in Online Social Media," Complex Networks & Their Applications IX, pp. 928–940, 2020.
- [6] J. K. Lee, H. S. Kim, and Y. J. Kim, "Cyberbullying Detection Using Deep Learning Models," IEEE Access, vol. 9, pp. 119519–119529, 2021.
- [7] S. K. Saha, A. K. Pal, and M. S. Aktar, "Multimodal Cyberbullying Detection Using Deep Neural Networks," IEEE Access, vol. 10, pp. 88562–88574, 2022.
- [8] M. R. Islam, M. M. Rahman, and M. R. Karim, "Cyberbullying Detection on Social Networks Using Machine Learning Techniques," IEEE Access, vol. 8, pp. 178372–178382, 2020.
- [9] H. Al-Ahmad and M. Alsmadi, "Deep Learning Models for Cyberbullying Detection in Social Media," International Journal of Advanced Computer Science and Applications, vol. 12, no. 2, pp. 202–210, 2021.
- [10] S. B. Khanday, M. A. Rabani, Q. Khan, and N. Rouf, "Deep Learning Based Approaches for Detecting Offensive Language in Social Media," IEEE Access, vol. 9, pp. 123453–123463, 2021.
- [11] Y. Liu, M. Ott, N. Goyal et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," arXiv preprint arXiv:1907.11692, updated 2020.
- [12] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," NAACL-HLT, updated applications widely used in 2020–2023.
- [13] D. Jurafsky and J. H. Martin, Speech and Language Processing, 3rd ed., Draft, 2021.
- [14] T. Wolf et al., "Transformers: State-of-the-Art Natural Language Processing," Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 38–45, 2020.
- [15] S. Rajamanickam, P. M. Kumar, and V. Subramaniaswamy, "Real-Time Cyberbullying Detection Using Deep Learning Models," IEEE International Conference on Artificial Intelligence and Knowledge Engineering, pp. 120–126, 2022.