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Deep Learning–Based Plant Disease Detection with IoT-Enabled Monitoring Systems: A Comprehensive Review

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Abstract— **Plant diseases are a major factor affecting agricultural productivity and crop yield. Disease-induced losses during plant growth pose significant challenges for farmers, particularly in rural and farming communities. Therefore, early detection and timely prevention of plant diseases are crucial to minimize yield loss and improve overall agricultural sustainability. To address this challenge, an efficient and automated plant health monitoring system is required, along with effective control mechanisms for early disease and pest identification. In recent years, automated plant disease detection has been widely explored using deep learning techniques, especially Convolutional Neural Networks (CNNs), including architectures such as ResNet50, InceptionV3, and VGG19. This paper presents an efficient CNN-based approach for the detection and classification of plant leaf diseases. The proposed system follows a structured methodology involving dataset collection, image preprocessing, model training, testing, and classification to accurately distinguish between healthy and diseased plant leaves. Furthermore, the developed system integrates an IoT-based monitoring framework to support disease mitigation by providing real-time alerts through a mobile application and email notifications. This enables farmers to take timely preventive measures, thereby reducing crop losses and enhancing productivity. The experimental results demonstrate that the proposed deep learning model achieves reliable performance in plant disease detection, making it a practical and effective solution for smart agriculture applications.**

Keywords— **Image Classification, Plant Leaf Disease Detection, Deep Learning, Convolutional Neural Network (CNN), ResNet50, Smart Agriculture, IoT-Based Monitoring**

I. INTRODUCTION

Agriculture is the backbone of economies worldwide, and improving crop quality and yield while minimizing production costs remains a major research objective in modern farming. Plant diseases significantly affect agricultural productivity and crop quality. These diseases are commonly caused by bacteria, viruses, and fungi, and early identification is essential to prevent large-scale crop losses. Traditionally, disease detection relies on manual inspection by agricultural experts, which is time-consuming, labor-intensive, and often expensive for farmers.

With the advancement of image processing and artificial intelligence, automated plant disease detection techniques have gained significant attention. Various methods have been developed to analyze plant leaf images and perform disease classification using machine learning and deep learning approaches. In the Indian agricultural context, crops such as banana contribute substantially to overall agricultural output, making effective disease management particularly important. Recent research in smart agriculture focuses on improving efficiency and productivity by employing automated systems that reduce human effort while delivering accurate and timely results. Manual disease detection through visual inspection is challenging, subjective, and inefficient, especially when dealing with large-scale farming. In contrast, automated image-based disease detection systems can process leaf images quickly and accurately, even with limited human intervention. In this work, a deep learning–based system is proposed for plant leaf disease detection using image classification techniques. When a plant leaf image is uploaded to the system, it undergoes several stages of processing, including feature extraction and classification, to identify whether the leaf is healthy or diseased. The system is trained using plant leaf images, including banana leaves, as a case study. Additionally, the proposed framework provides disease-specific recommendations and preventive measures, such as fertilizer suggestions, to support effective disease mitigation. This approach aims to enhance crop productivity and promote sustainable and intelligent farming practices.

II. CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN is a kind of deep learning model for processing data with a grid pattern, like images, and is intended to learn spatial features hierarchies from low level to high level pattern automatically and adaptively, which is inspired by the structure of the animal visual cortex. Convolution, Pooling and fully connected layers are three types of layers that make up a CNN, a mathematical construct. As the third fully connected layer, convert the retrieved features into the final output, such classification, and the first two convolutions and pooling layers carry out features extraction.

Convolutional Neural Network (CNNs) rely significantly on their convolutional layer which consist of series of mathematical operations, including-convolution- a specific type of linear operation, due to the pixel values being organized in a two dimensional (2D) grid, CNN exhibit exceptional efficiency in image processing in image processing, each position in the image applies an array of numbers and a small grid of parameters, known as the kernel, which functions as a optimizable feature extractor. Features can be detected anywhere in the image. As the output from one layer is fed into the next, the complexity of the extracted features can progressively and hierarchically increase. Training is the process of fine tuning parameters such as kernels, using optimization algorithms like gradient descent and back propagation, among others to reduce the discrepancy between output and ground truth labels.

The Key Component of CNN Architecture

The architecture of Convolution Neural Network (CNNs) comprises several fundamental components, including convolutional layer, pooling layer and fully connected layer. In a typical architecture, multiple convolutional layers are stacked sequentially, followed by pooling layer, with this pattern being repeated multiple times. Subsequently one or more fully connected layers are introduced. Forward propagation is the mechanism by which input data is processed through these layers, transforming it into the final output. Although the convolutional and pooling techniques discussed primarily pertain to two-dimensional (CNNs), analogous methodologies can be applied in three-dimensional (3D) CNNs [24] (Figure 1).

Convolution Layer

The CNN architecture comprises various types of layer, including convolutional layer, Softmax layer, pooling layer and fully connected layer. CNN are adept and at identifying the edges and shape within an image. The Convolutional Neural Network take an input of dimensions M*N*1 where M and N represent the height and width of the image respectively and the depth is 1, indicating the image is in grayscale. As a result the input image is processed using this form which produces the final image [1]. During the convolutional process, the parts of the input that closely match the input filter shape will have a higher value equation (1) can be used to represent the convolution process as follows:

$$s(t) = (x * w)(t) \qquad (1)$$

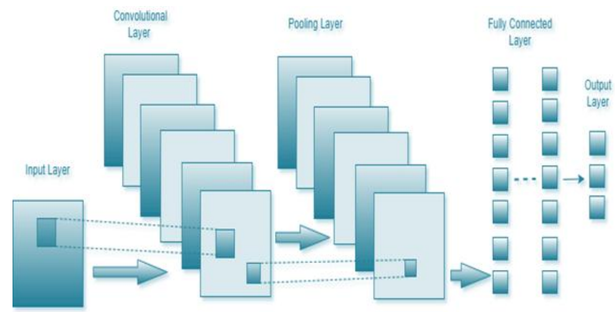

Figure 1 CNN Model

Pooling Layer

The pooling layer is a fundamental aspect of CNN architecture, utilized to decrease the spatial dimensions of features maps that arise from convolutional layer [1]. The reduction plays an important role in lessening computational demand and managing over fitting, max pooling approach extract the maximum value from each section of the features map, ensuring that the most significant feature identified by the convolutional layer retained the mathematically expression as:

$$Y(i, j) = \text{Max}(X(i+m, j+n)) \qquad (2)$$

Where X is the input feature map and Y is the output after pooling. Average pooling calculate the average value of each patch of the feature map mathematically representation, accomplished through the use of camera and smartphone, resizing is the altering the size of images to a uniform measurement aids in achieving a standardized input for the model, transforming the pixel value to fall within a defined the range, most commonly in between 0 and 1. To enhance the image quality, it is essential to remove any extraneous noise by utilizing filters [1].

$$Y(i, j) = 1/k^2 \sum (X(i+m, j+n)) \qquad (3)$$

Training a Neural Network

Training a neural network involves identifying kernels in convolutional layer and weights in fully connected layer to minimize the discrepancies between the predicted outputs and the actual ground truth labels on the training dataset. The back propagation algorithm is commonly used for the training process, playing very crucial role alongside the loss function and gradient descent optimization play important role. In essence, the performance of the model is evaluated based on specific kernels and weights using a loss function through a process is called is forward propagation on a training dataset, the learnable parameters are then adjusted according to the calculated loss value through an optimization algorithms.

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This algorithm often involves technique such as back propagations and gradient descent, among others to minimize the loss and improve the model performance. The continuous process of training and refinement enhances the model performance and adaptability of the model [28].

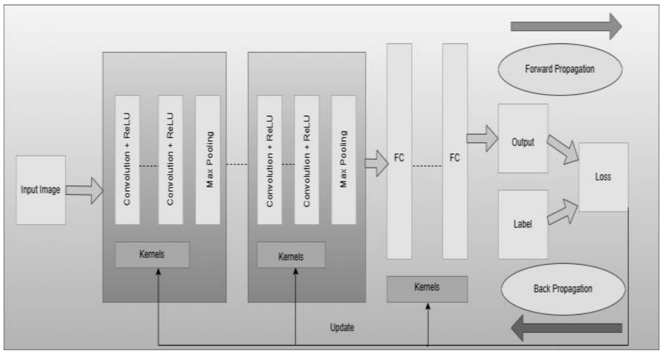

Figure 2 Building Block of CNN Architecture

Loss Function

A loss function is also known as cost function, evaluate how well the model predicted outputs match the actual correct labels during forward propagation. For multiclass classification tasks, the commonly used loss function is cross entropy, hyper parameters play crucial role in influences the model performances. Optimizer decide how the model's during training, whereas loss functions define the penalties for incorrect predictions, the number of epochs specifies how many the model will go through the entire training dataset, the mini batch-size determines the number of training examples used in each training iteration.

Fully Connected Layer

A fully connected layer is also known as dense layer serves as a crucial element in convolutional neural network especially in the context of deep learning, each neuron maintain connection with all neuron of previous layer, thereby establishing a network with extensive interconnectivity [24]. In fully connected layer, dimensions are adjusted to fit the network architecture every input and output of the layer are interlinked. All activations from the privies layer are passed on to the next layer [1]. The mathematical expression for the output of a fully connected layer as:

$$Y = f(W.X+b) \qquad (5)$$

Softmax Layer

The softmax layer is the vital part of convolutional neural network especially in tasks related to classification; the softmax layer is generally utilized as the concluding layer a neural network aimed at classification. It transforms the raw output scores referred to as logits into probabilities that sums to one, thus the simplify the interpretation of the result. Each element in the input vector is exponentiated; normalization is each exponentiated value is divided by the total of all exponentiated values, the resulting values create a probability distribution where each values lies between 0 and 1. The mathematical representation as the output probability of Yi for the i^{th} classes can be expressed as:

$$Yi = e^{zi} / \sum_j e^{zj} \qquad (6)$$

Image can be categorized using modified convolutional neural network, which are generally pre-trained to identify different image types, these network can be customized to address specific classification through transfer learning by adjusting fundamental parameters.

III. Related Work

The high incidence of various plant leaf diseases poses a serious threat to overall agricultural production, directly impacting the economic stability of many nations. To effectively address these challenges, efficient monitoring systems must be established, and advanced management techniques for early disease and pest identification must be developed. In recent years, convolutional neural networks (CNNs) with deep architectures have demonstrated strong performance across multiple domains and have therefore been increasingly adopted in agricultural applications to detect diseases across a wide range of crops.

The primary objective of this work is to implement a Deep Convolutional Neural Network (DCNN) designed to predict different plant leaf diseases and insect infestations. By utilizing DCNN-based systems, farmers can obtain critical information at early stages, enabling the careful application of fertilizers and preventive measures to reduce disease outbreaks. Compared with other deep learning methods, CNN-based approaches have demonstrated superior performance in plant disease identification, achieving high accuracy rates, in some cases exceeding 99% [1].

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Numerous techniques have been proposed for plant leaf disease detection, and several studies have explored different image processing and deep learning strategies. V. Gokula Krishnan et al. [1] applied a hybrid fuzzy C-means approach for segmentation and classification, extracting color, shape, and texture features from leaf images. Their MATLAB-based system involved image acquisition, preprocessing, segmentation, and classification stages, using TGVFCMS for affected-area segmentation and CNN for disease classification. This method proved more accurate than manual inspection and highlighted the potential of automated disease detection systems. The authors suggested that future work could incorporate climatic parameters such as temperature, humidity, soil conditions, and water levels to build an early warning system.

To identify suitable segmentation techniques for plant leaf analysis, various methods such as adaptive thresholding, Canny, color segmentation, fuzzy C-means, geodesic, global thresholding, K-means, multithresholding, Prewitt, region growing, Roberts, Sobel, and zero crossing were evaluated [2]. Performance metrics including Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) were used for comparison. The results indicated that the geodesic method achieved lower MSE and higher PSNR and SSIM values, suggesting reduced randomness and better segmentation quality, making it a suitable preprocessing technique for automated plant disease detection systems. Deep learning architectures such as InceptionV3, VGG-19, and VGG-16 have also been widely explored for plant disease classification. InceptionV3 is known for its ability to handle varying image sizes with minimal preprocessing, while VGG-19 offers robust feature extraction and high accuracy for complex image patterns. VGG-16, due to its simpler architecture, provides competitive results in scenarios with limited computational resources [3]. Several studies have utilized transfer learning techniques to improve disease detection performance. Kevin Yan et al. fine-tuned a pre-trained ResNet50 model to identify Fusarium wilt, employing data augmentation and dataset splitting strategies to enhance generalization [6]. Their model correctly classified 492 out of 500 test images, achieving an F1-score of 0.98. Similarly, other studies leveraged plant disease datasets and transfer learning using models pre-trained on ImageNet and PlantCLEF2015, reporting superior performance for ImageNet-based models [8].

To mitigate the negative impact of plant diseases on productivity and quality, Khaoula Taji et al. [9] proposed a hybrid framework combining preprocessing techniques with AlexNet and ResNet18 models, achieving an accuracy of 99.8%. Another study introduced a DCNN with multiple convolutional and pooling layers for predicting disease and pest occurrences in plant leaves, achieving 99% accuracy and demonstrating reliability for sustainable farming applications [10]. Explainable AI (XAI) techniques have also been introduced to improve transparency in disease detection systems. A novel XAI framework using EfficientNetB0 was evaluated on multiple plant disease datasets, achieving high accuracy and outperforming existing methods [11]. Additionally, hybrid approaches combining CNNs with traditional classifiers such as K-Nearest Neighbors, along with IoT-based alert systems, have been proposed to enhance real-time disease mitigation, achieving accuracy rates of up to 90% [24]. Further studies explored DenseNet, MobileNet, Faster R-CNN, and hybrid CNN architectures for plant disease detection, reporting accuracy levels ranging from 91% to 98.7% [27–33]. These methods demonstrated the effectiveness of deep learning in accurately identifying healthy and diseased plant leaves, reducing manual effort, and supporting precision agriculture.Overall, existing literature confirms that deep learning–based plant disease detection systems provide reliable, accurate, and scalable solutions for early disease identification. Such systems not only assist farmers in timely decision-making but also contribute to improved crop yield, reduced losses, and sustainable agricultural practices.

IV. METHODOLOGY

In this study, an innovative deep learning–based framework is proposed for the early detection of plant leaf diseases. The proposed approach integrates an efficient Convolutional Neural Network (CNN) with IoT technology to enable accurate disease and pest identification, thereby supporting effective risk management in agriculture. The overall methodology consists of dataset collection, image preprocessing, data augmentation, transfer learning–based model development, training and validation, disease classification, and IoT-based alert generation.

Dataset Collection

The dataset used in this study consists of digital images of plant leaves affected by several common diseases, along with healthy leaf samples. The images were collected from a publicly available dataset [22].

A total of 1000 images were included, comprising both healthy and diseased leaf samples belonging to multiple disease categories. The images were captured under varying environmental conditions and at different times of the day, ensuring diversity in illumination, background, and leaf orientation. This diversity enhances the robustness and generalization capability of the proposed model.

Image Pre-Processing

Prior to training, all images underwent a series of preprocessing steps to ensure uniformity and improve learning efficiency. Each image was resized to a resolution of 224 × 224 pixels to meet the input requirements of the CNN architecture. Pixel values were normalized to reduce computational complexity and improve convergence during training [11]. These preprocessing steps help in minimizing noise and ensuring consistent feature extraction across the dataset.

Data Augmentation

To address the challenge of limited dataset size and to prevent overfitting, data augmentation techniques were applied. Augmentation operations included random horizontal and vertical flipping, image rotation, and noise addition. These techniques artificially expand the dataset by generating new image variations, allowing the model to learn invariant features and improving its ability to generalize to unseen data. The dataset was divided into two subsets: 80% for training and 20% for validation. This clear separation ensured reliable performance evaluation and reduced the risk of data leakage during training.

Transfer Learning and Model Selection

To achieve high classification accuracy while maintaining computational efficiency, a transfer learning approach was adopted. Transfer learning enables the reuse of knowledge from pre-trained models, significantly reducing training time and improving performance when working with limited datasets. In this study, the ResNet50 architecture was selected due to its strong performance in image classification tasks and its ability to overcome vanishing gradient problems through residual connections.

The model was implemented using TensorFlow, a widely used machine learning framework, along with Keras, a high-level neural network API. The pre-trained ResNet50 model, originally trained on the ImageNet dataset, was fine-tuned by modifying the final fully connected layers to suit the plant disease classification task. This approach allowed the model to retain low-level feature representations while learning disease-specific patterns from plant leaf images.

Model Training and Validation

The fine-tuned CNN model was trained using the augmented training dataset, while its performance was evaluated on the validation dataset. During training, performance metrics such as accuracy, loss, precision, recall, and F1-score were monitored to assess model effectiveness. Appropriate optimization techniques and loss functions were employed to ensure stable convergence and to minimize overfitting. The validation process confirmed that the model generalized well to previously unseen data.

Disease Classification

After training, the model classifies input plant leaf images into predefined categories, including healthy leaves and multiple disease classes. The classification is based on deep features extracted from convolutional layers. The output layer generates probability scores for each class, and the class with the highest probability is selected as the final prediction.

IoT-Based Alert and Mitigation System

To enhance practical applicability, the proposed system integrates an IoT-based alert mechanism. Upon detection of a plant disease, the system generates real-time notifications through a mobile application and email alerts to inform farmers. This enables timely intervention through appropriate preventive measures, such as the application of fertilizers or pesticides, thereby reducing crop losses and improving overall agricultural productivity. The integration of deep learning with IoT technology supports smart farming by enabling automated monitoring and decision support.

V. Result And Discussion

The proposed plant leaf disease detection framework was evaluated using extensive experiments implemented in the Python programming environment with the TensorFlow deep learning framework. Both baseline learning and transfer learning strategies were employed to assess the effectiveness of convolutional neural network (CNN)–based feature extraction and classification. The dataset was divided into 70% for training and 30% for testing**,** ensuring a fair evaluation of model generalization performance. During the training phase, the ADAM optimizer was used for parameter optimization due to its adaptive learning rate and faster convergence properties.

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All input images were resized to a fixed resolution compatible with the network input layer, and grayscale images were converted into RGB format to maintain consistency with pretrained CNN architectures. Image augmentation techniques were applied to improve robustness and reduce overfitting.

Feature Extraction and Classification Performance

Deep features were extracted from the fully connected layer (fc8) of the CNN model. These features represent high-level semantic information related to plant leaf disease patterns. A linear Error Correcting Output Codes (ECOC) classifier was trained using the extracted feature vectors and corresponding class labels.The trained classifier was then evaluated on the test dataset. The predicted labels were compared with the ground-truth labels to compute the confusion matrix, which provides a detailed insight into class-wise classification performance.

Confusion Matrix Analysis

The confusion matrix was normalized by dividing each element by the sum of its corresponding row. This normalization helps in understanding the proportion of correct and incorrect predictions for each class. The diagonal elements of the normalized confusion matrix indicate correct classifications, while off-diagonal elements represent misclassifications. The normalized confusion matrix shows strong diagonal dominance, demonstrating that the proposed framework can accurately distinguish between different plant leaf disease categories with minimal confusion.

Performance Metrics Evaluation

To quantitatively evaluate the effectiveness of the proposed system, several standard performance metrics were calculated using the confusion matrix, including accuracy, precision, recall, sensitivity, and specificity.

Accuracy reflects the overall correctness of the model by measuring the proportion of correctly classified samples.

Precision indicates the reliability of positive predictions and measures how many predicted positive samples are truly positive.

Recall evaluates the model's ability to correctly identify relevant samples.

Sensitivity (True Positive Rate) measures how effectively the model detects diseased plant leaf samples.

Specificity (True Negative Rate) evaluates how accurately the model identifies healthy or non-target samples.

The experimental results demonstrate that the proposed framework achieves high accuracy and balanced precision–recall performance, indicating that the model is effective in identifying plant leaf diseases while minimizing both false positives and false negatives. High sensitivity values confirm the model's strong ability to detect diseased leaf samples, whereas high specificity values indicate reliable discrimination of non-diseased samples. Overall, the results validate that combining CNN-based deep feature extraction with a linear classifier provides a robust and computationally efficient solution for plant leaf disease detection.

VI. CONCLUSION

In this study, a deep learning–based framework for plant leaf disease detection was presented and experimentally validated. The proposed approach integrates convolutional neural network–based feature extraction with a classical machine learning classifier to achieve accurate and reliable classification performance. Both baseline learning and transfer learning strategies were explored to assess model robustness. Experimental results demonstrate that the proposed system effectively captures discriminative features from plant leaf images and achieves high performance across multiple evaluation metrics, including accuracy, precision, recall, sensitivity, and specificity. The use of image preprocessing, augmentation, and deep feature extraction significantly enhances the model's generalization capability. The findings confirm that the proposed framework can serve as a practical and scalable solution for automated plant leaf disease detection in real-world agricultural applications. Future work may focus on extending the framework to real-time deployment, integrating edge or IoT-based systems, and evaluating performance on larger and more diverse plant disease datasets to further improve generalization and robustness.

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