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DETECTION AND CLASSIFICATION OF POTATO LEAF DISEASE USING DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

The main objective of this project is to develop a robust and efficient system capable of automatically detecting and classifying diseases in potato leaves using Deep Convolutional Neural Networks (DCNNs). Traditional methods for diagnosing plant diseases are often manual, time-intensive, and prone to errors, which can delay timely intervention and ultimately reduce crop yields. Accurate and early detection of diseases in potato leaves is essential for improving crop health and optimizing agricultural output. This study utilizes a dataset consisting of images of both healthy and infected potato leaves, particularly those affected by Early Blight and Late Blight. A DCNN is trained on these annotated images to learn distinguishing visual features, enabling automated classification of leaf conditions. The model's performance is assessed based on its accuracy in categorizing images, and it demonstrates strong results in identifying various disease types. Findings from this research highlight the effectiveness of deep learning—especially CNNs—in providing a scalable, precise, and practical solution for disease detection in agriculture, aiding farmers and agronomists in proactive crop management.

1. INTRODUCTION

Diseases in crops pose a significant threat to agricultural productivity and remain a major challenge for the farming community. Traditional methods of detecting plant diseases are often inefficient, costly, and prone to inaccuracies, resulting in delayed treatment and reduced yields. In recent years, advancements in machine learning—particularly Deep Convolutional Neural Networks (CNNs)—have transformed the way plant diseases are diagnosed, offering faster and more reliable solutions.This study focuses on identifying an optimal deep learning framework to accurately classify and localize diseases in potato leaves. We introduce a CNN-based system enhanced through data augmentation, transfer learning, and fine-tuning of hyperparameters. The experimental setup relies on the publicly available Potato Leaf Disease dataset, which includes categorized images of healthy and diseased leaves. The system is designed to not only distinguish between healthy and infected samples but also pinpoint the specific regions affected by diseases. A lightweight, custom-built CNN architecture is employed for classification to ensure efficient training and inference. For localization, the dataset undergoes preprocessing to extract meaningful patterns that indicate disease presence. Given the limitations of manual inspection methods—such as labor intensity and susceptibility to error—automated detection offers a substantial advantage in agricultural diagnostics.The dataset comprises images of potato leaves, annotated to reflect various health conditions including Early Blight and Late Blight. The deep learning model is trained to identify key visual cues that differentiate between disease states. Performance evaluation is conducted based on classification accuracy, and results indicate strong effectiveness in detecting leaf diseases.In conclusion, this research confirms the potential of CNN-based deep learning techniques for automated detection and classification of potato leaf diseases. Such systems can play a critical role in

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enabling timely and informed decisions in agricultural disease management, ultimately improving crop outcomes and supporting sustainable farming practices.
Accurate detection and classification of potato leaf diseases using deep convolutional neural networks (DCNNs) is a vital yet complex task in modern agriculture. Conventional approaches to disease identification are often inefficient and susceptible to misdiagnosis, resulting in delayed responses and reduced crop yields. To address this, the initial phase of our project involves collecting a comprehensive dataset of potato leaf images. For this purpose, we employ the publicly accessible Potato Leaf Disease dataset from Kaggle. It consists of over 1,000 images per category, representing healthy leaves, early blight, and late blight, ensuring a well-balanced dataset for both training and testing. These curated images serve as the basis for developing a DCNN model capable of accurately learning and distinguishing between different disease conditions in potato leaves.
Plant diseases remain one of the major obstacles to improving agricultural productivity. Conventional methods for identifying such diseases are often inefficient in terms of both time and cost, with a high likelihood of incorrect diagnoses. These inaccuracies can lead to decreased crop yields and substantial financial losses for farmers. This project is focused on developing a dependable, automated system for detecting and classifying diseases in potato leaves. By harnessing the capabilities of Deep Convolutional Neural Networks (DCNNs), the goal is to enhance the accuracy, speed, and reliability of disease identification, ultimately supporting better crop management and early intervention.

2. LITERATURE SURVEY

In recent years, deep learning—especially Convolutional Neural Networks (CNNs)—has become one of the most powerful tools for identifying plant diseases from images. Numerous researchers have explored how these models can help automate the detection of potato leaf diseases, which are a major concern for farmers around the world.
Pasalkar et al. (2023) laid the groundwork by exploring traditional machine learning techniques to detect potato leaf diseases. While their method showed promise, it lacked the flexibility and accuracy offered by more advanced deep learning models [1]. Building on this, Tambe et al. (2023) proposed a CNN-based approach that improved classification performance significantly by allowing the model to learn patterns directly from raw image data [2].One of the major improvements in this space has been the use of **transfer learning**, where pre-trained models are adapted to new tasks. Charisma and Adhinata (2024) used DenseNet201 for this purpose and achieved impressive results with less training time, showing that such techniques are well-suited to tasks with limited data [3]. Recent study and took a different route. They combined deep learning with feature selection techniques to improve performance. By selecting the most relevant image features before classification, they achieved more accurate results even for similar-looking diseases like early and late blight [4]. Several studies have emphasized the importance of real-world usability. For example, one paper in the *International Journal of Intelligent Systems and Applications in Engineering* developed a CNN model that performed reliably across a broad range of images, suggesting that deep learning can be robust even in field conditions [5]. Similarly, research published by EAI (2023) explored not just classification but also disease **prediction**, showing the potential of CNNs for proactive crop management [6]. To make these models faster and more efficient, researchers in the *Journal of Plant Pathology* fine-tuned CNN architectures for speed without sacrificing accuracy [7]. Meanwhile, studies presented at the ELECO 2023 conference addressed practical deployment issues like changing lighting conditions and noisy backgrounds—problems commonly faced by farmers using smartphone cameras [8]. Lightweight models have also gained attention. A 2024 paper in the CEUR Workshop Proceedings introduced a DCNN architecture designed specifically for use on mobile devices, making disease detection more accessible to small-scale farmers [9]. Some researchers have

10.48047/jocaaa.2024.33.08.142

combined DCNNs with other models to further improve reliability. One such study introduced a hybrid system using both CNNs and Random Forest classifiers, which balanced deep learning's pattern recognition abilities with the decision-making strength of ensemble methods [10]. Finally, a comprehensive review published by Springer (2024) compared several CNN models, such as ResNet, VGG, and MobileNet. They concluded that while deeper models tend to be more accurate, they also require more computing power—highlighting the need to balance performance with practicality [12]. Although many of these models demonstrate a fair level of accuracy, challenges remain—particularly in reliably distinguishing between similar disease types like early blight and late blight.[2][4] Differences in image quality, lighting conditions, backgrounds, and environmental factors often affect model performance, leading to misclassification.[5] Despite these limitations, literature consistently highlights the strong capabilities of DCNNs in plant disease detection, especially due to their ability to learn complex visual features without manual intervention[13-15].

3. METHODOLOGY

The potato leaf disease detection is implemented using Deep Convolutional Neural Networks (CNNS). The Convolutional Neural Networks (CNNs) for their strength in automatically learning relevant patterns from image data. These models can differentiate between healthy and infected leaves without relying on manual feature engineering.The two main operational phases: training and testing. During training, the dataset is cleaned and standardized through preprocessing steps. The refined data is then subjected to feature extraction, where significant image patterns are identified. These features are used by the CNN to learn disease-specific characteristics.In the testing phase, unseen images undergo similar preprocessing and feature extraction. The CNN then classifies the image based on learned patterns, delivering the result as output.

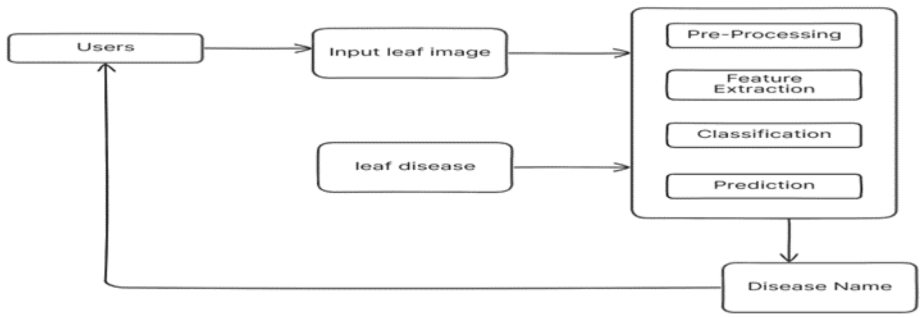

Fig1: The architecture of proposed system.

Key components included in architecture:

- User Interaction Point: Image input
- Preprocessing Stages: Initial and secondary cleaning and formatting
- Feature Extraction Layer: Identifies critical visual elements
- CNN Module: Performs final classification
- Data Storage & Output: Manages results and system feedback

The Fig2 shows entire flow of potato leaf disease detection process. The process begins when the user uploads a set of input images into the system. These images are first processed in the initial preprocessing stage, which handles basic cleaning and formatting. A second-level preprocessing stage further refines the images to standardize input quality.The cleaned images are then sent to the feature extraction module, where the model identifies critical visual patterns relevant for classification. Finally, a Convolutional Neural Network (CNN) processes these features to determine the presence or absence of disease. The model completes the classification by assigning the input to a specific category, such as healthy, early blight, or late blight [16-20].

10.48047/jocaaa.2024.33.08.142

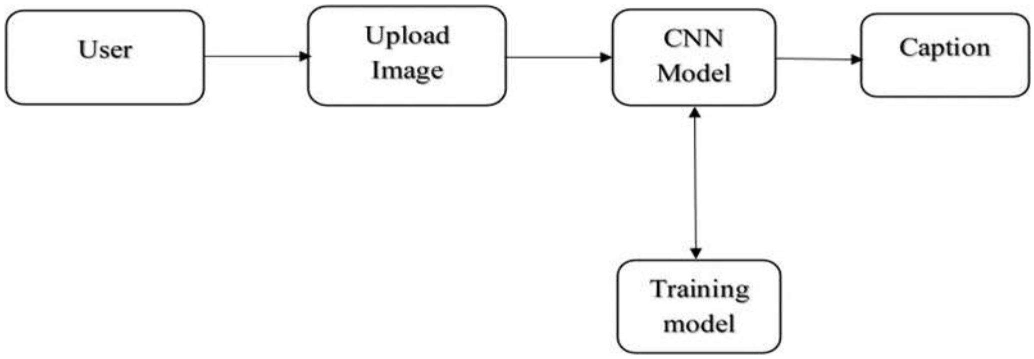

Fig 2 : Flow Diagram

Picking the Model

Selecting the right CNN model is a vital task in building an efficient disease detection system. The model must be trained thoroughly to achieve optimal accuracy and generalization. During this phase, different architectures may be evaluated, and the one offering the best balance of speed and accuracy is chosen.

Once the CNN is successfully trained and validated, it is saved and integrated into the system. Saving the model allows it to be reused for multiple predictions without retraining, significantly improving system responsiveness and reducing computational overhead. This enables users to receive instant feedback upon uploading new leaf images, making the application practical for real-time usage.

Images from a dataset:

Careful curation of the dataset plays a critical role in model performance. For this project, only images that prominently featured a single, clearly visible potato leaf were selected. This helped reduce background noise and improved classification precision.To prepare the dataset for training, unnecessary background elements were removed during preprocessing. This focused the model's attention on disease-specific patterns present in the leaf. The dataset was organized into three well-defined classes: Healthy, Early Blight, and Late Blight. These labeled samples formed the foundation for training and evaluating the CNN, ensuring the system could learn to accurately distinguish between different disease types.

Leaves showing disease symptoms

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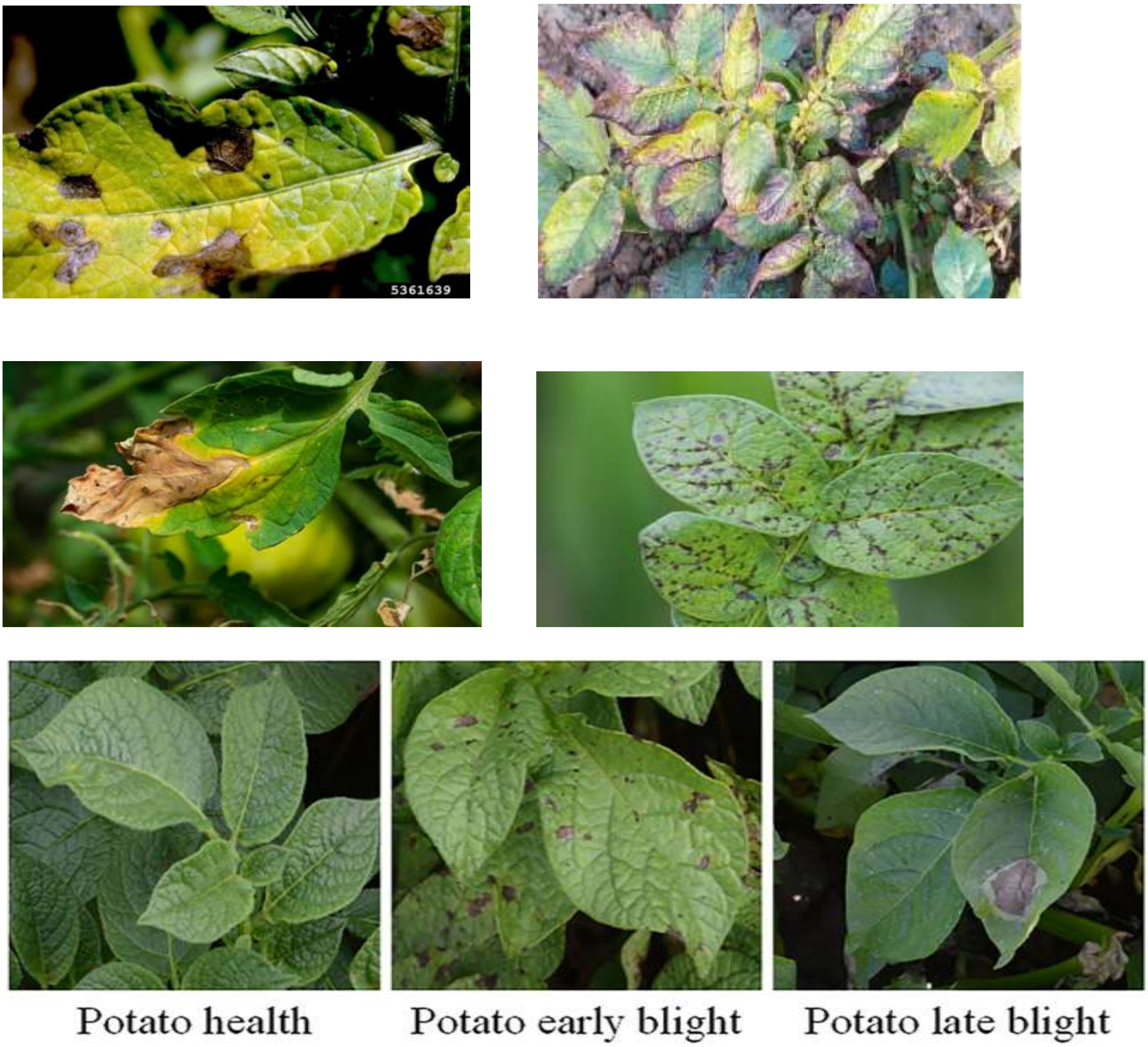

Fig 3 :Images from the dataset

Pre-processing the Dataset

Preprocessing plays a pivotal role in preparing image data for training deep learning models. In the context of this Potato Leaf Disease Detection project, the raw images—sourced from diverse online platforms—varied in resolution, format, and quality. To ensure consistency across the dataset and facilitate effective training, each image was resized to 150×150 pixels. This resizing standardizes the input dimensions, reduces computational demands, and ensurescompatibility with the Convolutional Neural Network (CNN) model. Such uniformity is essential for achieving stable and reliable model performance during both training and inference phases.

Train and Test Split

To develop a model that generalizes well to unseen data, the dataset is divided into two subsets: training and testing. In this project, a total of 100 image samples were used—90 for training and 10 for testing. Each image is labeled according to its health status: Healthy, Early Blight, or Late Blight. These labels serve as the target outputs in a supervised learning setup, allowing the CNN to learn disease-specific patterns during training and evaluate its predictive capability during testing. The

10.48047/jocaaa.2024.33.08.142

train-test split ensures the model's performance can be objectively measured without relying on data it has already seen.

Training the CNN Model

At the core of this project is the training of a Convolutional Neural Network (CNN) designed to classify potato leaf diseases based on image data. CNNs are well-suited for image recognition tasks due to their ability to capture spatial hierarchies and local features through convolutional operations.

Training Pipeline Overview:

The CNN model processes input images through a series of specialized layers:

- **Convolutional Layers:** These apply multiple filters (kernels) across the input image to extract relevant features such as edges, spots, or disease patterns. Each filter creates a feature map that highlights a particular visual trait.
- **Pooling Layers:** Used primarily to downsample the feature maps, pooling layers reduce the number of parameters and computational complexity. This step also helps control overfitting. Two common techniques are:
- **Max Pooling**: Selects the maximum value in each feature region, preserving the most significant features.
- **Average Pooling:** Computes the average of values in each region, offering a more generalized output. In this project, Max Pooling is preferred for its ability to retain distinct disease markers.
- **Fully Connected (Dense) Layers:** After convolution and pooling stages, the extracted features are flattened and passed through one or more fully connected layers. These layers combine the learned features to make a final prediction.
- **Output Layer:** The last layer employs a SoftMax activation function, which transforms the raw output scores into a probability distribution across the target classes (Healthy, Early Blight, Late Blight), providing interpretability and confidence in the predictions.
- **Activation Function:** The ReLU (Rectified Linear Unit) function is applied throughout the network to introduce non-linearity and improve training efficiency.

Adaptive Flexibility:

To allow the network to handle input images of varying sizes during experimentation or real-world deployment, an Adaptive 2D Layer is incorporated. This layer dynamically adjusts feature maps, making the model more robust to changes in input dimensions without compromising classification accuracy. Through iterative training using this architecture, the CNN learns to distinguish disease-specific visual cues and becomes capable of accurately classifying new leaf images it has never encountered before.

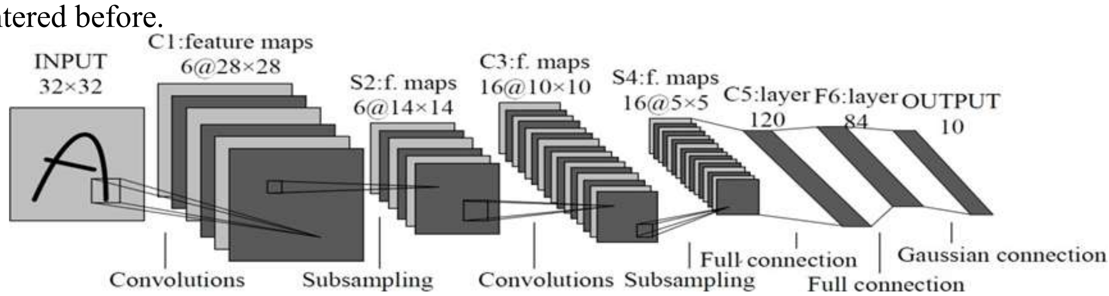

Fig 4 **:**Trainingthe CNN model

4. RESULTAND ANALYSIS

To validate the system's real-world applicability, experiments were conducted using a comprehensive dataset. The model's performance was tested using 7,632 labeled images of potato leaves. The dataset includes healthy leaves and leaves affected by Early Blight and Late Blight. For effective training and testing, the dataset was split as follows:

90% (6,869 images) for training

10% (763 images) for validation

10.48047/jocaaa.2024.33.08.142

This split ensures that the model is trained on a wide variety of samples and then tested on unseen data to assess its generalization capabilities. The results of these experiments help confirm the system's ability to accurately classify potato leaf diseases based on image input. The model's accuracy is 82.77%

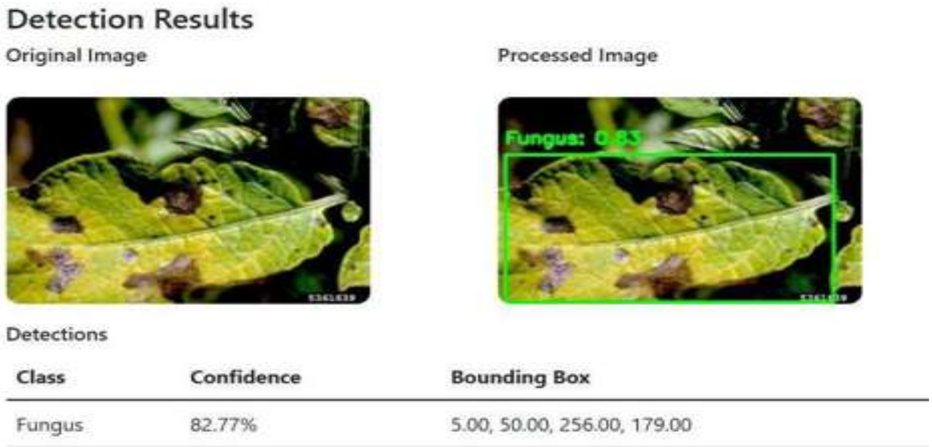

Fig 5: Result

5. CONCLUSION

The use of Convolutional Neural Networks (CNNs) for the detection and classification of potato leaf diseases presents a major leap forward in precision agriculture. Unlike traditional approaches, CNNs automatically learn visual features from raw image data, enabling faster and more accurate diagnosis. This system leverages deep learning to recognize disease patterns in potato leaves with high reliability, offering farmers a valuable tool for early detection and intervention.Studies in this field have confirmed the effectiveness of CNN models. For example, some research has reported classification accuracies as high as 97.4% and 99.1% when using pre-trained CNN models fine-tuned on datasets comprising healthy, Early Blight, and Late Blight-infected leaves. These outcomes underscore the transformative potential of deep learning in agricultural diagnostics.

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