Enhanced Plant Health Monitoring with Deep Learning for Leaf Disease Detection

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***Abstract*—Deep neural networks (DNNs) have proven highly effective in classifying various plant diseases, playing a key role in addressing agricultural risks and improving crop yield. When left untreated or unidentified, plant diseases can seriously impact the quality and quantity of produce, posing significant challenges to farmers. Early detection of plant diseases is essential, as it enhances crop quality and minimizes production losses. In response, a modern approach has been developed that incorporates image acquisition techniques and diverse image types for more accurate disease identification. This approach leverages DNN models to evaluate model performance through metrics such as recall, F1 score, accuracy, and precision, ensuring a comprehensive assessment. The variability in results helps distinguish between healthy and diseased plant leaves, providing precise information about bacterial infections. The methodology has been tested on two plant types: pepper and potato leaves, which are commonly susceptible to diseases. Additionally, the model is designed to estimate the infection percentage on each leaf, offering farmers valuable insights into the extent of damage. This combination of DNN-based analysis and detailed performance metrics allows for a robust system that not only identifies the presence of disease but also quantifies its severity. Such advancements in plant disease identification hold the potential to significantly improve crop management practices, reduce the risk of disease spread, and ultimately contribute to a more sustainable agricultural process.**

***Index Terms*—Deep learning, leaf disease, intelligent recognition, DNN.**

I. INTRODUCTION

In biological sciences, images are essential tools for conveying critical data and knowledge, particularly in biological and agricultural fields where digital image processing and image analysis technologies are transformative. Classification of plant leaves and fostering the growth of healthy plants are key components of agricultural automation, which streamlines farming processes and enhances crop production. Plant diseases primarily affect the color and condition of roots, flowers, fruits, leaves, and buds, leading to reduced crop yield when left unchecked. The advancement of image processing technology has not only captured public interest but has also created new methods for improving crop yield through enhanced disease detection. Agriculture has a significant impact on a nation's economy, and excessive use of fertilizers and pesticides to control crop diseases can, paradoxically, hinder crop growth. Thus, improved farming techniques are crucial for helping farmers cultivate healthier crops with greater efficiency.

Detecting plant diseases visually can be challenging for many individuals, and even if a disease is spotted, identifying the correct treatment can be equally difficult. Early detection of crop diseases, however, can help mitigate extensive crop damage, emphasizing the need for new and advanced techniques for plant classification. Deep learning and machine learning offer powerful solutions for identifying plant leaf health, effectively detecting whether leaves are healthy or infected using image processing techniques. Leaf classification is especially significant in agriculture, where its effects indirectly shape the economy. Precise and timely identification of plant health requires close attention to distinguish between healthy and diseased plants at an early stage. With minimal human intervention, new image processing technology now enables accurate plant classification, making it easier to monitor crop health and reduce reliance on manual inspection. This technological advancement is poised to play a pivotal role in the sustainable growth of agricultural sectors worldwide.

A. Common Plant Diseases

i. Black Spot

Black spot is one of the most common diseases found on roses, but it can also occur on other ornamental and garden plants. This fungal disease causes black, round spots that form on the upper sides of leaves. Lower leaves are usually infected first. Severe infestations cause infected leaves to turn yellow and fall off the plant. Black spot is a problem during extended periods of wet weather or when leaves are wet for 6 hours or more. Black spot spores overwinter in the fallen leaves.

Figure 1.1: Black Spot

ii. Powdery Mildew

Powdery mildew is a fungal disease that affects many of our landscape plants, flowers, vegetables and fruits.

Figure 1.2: Powdery Mildew

Powdery mildew is an easy one to identify. Infected plants will display a white powdery substance that is most visible on upper leaf surfaces, but it can appear anywhere on the plant including stems, flower buds, and even the fruit of the plant.

This fungus thrives during low soil moisture conditions combined with high humidity levels on the upper parts of the plant surface. It tends to affect plants kept in shady areas more than those in direct sun.

iii. Downy Mildew

Because downy mildews differ from powdery mildews, it is important to understand the differences between the two. Powdery mildews are true fungal pathogens that display a white powdery substance on the upper leaves. Downy mildews, on the other hand, are more related to algae and produce grayish fuzzy looking spores on the lower surfaces of leaves. To identify downy mildew, look for pale green or yellow spots on the upper surfaces of older leaves. On the lower surfaces, the fungus will display a white to grayish, cotton-like downy substance. Downy mildew occurs during cool, moist weather such as in early spring or late fall. Spore production is favored by temperatures below 65°F and with a high relative humidity.

Figure 1.3: Downy Mildew

iv. Blight

Plant blight is a common disease. Remember the potato famine in the 1840‘s? As a result of the blight, one million people died. But other than potatoes, blight also affects other plants, particularly tomatoes. Blight is a fungal disease that spreads through spores that are windborne.

Figure 1.4: Blight

II. RELATED WORK

G. Bhadur's research focuses on enhancing the efficiency of classification techniques in plant disease detection, leveraging machine learning and computer vision technologies. His work reviews various factors, benefits, and limitations of existing research while exploring different disease detection and classification scenarios for multiple crops. Bhadur's approach consists of four essential steps: pre-processing, segmentation, feature extraction, and classification, mainly using region-based and edge-based segmentation methods. His findings highlight that pre-processing steps improve segmentation accuracy, with texture features proving effective for representing diseased leaves. Comparing deep learning and machine learning results, he concluded that deep learning holds greater promise for crop disease classification and identification.

In his research, B. Ma explores a computer vision-based system for automated plant disease detection and leaf classification. His proposed genetic DCNN designer is an autonomous algorithm that can generate a DCNN architecture based on data from a specific image classification task. This system converts the DCNN into an integer vector by partitioning it into stacked convolutional and fully connected blocks, which include convolution, pooling, fully connected layers, batch normalization, activation, and dropout. By evolving DCNN architectures using selection, mutation, and crossover, the designer achieved results on datasets like MNIST, Fashion-MNIST, EMNIST-Digit, EMNIST-Letter, CIFAR10, and CIFAR100, demonstrating that it could create architectures matching or surpassing state-of-the-art DCNN models.

K. Jagan developed a robust image processing method for predicting paddy crop diseases, focusing on Brown Spot Disease (BSD), Leaf Blast Disease (LBD), and Bacterial Blight Disease (BBD). His method uses histogram estimation and analysis for disease recognition and disease detection, relying on Haar-like features and the AdaBoost classifier to achieve an 83.33% detection accuracy. Disease recognition utilizes Scale Invariant Feature Transform (SIFT) and classifiers like k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM), achieving 91.10% accuracy with SVM and 93.33% with k-NN. This approach helps detect diseases early, enabling timely action to reduce crop loss.

Suyash S. Patil proposed an early-stage leaf disease detection system that uses sensors for leaf wetness, humidity, and temperature to continuously monitor crop conditions. Image preprocessing, smoothing, enhancing, and resizing help save memory and processing time. Using K-means clustering for segmentation, the system achieves nearly 90% accuracy in Black rot testing. A Hidden Markov Model with the Baum Welch algorithm monitors grape diseases and alerts farmers via SMS. This model features three hidden states (S1, S2, S3) and seven observable states: Anthracnose (AN), Powdery Mildew (PM), Rust (RU), Downy Mildew (DM), Bacterial Leaf Spot (BLS), Bacterial Leaf Cancer (BLC), and No Disease.

Harshal Waghmare's system captures farm images using mobile cameras and compares various techniques like fuzzy logic, SVM, and BPN for processing. His model employs Support Vector Machine (SVM) for classification, converting images to HSV from RGB for better color analysis. Background subtraction is used to eliminate unnecessary details, achieving an average accuracy of 89.3%. BPN, or Back-propagation Neural Network, enhances training by calculating the gradient of a loss function relative to weights. This comprehensive approach supports accurate disease identification directly from farm images.

"Deep Learning-Based Detection and Diagnosis of Plant Diseases" by Mohanty et al. (2016) presents a deep learning framework utilizing CNNs and transfer learning for high-accuracy disease identification using a large leaf image dataset. "Deep Plant Phenomics: A Deep Learning Platform for Complex Plant Phenotyping Tasks" by Ubbens and Stavness (2017) introduces a platform combining CNNs with image segmentation for detailed plant phenotyping, including disease detection. Holman et al. (2016) explore CNN-based weed detection in crops, which aligns with plant disease recognition tasks. "Deep Learning-Based Grapevine Pruning Cane Detection" by Minervini et al. (2017) applies CNNs and image segmentation for grapevine cane detection, highlighting deep learning's versatility in plant-related tasks.

III. PROPOSED METHODOLOGY

This part of the study gives an overview of the methodology that is used in this study. The methodologies contain 4 important stages. In the first stage, the data are collected, in the second stage a required model is developed, in the third stage the data is trained and in the final stage we do the testing of the model. Further we also use some machine learning algorithms to compare the results. In addition to the methodology, a concise description of the various tools and libraries that are used in the research will be explained. The technologies and tools made used for the major process is discussed in that section. The complete process for developing a model for the classification and recognition of healthy and bacterial plant leaves by using the deep Neural Network (DNN) is explained in detail. The entire procedure is classified into many required stages in the below sections, starting from collecting the pictures for sorting the procedure with the use of this DNN network.

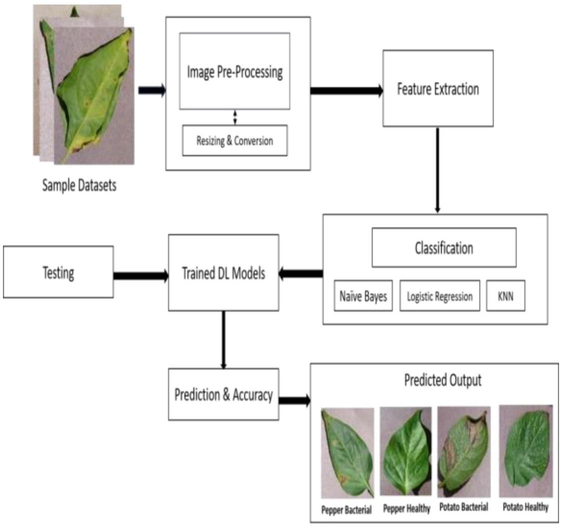

Figure 3.1: Block Diagram

A. Experimental Dataset:

Collected samples are input to the model under the different angles, which becomes the reference for development of proposed system. Kaggle allows users to collaborate with other users, find and publish datasets, so in the proposed system we have considered Kaggle and internet sources website to collect images of pepper and potato leaves which are healthy and infected.

Figure 3.2: (a) Infected Pepper Plant leaves (b) Healthy Pepper Plant Leaves

Figure 3.3: (a) Infected Potato Plant leaves (b) Healthy Potato Plant Leaves

B. Pre-processing Techniques

Before being used for model training and inference, pictures must first undergo image pre-processing. This includes, but is not limited to, adjustments to the size, orientation, and color. The purpose of pre-processing is to raise the image's quality so that we can analyse it more effectively. Pre-processing allows us to eliminate unwanted distortions and improve specific qualities that are essential for the application we are working on. Those characteristics could change depending on the application. An image must be pre-processed in order for software to function correctly and produce the desired results.

C. Feature Extraction

Feature extraction is an important subset of feature engineering that data scientists utilize when raw data is not immediately suitable for analysis. In cases where raw data is unusable, feature extraction becomes essential as it transforms this data into meaningful numerical features compatible with machine learning algorithms. For instance, when working with raw data in the form of image files, data scientists may extract specific characteristics, like the shape of an object, texture, or even the redness value in images, to create new and relevant features. These features are then used as inputs in machine learning applications, enhancing the algorithm’s ability to recognize patterns and make accurate predictions. Through feature extraction, complex data is converted into a structured format, allowing machine learning models to process and analyze it more effectively.

D. Training & Classification

DNN stands for Deep neural network or also known as DeeoNet, is generally used to analyze the visual images and is a type of class in deep neural networks. It is a regularized version of fully connected layers called as multilayer perceptron which basically means that every single neuron on a layer is connected to all the other neurons in the next available layer. The architecture of the DNN consists of input layers, hidden layers and an output layer. Hidden layers are basically all the middle layers possible between the output layer and the input layer because the activation function and the final convolution masks their inputs and outputs. It includes convolution layers followed by pooling, normalization, and fully connected layers. The convolutional layer has the task to extract the set of features, maps for classification. A filter is composed of weight and various filters are used for feature extraction purpose.

To increase the non-linearity to the network, an activation function is included on the top of the convolutional layer. We have used ReLU, known as rectified linear unit as its generally used in image processing because it is quicker than the other functions.

E. Deep Learning

Deep learning has evolved together with the digital era, which has brought about an explosion of data in all forms and from every region of the world. This data, known simply as big data, is drawn from sources like social media, internet search engines, e-commerce platforms, and online cinemas, among others. This enormous amount of data is readily accessible and can be shared through fintech applications like cloud computing. However, the data, which normally is unstructured, is so vast that it could take decades for humans to comprehend it and extract relevant information. Companies realize the incredible potential that can result from unravelling this wealth of information and are increasingly adapting to AI systems for automated support. Deep learning models are designed to extract patterns from input data to make predictions on new unseen data. These models learn and improve on their own. Deep learning models are designed keeping in mind the functional design of the human brain.

In the human brain there are pattern recognition modules (consisting of a group of neurons, roughly 50 to 100 in size) that are responsible for recognizing individual patterns. There is a hierarchy in the arrangement of these modules. The modules in the lower levels of this hierarchy recognize the basic patterns for example in case of reading, these modules recognize individual letters, The module responsible for the letter A, fires when it sees an A, as we move up the hierarchy, modules can start recognizing and making sense of words and sentences, and in even higher levels, modules can make sense of the sarcasm and metaphors in a sentence.

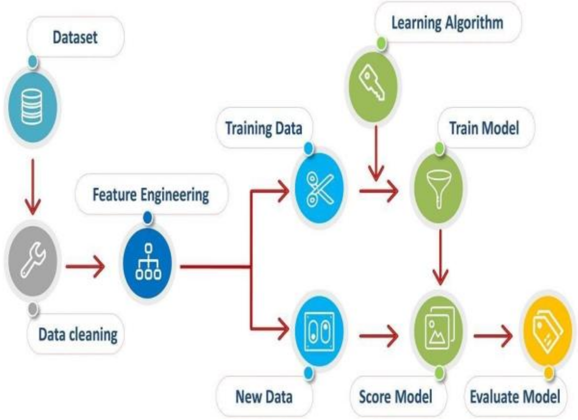

Figure 3.4. Block Diagram of proposed system

IV. RESULTS AND DISCUSSIONS

A. Graphical User Interface

There are various options available in Python for creating a Graphical User Interface (GUI). However, we are using tkinter in our proposed concept because it is a standard Python interface to the Tk GUI toolkit that comes bundled with Python. With tkinter, Python provides a simple and efficient way to develop GUI applications. Using tkinter, creating a GUI is a straightforward process that can be accomplished quickly.

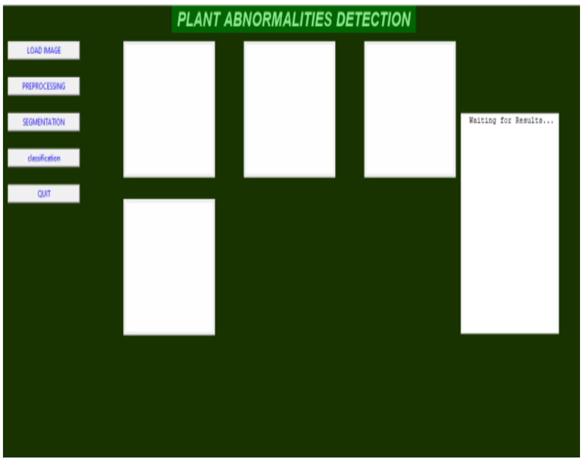

Fig. 4.1. GUI for Proposed System

B. Training

Fig. 4.2. Training Process

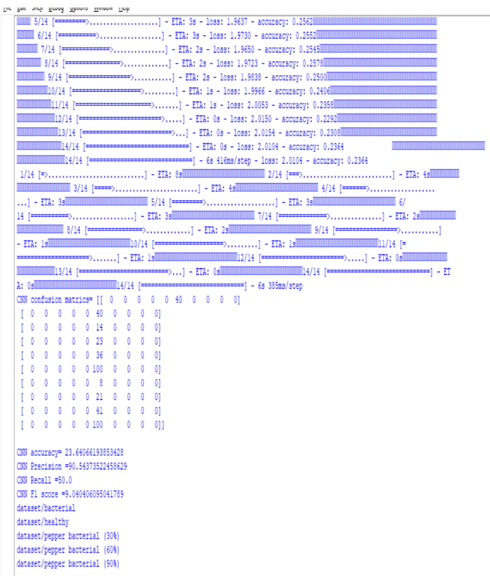

Fig. 4.3. Trained Accuracy Levels

A. Testing

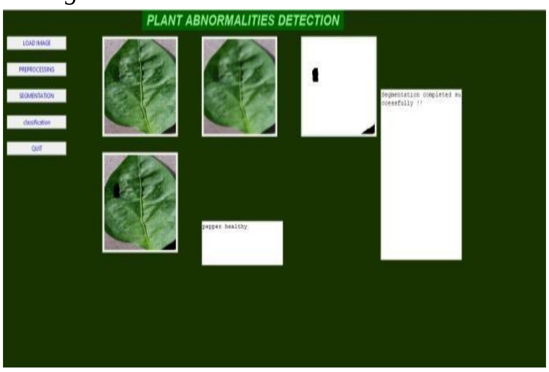

Fig. 4.4. Tested Plant Leaf

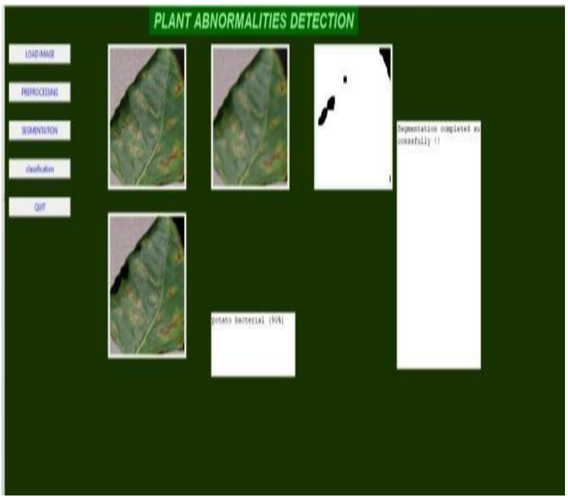

Fig. 4.5. Tested Plant Leaf

Table 1. Accuracy of Tested Plant Leaf

No.	Epoch Value	CNN Accuracy	DNN Accuracy
1	20	51.3%	88.3%
2	30	62.6%	89.7%
3	50	68.3%	91.2%
4	70	76.5%	92.3%

V. CONCLUSION

The DNN model proposed in this study has demonstrated superior accuracy compared to other machine learning models. It outperformed previous deep learning and machine learning models, providing more precise classification results for leaf samples. Additionally, the model has been trained to identify the degree of infection in pepper and potato plants at an early stage, enabling prompt action to be taken.

In the future, a more efficient path for visually analyzing the health and bacterial level plants should be introduced since it will only help the users to save costs by only using the chemical products and fertilizers. Thus, it should be merged along with beneficial Deep Learning architectures which would assist in identifying the plant infection before the symptoms are visually observed. Furthermore, real time detection can be applied using these techniques. Cameras can be placed on different angles over the field and will monitor the leaves on regular intervals. This might lead to efficient farming as it will save time and will keep the crops healthy as it is being monitored on regular intervals. This will lead to producing a Deep Learning architecture/model which would be highly effective for deeper insights and analysis of the subject.

ACKNOWLEDGMENT

We extend our heartfelt gratitude to our mentors and colleagues for their invaluable support and guidance throughout this work. We also appreciate the resources provided by the research community that facilitated our work. Finally, we thank our families and friends for their unwavering encouragement during this journey.

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