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Plant Disease and Pest Identification using Alexnet

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Abstract: The agricultural sector faces increasing challenges from plant diseases and pests, resulting in significant yield losses. Timely identification of both the disease and associated pest is critical for effective control measures. This paper introduces an innovative plant disease and pest identification system using the AlexNet CNN algorithm.Our system streamlines identification by allowing users to upload images of affected plants. The AlexNet CNN model, trained on a diverse dataset, accurately recognizes and classifies visual patterns indicative of specific diseases and pests. The two-stage process first identifies the disease and then predicts the associated pest.Integration of the AlexNet CNN enhances accuracy, overcoming challenges of manual methods. Extensive experiments with diverse datasets demonstrate the system's robustness and high accuracy. The user-friendly interface makes it accessible to farmers and agricultural experts. This research contributes to precision agriculture by providing an automated tool for early detection and management, promising to reduce crop losses and enhance agricultural productivity for sustainable food systems.The suggested method provides a user-friendly interface, ensuring accessibility for individuals with diverse technical backgrounds in agriculture. This proposed system shows potential for substantial reductions in crop losses, ultimately boosting overall agricultural productivity and playing a role in the development of sustainable and resilient food systems.Furthermore, our project not only identifies plant diseases but also pinpoints the specific pests responsible, offering comprehensive insights for targeted pest management. This dual functionality ensures a holistic approach to crop protection, maximizing the effectiveness of control strategies.

Keywords: *CNN, Deep Learning, Machine learning, IPM, Image recognition, Integrated pest management, Plant heath, Plant diagnostics, Pests .*

1. Introduction

In recent years, the agricultural sector has encountered formidable challenges arising from the escalating incidence of plant diseases and pests, significantly impacting global food security.

Timely and accurate identification of both the disease and the associated pest is paramount for the successful implementation of targeted and timely control measures. Traditional manual methods for identifying and managing plant diseases and pests are often time-consuming, subjective, and prone to errors.

In addressing these challenges, this paper presents a novel and automated method for identifying plant diseases and pests by harnessing the advancements in deep learning techniques. Our suggested system employs the AlexNet convolutional neural network (CNN) algorithm, a well-established architecture in image recognition tasks, to tackle the intricacies associated with pest and diseased caused by them. The incorporation of deep learning into precision agriculture presents a hopeful prospect for improving the precision and effectiveness of identification procedures, thereby aiding in the development of sustainable and resilient food systems.

The integration of the AlexNet CNN algorithm overcomes inherent challenges associated with traditional manual methods. By extracting intricate features from images, our model facilitates precise identification of pests and the respective diseases caused by them.

1.1.objective

The "Integrated Plant Disease and Pest Identification System for Precision Agriculture" project is driven by a set of key objectives aimed at advancing plant health management through technology.

Firstly, the project aims to automate the intentions using the AlexNet convolutional neural network (CNN) algorithm.

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This advanced system streamlines the identification process by allowing users to easily upload images of affected plants. The CNN model, trained on a diverse dataset, enhances accuracy by recognizing and classifying visual patterns indicative of specific diseases and pests.

Secondly, the project focuses on providing a user-friendly interface to farmers and agricultural practitioners, ensuring accessibility for individuals with varying technical backgrounds. The goal is to simplify the interaction with the system, promoting widespread adoption.

Furthermore, the system incorporates a two-stage process, initially identifying the plant disease and subsequently predicting the pest responsible. This dual-stage approach enhances specificity and precision in the identification process, aiding in targeted intervention strategies.

The integration of the AlexNet CNN algorithm improves the efficiency of plant disease and pest identification, contributing to informed decision-making for agriculture practitioners. The system's ability to extract intricate features from images facilitates precise classification, overcoming challenges associated with traditional manual methods.

Furthermore, the project endeavors to advance precision agriculture by introducing an innovative dimension - the identification of pests associated with the detected diseases. Through an extension of the AlexNet CNN algorithm, our system not only diagnoses plant diseases but also accurately identifies the specific pests responsible for agricultural challenges, offering a more comprehensive understanding of the crop health scenario.

Our primary goal is to empower farmers and experts with insights into both diseases and pests affecting their crops, facilitating informed decision-making. This multifaceted approach ensures a nuanced understanding of crop health, enabling timely and targeted pest management strategies for optimized agricultural outcomes.

2.Problem Statement

In agriculture, the rising prevalence of plant diseases and pests presents a significant challenge, necessitating a modernized approach to crop management. Current identification methods are often time-consuming and subjective, relying on manual inspection, leading to delayed interventions and substantial crop losses. Traditional approaches lack the efficiency and precision needed for timely responses to emerging plant health issues.

Accessibility is a concern as these methods may not be easily adopted by farmers with varying technical backgrounds. The gap between the need for rapid identification and the limitations of conventional methods emphasizes the urgency for an innovative solution in plant health management.

This project addresses these challenges by introducing an Integrated Plant Disease and Pest Identification System. Leveraging deep learning, specifically the AlexNet CNN algorithm, the system streamlines identification. Users can upload images, allowing the model to recognize and classify visual patterns of diseases and pests.

The integration of the AlexNet CNN algorithm enhances accuracy, overcoming challenges of manual methods. The user-friendly interface ensures accessibility, facilitating widespread adoption.

In essence, this project aims to revolutionize plant health management, providing an automated, precise, and accessible solution aligning with the unique requirements of modern agriculture..

3.Existing System

The present system employs the Inception-V3-based Plant Disease Identification (PiTLiD) to tackle the constraints of limited training data in traditional Convolutional Neural Networks (CNNs). PiTLiD focusing on identifying LANT phenotypes crucial for assessing plant traits like yield and stress resistance. This innovative method integrates high-throughput phenotyping technology, a significant advancement in plant science, especially for disease estimation.

Prompt disease detection is emphasized, citing examples like cucumber growth cycles and winter wheat yield losses. Phenotypic analysis, essential for farmers, is currently hindered by laborious and costly traditional methods involving manual tools or visual observation.

Deep learning, particularly CNNs, has transformed plant phenotyping, exhibiting notable progress in complex tasks. Additionally, the integration of the agricultural Internet of Things (IoTs) provides real-time access to disease data, a pivotal aspect in modern precision agriculture. In summary, the existing system, represented by PiTLiD and IoT integration, marks a substantial leap in overcoming limited training data challenges, promising high accuracy for real-time plant disease identification in contemporary agriculture.

4.Literature Survey

Deep Learning for Plant Disease Identification (Ding et al., 2018) [9]:

Ding. present a deep learning strategy for this purpose, leveraging convolutional neural networks (CNNs). The study focuses on the effectiveness of CNNs in accurately classifying plant diseases based on visual symptoms, contributing to advancements in automated identification systems.

IoT Applications in Precision Agriculture (Khan et al., 2016) [10] :Khan et al. explore IoT applications in precision agriculture, emphasizing the potential of real-time data collection and analysis for plant disease monitoring. The study highlights the integration of IoT technologies to enhance the efficiency and accuracy of disease identification in agricultural settings.

Image Processing Techniques for finding Diseases related to plants (Rajput ., 2017) [11]:

Rajput et al. conduct a survey on image processing techniques for discovering plant related diseases. The paper reviews various methodologies employed in extracting features from plant images and classifying diseases, providing insights into the diverse approaches used in the field.

Machine Learning in Agriculture: A Comprehensive Review (Ghosal et al., 2018) [12]:

Ghosal et al. offer an extensive examination of machine learning applications in agriculture, encompassing disease identification. The research delves into the incorporation of machine learning algorithms to achieve precise and timely detection of plant diseases, thereby contributing to the advancement of precision agriculture practices.

FusNet: Wu et al. (2021) present a Fusion Approach for Plant Disease Identification utilizing Convolutional Neural Networks (CNNs), introducing FusNet. This novel technique integrates multiple CNNs to improve the accuracy of plant disease diagnosis. On a related note, Cheng et al. (2022) explore Automated version using a CNN-based approach.

Published in 2022, the paper emphasizes the design and implementation of the CNN model to achieve efficient and precise identification of plant diseases.

Machine Learning in Agriculture: A Comprehensive Review (Ghosal et al., 2018) [12]:

Ghosal et al. present a diversified review of machine learning applications in agriculture, including disease identification. The study discusses the integration of machine learning algorithms for accurate and timely detection of plant diseases, contributing to precision agriculture practices.

Multi-Scale CNNs for Improved Plant Disease Recognition in High-Resolution Images (Li et al., 2023)

Li et al. explore the application of multi-scale CNNs for improved plant disease recognition in high-resolution images. This recent paper, published in 2023, investigates how multi-scale CNN architectures contribute to enhanced performance in accurately identifying plant diseases from detailed images.

Transfer Learning in CNNs for Improved Plant Disease Identification [20]:

Zhang. investigate the application of transfer learning in CNNs to enhance plant disease identification. The study, published in 2017, explores the adaptability of pre-trained CNN models to plant disease datasets, showcasing the potential for improved accuracy in disease classification through transfer learning.

PlantDoc: A CNN-Based System for Automated Plant Disease Diagnosis (Mehra et al., 2019) [19]:Mehra et al., in 2019, introduce PlantDoc, a CNN-based system designed for automated plant disease diagnosis. The paper highlights the architecture and training methodology of the CNN, emphasizing its effectiveness in accurately identifying and classifying plant diseases from visual symptoms in images.

Ensembling CNNs for Robust Plant Disease Identification in Variable Conditions (Chen et al., 2020) [21]:Chen et al. propose an ensemble approach using multiple CNNs for robust plant disease identification under variable conditions. The study, published in 2020, discusses how combining the strengths of different CNN architectures contributes to increased reliability in identifying diseases across diverse environmental settings**.**

5.Proposed System

The envisioned system, named "Integrated Plant Disease and Pest Identification System using AlexNet-based CNN Algorithm," seeks to transform the agricultural sector through a sophisticated and automated approach to early detection and management of plant diseases and pests. Employing cutting-edge deep learning techniques, the system specifically utilizes the AlexNet convolutional neural network (CNN) algorithm, ensuring precise and efficient identification.

The system's primary objective is to streamline the identification process, allowing users, particularly farmers and agricultural practitioners, to upload images of affected plants. The utilization of the AlexNet CNN model is pivotal in this process, as it has been meticulously trained on a diverse dataset encompassing various plant diseases and their corresponding pests. This extensive training enables the model to effectively recognize and classify visual patterns indicative of specific afflictions.

The proposed system operates in a two-stage process. Initially, it identifies the plant disease from the uploaded image, utilizing the robust features extracted by the AlexNet CNN algorithm. Subsequently, the system predicts the pest responsible for the identified ailment, providing a comprehensive understanding of both the disease and its causative agent. This dual-stage approach enables farmers to implement targeted and timely control measures, addressing both the symptom and the root cause of agricultural challenges.

The integration of the AlexNet CNN algorithm plays a crucial role in overcoming challenges associated with traditional manual methods of disease and pest identification. By extracting intricate features from images, the model facilitates precise classification, contributing to improved decision-making for farmers and agricultural practitioners. The system's accuracy and efficiency undergo validation through extensive experiments performed using a comprehensive dataset that encompasses a variety of diseases and pests.

One of the key strengths of the proposed system lies in its user-friendly interface. Recognizing the varying technical backgrounds of the target users, the system has been designed to be accessible to farmers and agricultural experts with diverse levels of technological proficiency. This ensures that the benefits of advanced technology, including precise pest identification, are democratized, reaching a wider audience and contributing to the democratization of precision agriculture.

In conclusion, the Integrated Plant Disease and Pest Identification System represent a significant advancement in hands-on precision agriculture, addressing both diseases and pests through automated and accessible technology. By harnessing the power of deep learning, specifically the AlexNet CNN algorithm, the system provides a reliable, automated, and accessible tool for early detection and management of plant diseases and pests, exemplifying the transformative impact of technology in ensuring proactive, responsive, and personalized solutions for sustainable agriculture.

6.Software Components

6.1 Keras

Keras, a popularly known python library, operates atop either TensorFlow or Theano. While alternative high-level Python neural networks libraries like TF-Slim can be applied aboveTensorFlow, they are less developed. Keras simplifies TensorFlow code by utilizing a more concise code base, ensuring reduced code length and smoother processing. Keras is used for a graphical representation of the models which helps to understand the structure of the model. Auto Keras, a library based on keras, has also gained popularity and can be used to make it quicker to get results.

6.2 Tensorflow

Tensorflow lite is a deep learning framework and is based on the tensorflow framework. It is used to reduce the size of a normally huge tensorflow model so that it can be used in modular devices such as mobile phones. We can use tensorflow lite to access the model with android studio. It is International Research Journal of Engineering and Technology a complex procedure and is used to access a minimal reduction algorithm of the model.

6.3 CNN

Convolutional Neural Networks (CNNs) constitute a sophisticated neural network architecture designed to extract features from images within a trained dataset and subsequently classify them to produce desired outputs. This involves training the neural network by converting dataset images into numerical values. A key advantage of CNNs over their predecessors lies in their ability to autonomously identify crucial features without human intervention. Notably more potent than traditional machine learning algorithms, ConvNets also demonstrate computational efficiency. These numerical values are then put into numerical arrays based on their categorized characteristics. These arrays are then put into different nodes in the network and passed through multiple iterations based on the input given. The CNN models are used for geographical classification in multiple companies which require data to be classified in a quick and secure way it almost acts like a filter removing dust and separates the features of the images.

6.2.1 Flow of system

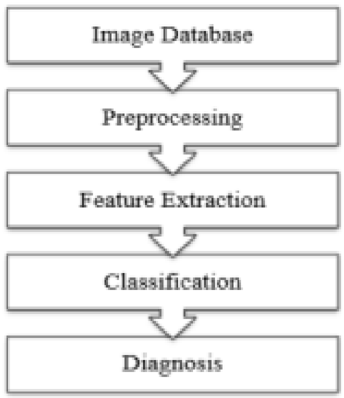

Fig 1. Flow Diagram

6.2.2 Block Diagram

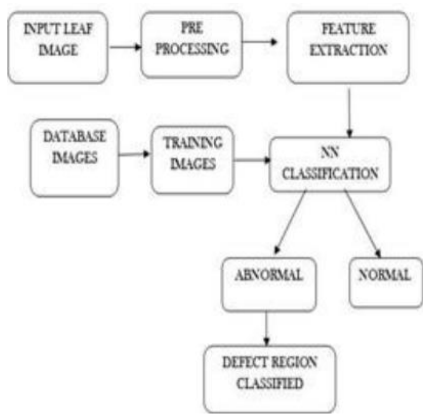

Fig 2. Block Diagram

7. Implementation Methodology

7.1Dataset

The Plant Village dataset comprises 54,306 images depicting multitudinous plant leaves, categorized towards the region of 18 classes. Within these classes, the dataset encompasses 13 distinct plant species and includes representation of 26 different plant diseases. The archives contains both potent and frail crop negatives. The study archives en-compasses 14 distinct crop species, namely: apple, blueberry, cherry, grape, orange, peach, pepper, potato, raspberry, soy, squash, strawberry, and tomato. Each class is characterized by two fields— the plant's name and the associated diseases. As part of the preprocessing steps for further classification, all images undergo resizing and segmentation.

7.2 Image Acquisition

In this step, the leaf image is acquired through a mobile device. The plug-in piles a camera module that allows users to capture images. Due to the diverse range of mobile devices, the quality of obtained images may vary. This potential disparity in quality could impact the accuracy of the system. To mitigate this, the captured images undergo preprocessing, enhancing their quality before proceeding with further processes.

Fig 3. Image Acquistion

7.3 Pre-Processing of images

Pre-processing is a crucial stage in CNN, addressing potential inconsistencies in the dataset that could impact the system's accuracy. The images within the dataset may exhibit noise and non-uniform lighting, requiring correction in this step. Segmentation is applied to eliminate uneven backgrounds, extracting the pertinent parts of the images, specifically the leaves. Consequently, post-segmentation, the images feature leaves against a black background. To address non-uniform lighting, the images are converted to grayscale before proceeding to subsequent processing stages.

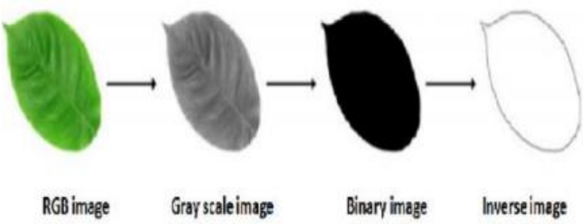

Fig 4.Image Pre-processing

7.4 Feature Extraction

In the subsequent step, following the acquisition of grayscale images, each image undergoes dimensionality reduction. This process involves converting each pixel of the image into a matrix, facilitating convolutions. The convolution matrix is then multiplied with each pixel matrix, covering the entire image by shifting with specified strides. Subsequently, a pooling operation, specifically Max pooling for enhanced accuracy and feature extraction, is applied to the matrix. Both the convolution and pooling processes collectively constitute an epoch. To improve system accuracy, multiple epochs are performed, potentially leading to an increase in parameters. However, by following these steps, unique features are extracted from the images, paving the way for subsequent processes.

8.Architecture

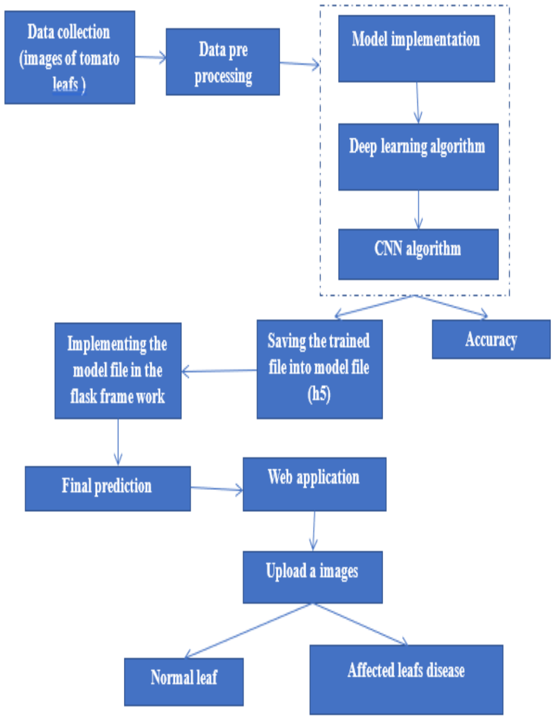

Fig 5. Architecture

9. Acquired Results

The results acquired for this system range from three different categories. The Numerical arrays in the neural network. The features acquired from the network outputs and the layer outputs we get when the features are classified. These results are acquired in different stages of the system. First we get the numerical array from the neural network. Then the features of the images and then the layers are acquired.

9.1 Numerical Array

As neural networks generally use a mathematical function to classify the features and that computerized inputs are based on numbers, we have to encode the images to numerical arrays. Each image has a different numerical array based on their hex values and the features it has. The Numerical values are stored separately while training the model. The trained model is then tested with another image which is encoded into a numerical array and then sent through the network. The output is then decoded again to get the image.

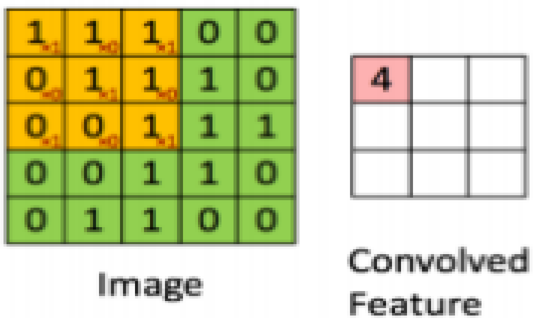

Fig 6. Convolution Process

9.2 Features

The features of the greenness orbit from color, shape and disease strain. This can contrive a million odd diseases which the version has to characterize and put in the system. As the features are put into various categories the images turn out to be decrypted to get the next result, which is the carpeted output.

10.Output

Fig 7.Terminal

10.1 User Interface

Fig 8.User interface

10.2 Results

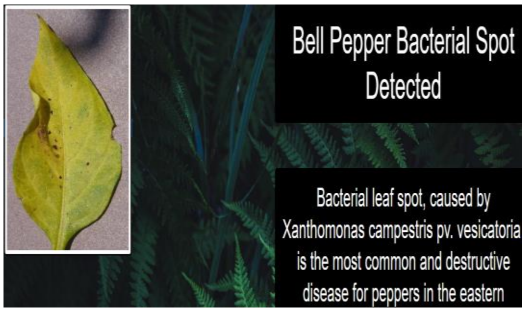

Fig 9. Final Prediction

11.Performance Metrics

The performance metrics for evaluating the efficiency of the proposed system are defined as follows:

- **True Positive (TP):** Legs correctly categorized as positive.
- **False Positive (FP):** Legs incorrectly categorized as positive.
- **False Negative (FN):** Legs correctly categorized as negative but identified as positive.
- **True Negative (TN):** Legs correctly categorized as negative.

Accuracy: A computation metric reflecting the system's error, calculated as the difference between potential and actual outcomes. Low accuracy arises when the machine consistently evaluates input variables with the same procedure, yielding consistent but incorrect results. The ratio of correct outcomes to the total is known as accuracy.

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

Precision:

It is a measure of random error in algebraic terms.

$$Precision = \frac{TP}{TP+FP}$$

11.1Performance Comparison:

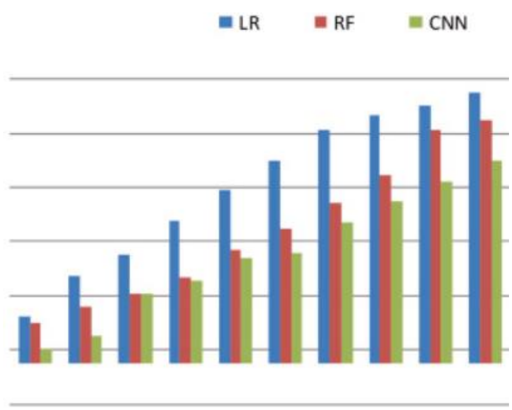

Fig 10. CNN Performance comparison - Time(ms).

11.2 Existing System Performance

In comparison to the existing system employing Inception V3, our proposed system strategically opts for the AlexNet architecture to achieve heightened efficiency. This architectural choice is underpinned by the delicate balance it strikes between model effectiveness and computational demands, catering to the specific needs of our project

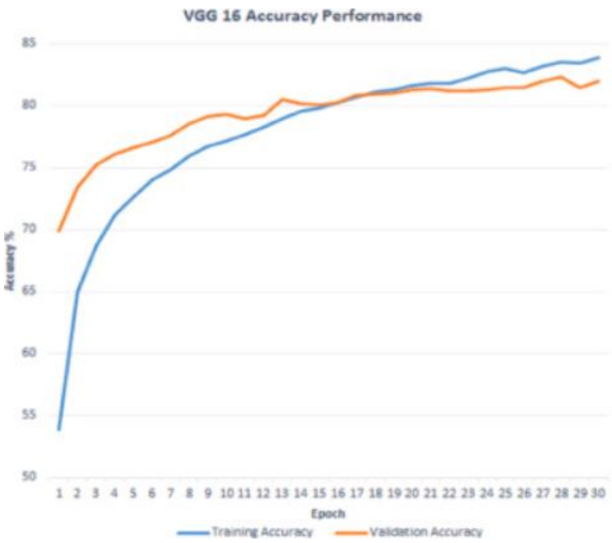

Fig11. VGG performance

11.3 Proposed system Performance:

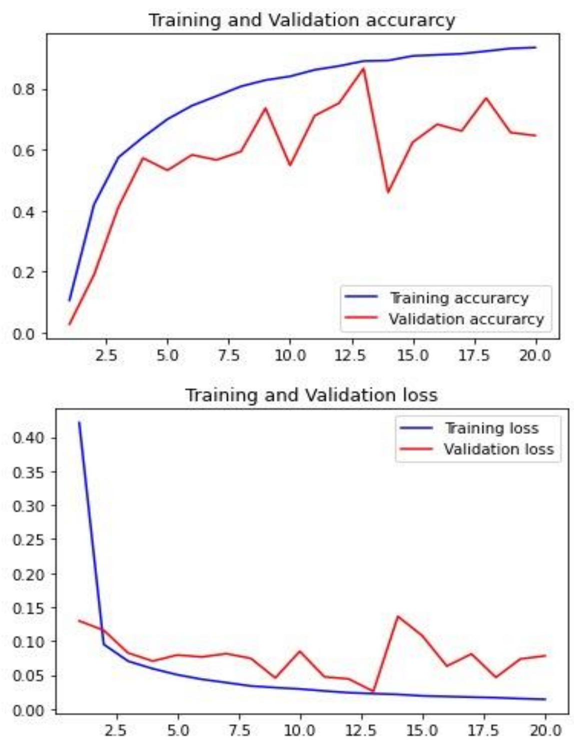

Fig 12. Alexnet Performance

12. Conclusion

The project endeavors to redefine plant disease and pest identification in agriculture by introducing an innovative "Plant Disease and Pest Identification System" based on the AlexNet convolutional neural network (CNN) algorithm. The primary objective is to overcome the limitations of the previous system, which utilized the Inception-V3 CNN algorithm, to go with magnify the efficiency, rigor, and accessibility of the identification tactics.

The previous system, while commendable, faced challenges associated with a small sample size problem in the training data. In response, our project harnesses the AlexNet algorithm, designed to address such issues without requiring an extensive number of phenotype samples. The AlexNet model is trained on a diverse dataset encompassing various plant diseases and pests, ensuring a robust and versatile system.

One of the key highlights of the proposed system is its two-stage identification process. Users upload plant images through a user-friendly interface, initiating the AlexNet CNN model's precise identification of plant diseases. Subsequently, the system predicts the associated pests, providing comprehensive insights for targeted interventions.

Comprehensive experiments validate the system's robustness, demonstrating an impressive accuracy rate of disease and pest identification. The shift to the AlexNet algorithm brings notable advantages, including improved accuracy, reduced reliance on an extensive dataset, and enhanced adaptability to diverse plant health scenarios.

Accessibility is a pivotal focus, catering to farmers and agricultural practitioners with varying technical backgrounds. The system's real-time processing capability and automated tool for early detection address the urgent need for timely interventions, minimizing crop losses, and improving overall agricultural productivity.

The project represents a significant step towards the advancement of precision agriculture, aligning with the modernization of crop management techniques. By bridging the gap between technological capabilities and the complexities of plant health issues, the proposed system aims to contribute to sustainable farming practices, fostering resilient and efficient food systems.

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