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SMART LEAF INFECTION IDENTIFICATION AND FERTILIZER SUGGESTION

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Abstract: The agricultural sector serves as the backbone of a country's innovative growth, providing sustenance and raw materials essential for development. Agriculture is not only vital for human sustenance but also for the provision of resources. Consequently, the detection of leaf diseases has emerged as a critical concern. While traditional methods for identifying leaf diseases exist, they often rely on manual inspection by agriculture professionals or leaf pathologists. This conventional approach is subjective, time-consuming, expensive, and demands extensive expertise and data on leaf diseases.
In recent years, advancements in technology have facilitated the use of machine learning and deep learning for leaf disease detection. This study focuses on implementing a Plant Leaf Disease Detection and Classification Network (PDDC-Net) using deep learning models. Pre-processing techniques are applied to eliminate various types of noise and standardize the dataset images. The PDDC-Net utilizes a residual network-based convolutional neural network (ResNet-CNN) for feature extraction and classification. Additionally, the model suggests appropriate pesticides for corresponding plant leaf diseases.
Experimental results demonstrate that the proposed PDDC-Net model achieves high accuracy rates in leaf disease detection and classification, marking a significant advancement in agricultural technology.

***Index Terms* -** ResNet-CNN, PDDC-Net, Support Vector Machine Algorithm.

I. INTRODUCTION

Leaf diseases and pests play crucial roles in determining both the yield and quality of foliage. Digital image processing offers a viable means for their identification. Recent advancements in deep learning have revolutionized this field, surpassing traditional methodologies significantly. This review delves into the essence of leaf disease and pest detection, juxtaposing it against conventional methods. It delineates recent developments in deep learning-based approaches for leaf disease and pest detection, categorizing them into classification, detection, and segmentation networks, while assessing the merits and demerits of each method.

Across the globe, mobile applications integrated with deep learning models aid farmers in detecting and categorizing diseases. These applications leverage various techniques such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to diagnose leaf diseases, leveraging image features for detection and diagnosis. Noteworthy pre-trained models like AlexNet, GoogLeNet, LeNet, ResNet, VGGNet, and Inception, boasting substantial learnable parameters, have demonstrated proficiency in classifying or detecting leaf diseases.

The timely identification of early-stage leaf diseases is paramount, given its potential to detrimentally impact both crop quality and quantity in agriculture. Various approaches, including image processing, machine learning, artificial neural networks, and deep learning, are employed for leaf disease identification. This review offers a comprehensive examination of emerging deep learning-based methodologies, commencing from machine learning techniques. It elucidates the crop diseases under scrutiny, the utilized models, the data sources, and the overall performance based on distinct performance metrics employed across different studies for leaf disease identification.

Review findings demonstrate that Deep Learning surpasses commonly used disease identification techniques in terms of accuracy, with significant improvements. This paper endeavors to catalogue various approaches aimed at enhancing performance accuracy and reducing response time in leaf disease identification. The authors also detail efforts towards disease diagnosis in Indian conditions using real datasets.

Image processing algorithms have been devised to detect leaf infections or diseases by analyzing color features of leaf areas. The K-means algorithm is employed for color segmentation, while GLCM (Gray-Level Co-occurrence Matrix) is utilized for disease classification. Vision-based leaf infection detection has exhibited efficient results and promising performance.

Machine Learning (ML) enables machines to interact with humans, understand their requirements, and make decisions on their behalf, mirroring human-like behavior. ML has experienced rapid growth in recent years, aiding in the classification of leaf diseases and contributing to increased productivity in cultivation. Visualization techniques have also advanced in ML technology over the past three years. The challenges posed by leaf diseases in today's world are addressed through ML advancements.

Leaf images possess three primary features: color, shape, and texture. While color and texture features are useful for identifying leaf diseases, shape features alone may not suffice. For instance, Hlaing and Zaw classified tomato leaf diseases by combining texture and color features. They utilized the Scale Invariant Feature Transform (SIFT) to extract texture information, including details about shape, location, and scale, while RGB channels provided color information.

Automatic detection techniques have the potential to elevate food production quality and mitigate economic losses. In recent years, deep learning has significantly advanced the accuracy of image classification and object detection systems. Consequently, the primary objectives are as follows:

1. Designing a system capable of accurately detecting crop diseases and pests.
2. Establishing a database of insecticides tailored to specific pests and diseases.
3. Providing remedies for detected diseases.

The aim of leaf disease management is to mitigate the economic and aesthetic harm caused by leaf diseases. Traditionally termed as leaf disease control, contemporary societal and environmental perspectives consider "control" too rigid and absolute.

II. LITERATURE SURVEY

Mustafa Ahmed Jalal AI-Sammarraie and Noor Ahmed Jasim [1] explored the efficiency of a Smart Spraying Robot for Crop Protection utilizing Image Processing Technology. Their microcontroller-based robot integrates a digital camera compatible with the Arduino Uno and a transceiver module. Due to its affordability and user-friendliness, the Arduino Uno is commonly employed in small-scale robotics and artificial intelligence projects. Capable of receiving 50 images per second (equivalent to 1 image every 20 milliseconds), the robot can interface with a computer via USB.

D. A. Shaikh, Ghorale Akshay G, Chaudhari Prashant A, and Kale Parmeshwar L[2] introduced an Intelligent Autonomous Farming Robot with Plant Disease Detection using Image Processing. This robot aids in early-stage identification of plant diseases and facilitates crop management, disease identification, and pesticide application. Through this system, they effectively monitor extensive crop fields, leveraging the speed and accuracy of image processing for disease detection and pesticide application tailored to the needs of the crops.

Ramya R, Kiran M, Marimuthu E, Naveen Kumar B, and Pavithra G[3] proposed a system for Plant Monitoring and Leaf Disease Detection with Classification using Machine Learning in MATLAB. They employ edge detection via genetic algorithms to achieve effective results. Their system focuses on three objectives: monitoring, detection, and service quality improvement. By reducing farmers' efforts and enhancing farm productivity, this application proves invaluable. Image processing serves as a method to digitize images and perform various operations on them.

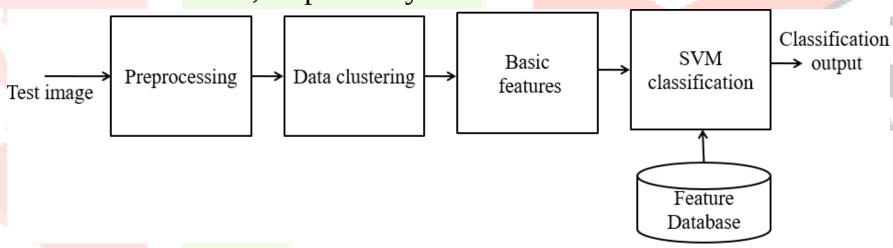
Neethu K. S and P. Vijay Ganesh[4] introduced a system for Leaf Disease Detection and Fertilizer Selection using Artificial Neural Networks. Leaf diseases significantly impact both the quality and quantity of food crops. Their system leverages 7,520 cucumber leaf images, including healthy leaves and those infected by various viral diseases, to establish an automated approach for grading leaf defects. This practical plant disease detection system promises significant benefits for agricultural practices.

III. PROBLEM STATEMENT

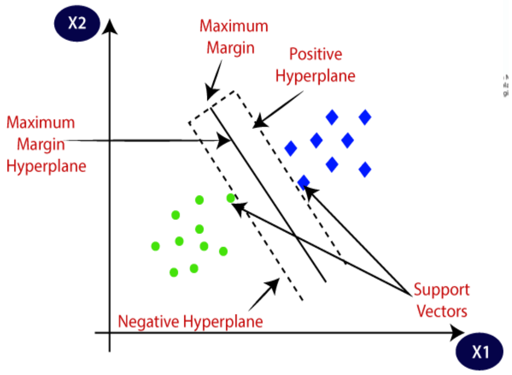
Crop diseases are a major problem for farmers and can significantly impact the yield and quality of crops. Traditional methods for disease identification and pesticide suggestion involve manual observation and analysis, which can be time-consuming and prone to errors. The proposed solution aims to automate the process by using a CNN-based model that can accurately identify crop diseases from images of the affected leafs. The model will be trained on a dataset of images of healthy and diseased crops, and will be able to classify the images into various categories of diseases. Once the disease is identified, the model will suggestappropriate pesticides that can be used to treat the disease. The key challenges in developing such a system are to obtain a large and diverse dataset of crop disease images, to design an accurate CNN architecture that can classify the images with high accuracy, and to suggest appropriate pesticides based on the identified disease. Additionally, it is important to ensure that the suggested pesticides are safe and effective for use in agriculture, and to take into account the potential environmental and health impacts of their use.
So, the development of an accurate recognition model for crop diseases using a CNN significantly improve the efficiency and accuracy of crop disease management, ultimately leading to higher crop yields and improved food security.

IV. Existing Environment

Fig. shows the block diagram of existing system. All the images are trained using the SVM network model with basic features, statistical and texture features. And random unknown test sample is applied to the system for detection and classification, respectively.



Support Vector Machine (SVM) stands as one of the most renowned Supervised Learning algorithms, catering to both Classification and Regression tasks. Nonetheless, its primary application lies in Classification problems within Machine Learning. The fundamental objective of the SVM algorithm is to craft the optimal line or decision boundary capable of partitioning n-dimensional space into distinct classes, thus facilitating the accurate categorization of new data points in the future. This optimal decision boundary is referred to as a hyper plane.
SVM chooses the extreme points/vectors that help in creating the hyper plane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyper plane.



SVM can be illustrated using a scenario akin to that of the KNN classifier. Let's imagine encountering a peculiar creature that exhibits characteristics of both cats and dogs. In order to develop a model capable of accurately discerning whether it's a cat or a dog, SVM proves to be a valuable algorithm. We start by training our model with a diverse array of cat and dog images, allowing it to glean insights into the distinct features of each species. Subsequently, when confronted with this enigmatic creature, the model is put to the test.

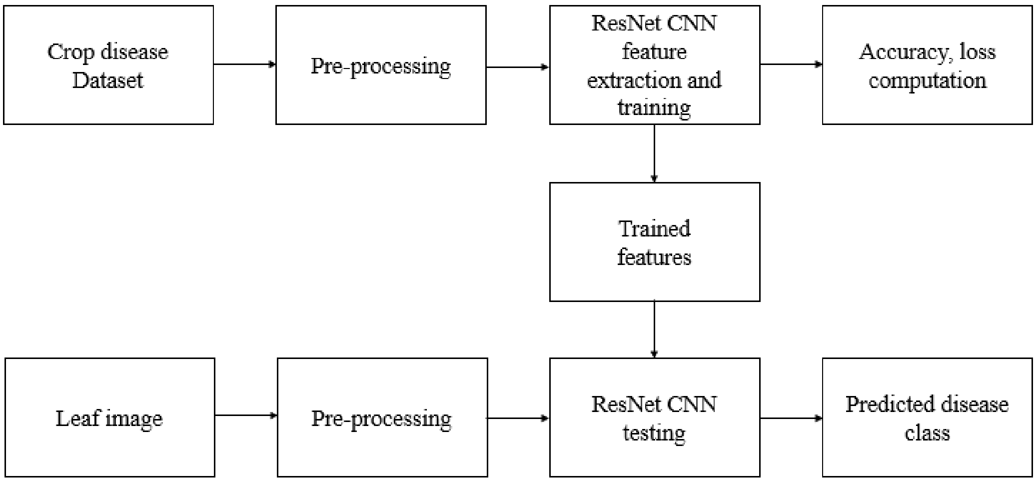
SVM, by creating a decision boundary between the cat and dog data, selects extreme cases known as support vectors. In our scenario, it recognizes the extreme cases of cats and dogs. Leveraging these support vectors, the SVM algorithm classifies the creature as a cat. This process is visually depicted in the diagram below:

V. PROPOSED SYSTEM

Agriculture stands as one of the foremost pillars supporting human sustenance on Earth. Not only does it furnish the essential food necessary for human survival and consumption, but it also occupies a pivotal position in the economic framework of nations. However, leaf diseases have emerged as a significant challenge, posing a threat to both the quality and quantity of agricultural produce. Farmers today grapple with various critical issues, including the rapid fluctuations in climate and unforeseen surges in insect populations, all of which impede efforts to achieve optimal yields.

To bolster yields, it is imperative to mitigate the prevalence of pest insects, a task that incurs substantial financial investment globally to safeguard crops and ensure healthy yields. Protecting crops from bio-aggressors such as pests and insects is paramount, as their unchecked proliferation can result in widespread damage and crop loss. In countries like India, approximately 18% of crop yields succumb to pest attacks annually, translating to a staggering loss valued at around 90,000 million rupees.

Traditionally, manual pest monitoring techniques, alongside the deployment of sticky traps and black light traps, have been employed for pest surveillance and detection on farms. However, in the face of evolving agricultural challenges, innovative solutions are imperative to address these pressing concerns effectively.



Manual pest monitoring techniques entail a significant investment of time and rely heavily on the presence of a human expert for detection. Diseases are typically instigated by pathogens, which encompass any agents capable of causing disease. Pests or diseases commonly manifest on the leaves or stems of plants. Hence, the accurate identification of leaves, stems, and the subsequent detection of pests or diseases, alongside assessing the percentage of pest or disease incidence and recognizing symptoms of pest or disease attacks, are pivotal for successful crop cultivation.

Broadly speaking, factors contributing to the demise and detriment of leaves can be categorized into two main types: living (biotic) and non-living (abiotic) agents. Living agents encompass insects, bacteria, fungi, and viruses, while non-living agents include extremities of temperature, excessive moisture, inadequate light, insufficient nutrients, unfavorable soil pH, and air pollutants. Understanding and addressing these factors are crucial for the preservation and health of crops.

In recent years, deep learning has revolutionized the field of digital image processing, offering advancements far beyond traditional methods. The utilization of deep learning technology for the study of leaf diseases and pest identification has become a focal point of research interest among scholars.

The process involves preprocessing crop disease datasets, which are then fed into a Residual Network-CNN (ResNet-CNN) for feature extraction. Simultaneously, leaf images undergo preprocessing and are also inputted into the ResNet-CNN for testing purposes. These leaf images and crop disease datasets are compared against trained features, previously trained with knowledge of leaf diseases. The extracted features undergo computation for loss and accuracy evaluation. Ultimately, a comparison graph is generated, which aids in predicting the classes of leaf diseases based on the extracted features.

Crop Disease Dataset:
The dataset totally contains 15 classes of crop diseases, such as pepper bell bacterial spot', 'Pepper bell healthy', 'Potato Early blight', 'Potato healthy', 'Potato Late blight', 'Tomato Target Spot', 'Tomato mosaic virus', 'Tomato Yellow Leaf Curl Virus', 'Tomato Bacterial spot','Tomato Early blight', 'Tomato healthy', 'Tomato Late blight', 'Tomato Leaf Mold', 'Tomato Sartorial leaf spot', 'Tomato Spider mites Two spotted spider mite. Here, Pepper, Potato, and Tomato are the major crop classes with different disease sub-types.

Image Pre-processing:
Digital image processing involves the application of computer algorithms to manipulate digital images, offering numerous advantages over analog image processing. As a subfield of digital signal processing, it facilitates a broader range of algorithms to be applied to input data. The primary objective of digital image processing is to enhance image data by mitigating undesirable distortions and enhancing significant image features. This improvement enables AI-Computer Vision models to effectively operate on the refined data.

To ensure compatibility with network input sizes during training and prediction, images must be adjusted accordingly. Rescaling or cropping the data to meet the required size is a common practice in this regard. Augmentation techniques play a pivotal role in increasing the volume of training data and enabling networks to be invariant to distortions in image data. For instance, introducing randomized rotations to input images ensures network robustness to rotational variations.

An augmented Image Data store facilitates the application of a limited set of augmentations to 2-D images, particularly beneficial for classification problems. Image data can be stored as a numeric array, an Image Data store object, or a table. An Image Data store permits the importation of data in batches from large image collections that exceed memory capacity. Resized 4-D arrays or augmented image data stores are typically employed for training, prediction, and classification purposes, whereas resized 3-D arrays are suitable for prediction and classification exclusively.

Resizing image data to match the input size of a network can be achieved through two methods: rescaling and cropping. Rescaling involves multiplying the image's height and width by a scaling factor, potentially altering spatial extents and aspect ratios if the scaling factor differs between vertical and horizontal directions. Conversely, cropping extracts a sub-region of the image while preserving the spatial extent of each pixel.

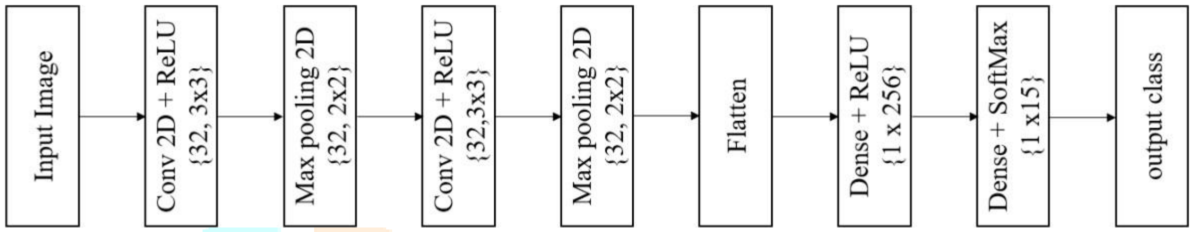
Fundamentally, an image is represented as a two-dimensional array of numbers, or pixels, ranging from 0 to 255, defined by the mathematical function f(x,y) where x and y denote horizontal and vertical coordinates, respectively.

Resize image:

In this step-in order to visualize the change, we are going to create two functionsto display the images the first being a one to display one image and the second for two images. After that, we then create a function called processing that just receives the images as a parameter. Need of resize image during the pre-processing phase, some images captured by a camera and fed to our AI algorithm vary in size, therefore, we should establish a base size for all images fed into our AI algorithms.

ResNet-CNN:

Deep neural network is gradually applied to the identification of crop diseases and insect pests. Deep neural network is designed by imitating the structure of biological neural network, an artificial neural network to imitate the brain, using learnable parameters to replacethe links between neurons.



Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32
Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 15	1 x 15

The Convolutional Neural Network (CNN) stands as one of the most prevalent structures within deep neural networks, representing a branch of the feed-forward neural network paradigm. The notable success of the AlexNet network model underscores the significance of CNNs. Subsequently, CNNs have witnessed substantial development and found widespread application across various domains including financial supervision, text and speech recognition, smart homes, medical diagnosis, and more.

A CNN typically comprises three primary components: the convolution layer for feature extraction, the pooling layer (also known as the convergence layer) for feature selection, and the fully connected layer for feature summarization and output. The convolution layer entails both a convolution process and the application of a nonlinear activation function, often ReLU (Rectified Linear Unit). A typical architecture of a CNN model for crop disease recognition is depicted in Fig. 4.2.

The input layer, depicted as the leftmost image, is interpreted by the computer as the input of several matrices. Following this, the convolution layer utilizes ReLU as its activation function, while the pooling layer does not employ an activation function. The combination of convolution and pooling layers can be iteratively constructed multiple times. The pairing of convolution layers with either convolution layers or pooling layers can be highly flexible during model construction, with no strict limitations. Nonetheless, the most common CNN architecture typically comprises several convolution layers followed by pooling layers. Finally, the fully connected layer serves as a classifier, mapping the learned feature representations to the sample label space.

VI. RESULTS

Modules:

1) Upload Crop Disease Dataset: This module is used to select the dataset.
2) Image Processing & Normalization: The image pre-processing and normalization ofdataset is achieved by this module.
3) Build Crop Disease Recognition Model: Either selection of trained model or retrainingof module is achieved by this module.
4) Upload Test Image & Predict Disease: This module is used to identify the disease classfrom the test image.
5) Accuracy & Loss Graph: This module is used to plot the accuracy and loss comparisongraph various iterations (epochs).

Discussions:

VII. APPLICATIONS

Smart irrigation: By using sensors and machine learning algorithms, we can develop a system that can determine when to irrigate crops, and how much water to use. This can help reduce water waste and improve crop yields.

Disease detection: Using computer vision and machine learning algorithms, we can developa system that can detect the presence of diseases on crops. This can help farmers take action to prevent the spread of disease and minimize crop loss.

Yield prediction: By analysing historical data on crop yields and weather patterns, we can develop a model that can predict future yields. This can help farmers plan their planting and harvesting schedules more effectively.

Pest control: By using sensors and machine learning algorithms, we can develop a system that can detect the presence of pests on crops. This can help farmers take action to prevent the spread of pests and minimize crop loss.

Soil analysis: By analysing soil samples using machine learning algorithms, we can developa system that can determine the optimal amount of fertilizer to use on crops. This can help farmers reduce fertilizer waste and improve crop yields.

Weather prediction: Using machine learning algorithms and historical weather data, we can develop a system that can predict future weather patterns. This can help farmers plan their planting and harvesting schedules more effectively.

Harvesting automation: By using computer vision and machine learning algorithms, we can develop a system that can automatically harvest crops. This can help reduce labor costs and improve efficiency.

Livestock monitoring: By using sensors and machine learning algorithms, we can develop a system that can monitor the health and behavior of livestock. This can help farmers detect andprevent diseases, and improve animal welfare.

VIII. CONCLUSION & FUTURE SCOPE

This study investigated 15 types of crop diseases using deep learning theory and ResNet-CNN technology. The constructed model effectively identifies the dataset with an impressive overall recognition accuracy of 98.23%. Comparatively, the recognition accuracy of this hybrid network model surpasses that of traditional models, making it a viable solution for leaf disease identification and detection.

In future endeavors, several avenues for improvement are identified. Firstly, expanding the dataset and optimizing the model are key priorities. While the current dataset comprises 27 diseases across 10 crop species, there remains a gap in coverage, particularly for crops like rice and wheat and their associated diseases. Therefore, the next phase involves acquiring additional images of crop species and diseases for comprehensive research. Furthermore, the model's commendable recognition accuracy underscores its potential for further refinement and optimization. Additionally, there is a need to design a network model capable of classifying crop images with even higher accuracy. Moreover, exploring the possibility of identifying suitable pesticides for specific diseases is another aspect worth considering in future research efforts. Overall, the model's success warrants continued exploration and enhancement in the pursuit of more accurate and effective crop disease detection and management strategies.

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