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Farm Click-A Farm Log Plant Disease Detection System Using Machine Learning

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ABSTRACT - Annual crop output losses from pest attacks amount to around 18% of the global total and are estimated to be worth approximately Rs. 90 billion in India. Large-scale pesticide use harms the soil, is harmful to humans and animals, affects pest status in agroecosystems, is costly to administer, leaves residues in the environment, and so on. White flies are well-known harmful insects that cause plant yellowing or death, excrete sticky honeydew, and feed on plant leaves. Farmers have relied mostly on their visual assessment of the increase of white flies. Farmers' eye evaluations of the number of white flies have proven less trustworthy due to variable levels of identification ability. Furthermore, it takes some time to identify white flies. In the lab, it was found on leaves. Because of the economic worth of crops and the significant consequences of damage levels, early white fly identification has become critical. In the proposed solution, we establish the affected area of the plant, and based on that region, we evaluate the degree of the disease. We will also provide Hindi treatment advice for any ailments discovered. The automatic diagnosis of plant illnesses from symptoms that appear on plant leaves is an exciting study subject since it has the potential to be beneficial in monitoring vast fields of crops. As a result, using image processing to autonomously detect plant illnesses provides more precise disease management robot assistance. Visual recognition, on the other hand, takes longer and is less exact. Farmers are unable to invest. Rather than forcing them, we can supply them with a solution by building a rental platform for machinery such as tractors, seed drills, harvesters, rollers, sprinkler systems, and so on. Even though our farmers face numerous challenges, the younger generation's attempts to become involved in farming have failed due to a lack of understanding. Better recommendation systems are needed to improve the current situation by supporting those in need in making well-informed judgments before starting crop farming. Our crop management program includes a full crop forecasting function, crop and plant disease prediction, and a list of soil testing facilities.

Keywords: Early identification, Automatic diagnosis, Image processing, Sticky honeydew, Crop forecasting, White flies, Harmful insects

I. INTRODUCTION

India is an agricultural nation since agriculture employs roughly 70% of the people. Farmers have a vast range of fruit and vegetable crops to choose from. However, growing these crops for maximum yield and productivity requires a high level of technical skill. It can be improved with the help of technology. Close monitoring is required for the management of perennial fruit crops, particularly for the control of diseases that can have a significant influence on output and, as a result, post-harvest life. Agriculture currently serves far more objectives than simply feeding an expanding population. Plants are now a substantial source of energy and are critical to combating global warming. Many diseases have the potential to be dangerous. inflict devastating effects on the economy, society, and ecology. It is critical in this situation to accurately and rapidly diagnose illnesses. Plant illnesses can manifest themselves in a variety of ways. Some diseases have no evident signs at all, or they appear when it is too late to intervene. In such cases, a detailed analysis, typically utilizing powerful microscopes, is usually required. At times, the hints are only apparent in portions of the electromagnetic spectrum that humans cannot see. A common tactic, in this case, is to study multi- and hyper-spectral image captures utilizing remote sensing methods. This strategy's approaches usually employ digital image processing tools to achieve their goals. However, because of their various peculiarities and the wealth of literature on the subject, they will not be dealt with using this manner. However, the vast majority

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of ailments manifest in some way. A human conducts a visual diagnosis or at least a preliminary guess about the condition the vast majority of the time. Although skilled raters are efficient in identifying and quantifying abnormalities, some important limitations might occasionally undercut the efforts. Our research focuses on identifying plant ailments using edge detection and color-matching histogram algorithms. We require two very critical properties to diagnose image ailments fast and reliably. We can identify the plant illness using edge detection, histogram, and color space approaches. The key to preventing losses in the production and quantity of agricultural products is the identification of plant diseases. Research on plant diseases focuses on visually discernible patterns in the plant. For agriculture to be sustainable, plant health monitoring and disease detection are essential. Monitoring plant diseases manually is exceedingly challenging. It necessitates a great deal of labor, knowledge of plant diseases, and lengthy processing. Consequently, plant disease detection uses image processing techniques. The processes of picture acquisition, image preprocessing, image segmentation, and feature extraction classification are all involved in disease detection.

Table I: Sample Leaf Disease

Leaf Disease	Impact on Plant	Cause	Fertilizers help to prevent
Powdery Mildew	10-20%	This disease appears as a white or grayish powdery coating on the leaves, stems, and flowers of plants. It can cause stunted growth, leaf curling, and reduced photosynthesis, resulting in a 10-20% impact on plant growth.	Potassiumsulfate/potassium nitrate Nitrogen Phosphorus
Rust	5-30%	Rust appears as small orange, brown, or black spots on leaves and stems. It can cause leaves to turn yellow and drop prematurely, resulting in a 5-30% impact on plant growth.	Nitrogen (Urea, Ammonium Nitrate)
Leaf Spot	5-20%	Leaf spot appears as small, circular or irregular-shaped spots on the leaves, which can turn yellow, brown or black over time. It can cause leaves to fall off, reducing photosynthesis and resulting in a 5-20% impact on plant growth.	Nitrogen (10-10-10) Phosphorus (20-20-20)
Anthracnose	5-20%	This disease can cause leaves to curl and dry out, and may also affect stems and fruits. It can cause significant yield losses and up to a 5-20% impact on plant growth.	Nitrogen Potassium (Urea, Potassium chloride)
Downy Mildew	10-50%	Downy mildew appears as yellow or pale green	Potassium sulfate

		spots on the upper surface of leaves, with a downy, grayish coating on the undersides.	Potassium nitrate
Leaf Disease	**Impact on Plant**	**Cause**	**Fertilizers help to prevent**
Black Spot	10-50%	Black spot appears as dark, circular spots on the leaves, which can cause them to yellow and drop off prematurely. It can reducephotosynthesis and cause significant yield losses, resulting in a 10-50% impact on plant growth.	Potassium sulfate Potassium nitrate
Scab	5-20%	Scab appears as brownish or black spots on leaves, fruits, and stems. It can cause reduced growth and yield losses of up to 5-20%.	Potassium sulfate Potassium nitrate

II. LITERATURE SURVEY

A. Machine learning in detecting and classifying diseases of a plant leaf

Though various practices have been developed and adopted to address this issue, swift and accurate disease identification remains an unfinished business. The use of machine learning to aid in identification and detection helps to mitigate this issue to a much higher level.[1]

B. Reviewing classification and detection on plants using ML

The study provides an in-depth look at the strategies that can be used to detect and classify plant leaf diseases caused by bacteria, viruses, and fungus. Diseases diagnosed by classification are classified based on their morphology, or its specific form, shape, or structure. The classification approaches utilized aid in the automatic detection of plant leaf diseases.[2].

C. Machine learning in detection of stem diseases of jute plant

In this study, diseases of the stem plant are detected using the HSV algorithm, the GLCM algorithm, and SVM to execute and commence the segmentation process, which is then followed by feature extraction and classification. It goes over noise removal, RGB to HSV conversion, and vice versa [3].

D. Detection of abnormalities of the leaves of plants and training using papaya leaves.

This work discusses the identification and recognition of plant anomalies for training and study of papaya leaves. A random forest classifier was employed for classification, and it was trained using photos of leaves with nearly 70% accuracy.[4].

E. Apple leaf disease detection.

Common Apple leaf diseases such as rust, grey spot, and brown spot were discussed and discovered using deep learning techniques and upgraded CNNs. The diseased leaf dataset was developed, analyzed, and gathered. A new deep CNN model has been developed to detect microscopic sick areas.[5].

Improvisation in our work**:**

We comprehended the operation of classification algorithms, feature extraction methods, segmentation algorithms, and so forth. We investigated how disease diagnosis is done automatically and how this is effectively implemented in the real-time project. We picked tomato plant leaves for disease research, training, testing, and detection. Plant leaf disease research and digital image processing Through the numerous methods it supports, digital image processing opens up a huge field for illness identification.

F. Image processing techniques in identifying fungal crop diseases.

The most prevalent bacterial, fungal, and viral illnesses that harm plant leaves and roots on a large scale and diminish plant productivity can be easily examined and recognized using RGB to grey scale conversions. [6].

G. UAV for pests and weed using open computer vision

Drone camera systems are utilized in this paper to identify pests, diseased weeds, and crops. When infected regions are detected, just those areas are treated with fertilizers or pesticides, rather than the entire region, in order to control the illness as quickly and as efficiently as feasible. [7].

H. Severity measurement using image processing.

Simple threshold approaches and triangle threshold methods are utilized to segment the lesion area and leaf area. The quotient of lesion and leaf regions is used to categories the regions. Sugarcane, for example, has a variety of such illnesses that can impair crop quantity and quality, as well as yield. To avoid this, it is critical to understand the severity of the diseases so that the right amount of fertilizer can be applied on time.[8]

Improvisation in our work:

Understanding the farmers' suffering and efforts, as well as how much time is spent producing a crop for one season, we applied digital image processing, a technology that monitors the plants and their leaves from the start.Because early disease detection can save farmers from substantial losses, our research focuses on early and accurate disease detection utilizing digital image processing, so that neither the crop nor its productivity is damaged.Furthermore, image processing techniques have proven useful in segmentation and feature extraction, which are critical aspects of the project.

I. Selection of algorithms

There are numerous techniques available in machine learning for feature extraction, grouping, and segmentation. Choosing the best option for the job might be difficult at times. To reduce complexity and improve response time, the most appropriate algorithm must be chosen. We conducted a comparative analysis of the algorithms used in previous projects and determined the best one for the project.[9]

J. Pre-processing and filters

Before we begin working on the image, we must smooth it out and resize it for future use. There are also other types of noises in the photographs, such as Gaussian noise, shot noise, noise linked to salt and pepper representation, Quantization Noise (Uniform Noise), film noise, and so on. [10]

There are different methods for removing different kinds of noise in our case we have salt and pepper noise hence to remove such kind of noise median filter is considered to be one the best algorithms, so we went ahead with the same.

1) Segmentation

The working and well-known and significant area of image processing has to be segmentation, as it extracts useful and, more appropriately, meaningful data sets from meaningless data by segmenting the image into multiple pieces. It is categorized according to region, edge threshold, feature, and model. Our project deals with feature extraction, thus segmentation on that basis is vital to simplify future work. We discovered that the K-Mean technique, which works well for feature extraction segmentation, is also one of the most extensively used and simple to implement algorithms. As a result, we decided to go with it.

2) Feature extraction

In feature extraction, the primary geometric features extracted are diameter, physiological breadth, leaf area, leaf perimeter, morphological features, rectangularity, and so on. A traditional approach, the GLCM or Grey level Co-occurrence Matrix, is frequently used to extract the spatial dependencies of the texture. Similarly, another feature extraction approach is HOG, which stands for Histograms of Oriented Gradients in the phrase we proposed. We used this system since it guarantees performance. Another advantage of HOG is that it captures the extremely general structure of the item. As a result, we choose to collaborate with GLCM and HOG.

3) Classification

Classification methods, such as SVM (Support Vector Machine), CNN, and KNN, are widely employed in practically all such tasks. The classification phase is required because it compares the values obtained after the feature extraction step with a pre-calculated set of data. We chose the KNN approach because, while both are supervised algorithms, the KNN is simple, easy, and flexible to apply. It is also extremely resistant to noisy data.

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Improvisation in our work:
Different plants require different algorithms based on a variety of parameters, including morphology [10]. We compared and contrasted each of the aforementioned algorithms before deciding on one using test and trial methods

4) Current trends and future

The tomato plant is the world's second most produced and growing vegetable. It is also afflicted by over 200 ailments. The need for vegetables will only increase in the future as the human population grows.

5) Disease detection in tomato plants

Disease detection in tomato plants is rather simple in comparison to other plants such as sugarcane, jute, papaya, cucumber, paddy, and so on. With technological improvements, various new methods for detecting illnesses in tomatoes have been developed, however most of them fail in speedy and early identification of infections, which ultimately impair crop productivity.

6) Advances in Research of plant Pathology

We know that plants have natural resistance to illnesses, but infections find a method to develop resistance to them. The most recent innovations and research, such as the Nano-sequencing technique, have helped to increase tomato output and production.

7) Genetic algorithm methods

The genetic algorithm approaches take advantage of the initial set of features' distinguishing traits on the chromosomes. When compared to other algorithms, the genetic algorithm can extract a huge amount of information from an image. It is also used in the reduction of dimensionality. [15].

8) Usage of Fuzzy Logic

Fuzzy logic is often used for illness classification and even determining the rawness or maturity of foods. Various techniques, such as the RGB color technique, can be utilized to extract features, and then fuzzy logic can be used for categorization.[16]

9) Artificial neural network and identification of diseases.

Detection of pathogens in cucumber plants using an artificial neural network [17]. This algorithm has an identification accuracy of up to 89.9 percent. Because of its ease of implementation and application, it is one of the most widely used algorithms today. It also contains a punishment for spotting errors that does not rise with the number of faults.

10) Naïve Bayes algorithm.

This method is mostly used to detect fungal infections. This algorithm, like its predecessor, has an extremely high prediction ratio. We investigated how the optimality of the Nave Bayes algorithm can be improved under the Gaussian distribution in our study [18]. The method is an effective classification option.
Improvisation in our work:

We reviewed the work done in each study and reasoned out how the various algorithms work and function in specific conditions, implementing the most suitable for the tomatoes and choosing our methods accordingly.

III. PROPOSED SYSTEM

A. Disease Detection and Treatments

To use it as data, collect a substantial number of images of both healthy and ill-looking plant specimens. The dataset needs to be diverse and contain images obtained from various types of cameras, angles, and lighting configurations.

Clean and prepare the dataset by removing duplicates, outliers, and low-quality images. Then ensure consistency across the dataset, scale and normalize the images to uniform size.

Use techniques such as feature extraction and Convolutional Neural Networks (CNNs) glean important properties from preprocessed data. CNNs are powerful deep-learning models that have been shown in studies to be excellent at identifying images.

Train the ML model to extract features from the preprocessed dataset and input the preprocessed photos into the model.

Adjust the model's parameters to optimize its performance.

For validation, use a separate dataset to evaluate the effectiveness, accuracy of the ML model. Ensure the model can identify plant illnesses in new images without overfitting.

Integrate the trained ML model into FarmClick, allowing it to swiftly identify and diagnose plant diseases. Develop the system to be user-friendly, enabling farmers to easily submit images and receive precise diagnoses.

Implementation: To boost the model's accuracy over time, install the FarmClick system in the field, maintain the collected data and make adjustments. With frequent updates and improvements, the system will remain an important tool for farmers to track the health of their crops.

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The Plant Disease Detection is composed of four blocks, they are:

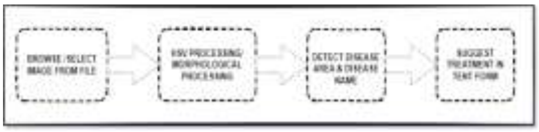

Fig I. The Development and Spread of Leaf Diseases

To begin the disease identification process, select an image from the file that exhibits any type of ailment damaging the leaves. After that, examine the image and scrutinize the leaves thoroughly.

The following stage is HSV Processing/Morphological Processing, which is ideally suited for processing binary and grayscale images. This model is used to analyze the image and detect the disease that has affected the leaf's name and position. It all comes down to the relative ordering of pixel values. After the treatment is completed, the section of the leaf from where the sickness is emerging is also recognized.

After completing the HSV processing, the name and location of the disease that has impacted the leaf, as well as the section or component of the leaf where the illness is originating, are discovered.

Once a disease has been identified on a leaf, a treatment plan should be proposed to ensure that no further problems arise, and a cure is available.

B. Crop Recommendation

Crop suggestion using NPK, humidity, temperature, pH value, and rainfall involves the analysis of several factors that affect plant growth and development. These factors are crucial in determining the appropriate NPK ratio for a specific crop and ensuring optimal growing conditions for maximum yield.

1) NPK Ratio:

The first consideration is the nutrient requirements of the crop. Nitrogen (N) is essential for vegetative growth, while Phosphorus (P) is necessary for root development, flower formation, and fruit production. Potassium (K) is vital for overall plant health, disease resistance, and stress tolerance. The appropriate NPK ratio for a specific crop will depend on its nutrient requirements.

2) Humidity:

Humidity refers to the amount of moisture in the air. High humidity can cause fungal diseases, while low humidity can cause wilting and reduce plant growth. The ideal humidity for a specific crop will depend on its tolerance to moisture stress.

3) Temperature:

Temperature affects plant growth, flowering, and fruit development. Each crop has a specific temperature range at which it grows best. For example, cool-season crops like lettuce and cabbage prefer cooler temperatures, while warm-season crops like tomatoes and peppers prefer warmer temperatures.

4) pH Value:

pH refers to the acidity or alkalinity of the soil. Each crop has a specific pH range at which it grows best. The pH affects nutrient availability, and an incorrect pH can lead to nutrient deficiencies or toxicities.

5) Rainfall:

Rainfall is essential for plant growth and development, but too much or too little rain can have adverse effects on crops. Each crop has a specific water requirement, and the rainfall should be adequate for the crop to grow and develop properly.

IV. SYSTEM ARCHITECTURE

The architectural structure depicts the system's interactions and control flow from one stage of the cycle to the next. There, we'll discuss the system's hardware control flow, from image acquisition through ailment detection and presentation.

The following is an overview of the system architecture for a machine-learning system that identifies plant leaf diseases:

A. User Interface

The user interface of the system is whatallows users to communicate with the software. Desktop software, a mobile application, or a web-based interface can be used to construct the user interface. The user interface allows you to upload plant leaf images for analysis as well as examine the results of the examination.

B. Image preparation for analysis:

This is handled by the preprocessing module. To ensure consistency, procedures such as scaling, cropping, and normalizing the photographs may be required.

C. Feature Extraction

The feature extraction module is in charge of locating relevant traits in plant leaf pictures that may be used for disease detection. Techniques like segmentation, color analysis, and texture analysis can be used to identify parts of the image that are likely to be affected by sickness.

D. Machine Learning Model

The machine learning model must assess the obtained data to identify whether a plant leaf is healthy or sick. The model may use methodologies such as decision trees, support vector machines, or neural networks to make predictions.

E. Feedback

When the analysis is finished, the feedback module informs the user of the results. The feedback module may include visualizations of the afflicted plant leaf regions, information on the type of sickness discovered, and treatment recommendations.

F. Database

The database component of the system stores images, feature vectors, and other relevant data. This data may be used to train a machine learning model, which can then be used to improve feature extraction methods and learn more about the prevalence and spread of plant leaf diseases.

V. SYSTEM FLOWCHART

The flowchart below depicts how the leaf disease detection system functioned from start to finish. It shows the steps taken by the application to execute tasks. The flowchart includes crucial activities such as image segmentation, image preprocessing, the Blob and HSV algorithms, and conditions that ensure the user-supplied image matches the photographs in the dataset.

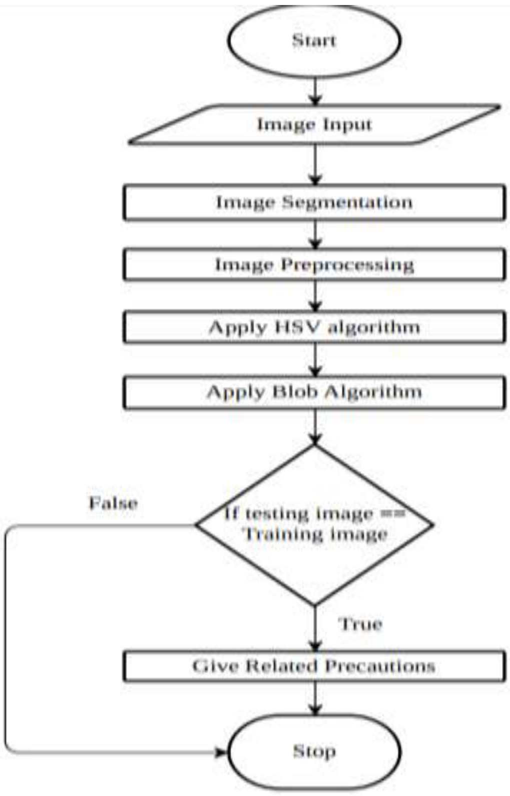

Fig II. System Flowchart

A. Input Image

The user must enter the testing image to detect leaf disease. The user can select a leaf image from the collection and then record a movie of it.

B. Image Segmentation

Image segmentation is an important stage in identifying plant leaf diseases. This procedure comprises dissecting an image into its component portions or objects, which are then analyzed further for signs of sickness. Photo segmentation is used to diagnose plant leaf disease by identifying the region of interest in a photograph that contains a leaf and separating it from the background. This is critical because it can reduce noise and other extraneous information that could hamper disease detection and categorization.

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C. Image Processing

Image processing is important in the identification of plant leaf diseases because it improves the quality of the acquired plant leaf images and prepares them for analysis. The following are the most common image processing technologies used in plant leaf disease detection systems: picture scaling, noise reduction, feature extraction, segmentation, color correction, picture registration, and enhancement are all examples of image processing.

D. Apply HSV algorithm

The HSV algorithm can be used in plant leaf disease detection systems to segment images based on color and locate diseased sections of plant leaves. By segmenting images based on color, the method can help to reduce noise and other unnecessary information in the image, making it easier to detect and diagnose disorders.

E. Apply Blob algorithm

A feature extraction method is used to detect and identify areas of interest in photographs, such as lesions on plant leaves or disease-related patches. The method compares the user-supplied image with the training images in the dataset. If a match between the testing and training photos is discovered, the necessary precautions are shown. Otherwise, the program control terminates the execution.

VI. MATHEMATICAL MODEL

We can create a mathematical model of a machine-learning plant leaf disease diagnosis using deep convolutional neural network (CNN) architecture. This method uses photos of plant leaves to classify crop species and the presence of diseases. To train the CNN model, we collected 54,306 pictures of healthy and damaged plant leaves under controlled conditions

In addition to the CNN model, other methods for diagnosing plant leaf diseases have been proposed. These include pre-processing, leaf segmentation, feature extraction, and grey-level co-occurrence matrix (GLCM). AGROdet is a unique technique introduced by researchers that can diagnose plant diseases and quantify the severity of leaf damage. Additionally, a DWT+PCA+GLCM+CNN model has been proposed for diagnosing leaf diseases.

A. Implementation Of model

S represents the system, where, S = {I, O, F, DD, NDD}

> I = Input to the system

I= {image_file}

> O = Output from system

O = {Disease, Severity, Cure}

> F = Set of functions

F=(upload_image, HSV_conversion, blob_detection, disease_prediction, severity_calculation, cure}

> DD = Deterministic Data

DD = {HSV_range}

> NDD = Non-Deterministic Data

NDD = {image_file, disease, severity, cure}

> Success = Disease, Severity & Cure detected successfully.

> Failure = Smart phone battery discharged or any problem in Smart phone hardware.

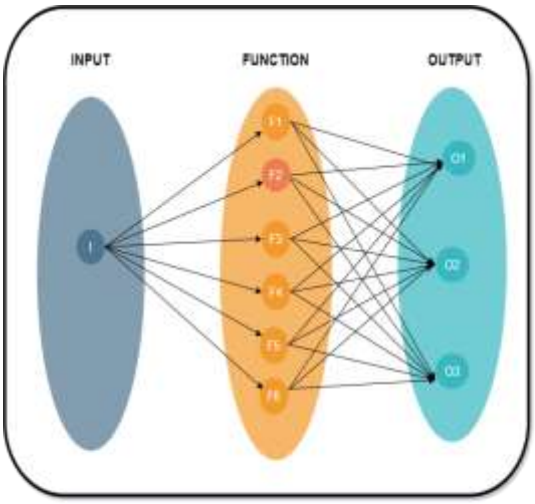

Fig III. Venn Diagram

B. Functional dependency

A set of Functional Dependencies for a data model can be documented in a Functional Dependency Diagram (also known as a Determinacy Diagram). In a Functional Dependency Diagram each attribute is shown in a rectangle with an arrow indicating the direction of the dependency.

Table II: Functional Dependency

	F1	F2	F3	F4	F5	F6
F1	1	0	0	0	0	0
F2	0	1	0	0	0	0
F3	0	0	1	0	0	0
F4	0	0	0	1	0	0
F5	0	0	0	0	1	0
F6	0	0	0	0	0	1

F1-Node 1: Upload Image

F2-Node 2: HSV Conversion

F3-Node 3: Blob Detection

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F4-Node 4: Disease Prediction
F5-Node 5: Severity Calculation
F6-Node 6: Cure

VII. ALGORITHMS

A. Blob Algorithm

Using blob detection techniques, plant leaf disease detection systems may locate and isolate regions in digital images that differ in brightness or color from surrounding areas. By sensing these zones, the technology may locate possible disease or damage locations on plant leaves.

One way to use blob detection in plant leaf disease diagnosis is to preprocess the image by separating the leaf from the backdrop and then collecting relevant data such as texture, color, or form. These features may then be used to train a machine learning model, such as convolutional neural network (CNN), to classify the image as healthy or unwell based on the presence or absence of specific attributes.

Another approach is to use blob descriptors, such as the grey-level co-occurrence matrix (GLCM), to extract features straight from the image, without the need for preprocessing or segmentation. These properties can then be used to build a machine-learning model to identify and categorize plant leaf diseases.

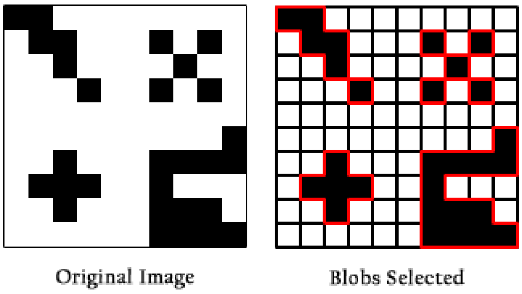

Fig IV. Blob Algorithm

B. HSV Algorithm

The program splits a color image of a plant leaf into hues, saturations, and value components before converting the results to the HSV color space.

The image's color and saturation are then thresholder to produce a binary image that highlights the leaf's problematic parts. The threshold levels are determined experimentally and are dependent on the individual sickness being recognized.

After gathering the binary picture, the corresponding components are located, and the many properties of each component, including area, perimeter, and shape, are recovered. These attributes are then used to establish the kind and severity of the sickness present on the leaf, which is then fed into a classifier such as a support vector machine (SVM) or artificial neural network. (ANN).

1) The hue(H) of a color refers to which pure color it resembles. Hues are described by a number that specifies the position of the corresponding pure color on the color wheel.
2) The saturation (S) of a color describes how white the color is.
3) The value (V) of a color, also called its lightness, describes how dark the color is.

The algorithm works as follows:
1) Convert the RGB color values to values between 0 and 1 by dividing each value by 255.
2) Find the minimum and maximum values among the R,G, and B values.
3) Calculate the value (V) as the maximum of the R, G, and B values.
4) Calculate the saturation (S) as follows:
- If the maximum value is 0, the saturation is 0.
- Otherwise, the saturation is (V – min (R, G, B))/V

5) Calculate the hue (H) as follows:
• If R = G = B, then H is 0 (it doesn't matter what value we assign).
•Otherwise, calculate the hue based on which color component is the maximum value:
- If the maximum value is R, then H = 60 * ((G - B) / (V – min (R, G, B))) (result in degrees)
- If the maximum value is G, then H = 60 * ((B - R) / (V – min (R, G, B))) + 120
- If the maximum value is B, then H = 60 * ((R - G) / (V – min (R, G, B))) + 240
- If H is negative, add 360 to make it fall within the range of 0 to 360 degrees.
6) Convert the hue value to a range of 0 to 1 by dividing by 360.
The resulting values for H, S, and V are the HSV values that correspond to the original RGB color.

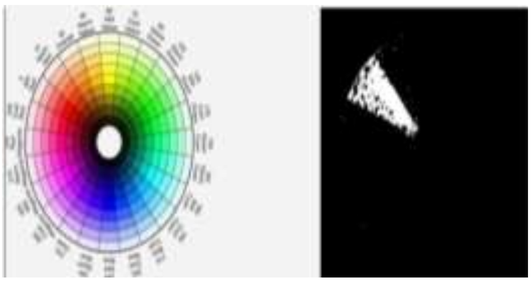

Fig V. HSV Algorithm

C. NPK Algorithm

The NPK AI algorithm uses machine learning techniques to make predictions based on input data. Here is a mathematical implementation of the algorithm:

1) Data Collection

Suppose we collect data on soil nutrient levels (N, P, K), weather patterns (temperature, precipitation), and crop yields (Y) for a specific region over a period of time

2) Data Preprocessing:

Suppose we have N samples, each with K features (N, P, K, temperature, precipitation) and a corresponding crop yield value Y.

We need to preprocess this data by normalizing the feature values and splitting the data into training and testing sets. We can represent the data as a matrix X with dimensions N x K, where each row represents a sample and each column represents a feature. We can represent the corresponding crop yield values as a vector Y with dimensions N x 1.

3) Model Training:

We can use a machine learning model such as linear regression, decision tree, or random forest to train the NPK AI algorithm. Here, we will use linear regression as an example.

The goal of linear regression is to find a linear relationship between the input features and the output values. We can represent the relationship as:

- Y = b0 + b1N + b2P + b3K + b4temperature + b5precipitation
- where b0 is the intercept, and b1, b2, b3, b4, and b5 are the coefficients for each feature.
- We can train the model by minimizing the sum of squared errors between the predicted values and the actual values. This can be represented as:
- minimize (Y - (b0 + b1N + b2P + b3K + b4temperature + b5precipitation)) ^2
- We can use techniques such as gradient descent or normal equations to find the optimal values of the coefficients b0, b1, b2, b3, b4, and b5.

4) Model Evaluation:

- We can evaluate the performance of the model using the testing data. We can calculate the mean squared error (MSE) between the predicted values and the actual values:
- MSE = 1/N * sum((Y_pred - Y_actual)^2)
- where Y_pred is the predicted crop yield value, and Y_actual is the actual crop yield value.
- We can also calculate the coefficient of determination (R^2) to measure how well the model fits the data:
- R^2 = 1 - sum((Y_pred - Y_actual)^2) / sum((Y_actual - mean(Y_actual))^2)
- where mean(Y_actual) is the mean of the actual crop yield values.

5) Prediction:

Once the model is trained and evaluated, we can use it to make predictions for new input data. Given a set of input features (N, P, K, temperature, precipitation), we can predict the corresponding crop yield value Y_pred using the linear regression equation:

- Y_pred = b0 + b1N + b2P + b3K + b4temperature + b5precipitation

VIII. DATASET

1. Image ID

A unique identifier for each photograph in the database. It could be a UUID or an ever-increasing integer.

2. Plant Type

The type of plant whose leaves is shown in the image. (e.g., Tomato, Pepper, Potato). This column can be useful for organizing images by plant type and studying disease patterns among different plant types.

3. Disease Type

The type of disease that the plant leaves in the image is suffering from. (e.g., Early Blight, Late Blight, Leaf Spot). Using this column, the images can be classified by illness group, and the system's accuracy in recognizing different illnesses can be evaluated.

4. Image Path

The file path or URL of the image file. This section should contain the link to the image file on the local file system or a remote website.

5. Status

Indicates whether the image is being used to educate or assess the system. This variable can take one of two values: Testing vs. training: The trial photos are used to evaluate the precision of the system, whereas the training images are used to build the machine learning model.

6.Timestamp

The image was submitted to the dataset at the time and date indicated. This section can be used to keep track of picture ages and ensure that

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the collection contains a diverse range of pictures collected over time.

7.Source

The genesis of the picture (e.g., website, user upload, public dataset). This part can help you identify the image's author and ensure that the picture was taken legally and without violating any copyright.

8. Resolution

The image's pixel resolution (e.g., 640x480, 1024x768). This part can be used to determine how picture sharpness affects system accuracy and to ensure that the pictures are of good enough quality to detect illnesses.

9. Camera

The type of camera used to capture the photograph. (e.g., smartphone camera, DSLR). This section can help you identify the reasons of image quality variations and investigate how various camera kinds impact disease identification.

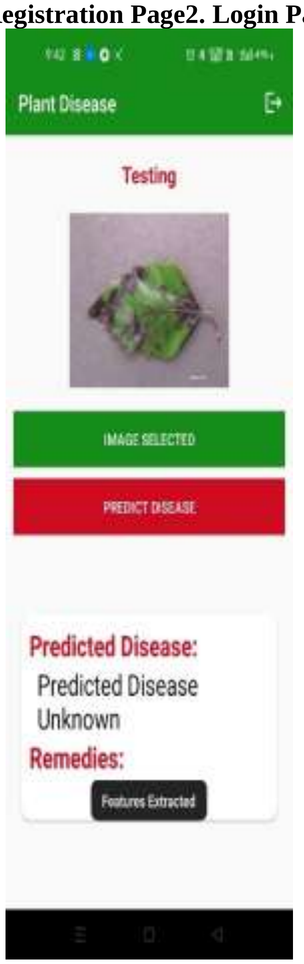
Table III. Dataset Table

ID	Column Name	Datatype	Size	Key
1	Image ID	Integer	A. I	Primary
2	Plant Type	VarChar	100	-
3	Disease Type	VarChar	100	-
4	Image Path	VarChar	500	-
5	Status	VarChar	100	-
6	Timestamp	Integer	100	-
7	Source	VarChar	100	-
8	Resolution	VarChar	200	-
9	Camera	VarChar	200	-

IX. SYSTEM OVERVIEW

The screenshots below demonstrate the execution of the FarmClick application's fronted, which makes the application simple to use and user pleasant.To use the program, the individual must first login or register. The user can join in by providing his or her account and password or by using Gmail directly.In the second screen, the user can select a picture to identify disease and obtain information about the provided fertilizers.In (3. discover illness), the user can discover an image by clicking on it or importing it from the gallery.Various plant information will be given to the viewer in (4. Crop statistics). When a user clicks on an image or crop name, they are redirected to a Google website that is connected to the crop in question.In (5. Crop Suggestion), the user needed NPK values, humidity, temperature, rainfall, and pH value of soil to find an appropriate crop to cultivate in the field.

1. Registration Page2. Login Page



3. Disease Detect

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4. Crop suggestion

5. Setting the threshold
Fig VI. Fronted Design of Application

X. GRAPHICAL OVERVIEW

A. Yearly Growth of Leaf Diseases

The term "year-by-year increase in therapy" refers to the evolution of the number of therapies accessible for a particular illness over time. A line graph depicts the rise in treatments for the plant diseases Black Spot, Downy Mildew, and Mosaic Virus over time, as well as the yearly pattern in the number of treatments given for each disease.

For example, if the graph of a disease shows an upward trend, it indicates that more therapies for that condition have become accessible over time. Numerous factors, such as an increase in illness frequency or advancements in accessible treatments, could be to blame.

Similarly, if an illness's trend on the graph is declining, fewer treatments for that disease have become accessible over time. This could be due to a variety of factors, such as a decrease in illness prevalence or the creation of more potent treatment options.

Graph Table:

Table IV. Yearly Growth of Disease

Year	Growth
2016	10
2017	10.5
2018	20
2019	30
2020	40
2021	35

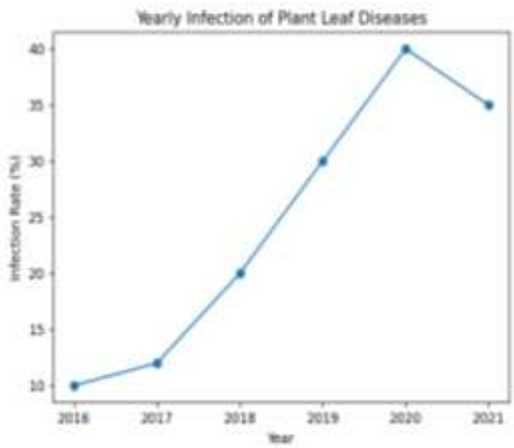

Fig VII. Yearly Growth of Leaf Diseases (Graph 1)

B. Infections in Plant Leaf Diseases Grow Yearly

Plant leaf diseases are caused by fungi, bacteria, and viruses that target plant foliage and appear as spots, blights, wilts, and other forms of damage. Several factors that interact intricately impact the yearly growth of infections in plant leaf diseases.

Environmental factors are among the most important in determining pathogen growth in plant foliage diseases. Temperature, humidity, moisture, and wind all have an effect on the growth and spread of plant pathogens. For example, while some fungi diseases favor wet, humid habitats, others may require moderate, arid conditions. Similarly, some bacterial diseases may profit from chilly,

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moist environments, whereas others may require warm, arid environments.

Plant variety and management methods are two other important factors that may influence the establishment of infections in plant leaf diseases. Different plant varieties have varying degrees of disease susceptibility. While some types are highly susceptible to certain illnesses, others may be resistant to them. Plant leaf diseases can be avoided or decreased by employing management tactics such as crop rotation, sanitary practices, and chemical treatments.

The globalization of commerce and transportation has allowed the spread of plant pathogens across borders and continents, allowing for the entry of new diseases and the emergence of new strains of existing diseases. Because changes in weather patterns affect the spread and quantity of plant pathogens, climate change has an effect on the formation of infections in plant leaf diseases.

To control the spread of infections in plant leaf diseases, farmers, scholars, and policymakers must implement a thorough and integrated strategy that addresses the myriad factors affecting disease incidence and severity. This may involve the use of societal practices such as farming rotation and sanitation, in addition to the development of disease-resistant plant varieties through conventional breeding or genetic engineering. Although there is a growing interest in using ecologically friendly disease control methods such as biological control and precision farming techniques, chemical treatments may still be used in some cases.

Table V. Yearly Growth of Leaf Disease Treatment

Year	Black Spot	Downy Mildew	Mosaic Virus
2016	30	20	10
2017	40	25	15
2018	35	30	20
2019	20.5	35	25
2020	20	40	30
2021	15	45	35

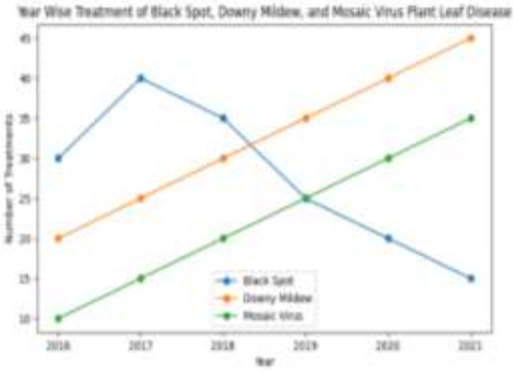

Fig VIII. Yearly Growth of Infections in Plant Leaf Diseases (Graph 2)

Finally, environmental circumstances, plant variety, management methods, international trade, and climate change all have an effect on the yearly growth of infections in plant leaf diseases. For successful management of plant leaf diseases, a comprehensive and integrated approach that takes into consideration these factors and addresses the underlying causes of disease incidence and severity is required.

XI. CONCLUSION

The plant leaf disease detection app has the potential to change agriculture by providing early identification of plant ailments. Using image processing technologies, machine learning algorithms, and computer vision, the program examines leaf photographs obtained with the user's smartphone camera to diagnose plant ailments.

The success of the application is dependent on the efficacy of the machine learning algorithms employed to diagnose plant illnesses. As a result, for the application's development, a large collection of great images of plant leaves affected by various ailments is required. The dataset must include photographs of healthy leaves for the algorithm to correctly distinguish between healthy and ill leaves.

The program's user interface should be basic and straightforward, allowing farmers and other agriculture professionals with little to no technical understanding to utilize it effectively. The program should allow users to swiftly photograph a plant leaf, process the image, and display the findings. The findings must include a diagnosis, a description of how serious the problem is, and therapy recommendations.

The app's reliability and accuracy are critical to its success. As a result, it should be thoroughly tested and validated to ensure that it can correctly diagnose plant diseases under a variety of conditions. To improve the app's accuracy, it should be updated often to include new ailments as well as new image processing and machine learning technologies.

The plant leaf disease detection app has the potential to significantly improve the efficacy of plant disease management by enabling early diagnosis and treatment of plant diseases. The accuracy of its algorithms, the quality of its dataset, and the reliability of its user interface determine the app's efficiency. With careful development and regular updates, the app can become a valuable tool for farmers and agriculture professionals worldwide, allowing them to detect and treat plant diseases early.

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