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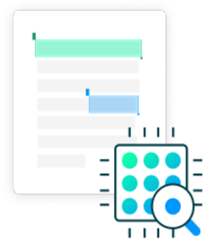

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Smart Farming System

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***Abstract*— Plant sicknesses create huge efficiency and financial misfortunes, as well as a decrease in both the quality and amount of farming products. In numerous agricultural fields, plant disease identification is now receiving more attention. monitoring. When switching disease management strategies, farmers face significant obstacles. The ordinary procedure utilized by and by for recognizing and distinguishing plant sicknesses is talented unaided eye investigation. We investigate the necessity of a straightforward plant leaf disease detection system to support agricultural innovations in this study. Early data on crop wellbeing and sickness distinguishing proof can help with infectious prevention through right administration measures. Productivity in agriculture will rise as a result of this strategy. Additionally, the benefits and drawbacks of these are examinedin this report.**

Keywords—Machine Learning, Disease Detection, CNN, Open CV

I. Introduction

The reason that agriculture is the foundation of any country is because it not only produces food but also many other essential resources like cotton, textiles, and many others. Through exports, India, the world's second-largest wheat and grain producer, contributes to global food security and economic expansion. India possesses the sixth- largest economy in the world, with the agricultural sector accounting for approximately 15% of its GDP. Knowing how essential our agriculture industry is makes it imperativeto safeguard it and implement policies that will maximize its potential. According to accounts, pests, weeds, and other diseases damage 15–25% of the crop output each year. This brings us to our project, "Early-Stage Crop Disease Detection Using Machine Learning Algorithm." Our project is based on a model where we first use a drone camera to survey the entire field, taking detailed pictures for our data and then scrutinizing the pictures for every tiny detail. Once we have the data, our model (using CNN, Opencv software's) works to find the precise disease and at precise positions on the field. Once we have identified the illness and the affected area, we search for the ideal treatment before using a drone to spread pesticides and medications over the affected area. It lessens the farmer's workload and, in our trials, had a precision of up to 95%, which, if put into practice, could be very effective. Giventhe significance of agriculture, it is our moral obligation to make improvements to this industry that will have a beneficial effect on the economy and development of our nation. Therefore, we are developing a model that will identify the illness at an early stage and tend to eliminate it, preventing it from spreading and harming our prosperous produce. We are equipped with information that will enable us to combat various illnesses and find the best treatment foreach one. We attempted to provide a way that will assist our farmers and get the best out of their produce because they work extremely hard for their crop and if it gets infected it causes them a lot of trouble.

II. Literature Review

[1]. Image processing is becoming more and more important in agriculture because it can help find flaws and diseases in crops that are hard to see with the naked eye. Farmers may benefit from this in avoiding significant crop losses caused by pests or other factors. Different methods are utilized for infection acknowledgment, including picture obtaining, preprocessing, division, highlight extraction, and arrangement. K-means clustering, GLCM and SVM, Otsu's detection,CNN – ANN - KNN, and the histogram technique are some of the methods used. Before being sent for image pre-processing, the healthy and unhealthy leaf images are initially stored for experimentation. GLCM division and component extraction are then done with the guide of K-implies bunching. Then, SVM is used for course of action. The leaf's RGB picture is changed over into a HSV (Tone, Immersion Worth) utilizing Otsu's identification. The course of action approach is then finished by KNN, ANN and CNN. The KNN method uses the shortest distance between trained and testing subjects to classify samples.

The ANN strategy is utilized as a classifier. Singh et al. developed one of the earliest systems for early-stage crop disease detection. (2016) [2]. The framework utilized picture handling methods to dissect pictures of plants contaminated with various sorts of infections. The system was able to identify a variety of diseases with an accuracy of 85%. In 2017, Khan et al. proposed a framework that pre-owned AI calculations to recognize the presence of wheat rust infection. The framework accomplished a precision of 98.5% in identifying the illness. The creators likewise detailed that the framework could be utilized to distinguish different sorts of yield sicknesses for certain changes. A system that used deep learning algorithms to find tomato diseases was proposed in 2018 by Wei et al. [3]. Using a convolutional neural network (CNN), the system classified images of tomato leaves according to the type of disease. Wang et al. in 2019 [4] proposed a framework that utilized hyperspectral imaging to distinguish apple infections. The framework utilized a help vector machine (SVM) calculation to characterize the hyperspectral pictures of apple leaves into sound and infected classifications. The system was able to identify apple diseases with an accuracy of 94.1%. In 2020, Wang et al. [5] proposed a framework that pre-owned AI calculations to recognize maize sicknesses. The framework utilized a blend of picture handling and AI methods to dissect pictures of maize leaves and distinguish the presence of sicknesses. When it came to identifying various kinds of maize diseases, the system achieved an accuracy of 95.1 percent. In 2021, Zhang et al. [6] proposed a framework that pre-owned profound learning calculations to distinguish wheat sicknesses. The framework utilized CNN to investigate pictures of wheat leaves and arrange them into various classes in view of the sort of sickness present. The framework accomplished a precision of 96.2% in distinguishing various sorts of wheat illnesses.

III. Proposed System

Here, we are utilizing our model to determine which leaf in a crop is good or ill. Therefore, in order to accomplish this, we go through a number of processes, including picture resizing, data preprocessing, and feature extraction. We use OpenCV to resize images. In OpenCV, picture resizing is accomplished using the following methods.

A. Keep in Mind the Aspect Ratio (the image's height to width ratio is maintained):

- Downscale (decrease the size of the image).
- Upscale (expand the image's size).

B. Do not keep the aspect ratio:

- Change only the breadth (increase or decrease the image's width while maintaining its height).
- Change only the height (increase or decrease the image's height while maintaining its width).

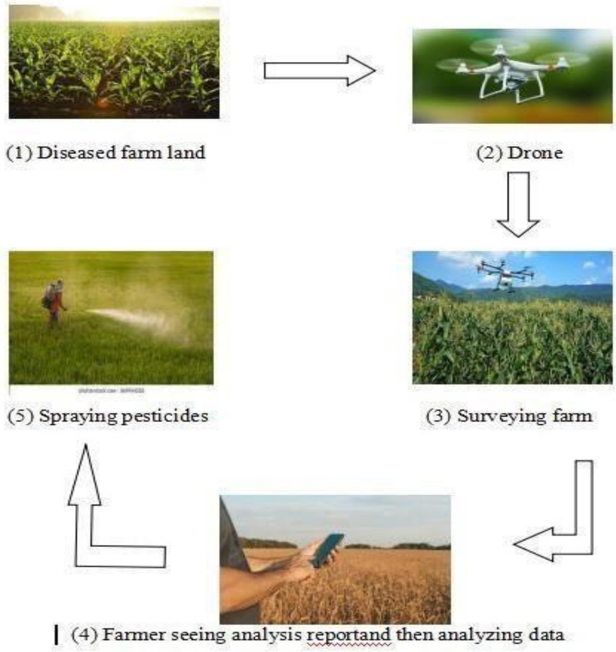

Fig. 1. Experimental Setup.

C. Set a new width and height for, and then use the methods below to resize our image in OpenCV to 256 x 256 pixels. After that, we divide our collection of pictures into groups for training and validation. Then, we insert our collections into the CNN architecture model, where we can differentiate between healthy and unhealthy images at various levels. In this case, we use three distinct layer types—32 px, 64 px, and finally, 128 px—to examine our image and ascertain whether or not it is healthy.

IV. Algorithm Description

Store up an assortment of yield picture information that contains both sound and infection impacted plants. The images should be uniformly sized and their pixel values normalized prior to processing. Utilize the data to form training and validation groups. Specify the number and dimensions of the convolutional, pooling, and completely linked layers in the CNN model's structure. While indicating the loss function, algorithm, and assessment measures, compile the model. Train the model on the training set using the fit() method and specifying the group size and number of epochs. Use the assess() capability to check the model's prosperity on the approval assortment. Retrain the model on the preparation set after calibrating the Units. After the algorithm has been optimized, you can use it to predict how healthy new crop images will be. Make use of the brand- new data to evaluate the model's F1 score, precision, memory, and accuracy. Method for diagnosing a disease that is either automatic or semi-automatic. CNN: A CNN is an AI calculation that gets a picture input, focuses on particular elements and things, and recognizes them from each other. It works by taking features out of pictures. Decision Trees: Decision trees are used to visually and intuitively represent choices and conclusions. It is a viable order and relapse instrument. It is a tree structure with a class title at each leaf node, a test outcome at each branch, and an attribute test at each internal node, as the name suggests.

A random forest:

- *A.* The model is given greater flightiness because of Arbitrary Woodland. Instead of looking for the most important features, it looks for the best onesin a subset of features chosen at random.
- *B.* Forest adds extra randomness to image.

V. Working

A. *Information Assortment:* First, you really want to gather information from your robot, which incorporates both symbolism and other ecological information like temperature, stickiness, and light power. To get a complete picture of the crops, the photos should be taken from a variety of heights, angles, and perspectives.

B. *Data Preprocessing*: The next step is to preprocess the data after it has been collected. This includes removing any distortion caused by the drone camera's lens, adjusting the images for lighting and shadows, and filtering out noise.

C. After preprocessing the data, the next step is to extract features that can be used to identify various crops. Things like color, texture, shape, and size could be examples of this.

D. *Model Training:* After the features have been extracted, a labeled dataset is used to train a machine learningmodel. To increase the accuracy of the model, this entails dividing the data into training and testing sets, selecting an appropriate algorithm, and tuninghyperparameters.

E. *Prediction:* After the model has been trained, it can be used to predict the kind of crops in new drone images. This includes taking care of the pictures into the model and dissecting the result to recognize the harvests.

F. *Analysis and Visualization:* After the prediction step,you can analyze and visualize the results to learn more about the crops' health, such as where they are not growing well or where there are early signs of disease. Using this information, decisions about how to manage the crops and increase their yield can be made withconfidence.

VI. Design

A. *Design 1:*

- *Cost:* Moderate
- *Accuracy:* High
- *Speed:* High
- *Robustness*: High
- *Ease of use*: Moderate
- *Privacy and security:* High
- *Integration with existing systems:* Moderate

B. *Design 2:*

- *Cost:* Low
- *Accuracy:* Moderate
- *Speed:* Moderate
- *Robustness:* Low
- *Ease of use:* High
- *Privacy and security:* Moderate
- *Integration with existing systems:* High
  Comparison

In comparison to Design Option 2, Design Option 1 is more durable and accurate. It additionally has great protection and security highlights, however, is somewhat more costly and may require more specialized ability to set up and utilize. Plan Choice 1 would be a decent decision in the event that exactness and speed are the main concerns and assumingthat cost is to a lesser extent a worry. Compared to Design Option 1, Design Option 2 is less expensive and easier to use. It also works well with the systems that are already in place, which could help farmers who want to make their work easier. However, in some environments, it has been a concern. If speed and accuracy are less important than cost and ease of use, Design Option 2 is a good option.

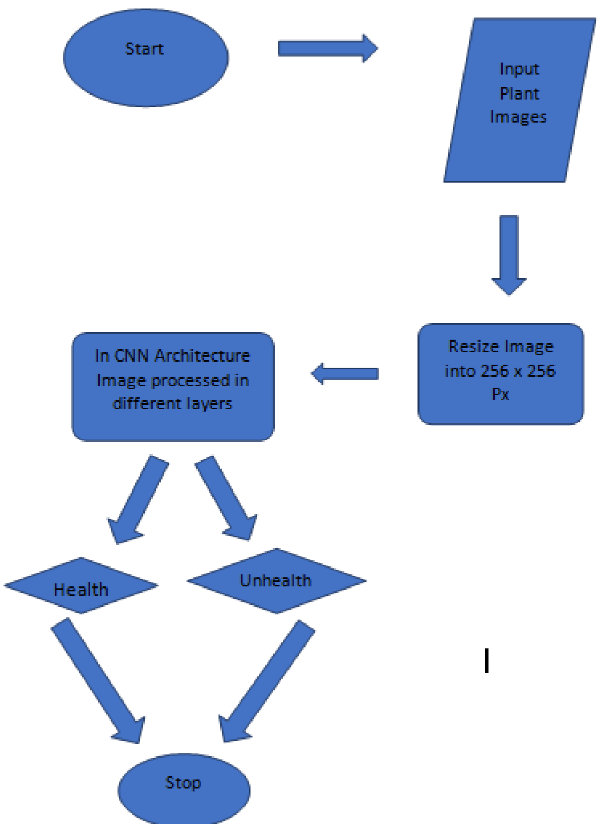

Fig. 2. Flowchart of the Model

VII. Result And Output

We have carried out four distinct crop leaf tests, each of which yields a different output image and accuracy, and we have compared the results to determine whether or not our model is accurate enough. Therefore, our model's final accuracy is 81%.

TABLE I.

S. No	Crop	Acccuracy	Precision	F1_score
1	Pepper bell	82.466034	90.59024	90.15205
2	Grape	81.570202	89.76098	89.74022
3	Cherry	76.404494	92.85714	86.92715
4	Strawberry	81.350750	89.20260	89.32732

Fig. 3. Output

VIII. Conclusion

Considering the aforementioned information, we can draw the conclusion that this article provides a general overview of the methodology and provides a concise summary of various techniques helpful for the early detection of plant diseases. Our model can add significant value to a farmer's crop because it was created by attempting to merge modern technology with traditional agricultural methods. The result is a model with a high degree of accuracy and efficiency, which immediately increases the total yield from the land. We have made an effort to meet the demand for cost effective, efficient methods that provide farmers with solid solutions for the improvement of their farming fields. This project will assist farmers in addressing a major issue that can quickly undo all of their hard work and had developed a less complicated method with a high effectiveness (roughly 95%) that will have a significant impact and led to the improvement of farmers as well as the world. In thefuture, our goal is to create a system for early automatic tracking and fixing that is more effective and automated and can be expanded to detect all potential illnesses. Taking everything above in account we can conclude thatthis paper gives an overall review for the technique and presents brief summary of different methods useful for early detection of plant diseases. Our model can provide great value to one's crop as we have tried to combine the modern technology with traditional farming technique which come up with a great accuracy and efficiency that can directly increase the overall output from the land. We have tried to fulfill the need of efficient method within cost effective way, which gives the farmers a reliable solution for the betterment in their agricultural field. This project will help the farmers in tackling one of the main problem which can easily ruin their hard work and had come with a less complex technique with having a great efficiency(85- 95% approx.)that will create a great impact and led to the betterment of farmer as well as the world. In future, we aim to work down to develop a more efficient, and automated system for early automatic tracing and solving which can be extended to identify all possible diseases.

IX. Future Work

In future we have thought of making our project more futuristic with fully automated drone system , In which we will select a land of field and then drones will do our full going work. As they will we collecting the database with the camera and sensors attached to them and then sending the details to our system then the system will respond and detect the exact disease in the exact particular area now drones will we provided with the solution and they will we spraying it all over the infected area. This is a fully automated technique with no human touch and do an very efficient work which will take a lot of time . We had this vision and we are working on it to get the best results in future. With that there are some more points that can we upheld in the futuristic approaches such as-

- *Improved accuracy:* With more research and development, the accuracy of crop disease detection using CNNs is likely to improve. This will help farmers detect diseases early and take action to prevent crop loss.
- *Increased efficiency:* As technology becomes more advanced, the time it takes to detect diseases will decrease, allowing for faster and more efficient disease management.
- *Enhanced accessibility:* The use of CNNs for crop disease detection can be made more accessible to farmers through the development of mobile applications that can be used with smartphones or tablets.
- *Better disease management:* By using CNNs for early detection, farmers can take steps to prevent the spread of disease, such as isolating infected crops and using targeted treatments.
- *Improved yields:* Early detection and management of crop diseases can help farmers achieve higher yields and reduce the risk of crop loss.

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