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Fruits Classification and Detection Application Using Deep Learning

ABSTRACT : Agricultural quality control is challenging. Drought, heat waves, floods, and an increase in plant diseases and pests are only a couple of the many ways in which climate change impacts agriculture. Agricultural output and quality are both negatively impacted. The inability to manufacture remarkable goods and satisfy human wants is a direct result of this climatic change. Fruit production would become unprofitable for farmers in the long run. It is of the utmost importance to keep farmers informed about climate change and its effects. Instead of relying on human grading standards, growers may benefit from an automated system that can increase both the yield and quality of pomegranate fruits. Due to the time and expertise required to detect and grade illnesses, fruit grading by hand is inefficient. It also doesn't provide the right outcomes. Pomegranate production, together with disease diagnosis and accurate fruit quality evaluation, are crucial jobs for researchers and farmers. Hence, we came up with a new way to categorize diseases based on size, color, and status in this research. This paper presents a Python-based image processing approach for pomegranate fruit grading and sickness detection. The pomegranate fruit is classified into distinct gradation groups using machine learning techniques such as SVM or CNN. This is done based on the discovered features.

Keywords : CNN algorithm, Diseases, Image processing, K-mean algorithm, Pomegranate.

INTRODUCTION : Conventional wisdom holds that a trained eye is the only reliable tool for detecting and diagnosing fruit diseases. It may be time-consuming and expensive to contact professionals in several developing countries due to their distant locations [1]. In order to catch indications of diseases in developing fruits at an early stage, automatic disease detection in fruits is crucial. Significant losses in harvest yield and quality may occur as a consequence of fruit diseases. It is vital to recognize what is being seen in order to establish what control measures to utilize next year to prevent losses.

Apple blotch and apple rot are two common illnesses that affect apples. Apple rot infections manifest as slightly flattened, spherical brown or black patches that may have a crimson aura surrounding them. The fungus that causes apple blotches makes the apple's skin seem black, uneven, or spotted. Automating the size and color inspection of apples is something the company has done using machine vision. Nevertheless, spotting anomalies is still difficult due to the natural skin tone variation across fruit varieties, the vast array of defect types, and the existence of illnesses. It is crucial to assess nutrition and find illness within a fruit, and research may be detected by apparent patterns of each fruit. To further aid in disease management and, by extension, quality, chemical treatments, pesticides, and fungicides are just a few examples. Deep learning, sometimes referred to as neural networks, is one of the several types of machine learning that is inspired by the structure and operation of the human brain. [2].You can image-search a phrase like "hug" thanks to deep learning's use in Google's search and picture search. Smart Replies are sent to your Gmail inbox using it. It's visual and spoken. I think it will be used in machine translation shortly. the renowned "Godfather" of neural networks, Geoffrey Hinton, said. It is much easier to extract complex information from input photos using Deep Learning models due to their multi-level architectures, as seen above.

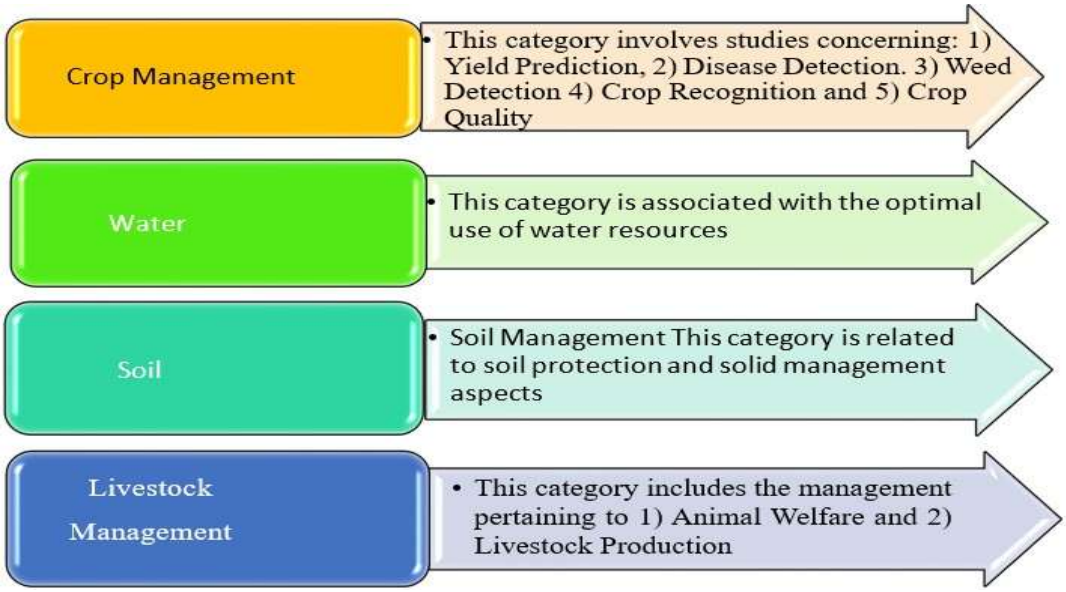


Figure 1: Four Overarching Types of Machine Learning in Agriculture

Figure 1.2 shows the several subfields that make up computer vision. Visual serving, 3D scene modeling, object identification, learning, indexing, Among these are scene reconstruction, object identification, event detection, video tracking, object recognition, and 3D position estimation. Recognition of objects, navigation by autonomous vehicles, identification of faces and fingerprints, processing of images quickly for computers, and robotic navigation were all accomplished by computer vision in 2022. Some incredible developments, such as visual simultaneous localization and mapping (SLAM) and object tracking, have been made possible by methods including line recognition, feature extraction, segmentation, optimization, feature matching and tracking, and reconstruction of 3D reality. Fig. 2 below shows the taxonomy of computer vision and related subjects, including science and technology, mathematics and geometry, physics and probability, and so on. Using computer vision techniques, large amounts of training data can be obtained and analyzed, which is a practical need for AI methods like deep learning and machine learning. It would seem that 4IR technologies, including computer vision and AI, are having an outsized impact

on many different industries, including healthcare, transportation, smart robots, virtual agents, vision-based AI systems, etc. The massive influx of capital into sectors and services powered by AI was a direct result of this. The analysis in its entirety may be found in references. In terms of how artificial intelligence is changing a number of sectors and new businesses that have emerged in the last five years, info graphic has been It is possible to use computer vision systems for:

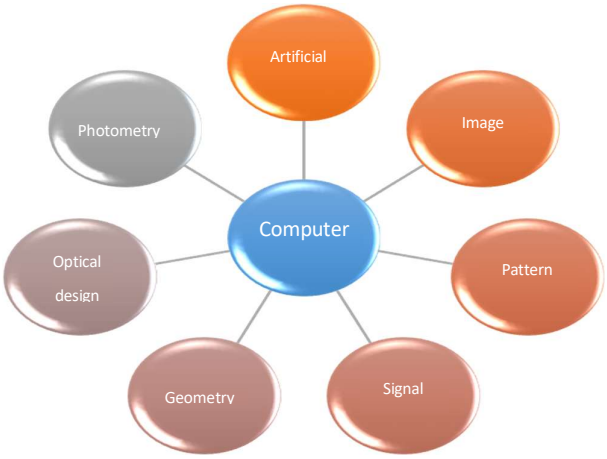


Figure 2 Computer Vision

Product Categorization. Using visual content analysis, the system sorts the items in the video or picture into predetermined groups. For instance, out of every item in a picture, the algorithm can identify a dog.

Recognition of Objects. By analyzing the visual information, the system is able to identify certain items in images or videos. For instance, out of all the dogs in the photo, the algorithm can identify a specific one.

Object Following. The system analyzes the footage in order to detect and follow moving objects that meet the search parameters.

Computer Vision Systems (CVS) They have the ability to replace manual (visual) inspection methods and have thus achieved widespread acceptance in industries as a tool for evaluating the quality of a wide variety of agricultural products. Research in the field known as "computer vision" focuses on creating tools so computers can "see" and understand the details contained in digital images. One of the main goals of computer vision is to use computers and software to simulate human eyesight in all its facets. CVS is computerized, allowing for low-cost, fully automated quality evaluation systems to replace manual inspection methods, eliminating errors and discrepancies in results showing in the figure 2 their use can also help to reduce the tediousness of manual inspections.

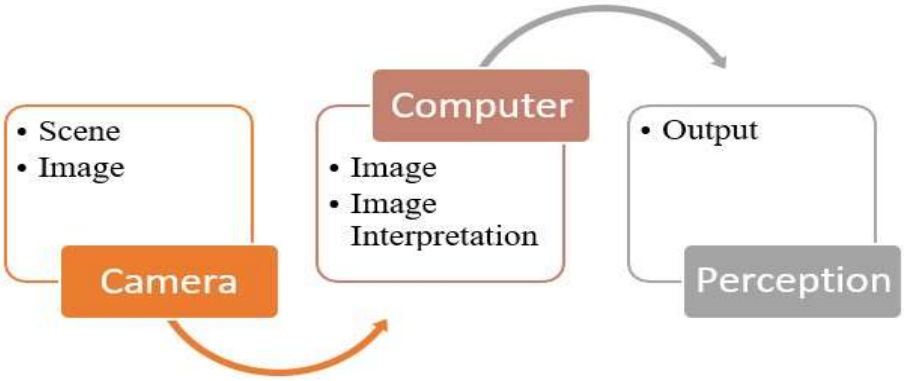


Figure 3 Computer Vision Block-Diagrams

FRUIT DISEASES : There are certain assessments that benefit greatly from the characteristics that digital photos can communicate. Finding the flaw in a fruit is a crucial step in the field of food science. A fruit's size, color, form, and lack of flaws determine its quality. Rot, blotch, scab, fungus attack, bitter pit, bruises, punches, holes caused by insects, and growth abnormalities are among the many types of defects. The agriculture business stands to benefit from early detection of fruit flaws, so several research articles have offered various machine vision approaches for detecting and categorizing apple problems. In order to achieve recognition levels comparable to those of humans, quality assessment via defect detection has emerged as a significant topic of study in computer vision. Numerous food-related applications have resulted from the use of image processing techniques. The following are only a few examples of their many potential uses: robot harvesting, yield mapping, fruit grading, weed identification, disease detection in leaves, etc.

Classification of Citrus Diseases: Plant diseases are the main cause of decreased production and monetary losses on a national scale in the agricultural sector. Nutrients like vitamin C are abundant in grapefruit, making it a vital food source across the world. The availability and quality of citrus fruits were devastated by citrus diseases. Plants that produce citrus fruits, such lemons, oranges, grapefruits, and limes, are susceptible to a wide variety of diseases and disorders. Here are a few citrus diseases and their short descriptions:

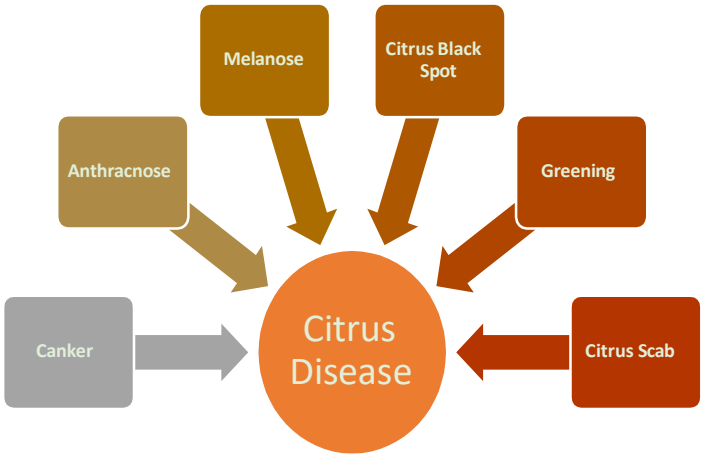


Figure 5 different types of citrus disease

Research methodology : Assuring food security on a worldwide scale is a major responsibility of the agricultural industry. Nevertheless, several fruit-related illnesses often jeopardize crop output and quality. To minimize crop losses, it is vital to diagnose these diseases early and treat them effectively. This project introduces a method for predicting fruit diseases using Python and machine learning in this specific situation. To identify fruit crop illnesses, the suggested approach combines machine learning with image processing. The first step is to gather picture datasets with both healthy and unhealthy fruit examples. Feature extraction from the photos is done in advance using computer vision frameworks like OpenCV. Recently, there have been significant advancements in the analysis of illnesses using deep learning and machine learning. At long last, the system has mastered the art of accurate and precise metric estimation, as well as recall and f1-score. When it comes to aiding experts and farmers in early illness detection, the first findings of the tests are encouraging. The trained model must then be included into a Python program that is easy for users to navigate.. Farmers or agricultural experts can upload images of fruit samples through a web or mobile interface. The system processes these images, predicts the likelihood of diseases, and provides real-time diagnostic results. Additionally, the application may offer recommendations for disease management strategies, including suggested treatments or preventive measures.

Method 2 : The suggested system retrieves the input picture from the dataset store. We may convert the original picture to grayscale and resize it in the pre-processing steps. Feature extraction methods like K-map clustering, GLCM, SIFT, and SURF may then be used to the pre-processed images. A test picture and a train image may be created from the same set of photographs. Afterwards, we may identify the input picture using several machine and deep learning techniques including SVM, Light Gradient Boosting, Random Forest, NB, and SVM + CNN. Finally, the system may make educated estimations about certain performance metrics, such as f1-score, recall, accuracy, and precision.



Fig 6. Proposed methodology

Classification Network : When working with regression, linear or nonlinear classification, or even outlier identification, Support Vector Machine (SVM) is a helpful machine learning tool. Text classification, picture classification, spam detection, handwriting recognition, gene expression analysis, face identification, and anomaly detection are just a few of the many uses for support vector machines. SVMs are adaptable and effective in a broad range of circumstances since they can handle high-dimensional data and nonlinear relationships. Support vector machine techniques appear to be highly effective when attempting to identify the biggest separation hyperplane between the several classes accessible in the target feature.

Random Forest : One well-known supervised learning method is Random Forest, which is used in machine learning. Classification and regression issues in machine learning are both amenable to its usage. The idea behind it is ensemble learning, which involves using a combination of classifiers help improve the model's functionality and manage challenging issues.As the name suggests, "Random Forest is a classifier that utilizes numerous decision trees on distinct subsets of the dataset and averages them to boost the dataset's projected accuracy." Instead of relying just on one decision tree to decide the final output, the random forest uses the forecasts of all the decision trees.A bigger forest increases accuracy and decreases the chance of overfitting. The figure below illustrates the Random Forest approach:

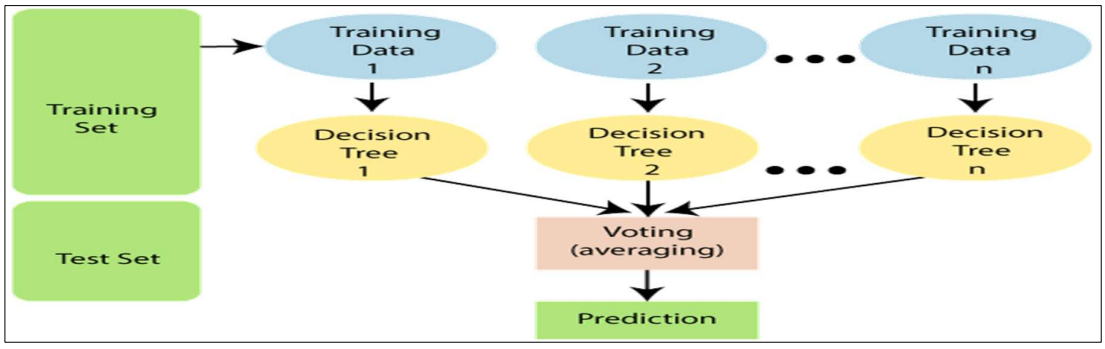


fig. 7 Random Forest algorithm

There are two steps to using a Random Forest: first, you combine N decision trees to construct the forest, and second, you use each tree to generate a prediction.
The following stages and graphic illustrate the working process:
Step-1: Pick out a random subset of K training set data points.
Step-2: Put together the decision trees that go along with the subsets of data that you choose.
Step-3: If you want to construct decision trees, choose the value N.
Step-4: Keep going until you reach Step 2.
Step 5: Find the forecasts of each decision tree for fresh data points, then place them in the category with the highest number of votes.

PROPOSED SYSTEM AND RESULT DISCUSSION

PROPOSED SYSTEM : The suggested system for detecting fruit diseases is an all-inclusive solution that makes use of cutting-edge techniques for machine learning and image processing. After receiving the Fruit Disease Image collection in several formats, the system goes through an important pre- processing stage that involves decrypting and improving photos by scaling and turning them to grayscale. Two distinct methodologies are proposed for feature extraction and classification. Incorporating sophisticated techniques like Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) with more traditional statistical metrics like standard deviation and mean are all part of the methodology. A wide variety of machine learning techniques, such as K-Nearest Neighbor (KNN), Decision Trees (DT), Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and a CNN+ANN hybrid approach, are used to accomplish classification.

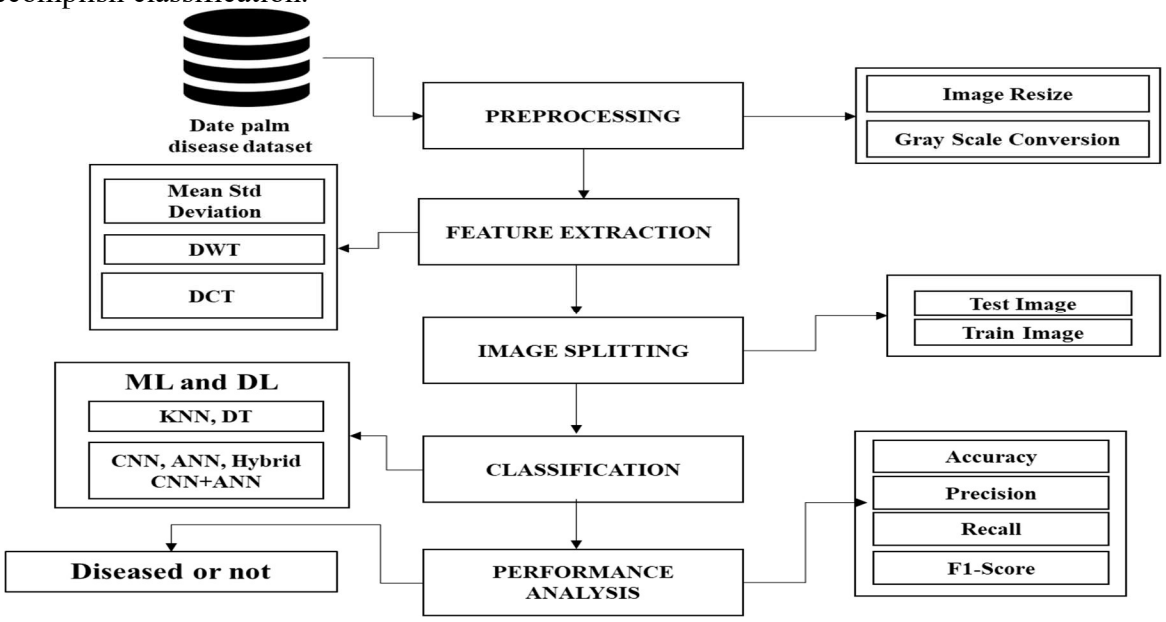


fig.8 proposed flow diagram

Utilizing picture data, preprocessing approaches, machine learning methods and feature extraction techniques, the suggested system for fruit disease diagnosis employs a holistic strategy. The system follows a systematic methodology:
Input Data: Utilizes the Fruit Disease Image dataset sourced from a repository, containing images in formats such as '.png' and '.jpg'.
Pre-processing: Preprocessing, which entails scaling and grayscale conversion of decrypted images, improves the dataset's quality and consistency.
Resize Images: Standardize the dimensions of the input images to a common size.

Resizing can be represented by a mathematical function where each pixel's new position is determined based on a scaling factor.
Let Inew(x′,y′)
stand for the reduced picture and Iold(x,y) for the original. It is possible to express the resizing function as: Inew(x′,y′)=Iold(fx·x′,fy·y′)
In this case, the x- and y-direction scaling factors are denoted as fx and fy, respectively.
Convert to Grayscale: Simplify the images by converting them to grayscale, reducing the dimensionality. Converting color images to grayscale involves representing each pixel with a single intensity value. One common method is to take the average of the color channels (R, G, B). For example, if we have two images, Igray(x,y) and Icolor(x,y), we may describe the conversion as :
Igray(x,y)=31(Icolor(x,y)R+Icolor(x,y)G+Icolor(x,y)B)
Alternatively, you can use weighted averages based on the perceived luminance of different color channels.
Hybrid CNN and ANN
Convolutional Neural Networks with Fully Connected Layers or a Convolutional Neural Network with a Dense Head are common names for hybrid models that combine CNNs with ANNs. Tasks requiring both visual feature extraction (conducted by the CNN component) and high-level decision-making (conducted by the ANN component) are typical applications of this model type.
Create the model's convolutional layers (the CNN component) to glean hierarchical information from the source pictures. To do this, it is common practice to stack pooling layers, activation functions (such as ReLU), and convolutional layers in order to decrease the spatial dimensions. Flattens the output or uses global average pooling to convert the 3D tensor into a 1D vector after the convolutional layers. This gets the information ready to be fed into the fully linked layers.
ANN (Dense) Layers: After the convolutional neural network (CNN) output has been flattened or pooled, add dense layers that are completely linked.Learning features and making decisions at a high level are the responsibilities of these levels.
Activation Functions: Choose appropriate activation functions for the dense layers, such as ReLU or sigmoid, depending on the task.
Output Layer:

- Use a task-appropriate activation function (such as softmax for classification) at the output layer.
- Define the output layer's neuron count according to the number of classes to be classified or the desired regression output dimension.
- A loss function that is appropriate for the job at hand (for instance, categorical cross entropy in the context of classification).

Table 1 pre-pre-processing result of all fruit

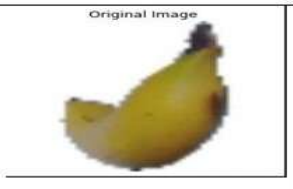
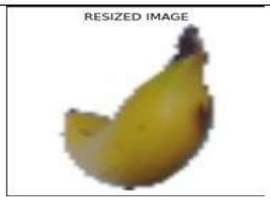
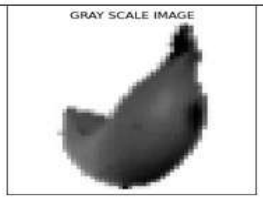
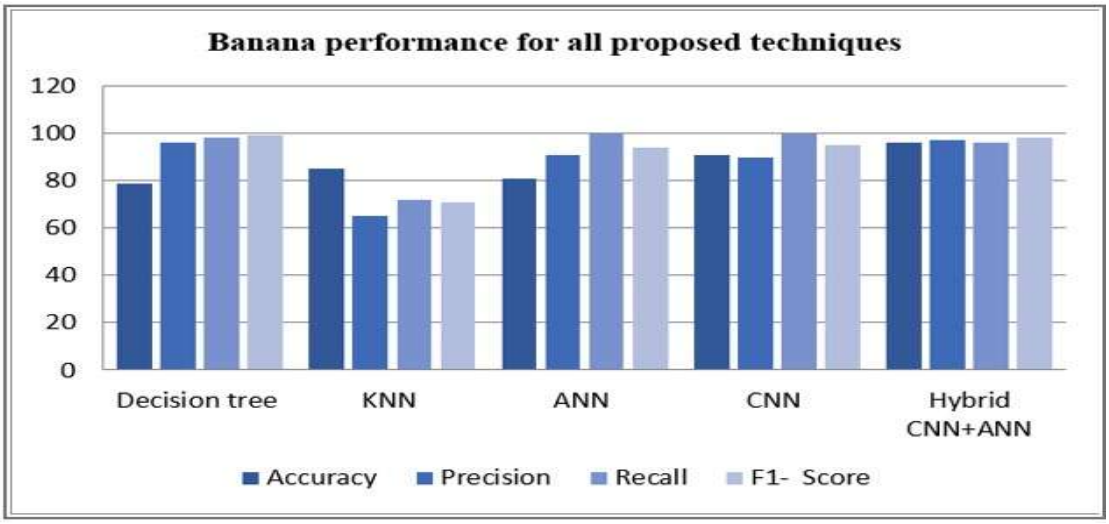
	Original Image	Resized image	Grey scale image
BANANA			

Table4: Banana performance for all proposed techniques

BANANA	Accuracy	Precision	Recall	F1- Score
Decision tree	79	96	98	99
KNN	85	65	72	71
ANN	81	91	100	94
CNN	91	90	100	95
Hybrid CNN+ANN	96	97	96	98

Table 4.4 presents the performance metrics of various techniques for detecting Banana diseases. The Decision Tree model shows dependable performance with a 79% accuracy, 96 precision, 98 recall, and 99 F1-score. Although KNN achieves a respectable 85% accuracy, it is not as successful as other methods because to its lower precision (65), recall (72) and F1- score (71). An F1-score of 94, a high precision of 91, a perfect recall of 100, and an accuracy of 81% are all superior outcomes achieved using ANN. With 91% accuracy, 90% precision, 100% recall, and 95% F1-score, CNN surpasses ANN. With the best accuracy (96%), precision (97), recall (96), and F1-score (98), the hybrid CNN+ANN technique clearly dominates all other approaches when it comes to accurately recognizing banana illnesses.



CONCLUSION : In order to tackle the pressing problem of illnesses impacting fruit harvests, this research project presents a Fruit Disease Prediction system. The system provides a strong answer to the problem of fruit disease diagnosis and control by using Python, image processing methods, and machine learning algorithms. There were two separate approaches suggested, and they both made use of various feature extraction methods and machine learning algorithms. Method 2 uses K-map clustering, GLCM, SIFT, and SURF, whereas Method 1 uses DWT, DCT, Standard Deviation, Median, and Mean. The outcomes of the trials on these methodologies show promise when it comes to recall, accuracy, precision, and f1-score. Farmers and agricultural specialists may now submit pictures of fruit for real-time illness detection thanks to a user-friendly Python application that incorporates the learned models. Not only does the system give helpful suggestions for illness management tactics, but it also helps with faster intervention and

better decision-making. Sustainable agricultural practices, reduced economic losses, and improved global food security are all outcomes of this project's use of machine learning. The system's versatility and scalability make it an invaluable asset in the never-ending battle against the problems that the agricultural industry faces.

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