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An Intelligent Grading System for Automated Identification and Classification of Banana Fruit Diseases Using Deep Neural Network

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Abstract: This study proposes an intelligent system for automated diseases detect and categorization in banana fruit, as well as an integrated grading system. To accomplish accurate illness identification and grading, the suggested system combines computer vision methods, machine learning algorithms, and deep learning models. The system extracts key information from banana fruit images using image processing techniques, which are subsequently input into a trained classification model. The categorization model uses cutting-edge algorithms to categorize the banana fruit into several illness groups. Furthermore, the sophisticated grading system evaluates the severity and quality of the diseased fruit based on a variety of characteristics such as size, color, and texture. The experimental findings reveal that the proposed method is successful, with high accuracy rate of 99.8% in illness diagnosis and accurate banana grading. This automated technology provides a time-efficient and cost-effective approach for disease control in banana plantations, allowing producers and agricultural stakeholders to make more informed decisions.

Keywords: Diseases, Image processing, Deep Neural networks, Banana fruit, feature extraction and Classification.

1. INTRODUCTION

Bananas, one of the most popular fruits consumed worldwide, provide essential nutrients and contribute to global food security. However, a number of infections that can substantially reduce banana tree productivity and quality are communicable [1]. Early identification and correct categorization of illnesses affecting banana fruit are critical for effective disease control and the prevention of infection transmission within farms.

Manual inspection, which is labor-intensive, time-consuming, and prone to human error, is commonly utilized in traditional sickness detection and grading approaches. As a consequence of advancements in computer vision, machine learning, and deep learning approaches, there has been a surge in interest in developing automated systems for disease detection and intelligent grading of banana fruits.

The examination of visual symptoms displayed by the fruit, such as discoloration, spots, lesions, and deformities, is used in the automated diagnosis and categorization of banana fruit disorders. Computer vision techniques allow for the extraction of key characteristics from digital photographs of fruit, resulting in significant information for disease detection[2]. Machine learning techniques and deep learning models may then be trained on a collection of annotated photos to properly categorize banana fruit into illness categories.

An intelligent grading system for banana fruits can measure the severity and quality of contaminated fruits in addition to disease identification. Size, color, texture, and general look may all be used to assess the grade of the fruit[3]. This information is useful for growers, distributors, and consumers because it allows them to make educated decisions about how to use and distribute the fruits.

There are various advantages to developing an automated identification and classification system in conjunction with an intelligent grading system. It simplifies illness management by allowing for early identification and fast response to avoid infection spread[4]. It also decreases farmers' reliance on human effort, saving them time and resources. Furthermore, it permits objective and regular grading of banana fruits, assuring the market supply of high-quality goods. The suggested system's major purpose is to detect plant illnesses early on and give tailored management measures to reduce the impact of diseases on agricultural output. It is critical in India, where 70 percent of the population relies on agriculture for a living. Agriculture contributes significantly to the country's GDP and is inextricably related to the country's economy. Plant diseases can have a major impact on crop growth, resulting in lower yield and crop quality[5]. Viruses, bacteria, fungus, nematodes, and nutritional shortages can all cause these disorders. If left untreated, these diseases can cause plant damage and even plant mortality, impacting total land cultivation and farmer income[6]. Diseases can spread from plant to plant. Despite the fruit's popularity in Asia and the Pacific, diseases such as black sigatoka and yellow sigatoka, banana bunchy top virus and stripe virus, panama wilt and freckle leaf, cigar end rot and anthracnose threaten the banana industry[7]. If the presence of these diseases is detected and measures are taken as soon as feasible, banana plants and other nearby plants may be safeguarded. Larger farms, where diseases may spread fast, find the current method of disease detection, using the naked eye, to be inconvenient and time-consuming. To solve this, a continuous monitoring system for big farms with automatic disease identification is required, lowering labor and expenses associated with human monitoring. Plant diseases can be identified using image processing algorithms based on symptoms[8]. By cross-checking symptoms on plants, this method allows for faster and simpler disease identification. Image processing is more accurate and efficient than visual assessment with the naked eye, saving time and money. The proposed system would use image processing techniques to detect plant illnesses early on, giving farmers with timely information and particular management steps to reduce disease spread[9]. The purpose of deploying such a system is to increase agricultural productivity by lowering the impact of diseases on crops.

The goal of this paper is to provide the results of a detailed examination into the use of artificial intelligence to the problem of disease detection and categorization in bananas. It looks on the feasibility of employing computer vision technologies, machine learning algorithms, and deep learning models to accurately classify illnesses[10] . The effectiveness and reliability of the proposed system will be demonstrated by experimental results and assessments.

2. LITERATURE SURVEY

In recent years, there has been a lot of interest in the subject of automated identification and categorization of banana fruit illnesses, as well as an intelligent grading system. Researchers and scientists have investigated many strategies and techniques in order to produce efficient and accurate illness detection and grading systems. This review of the literature gives an overview of some significant research and techniques in this field.

D. S. Prabha and J. S. Kumar (2015) presented "Deep Learning-Based Classification of Banana Diseases: A Comparative Study". Deep learning models, such as convolutional neural networks (CNNs), were used in this study to classify banana fruit diseases[11]. A comparison of several CNN architectures was carried out, and their performance was assessed in terms of accuracy and efficiency.

A. Chandini and B Uma Maheswari. (2018). "Computer Vision Techniques for Banana Disease Detection: A Review." This review study takes an in-depth look at the various computer vision approaches used for banana disease diagnosis. It examines how image processing algorithms, feature extraction approaches, and machine learning techniques may be used to accurately identify diseases[12].

N. Saranya, L. Pavithra, and N. Kanthimathi (2020). "A Comprehensive Survey of Banana Diseases Detection Using Image Processing Techniques." This survey study provides an in-depth examination of image processing approaches used to identify banana diseases[13]. It discusses picture enhancement, segmentation, and feature extraction techniques used in numerous research to increase illness detection accuracy.

AR Mesa, JY Chiang (2021). "Automated Ripeness Grading System for Bananas Using Machine Learning Techniques." The purpose of this research is to create an intelligent grading system for banana fruits using machine learning techniques[14]. It investigates the use of color-based characteristics and machine learning algorithms to reliably judge the maturity of bananas.

Pereira, L.F.S., and S. Barbon (2018) offered "Detection and Classification of Banana Diseases Using Machine Learning Techniques." This study proposes a machine learning-based strategy for detecting and classifying banana diseases[15]. To accomplish reliable illness categorization, several feature extraction approaches, such as texture analysis and color-based features, were used in conjunction with machine learning algorithms. Helfer, G.A., and J.L.V. Barbosa (2020). "Banana Leaf Diseases Detection and Classification Using Image Processing Techniques." While most studies focus on fruit illnesses, this study looks at disease detection and categorization on banana leaves[16]. Image processing techniques such as segmentation and feature extraction were used to accurately diagnose and categorize various leaf diseases.

M. Bantayehu and M. Alemayehu (2020). "An Intelligent Grading System for Banana Fruits Based on Image Processing and Machine Learning." Based on image processing and machine learning approaches, this work presents an intelligent grading system for banana fruits[17]. It studies the utilization of numerous visual features, such as color, shape, and texture, for accurate quality grading of bananas.

These research provide light on the progress achieved in the automated diagnosis and categorization of banana fruit illnesses, as well as the creation of intelligent grading systems. They emphasize the use of computer vision techniques, machine learning algorithms, and deep learning models to provide accurate disease diagnosis and grading in banana farms, ultimately contributing to efficient disease management and quality control.

To detect ripe bananas, Le, T.T., and Lin, C.Y (2019) proposed utilizing a neural network for color detection in combination with visual processing. The red, green, and blue components of the banana images were utilized by the system[18]. Bananas of various sizes and maturities were utilized in the study. The bananas were photographed every day until they went rotten. A supervised neural network model with error propagation achieved an identification accuracy of 96%.

In a similar line, Ucat, R.C.et al. (2019) presented a system for measuring tomato ripening using visual cue observation and classification. The three essential components of their strategy were preprocessing, feature extraction, and classification[19]. Because the surface color of tomatoes is important in determining ripeness, the method used colored histograms to accomplish so. Principal components analysis (PCA) was used to extract features, and a support vector machine (SVM) was used to classify them.

Steinbrener, J et al. (2019) developed a computer vision system that automatically calculated banana size indicators such as length, ventral straight length, and arc height. Garillos-Manliguez, C.A et al. (2021) proposed an intelligent fruit sorting system based on digital image processing and artificial neural networks. The study looked at five distinct fruits (apples, bananas, carrots, mangoes, and oranges) and extracted 17 features based on their morphological and color qualities [20], [21]. The system was constructed with a standard digital camera in a MATLAB/SIMULINK environment, and it resulted in a significant improvement over previous study.

Watermelons, Strawberries, kiwis, and citrus fruits have all been studied for various objectives such as sizing and assessing contaminants in olive oil samples. Furthermore, Omid et al. (2020b) developed a smart system that classified eggs based on faults and egg size using a combination of fuzzy logic and machine vision technologies.

These studies may assist advance the state of the art in intelligent systems that employ image processing, computer vision, and machine learning methodologies for fruit recognition, maturity rating, quality grading, and impurity estimation. Each research has its own focus and approach, and they all have something to say about fruits.

3. BANANA FRUIT DISEASES

The yield, quality, and profitability of banana plantations are all vulnerable to infections that harm banana fruits. Bananas are susceptible to a variety of diseases caused by microbes such as fungus, bacteria, and viruses. The following are the most serious banana diseases:

Fusarium oxysporum f. sp. cubense, or banana rust: This fungal ailment, often known as Panama sickness, is spread through the soil[22]. This disease damages the vascular system of the plant, causing it to weaken, become yellow, and finally die. Farmers that grow bananas face huge financial losses as a result. Pseudocercospora fijiensis (Black Sigatoka) is a fungal disease that damages the leaves and fruit of banana trees. It generates black, uneven patches on the leaves, which might clump together and induce defoliation[23]. Black Sigatoka can drastically diminish banana output and quality.

Banana Bunchy Top Virus (BBTV): BBTV is a viral disease that damages banana plants and fruits. It causes stunting, irregular growth, and the leaves to have a distinctive ”bunchy top” look. Fruits that have been infected may be tiny, misshapen, and of low quality.

Banana Mosaic Virus (BMV): Banana Mosaic Virus (BMV) is another viral illness that affects bananas[24]. It results in mosaic-like patterns on the leaves and can impair plant growth, yield, and quality. Infected fruits may be discolored and deformed.

Banana Bract Mosaic Virus (BBrMV): BBrMV is a virus that attacks the banana plant’s bracts, which protect the growing fruit. Infected bracts have mosaic patterns and necrotic sores. This illness can have an impact on fruit growth and quality.

Other Sigatoka leaf spot illnesses caused by various species of the fungus Pseudocercospora, such as Yellow Sigatoka (Pseudocercospora musae), exist in addition to Black Sigatoka [25]. These diseases induce leaf spots of various colors and sizes, resulting in defoliation and a decrease in photosynthetic ability.

The fungal disease anthracnose (Colletotrichum musae) can infect both the plant and the fruit of bananas. The fruit develops dark, deep flaws that expire and reduce its value[26]. Anthracnose infection can also affect the plant’s leaves and stems. Gloeosporium musae, the fungus that causes anthracnose, affects banana plants at any stage of growth. The blossom, fruit, and peel of the banana are all ideal targets. Colletotrichum musae, the causative fungus, may survive in decaying or decomposing fruit. Anthracnose causes dark brown to black patches on fruit to dry out and disappear[27]. The sickness can spread by the air, water, or insects, among other vectors. Its spread is aided by high humidity and regular precipitation. Cultural and chemical controls are used to combat anthracnose. To inhibit the spread of the disease, cultural management entails eliminating affected leaves and plant debris[28]. Spraying fungicides such as chlorothalonil or Bordeaux mixture can provide chemical control. Anthracnose must be managed since it threatens not only the quantity but also the quality of bananas during shipment and storage. Figure 1 is an example of an anthracnose-affected fruit.

The fungal disease freckle affects both the leaves and the

Figure 1. Example of a fruit affected by anthracnose disease.

Figure 2. Example of a fruit affected by freckle disease.

fruits of banana trees. Freckle fruit disease causes overall yellowing and the formation of small dark brown spots on fruit and foliage[29]. The fruit is still edible, but its market value has plummeted due to the sickness. Both raindrops and sick tissues contribute to the propagation of freckle disease. Freckles generate black dots ranging in size from 1mm to 4mm. Freckle disease is controlled through a mix of physical, cultural, and chemical techniques. Physical management measures include removing the male bud from packaged bunches to avoid disease transmission to the fruit[30]. Cultural management entails removing unhealthy spots from the fruit. Spraying the Bordeaux combination, a fungicide, can provide chemical control. Figure 2 shows an example of a fruit with freckle disease

4. PROPOSED METHOD

The fundamental purpose of this planned endeavor is to identify and classify infections in banana plants as early as possible so that they may be managed and not spread to other plants. Images of banana leaves and fruits are collected to do this. These photos are then saved in a database for further use. 500 fruit samples are considered for disease detection. Figure 3 depicts a simplified illustration of the suggested strategy.

The identification and classification of banana fruit diseases using image processing and Deep neural networks (DNN) is an important use of this approach in agricultural management. Farmers may use this technology to evaluate the growth of banana fruits and diagnose infections at an early stage, decreasing crop losses. Image acquisition, the first stage, necessitates the employment of digital cameras or other imaging devices to acquire photographs of banana foliage or fruits. These images are used as input for further processing and analysis. The quality and clarity of the captured images have a significant impact on the accuracy of illness identification. Following that, image pre-processing techniques are used to increase the quality of the captured images. This may entail removing noise, adjusting brightness and contrast, and scaling or cropping the photographs to highlight certain areas of interest. Feature extraction is a critical stage that involves extracting relevant information or features from pre-processed images. These characteristics can include color, texture, shape, and other visual characteristics that distinguish healthy banana plants from diseased ones. Various techniques and algorithms for image analysis can be used to effectively derive these features. Using the extracted features, the diseases detection phase identifies the presence of diseases on the banana plant. This may involve the application of pattern recognition algorithms, such as ANN, which are able to learn from labelled training data and make predictions or classifications based on the patterns they have learned. As a technique for machine learning, ANN is capable of understanding intricate patterns and relationships between extracted features and the corresponding maladies. By training the ANN with a labelled image dataset, it can be taught to accurately classify diseases based on the extracted features. The effectiveness of the proposed system is contingent on the availability of a diverse and representative training dataset for the artificial neural network (ANN). The more extensive and varied the training dataset, the more accurately the system can generalize and classify diseases in real-world scenarios.

A. *Image Acquisition*

The image processing process begins with the capturing of images from an external source, which is often accomplished through the use of hardware devices. This stage includes the whole set of procedures used to process, compress, store, print, and show the photographs. Images of several illnesses affecting banana leaves and fruits were acquired for this investigation utilizing a digital camera with a resolution of 12 megapixels to assure picture accuracy. A total of 50 photos were taken, with 40 for fruit disease detection and 10 for healthy fruits. All captured photos were saved in JPG format and saved on a disc, resulting in the image database utilized for categorization. The precision and quality of this picture capture procedure have a considerable influence on the subsequent categorization jobs.

B. *Database*

First of all, 200 banana images were captured to act as a database for the investigation. One hundred defective bananas and one hundred flawless bananas were photographed. Before entering the image processing step, down sampling was utilized to reduce the overall resolution of the images. The photographs were down sampled from their

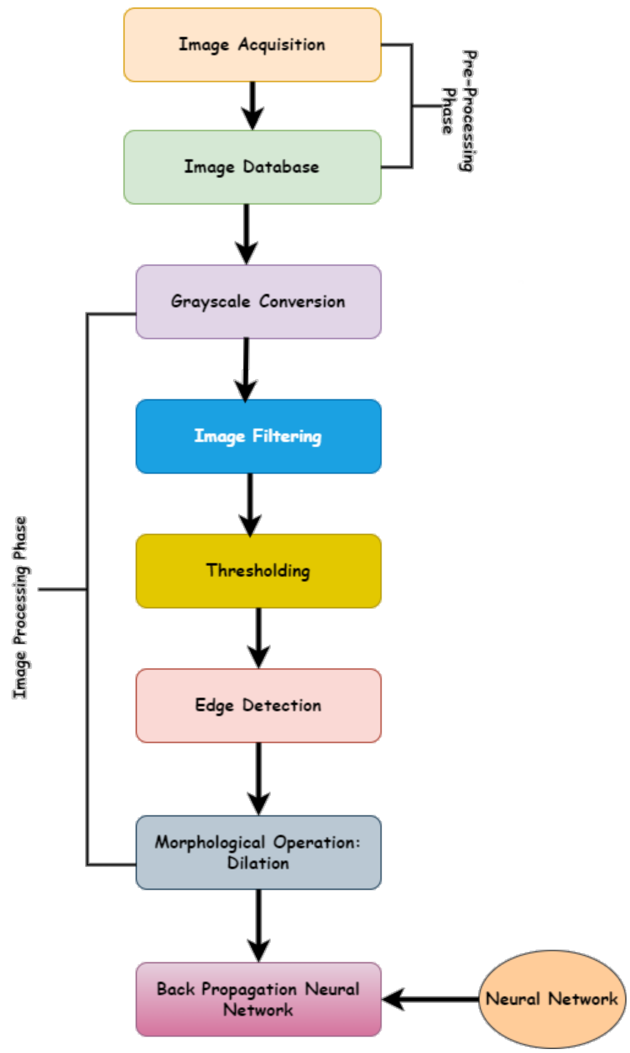

Figure 3. schematic flow of diagram of Proposed System.

original 960x720 resolution to 128 x 128. The image was down sampled to 128x128, with the purpose of emphasizing the region of focus while keeping important features. The photographs were down sampled with care to preserve as much information as possible. Because sorting bananas with a neural network is the major purpose of this project, scale invariance was introduced. The ability of system is to distinguish and accurately label banana images in any orientation is aided by its size invariance. To accomplish this, the 200 banana photos were rotated at 0°, 90°, and 180°angles. This yields a total database of 600 photos, 300 of which are healthy and 300 of which are faulty.

C. Image Pre-Processing

The pre-processing step of image processing tries to improve the usability of the pictures for further processing. It entails using particular approaches to improve image quality and retrieve useful information. This includes picture cropping, resizing, and color conversion. The two main pre-processing methods are image scaling and filtering. Because the size of the acquired images may vary, image scaling is necessary. To aid speedy processing, images are scaled down to a standard 256 by 256 pixel size. The leaves and fruits of the banana plant are filtered to eliminate dust and dew droplets that would otherwise gather. Low pass and high pass filters are two popular types of filters. A high pass filter preserves the highs while smoothing out the lows, whereas a low pass filter reduces the highs while emphasizing the lows. To clean up an image, Gaussian and median filters are frequently used. The proposed approach additionally use histogram-based equalization to convert color images to black and white. This approach enhances the image by adjusting the intensities based on the histogram of the original image. The shifting of intensities improves local contrast, resulting in increased global contrast. This enhancement improves the quality, legibility, and utility of the photographs for further processing.

Figure 4 depicts image processing processes applied to samples of faulty and normal bananas. Step-by-step instructions are as follows: Picture rotation (a) achieves scale invariance. (b) The defective and healthy banana's RGB to grayscale color output: The original color photographs of bananas are converted to grayscale, with the value of each pixel equal to the intensity of its color equivalent. (c) The following are the median filter results for a rotting and a healthy banana: A median filter is used to remove noise and smooth out irregularities in grayscale pictures. (d) Banana quality threshold of 0.5: Grayscale pictures are transformed to binary using a threshold of 0.5. The threshold is used to differentiate between the foreground (a healthy or faulty banana) and the background (below the threshold). (e) The Sobel operator and other edge detection techniques results applied to binary images of faulty and healthy bananas; these approaches are used to emphasize the boundaries between the various regions of the images. This method highlights the inherent beauty of the bananas' shape and structure. (f) Both damaged and healthy bananas exhibit dilation. Dilation is a morphological approach that enlarges the outlines of the subjects in a picture. It's used to smooth out wrinkles and make the bananas look more complete around the edges in binary images.

Every stage in the image processing pipeline helps to improve particular aspects or characteristics of the banana images, allowing for easier identification and classification of faulty and healthy bananas. Thresholding is a typical image processing technique for segmenting an image by distinguishing the foreground from the background. It is a straightforward and extensively used procedure. This approach turns a grayscale image to a binary image, with the foreground and background represented by separate sets of pixel values (often white and black).

The thresholding procedure begins with the determination of a gray threshold value for the image. Pixels with

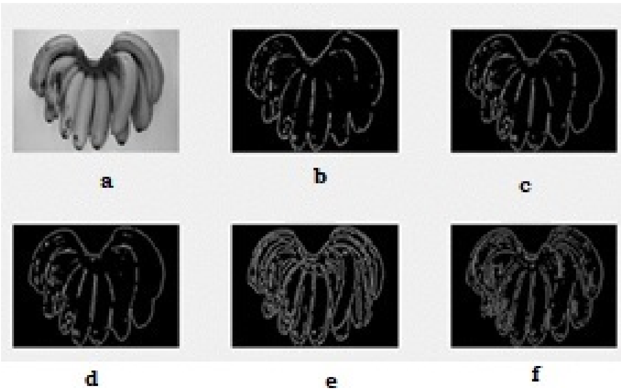

Figure 4. Illustrates different stages of image processing applied to the defective and healthy banana images.

values more than the threshold are considered to be in the front, while those with values less than the threshold are considered to be in the background. To explore what would happen with their investigation, the researchers started with a threshold value of 0.32. However, it was determined that significant visual features were lost with this threshold level. To address this issue, we increased the threshold value to 0.5, resulting in segmented photographs that retained the necessary features. Edge detection is a fundamental image processing approach that seeks to recognize and locate substantial changes in intensity, referred to as edges, inside an image. Typically, these edges reflect the boundaries between distinct sections or objects in the picture. We can reduce the picture data and extract crucial structural information for subsequent analysis and processing by recognizing edges. The Sobel operator was used for edge identification in the research cited. Two 3x3 convolution kernels make up the Sobel operator. One kernel is tuned for greatest horizontal edge response, while the other is optimized for maximum vertical edge response. The kernels are then applied to the image via convolution, which entails determining the weighted sum of the brightness of nearby pixels for each pixel. The Sobel operator is skilled in detecting vertical and horizontal boundaries in images. It computes the magnitude and direction of the gradient at each pixel, showing areas with large intensity changes. The generated edge map depicts the discovered edges visually, with brighter patches indicating the existence of edges.

D. Image Segmentation

The technique of splitting an image into meaningful and distinct parts or segments to make it easier to analyze and comprehend the information is known as segmentation. It entails isolating the regions of interest in the picture from the undesired parts. Segmentation techniques are classified into two types: boundary-based and region-based. The goal of boundary-based segmentation is to discover and extract boundaries or edges between various sections in a picture. It seeks to detect abrupt changes in pixel intensity or color gradients. Region-based segmentation, on the other hand, combines pixels or areas with comparable attributes together to generate coherent segments. It seeks uniformity within areas as well as variability between regions. Figure 5 shows our segmentation method, which is a fuzzy c-means clustering approach. Fuzzy c-means clustering is a popular method for categorizing data into groups based on similarities. Each pixel is assigned a membership value indicating its amount of association with one or more clusters. This technique works well with overlapping and complex image regions. To segment the image into groups with shared characteristics, the fuzzy c-means clustering algorithm is utilized. Segmentation is vital for isolating and extracting the relevant traits or regions of interest for later study and ailment classification. Fuzzy clustering is a data partitioning approach that allows data points to belong to more than one cluster to indicate their uncertain or ambiguous character. This approach is often used in segmentation, particularly in pattern recognition jobs when objective function reduction is sought. The fuzzy clustering approach relies heavily on iterations, membership degree, the fuzziness coefficient, and a termination condition. The approach's purpose is to assign membership coefficients to these attributes in order to identify the degree to which each data point belongs to multiple clusters. Unlike conventional clustering algorithms, which issue binary membership values, fuzzy clustering allows for values between zero and one. The primary goal of fuzzy c-means clustering is to divide a given collection of leaves and fruits into subsets that represent distinct groups. The clustering process is guided by two fundamental concepts. Homogeneity refers to the habit of grouping together comparable data components, such as leaves or fruits. In contrast, heterogeneity is generated by grouping the fruits and the leaves in order to create dissimilarity between data points that belong to different cluster groups. The suggested work may efficiently split the data points of leaves and fruits into clusters by utilizing fuzzy clustering algorithms, allowing the grouping and differentiation of different types of illnesses or traits inside the banana plant.

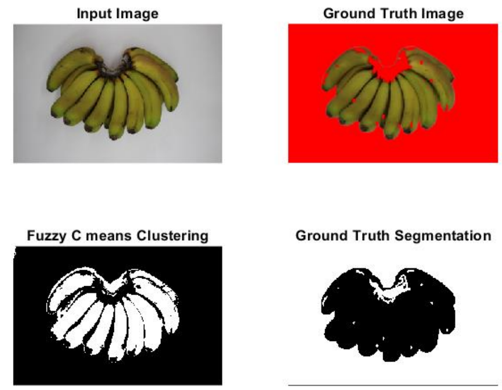

Figure 5. Segmented image

E. Feature Extraction

The feature extraction approach is critical for lowering a dataset's dimensionality while maintaining significant information. Feature extraction is used in the proposed study to categorize sick areas of banana leaves and fruits. The approach enables pattern recognition by extracting pertinent characteristics, allowing for the diagnosis of sick zones inside the banana plant. The fundamental purpose of feature extraction is to collect important traits while avoiding data loss. In the instance of disease categorization in banana plants, feature extraction is especially useful since it allows for quick identification and comprehension of the types of illnesses present. The use of pattern recognition to compare unknown data with known data recorded in a training dataset allows for reliable illness categorization.

The suggested model extracts characteristics based on statistical aspects. Accurate illness categorization requires proper training and storing of symptoms for all diseases in the dataset. Farmers can obtain a better knowledge of illnesses and take preventive steps at an early stage of agriculture by using statistical classifiers like the ones employed in this model. This enables farmers to properly control and limit disease effects on banana plants. Classification.

The purpose of histogram-based equalization, a nonlinear image processing approach, is to improve the brightness and overall quality of a picture. This is accomplished by analyzing the intensity levels of pixels in the image and redistributing them to produce a more balanced histogram. During the distribution analysis, pixels with higher intensity values are spread out across a larger range, whilst pixels with lower intensity values are concentrated in a smaller range. The histogram-based equalization can achieve improved accuracy in its output by choosing the maximum threshold values. The suggested method use histogram analysis to estimate the degree to which banana images display both leaf and fruit variation. The region of damage to the banana's leaves and fruit is estimated using variations in pixel intensity distribution. The images of the fruit and leaves are subjected to histogram-based equalization, which flattens the intensity levels of the pixels to create a more uniform distribution. This aids in locating the damaged bodily parts. One of the key advantages of histogram-based equalization is that it enhances picture quality without sacrificing data. The transformed image is of greater quality since the pixel intensities are distributed more uniformly. This enables for accurate illness diagnosis without jeopardizing the image data's integrity.

F. Detection and Classification

Feature extraction is followed by supplying the collected characteristics as input to an Artificial Neural Network (ANN) toolset in order to identify and categorize diseases in banana plants. Artificial neural networks (classifiers) have many real-world applications, including disease detection and classification. ANN-based categorization employs a variety of strategies, including constructing, learning, and testing. The neural network's three levels are an input layer, a hidden layer with ten neurons, and an output layer with a single neuron. Figure 6 depicts the information flow between the artificial neural network's various tiers. The use of ANN benefits banana plants since the results it generates for identifying ailments in the leaves and fruits are quite accurate. It is a fantastic tool for identifying illnesses because to its better pattern recognition and data categorization skills. The ANN technique consists of two critical phases: training and validation. Following feature extraction, the image is divided into two parts: the training feature set, which is used to train the neural network, and the testing feature set, which is used to evaluate the trained model's validation accuracy. Before the dataset for ANN classification of diseases in the banana plant can be made public, several aspects must be considered. Choosing the proper network type, deciding on a good training strategy, deciding on an acceptable number of neurons for the hidden layer, and so on are all optimal criteria for training a neural network. Each layer of an ANN provides a specific function. The input layer receives data from the outside world, which is then processed by the hidden layer before being delivered to the output layer. The output layer is in charge of showing the results after receiving information from the hidden layer. In this case, an FFNN (a kind of neural network) with feedforward backpropagation is utilized. The sigmoid activation function is used in the FFNN for applications that need a binary output, such as binary classification.

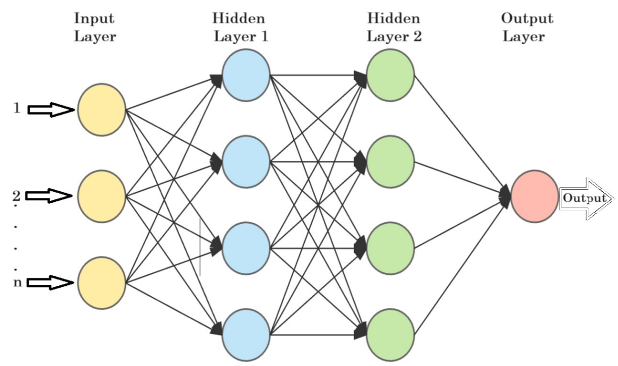

Figure 6. Architecture of Artificial Neural Network (ANN)

5. METHODOLOGY FOR IDENTIFYING BANANA FRUIT DISEASES

Data Collection: Compile a comprehensive data collection that includes images or samples of healthy banana fruits as well as a range of ill banana fruits that reflect various diseases. A well-labeled dataset with exact illness presence and type annotations for each sample is required.

Data Preprocessing: Prepare the dataset by performing the essential preprocessing steps. This might include shrinking the photographs to a normalizing the pixel values, consistent size, and improving the dataset's variety and resilience. Augmentation methods may involve rotation, turning, magnification, and the inclusion of noise to artificially increase the dataset.

Model Selection: Select a deep neural network architecture that is best suited for image classification tasks. Convolutional Neural Networks (CNNs) are often utilized for this purpose due to their ability to successfully collect spatial data. Depending on the task's difficulty, you can select between well-known CNN designs such as VGG, ResNet, and Inception, or custom-designed architectures.

Model Education: Initialize the chosen deep neural network model and train it with the training data given. This entails feeding the input photos into the network and adjusting the model's parameters to reduce the discrepancy between anticipated and real illness diagnoses. Iterative forward and backward passages (forward and back propagation) and gradient-based optimization techniques such as stochastic gradient descent (SGD) or Adam are commonly used in training.

Model Evaluation: Use image categorization-specific metrics to measure how well the training model worked. Accuracy, precision, recall, F1-score, and AUC-ROC (area under the receiver operating characteristic curve) are all common metrics. Cross-validation or holdout validation approaches may be used to detect overfitting and assess a model's generalization performance.

Disease Detection: Use the trained model to identify and categorize illnesses in new, previously unseen photos of banana fruit. Preprocess the images that are input in the same manner as the training data before submitting them to the trained model. The model will anticipate the existence and kind of illness for each input picture.

Performance Optimization: Improve performance by tweaking the model or experimenting with strategies such as transfer learning. Fine-tuning the model entails training it on a smaller dataset that is particular to the illness or topic of interest. Transfer learning is required to adapt pre-trained models built on large-scale picture datasets to the objective of detecting banana fruit disease.

Iterative Improvement: Include comments from disease specialists, refresh the dataset on a regular basis, and fine-tune the model architecture and hyper parameters. This iterative procedure improves the model's accuracy and resilience over time.

Deployment Integration: Integrate the trained model into a system or application that detects diseases automatically or in real time. This might include creating a user-friendly interface, linking the model to camera systems or Internet of Things devices, and implementing data collecting, analysis, and visualization. Overall, the suggested system provides a low-cost, automated way for detecting and classifying diseases in banana plants. Producers can detect infections at an early stage by combining image processing techniques

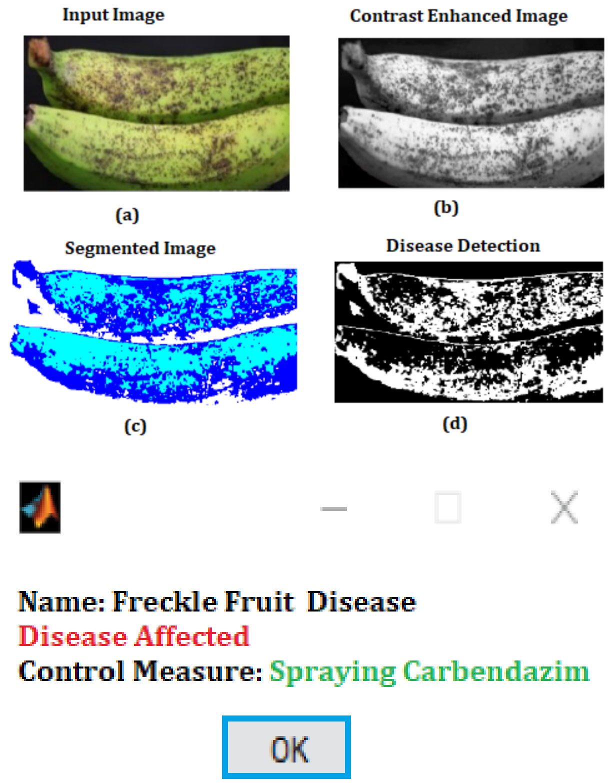

Figure 7. Various Simulation steps of Banana Fruit Disease detection

with ANN algorithms, allowing them to control and manage disease transmission, resulting in greater agricultural output and smaller crop losses.

6. SIMULATION OUTPUT

In the first phase, a dataset folder comprising photos of banana plant leaves and fruits is produced for testing reasons. The photos in the collection reflect various illness signs detected in the leaves and fruits. These photos have been correctly labelled and trained to be utilized in the testing procedure. Following that, a sick picture from the collection is chosen for fruit detection. The image is scaled to ensure that it is the proper size for further processing. Uneven dimensions are corrected to a predetermined dimension, usually to standardize the input size for effective processing. The image is transformed from RGB (Red, Green, Blue) to grayscale after resizing. This conversion simplifies image representation by eliminating color information and working with only black and white pixels. Histogram equalization is then applied to the grayscale image, which improves its brightness and contrast. This procedure enhances the image's overall quality and aesthetic appeal, making it simpler to analyze. Figure.6 shows the outcomes of these processes, which presumably depict the history of the picture from its initial sick state to the scaled and improved grayscale image. Figure 7 represents the many phases of processing a picture of a sick fruit: (a) Image

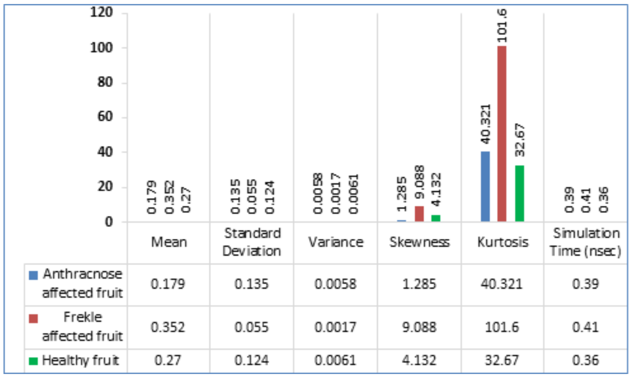

Figure 8. Statistical parameters

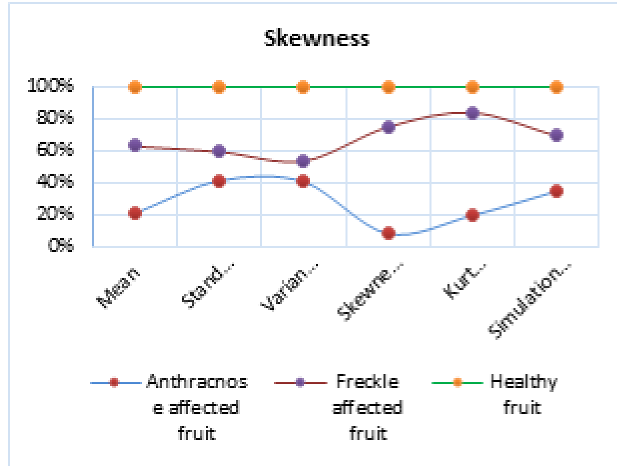

Figure 9. Measurement of Skewness

of infected Fruit: This is the original image of the infected fruit. It depicts the fruit's aesthetic look as well as the disease's symptoms. (b) Contrast Enhanced Image: The original image's contrast is increased to improve the visibility and distinguishability of the features. This technique helps to draw attention to the sick areas by emphasizing them. (c) Segmented Output: The picture is segmented to distinguish the unhealthy areas from the rest of the fruit. This segmentation procedure aids in identifying and concentrating on certain regions of interest. (d) Diseased Fruit Feature Extraction: Following segmentation, features are retrieved from diseased areas. These characteristics are distinct traits or measures that characterize the disease's characteristics. (e) ANN Classification result: The result of the Artificial Neural Network (ANN) classification procedure is shown in this picture. The ANN has been trained to recognize the presence of the freckle fruit disease by classifying photos. The categorization output may indicate whether or not the fruit is infected with the illness. Identifying and diagnosing the type of illness present in the fruit relies heavily on feature extraction. These processes are designed to preprocess the picture and retrieve useful information for future analysis, such as illness categorization or detection. The results in Figure.6 indicate how the image progressed through these several steps of processing. Figure 8 most likely depicts a statistical parameter measurement linked to banana fruit disease detection utilizing the ANN (Artificial Neural Network) approach. The following statistical parameters are being measured:

Mean: The mean is the average of a group of data points. It gives an indicator of the data's core trend. Standard deviation is a measure of the spread or dispersion of data points around the mean. It denotes the data's variability or diversity. Variance is defined as the square of the standard deviation. It calculates the average squared deviation from the mean.

Skewness: A measure of data distribution asymmetry (Figure.9). It shows if the data is skewed to the left or the right. Kurtosis: A measure of the data distribution's form. It describes the data's tailedness or peakiness.

Simulation Time (nsec): This is the amount of time it takes to run the simulation using the ANN approach. It represents the amount of processing time necessary for the illness detection procedure. These statistical measures aid in the analysis of the features and attributes of data relevant to the identification of banana fruit disease. They give insights into the data's distribution, variability, and form, which can help in understanding and interpreting the results of the ANN-based illness detection system.

7. BANANA GRADING SYSTEM

A grading system for banana illnesses is a useful tool for determining the severity and quality of banana fruits afflicted by different diseases. It allows producers, distributors, and consumers to make educated judgements regarding the fruit's utility and marketability. To award a specific grade to infected fruits, the grading system considers numerous aspects. Here are some crucial factors to consider while developing a banana disease grading system: Severity of the disease: The grading method assesses the severity of disease damage to the fruit. It takes into account things like the percentage of the fruit's surface area that is impacted by lesions, spots, discoloration, or other disease signs. Fruits with minor symptoms may be graded lower, while those with severe symptoms may be graded lower.

External Appearance: The grading method evaluates the sick fruits' overall external appearance. This comprises dimensions, shape, color, and texture. Fruits with a largely normal look despite illness signs may be graded higher than those with substantial malformations or abnormalities. Interior Quality: The grading system may also consider the fruits' interior quality. This covers things like hardness, texture, and flavor. Fruits having impaired interior quality as a result of disease infection may be graded lower.

Marketable Yield: The grading method takes into account the proportion of useable fruit that may be collected from a diseased bunch. Bunches having a larger percentage

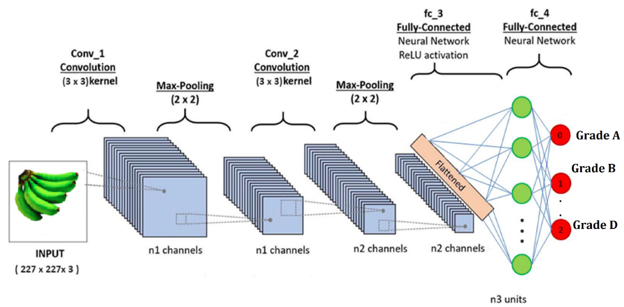

Figure 10. Phase of Classification that is Proposed for Banana Grading in the Food Processing Industry

of marketable fruits, even if some are sick, may obtain a higher grade.

Consumer Acceptance: The grading system may take into account consumer preferences as well as market demand. It examines if the illness signs have a major influence on the aesthetic attractiveness and consumer acceptability of the fruit. Fruits that fulfil consumer expectations and can still be efficiently sold despite illness signs may be graded higher. legislation and Standards: Banana disease grading systems may also be aligned with industry standards, regional legislation, and market demands. These principles provide consistency and uniformity in the grading process, easing commerce and maintaining quality standards compliance.

The grading method can assign sick fruits to different grades or categories, ranging from higher ratings for generally healthy-looking fruits with minor symptoms to lower grades for significantly impacted or unsalable fruits. This enables stakeholders to distinguish between different levels of illness severity and make informed decisions about product utilization, distribution, or disposal.

Implementing a standardized grading system improves sorting, quality control, and decision-making across the supply chain, allowing producers and distributors to maximize returns while retaining customer satisfaction.

In the suggested classification phase (Figure.10), the trained feedforward neural network is used to categorize and grade bananas in the food processing business. The following steps comprise the procedure:

The testing dataset, which consists of downscaled photos of bananas, is fed into the feedforward neural network.
par Feedforward Neural Network: Data is fed into the neural network's input layer, which is made up of the previously calculated optimal number of neurons in the hidden layer. At the hidden layer, the sigmoid activation function is used to introduce non-linearity and assist learning.

Output Layer: The neural network's output layer generates the projected categorization for each input picture. The output is compared to the testing goal, which reflects whether the bananas are healthy or faulty. Recognition Rate: The network's output is assessed by comparing it to the testing target. The recognition rate, which measures classification accuracy, is derived based on the number of successfully identified cases. The method seeks to precisely classify the bananas depending on their health status by following this proposed classification step, allowing for efficient sorting and processing in the food business. This phase's recognition rate will aid in determining the efficacy and applicability of the established model for industry applications. The category of fruits and the proportion of illnesses found are two methods for displaying the

Figure 11. Model input image: a banana (Case-1)

banana 10.jpg

....

The object appears to be a banana, and its 99.8% belongs to Gade A

Figure 12. Results of the input image's fruit categorization (Case-1)

Figure 13. Model's input image: a Banana (Case -2).

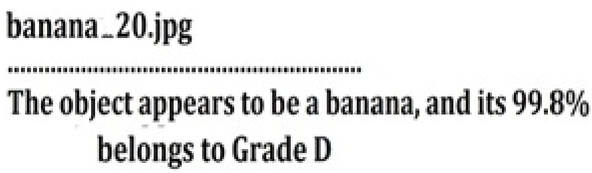

Figure 14. Results of the input image's fruit categorization (Case-2)

results of this experiment. Fruit Classification: The model has been trained to categorize fruits based on their visual properties. It may categorize a single fruit or numerous fruits at the same time. When a sample banana fruit is presented as input, the model classifies it with a particular level of certainty. The degree of confidence represents the chance that the supplied image is associated with a specific fruit. The model has 99.8% confidence that the input image is a banana in this scenario. percentage of Disease Identification: The model also includes fruit disease detection. A, B, C, and D grades are used to discern between different degrees of fruit damage or spoilage. A fruit with a grade of A is usually safe to eat; a grade of B indicates that just a small portion of the fruit has been damaged; a grade of C indicates that half of the fruit has been ruined; and a grade of D indicates that the entire fruit has been spoiled and is no longer edible. The percentage ranges shown below apply to each grade: There are four grades available: A (0-25%), B-(25-50%), C-(50-75%), and D-(75-100%). Figures 11 and 12 show the input image of a banana, while Figures 13 and 14 show the outcome of the algorithm. The outcome indicates that the model is 99% certain that the supplied image is of a banana. This high degree of certainty indicates that the model correctly categorized the fruit based on its visual qualities. Overall, this experiment confirms the model's success in fruit categorization and disease diagnosis, providing significant information about the quality of the fruit and assessing its acceptability for ingestion.Figure 15 illustrates that, as compared to previous experiments, the intelligent identification grading system achieves a higher recognition rate. Even if the difference in recognition rates amongst the three tested systems is slight (1-2%), having the highest recognition rate is critical for efficiency and accuracy when sorting bananas in the food processing industry. When compared to previous approaches, the intelligent identification system for grading bananas has shown to be more efficient and successful for this specific application in the food industry. The intelligent identification system's increased recognition rate suggests that it can more properly identify and grade bananas based on their visual qualities. This is crucial for the food business since it provides high-quality product production and allows for efficient quality control methods. The system's efficiency and accuracy help to boost production, decrease waste, and increase customer happiness. Figure 14 results reveal that the intelligent identification approach for grading bananas is superior in general, demonstrating its potential value and use in the food processing sector.

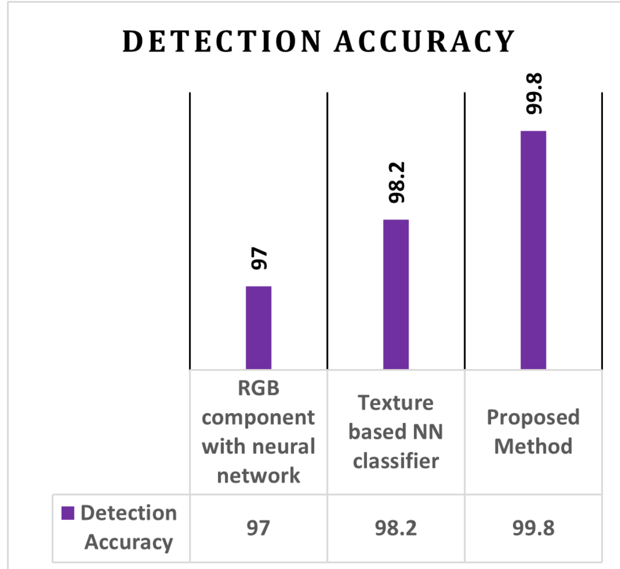

Figure 15. Comparison accuracy with existing methods

8. CONCLUSION

The suggested approach outlined in the research is extremely valuable to farmers since it aids in the identification and classification of many types of fruit illnesses and their symptoms in banana plants. Farmers can restrict the spread of illnesses and prevent them from damaging surrounding plants by precisely identifying the diseases. The system has a high accuracy rate, which means it can accurately identify and diagnose infections, allowing farmers to conduct timely disease management steps. Farmers may utilize this technology to acquire useful insights about the health of their banana plants and apply suitable preventative or control measures to ensure greater crop output and minimize disease losses. The created intelligent identification system for sorting bananas has successfully handled the issue of grading mistakes that may come from depending on human operators. The method eliminates human mistake and assures consistent and trustworthy outcomes by automating the grading process. In addition, the technology has various benefits over human operators. Furthermore, when compared to previously created systems, the intelligent identification system outperforms them. The 99.8% identification rate demonstrates the system's efficacy and accuracy in the food processing business. This high recognition rate means that the system can sort bananas consistently and precisely based on their quality and attributes. Overall, the food processing business may benefit from the intelligent identification system for sorting bananas since it provides a dependable, effective, and precise solution. It is a useful instrument for boosting productivity, quality assurance, and general efficiency in the banana sorting process due to its top performance and high recognition rate.

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