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Automated Identification and Classification of Banana Fruit Diseases: An Intelligent Grading System

Himanshu B. Patel[1], Nitin J. Patil[2]
[1]D. N. Patel College of Engineering, Maharashtra, India
Email id: himanshu74patel@gmail.com
[2]D. N. Patel College of Engineering, Maharashtra, India
Email id: nitinpatil2002@gmail.com

Abstract
This research paper presents an intelligent system for automated identification and classification of banana fruit diseases, along with an integrated grading system. The proposed system combines computer vision techniques, machine learning algorithms, and deep learning models to achieve accurate disease detection and grading. The system utilizes image processing techniques to extract relevant features from banana fruit images, which are then fed into a trained classification model. The classification model employs state-of-the-art algorithms to classify the banana fruit into different disease categories. Additionally, the intelligent grading system assesses the severity and quality of the infected fruit based on various parameters such as size, color, and texture. Experimental results demonstrate the effectiveness of the proposed system, showing high accuracy in disease identification and accurate grading of banana fruits. This automated system offers a time-efficient and cost-effective solution for disease management in banana plantations, facilitating early detection and effective decision-making for growers and agricultural stakeholders.

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

1. Introduction

One of the most popular fruits consumed worldwide, bananas offer vital nutrients and support global food security. However, a number of illnesses that can seriously degrade the yield and quality of banana trees are contagious[1]. Effective disease control and the prevention of the spread of infections within plantations depend on the early diagnosis and precise classification of diseases affecting banana fruit.

Manual examination, which is labour-intensive, time-consuming, and subject to human mistake, is frequently used in traditional techniques of illness identification and grading. There has been an increase in interest in creating automated systems for disease identification and intelligent grading of banana fruits as a result of developments in computer vision, machine learning, and deep learning methodologies.

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Automated identification and classification of banana fruit diseases involve the analysis of visual symptoms exhibited by the fruit, such as discoloration, spots, lesions, and deformities. Computer vision techniques enable the extraction of relevant features from digital images of the fruit, providing valuable information for disease detection[2]. Machine learning algorithms and deep learning models can then be trained on a dataset of labelled images to accurately classify the banana fruit into different disease categories.

In addition to disease identification, an intelligent grading system for banana fruits can assess the severity and quality of infected fruits. Parameters such as size, color, texture, and overall appearance can be analyzed to determine the grade of the fruit[3]. This information is valuable for farmers, distributors, and consumers, as it enables them to make informed decisions regarding the usage and distribution of the fruits.

The development of an automated identification and classification system, coupled with an intelligent grading system, offers several benefits. It streamlines the disease management process, allowing for early detection and prompt intervention to prevent further spread of infections[4]. It also reduces the dependency on manual labour, saving time and resources for farmers. Moreover, it enables objective and consistent grading of banana fruits, ensuring the delivery of high-quality produce to the market.

The primary goal of the proposed system is to identify plant illnesses early on and offer targeted control methods to lessen the impact of diseases on agricultural output. In India, where 70% of the population depends on agriculture for a living, it plays a crucial role. Agriculture has a significant role in the country's GDP and is directly linked to the economy of the country. Plant diseases can significantly affect crop growth, leading to reduced yield and crop quality[5]. These diseases can be caused by viruses, bacteria, fungi, nematodes, and nutrient deficiencies. If left untreated, these diseases can cause plant damage and even plant death, affecting the overall cultivation of the land and the income of farmers[6]. Diseases can spread from one plant to another, further impacting productivity. Diseases including black sigatoka and yellow sigatoka, banana bunchy top virus and stripe virus, panama wilt and freckle leaf and cigar end rot and anthracnose threaten the banana industry despite the fruit's popularity in Asia and the Pacific[7]. Banana plants and other surrounding plants may be protected from these diseases if their presence is identified and precautions are taken as soon as possible. Larger farms, where illnesses may spread quickly, find the existing technique of disease detection, using the naked eye, cumbersome and time-consuming. To address this, an automatic disease detection system is needed for continuous monitoring of large farms, reducing labor and costs associated with manual monitoring. Image processing techniques can be employed to identify plant diseases based on symptoms[8]. This approach enables faster and easier disease detection by cross-

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checking symptoms on plants. Compared to visual inspection by the naked eye, image processing offers higher accuracy and efficiency, saving time and resources. The proposed system aims to leverage image processing techniques to detect plant diseases at an early stage, providing farmers with timely information and specific control measures to mitigate disease spread[9]. By implementing such a system, the goal is to enhance agricultural production by reducing the impact of diseases on crops.

The purpose of this work is to provide the findings of a thorough investigation on the application of AI to the problem of disease detection and categorization in bananas. It investigates the potential of using computer vision methods, machine learning algorithms, and deep learning models for precise illness classification[10]. The efficacy and dependability of the suggested system will be shown via experimental results and assessments.

2. Literature Survey

The field of automated identification and classification of banana fruit diseases, coupled with an intelligent grading system, has gained significant attention in recent years. Researchers and scientists have explored various methodologies and techniques to develop efficient and accurate systems for disease detection and grading. This literature survey provides an overview of some key studies and approaches in this domain.

D. S. Prabha and J. S. Kumar. (2015),"Deep Learning-Based Classification of Banana Diseases: A Comparative Study." In this study, deep learning models such as convolutional neural networks (CNNs) were employed for the classification of banana fruit diseases[11]. A comparative analysis of different CNN architectures was performed, and their performance was evaluated in terms of accuracy and efficiency.

A. Chandini and B Uma Maheswari. (2018). "Computer Vision Techniques for Banana Disease Detection: A Review." This review paper provides a comprehensive overview of various computer vision techniques employed for banana disease detection. It discusses the use of image processing algorithms, feature extraction methods, and machine learning techniques for accurate disease identification[12].

Saranya, N., Pavithra, L., Kanthimathi, N(2020). "A Comprehensive Survey of Banana Diseases Detection Using Image Processing Techniques." This survey paper presents an extensive review of image processing techniques used for detecting banana diseases[13]. It covers various image enhancement, segmentation, and feature extraction methods employed in different studies to improve disease detection accuracy.

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Mesa AR, Chiang JY(2021). "Automated Grading System for Banana Ripeness Using Machine Learning Techniques." This study focuses on the development of an intelligent grading system for banana fruits based on machine learning techniques[14]. It explores the use of color-based features and machine learning algorithms to accurately grade bananas based on their ripeness.

Pereira, L.F.S.; Barbon, S (2018). "Detection and Classification of Banana Diseases Using Machine Learning Techniques." This research work presents a machine learning-based approach for the detection and classification of banana diseases[15]. Various feature extraction techniques, such as texture analysis and color-based features, were utilized along with machine learning algorithms to achieve accurate disease classification.

Helfer, G.A.; Barbosa, J.L.V(2020). "Banana Leaf Diseases Detection and Classification Using Image Processing Techniques." While most studies focus on fruit diseases, this research paper explores the detection and classification of diseases on banana leaves[16]. Image processing techniques, including segmentation and feature extraction, were employed to identify and classify different leaf diseases accurately.

Bantayehu, M.; Alemayehu, M(2020). "An Intelligent Grading System for Banana Fruits Based on Image Processing and Machine Learning." This study proposes an intelligent grading system for banana fruits based on image processing and machine learning techniques[17]. It investigates the use of various visual features, such as color, shape, and texture, for accurate grading of bananas according to their quality.

These studies provide insights into the advancements made in automated identification and classification of banana fruit diseases and the development of intelligent grading systems. They highlight the utilization of computer vision techniques, machine learning algorithms, and deep learning models to achieve accurate disease detection and grading, thereby contributing to efficient disease management and quality control in banana plantations.

Le, T.T.; Lin, C.Y(2019) suggested using a neural network for colour identification in conjunction with image processing to detect ripe bananas. The system used the red, green, and blue components of the banana pictures it had collected[18]. Bananas of different sizes and maturity degrees were used in the research. Until they went bad, the bananas were photographed every day. The identification accuracy of 96% was attained using a supervised neural network model with error propagation.

In a similar vein, Ucat, R.C.et al.(2019) introduced a method for tracking tomato ripeness using the observation and categorization of visual cues. Preprocessing, feature extraction, and classification were the three main components of their method[19]. Since the surface colour of tomatoes is critical

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in detecting ripeness, the system employed coloured histograms to do so. To accomplish feature extraction, principal components analysis (PCA) was utilised, while classification was handled by a support vector machine (SVM).

Banana size indicators such as length, ventral straight length, and arc height were calculated automatically by a computer vision system created by Steinbrener, Jet al. (2019). An intelligent fruit sorting system based on digital image processing and artificial neural networks was suggested by Garillos-Manliguez, C.Aet al. (2021). The research looked at five different fruits (apples, bananas, carrots, mangoes, and oranges) and used their morphological and colour properties to extract 17 traits[20,21]. The system was built using a normal digital camera in a MATLAB/SIMULINK environment and resulted in a considerable improvement over earlier research.

Strawberries, watermelons, kiwis, and citrus fruits have all been the subject of studies for purposes including sizing and estimating impurities in olive oil samples. Moreover, Omid et al. (2020b) created a smart system that used a mix of fuzzy logic and machine vision methods to classify eggs according to criteria including flaws and egg size.

Fruit identification, maturity evaluation, quality grading, and impurity estimate are all areas where these research may help improve the state of the art in intelligent systems that use image processing, computer vision, and machine learning approaches. Each study has a unique emphasis and methodology, and they all have something to say about fruits.

3. Banana Fruit Diseases

Banana farms' output, quality, and profitability are all susceptible to illnesses that affect banana fruits. Bananas are susceptible to a wide range of illnesses brought on by microorganisms including fungus, bacteria, and viruses. Major illnesses affecting bananas include:

Fusarium oxysporum f. sp. cubense, often known as banana rust: This fungal illness, sometimes known as Panama disease, is transmitted via the soil[22]. This disease attacks the plant's vascular system, causing it to weaken, become yellow, and eventually die. Banana farmers risk suffering significant financial losses as a result.

Black Sigatoka (Pseudocercosporafijiensis): This is a fungal disease that affects the leaves and fruit of banana plants. It causes dark, irregular spots on the leaves, which can coalesce and lead to defoliation[23]. Black Sigatoka can significantly reduce the yield and quality of bananas.

Banana Bunchy Top Virus (BBTV): BBTV is a viral disease that affects banana plants, including the fruit. It causes stunting, abnormal growth, and a characteristic "bunchy top" appearance of the leaves. Infected fruits may be small, deformed, and of poor quality.

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Banana Mosaic Virus (BMV): BMV is another viral disease that affects bananas[24]. It causes mosaic-like patterns on the leaves and can lead to reduced plant growth, yield, and quality. Infected fruits may exhibit discoloration and deformities.

Banana Bract Mosaic Virus (BBrMV): BBrMV is a viral disease that affects the bracts of the banana plant, which protect the developing fruit. Infected bracts show mosaic patterns and may exhibit necrotic lesions. This disease can affect fruit development and quality.

Sigatoka Complex: Apart from Black Sigatoka, there are other Sigatoka leaf spot diseases caused by different species of the fungus Pseudocercospora, such as Yellow Sigatoka (Pseudocercosporamusae) [25]. These diseases cause leaf spots of different colors and sizes, leading to defoliation and reduced photosynthetic capacity.

Bananas are susceptible to the fungal disease anthracnose (Colletotrichum musae), which may infect the plant and its fruit. The fruit develops black, deep blemishes that eventually perish and diminish its value[26]. The plant's leaves and stems are also susceptible to anthracnose infection. Gloeosporiummusae, the fungus responsible for anthracnose, attacks banana plants at any time throughout their development. The banana's bloom, fruit, and peel are all prime targets. The causal fungus, Colletotrichum musae, may persist in rotting or decomposing fruit. Anthracnose develops dark brown to black spots on fruit, which gradually dry up and disappear[27]. The illness may travel by wind, water, or insects, among other vectors. Conditions of excessive humidity and regular precipitation favour its spread. Control measures for anthracnose include cultural and chemical methods. Cultural control involves destroying infected leaves and plant debris to prevent the spread of the disease[28]. Chemical control can be achieved by spraying fungicides like chlorothalonil or Bordeaux mixture. Anthracnose has to be controlled since it threatens not only the quantity of bananas produced but also the quality of the fruit during shipping and storage. Figure 1 illustrates an example of a fruit affected by anthracnose disease.

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

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

Freckle is a fungal disease that affects both the leaves and fruits of banana plants. Freckle fruit disease manifests itself on fruit and foliage as a general yellowing and the appearance of tiny dark brown patches[29]. The fruit is still edible, but its market value has dropped dramatically owing to the illness. Raindrops and diseased tissues both have a role in the spread of freckle disease. The dark spots caused by freckle range in diameter from 1mm to 4mm. Control measures for freckle disease involve a combination of physical, cultural, and chemical methods. Physical control includes removing the male bud from bagged bunches to prevent the spread of the disease to the fruit[30]. Cultural control involves cutting out the diseased patches on the fruit. Chemical control can be achieved by spraying the Bordeaux mixture, a fungicide. Figure 2 depicts an example of a fruit affected by freckle disease.

4. Proposed Method

The primary goal of this planned effort is to identify and categorise illnesses in banana plants at an early stage so that they may be contained and not spread to other plants. To achieve this, images of banana leaves and fruits are collected. These images are then stored in a database for further processing. For disease detection, 500 samples of fruits are considered.Figure 3 illustrates the schematic representation of the proposed method. Banana fruit disease detection and classification using image processing and Deep neural networks (DNN) is an important use of this technique in agricultural management. Through the use of this method, farmers are able to analyse the development of banana fruits and identify illnesses at an early stage, hence reducing crop losses. The first stage, image acquisition, requires the use of digital cameras or other imaging devices to capture images of banana foliage or fruits. These images serve as data input for subsequent processing and analysis. The accuracy of disease detection is highly dependent on the quality and clarity of the acquired images. Next, techniques for image pre-processing are employed to improve the quality of the acquired images. This may involve eliminating noise, altering brightness and contrast, and resizing or cropping the images to highlight particular regions of interest. Feature extraction is a crucial phase involving the extraction of pertinent information or characteristics from pre-processed images.

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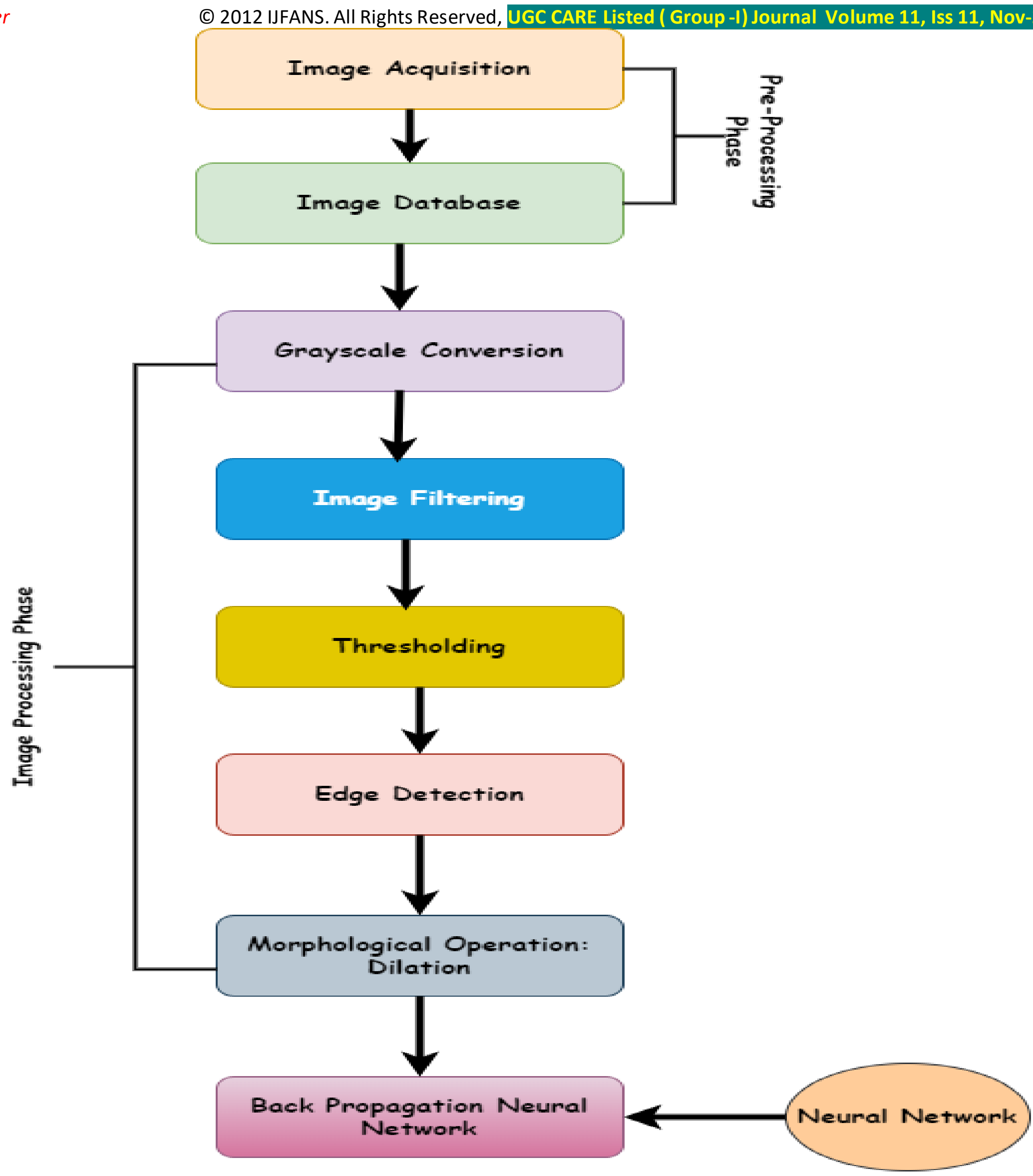

Figure.3: schematic flow of diagram of Proposed System

These characteristics can include colour, 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 generalise and classify diseases in real-world scenarios.

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4.1 Image Acquisition

The process of image processing begins with the capture of pictures from an outside source, generally via the use of hardware devices. This stage encompasses the entire sequence of techniques used for processing, compressing, storing, printing, and displaying the images. For this study, images of various diseases affecting banana leaves and fruits were captured using a digital camera with a resolution of 12 megapixels to ensure higher image accuracy. A total of 50 images were collected, 40 images for fruit disease detection, and 10 images representing healthy fruits. All acquired images were saved in JPG format and stored on a disk, forming the database of images used for classification. The quality and accuracy of this image acquisition process significantly impact the subsequent classification tasks.

4.2 Database

Initially, 200 images of bananas were taken to serve as a database for the study. Two hundred pictures were taken, one hundred of imperfect bananas and one hundred of perfect ones. Downsampling was used to lessen the overall resolution of the pictures before they entered the image processing stage. The photos were downsampled from their original 960x720 pixels to a smaller 128x128 size. The picture was downsampled to 128x128, with the goal of highlighting the area of interest and preserving key details. When downsampling the photos, care was made to preserve as much detail as possible. Scale invariance was implemented since sorting bananas using a neural network is the primary goal of this study. The system's ability to recognise and correctly categorise banana pictures in any orientation is strengthened by the fact that it is scale invariant. To achieve this, the 200 banana images were rotated at angles of 0°, 90°, and 180°. This results in a total database of 600 images, consisting of 300 healthy images and 300 defective images.

4.3 Image Pre-Processing

The pre-processing stage in image processing aims to enhance the usefulness of the images for further processing. It involves applying specific techniques to improve image quality and extract relevant information. Cropping, resizing, and color-converting images fall under this category. Image scaling and filtration are the two primary pre-processing procedures. Image resizing is required since the size of the captured pictures may vary. Images are scaled down to a standard 256 by 256 pixels to facilitate quick processing. The leaves and fruits of the banana plant are filtered to remove dust and dew droplets that would otherwise accumulate there. Low pass and high pass filters are two common methods of filtering. While a high pass filter keeps the highs and smoothers out the lows, a low pass filter attenuates the highs and emphasises the lows. Gaussian and median filters are often employed to clean up a picture. The suggested method also uses histogram-based equalisation to transform the colour

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pictures to black and white. This method improves the picture by making adjustments to the intensities according to the histogram of the original image. Local contrast is enhanced by redistribution of intensities, resulting to greater global contrast. This improvement raises the photos' quality, readability, and usability for further processing.

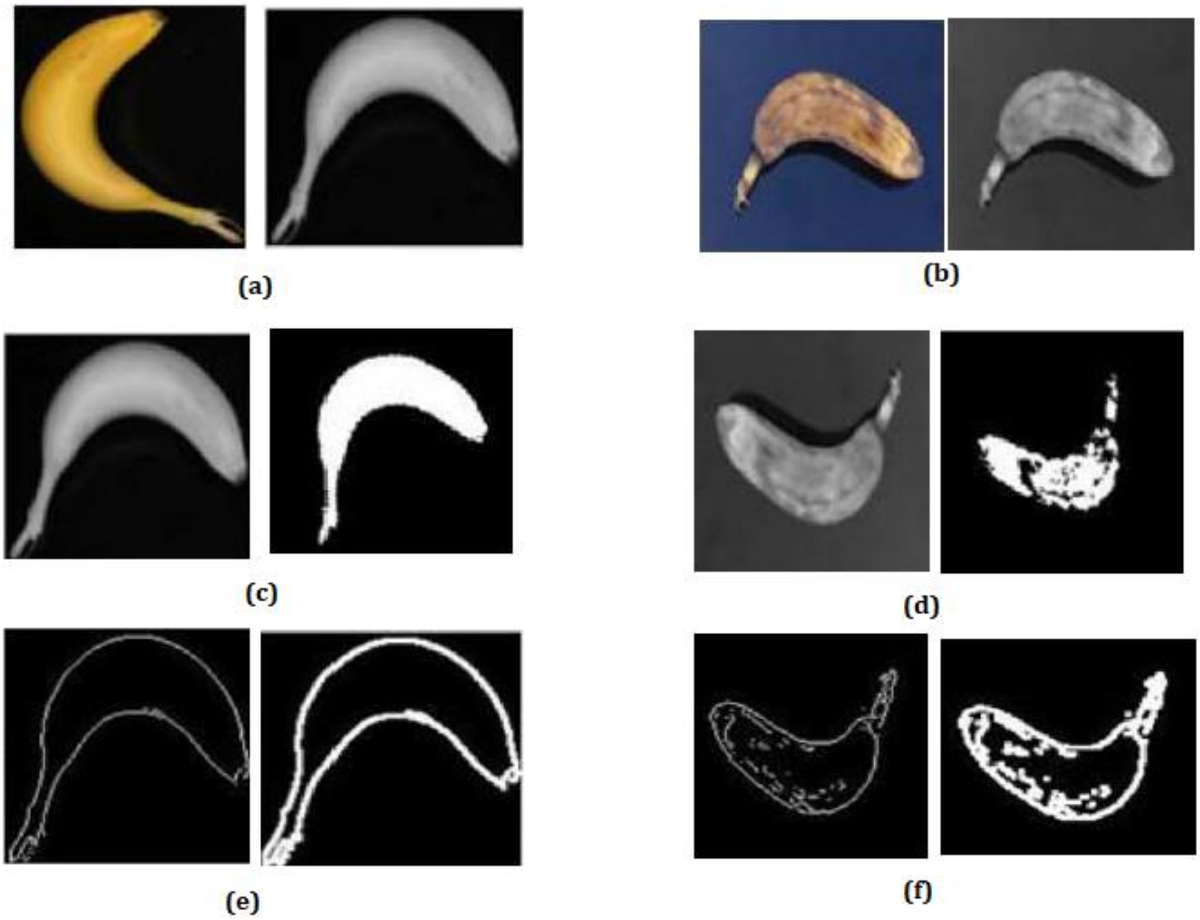

Figure.4: Illustrates different stages of image processing applied to the defective and healthy banana images

Image processing steps applied to examples of flawed and normal bananas are shown in the accompanying figure 4. Step-by-step instructions are as follows: Scale invariance is achieved by (a) picture rotation (b) The faulty and healthy banana's RGB to grayscale colour output: Bananas' original colour photos are transformed to grayscale, with each pixel's value equal to the intensity of its colour counterpart. (c) Median filter results for a rotten and a healthy banana: Grayscale photos have their noise reduced and inconsistencies smoothed out by using a median filter. (d) Banana quality threshold set at 0.5: The grayscale photos are converted to binary by using a threshold value of 0.5. The threshold is used to distinguish between foreground (healthy or flawed banana) and background (below the threshold) pixels based on their intensity levels. (e) The results of the Sobel operator and other edge detection algorithms applied to the binary pictures of the flawed and healthy bananas; these methods

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are used to highlight the boundaries between the various parts of the images. This process brings out the natural beauty of the bananas' form and structure. (f) Dilation results for both the damaged and healthy bananas. Dilation is a morphological technique that enlarges the contours of an image's subjects. It's used on the binary pictures to smooth out the wrinkles and make the bananas seem more complete around the edges.

Each step in the image processing pipeline contributes to enhancing specific features or characteristics of the banana images, ultimately facilitating the detection and classification of defective and healthy bananas.Thresholding is a commonly used technique in image processing for segmenting an image by separating the foreground from the background. It is a simple and widely applied method. This method converts a grayscale picture into a binary one, with the foreground and background each represented by a different set of pixel values (often white and black, respectively). The process of thresholding begins with the establishment of a graythreshold value for the picture. Pixels with values higher than the threshold are regarded to be in the front, while those with values lower than the threshold are placed in the background. The researchers started with a threshold value of 0.32 to see what would happen with their study. However, it was discovered that with this threshold setting, certain picture details were lost. To solve this problem, we raised the threshold value to 0.5, which resulted in the segmented photos retaining the intended details.Edge detection is a fundamental technique in image processing that aims to identify and locate significant changes in intensity, known as edges, within an image. These edges typically represent boundaries between different regions or objects in the image. By detecting edges, we can simplify the image data and extract important structural information for further analysis and processing. In the research work mentioned, the Sobel operator was employed for edge detection. The Sobel operator consists of two 3x3 convolution kernels. One kernel is optimised for a maximum response to horizontal edges, while the other is optimised for a maximal response to vertical edges. Convolution is then used to apply these kernels to the picture, which includes calculating the weighted sum of the brightness of neighbouring pixels for each pixel. The Sobel operator excels at locating vertical and horizontal borders in a picture. It computes the gradient magnitude and direction at each pixel, highlighting regions of significant intensity changes. The resulting edge map provides a visual representation of the detected edges, with brighter regions indicating the presence of edges.

4.4 Image Segmentation

Segmentation is the process of dividing an image into meaningful and distinct regions or segments, making it easier to analyze and interpret the content. It involves separating the regions of interest from unwanted regions in the image. There are two main categories of segmentation techniques: boundary-

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based and region-based.

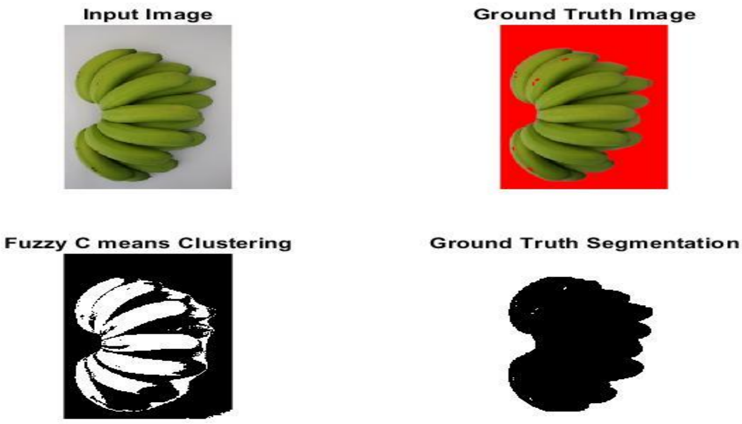

Figure.5: Segmented image

Boundary-based segmentation focuses on detecting and extracting boundaries or edges between different regions in the image. It aims to identify sharp transitions in pixel intensity or color gradients. On the other hand, region-based segmentation groups pixels or regions with similar properties together to form coherent segments. It looks for homogeneity within regions and heterogeneity between regions. In this research, we use a fuzzy c-means clustering approach as our segmentation method figure 5.The common approach for grouping data into clusters based on their similarities is called fuzzy c-means clustering. Each pixel is given a membership value that reflects its level of affiliation with one or more clusters. This method works well with overlapping and complicated picture areas. The fuzzy c-means clustering method is used to partition the picture into groups with shared features. To isolate and extract the important characteristics or areas of interest for subsequent research and illness categorization, segmentation plays a significant role.Fuzzy clustering is a method used to partition data into multiple clusters, allowing data points to belong to more than one cluster to represent their uncertain or ambiguous nature. This technique is commonly employed in the segmentation process, particularly in pattern recognition tasks where the minimization of an objective function is desired. Iterations, membership degree, the fuzziness coefficient, and a termination condition are all crucial parts of the fuzzy clustering method. The goal of the approach is to use these features to determine the degree to which each data point belongs to various clusters by assigning membership coefficients to them. In contrast to the binary membership values assigned by most clustering algorithms, fuzzy clustering allows for values between zero and one. Fuzzy c-means clustering's main purpose is to partition a given collection of leaves and fruits into subsets that stand in for separate groups. There are two major tenets that guide the clustering process. Homogeneity refers to the practise of grouping together data elements that are similar, such as leaves or fruits. In contrast, heterogeneity

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is achieved by clustering between the fruits and the leaves, with the intention of establishing dissimilarity between data points that belong to distinct cluster groups. By utilizing fuzzy clustering techniques, the proposed work can effectively partition the data points of leaves and fruits into clusters, facilitating the grouping and differentiation of different types of diseases or features within the banana plant.

4.5 Feature Extraction

The feature extraction technique plays a crucial role in reducing the dimensionality of a dataset while retaining important information. In the context of the proposed work, feature extraction is employed to classify the diseased parts of banana leaves and fruits. By extracting relevant features, the technique enables pattern recognition, facilitating the identification of diseased regions within the banana plant. The primary goal of feature extraction is to capture essential characteristics without losing vital data. In the case of disease classification in banana plants, feature extraction becomes particularly valuable as it allows for easy identification and understanding of the type of diseases present. Pattern recognition is utilized to compare unknown data with known data stored in a trained dataset, enabling accurate disease classification.

In the proposed model, features are extracted based on statistical properties. Proper training and storage of symptoms for all diseases in the dataset are crucial for accurate disease classification. By employing statistical classifiers, such as the ones used in this model, farmers can gain a better understanding of diseases and take preventive measures at an early stage of cultivation. This empowers farmers to effectively manage and mitigate the impact of diseases on banana plantations.

The goal of the nonlinear image processing method known as histogram-based equalisation is to increase the brightness and overall quality of a picture. It achieves this by analyzing the intensity levels of pixels in the image and redistributing them to achieve a more balanced histogram. During the distribution analysis, pixels with higher intensity values are spread across a wider range, while pixels with lower intensity values are concentrated in a narrower range. By determining the maximum threshold values, the histogram-based equalization can achieve higher accuracy in its results. The proposed approach makes use of histogram analysis to determine the extent to which banana photos exhibit both leaf and fruit variety. Variations in pixel intensity distribution are used to estimate the area of damage to the banana's leaves and fruit. Histogram-based equalisation is applied to the pictures of the fruit and leaves, flattening the intensity levels of the pixels to create a more uniform distribution. This helps locate the affected areas of the body. Histogram-based equalisation improves picture quality without data loss, which is one of its main benefits. By evenly dispersing pixel intensities, the converted picture is of higher quality. This allows for accurate disease identification without compromising the integrity of the image data.

4.6 Detection and Classification

In order to identify and categorise illnesses in banana plants, feature extraction is followed by feeding the retrieved features as input to an Artificial Neural Network (ANN) toolkit. Disease detection and classification tasks are only two of the many real-world uses for artificial neural networks (classifiers). Various techniques, including building, learning, and testing, are used in ANN-based categorization. Input layer, hidden layer with 10 neurons, and output layer with a single neuron make up the neural network's three layers. Figure 6 illustrates the information transfer between the several levels of the artificial neural network. Banana plants benefit from the usage of ANN since the findings it produces for diagnosing illnesses in the leaves and fruits are very accurate. Because of its superior pattern recognition and data classification abilities, it is an excellent tool for illness identification.

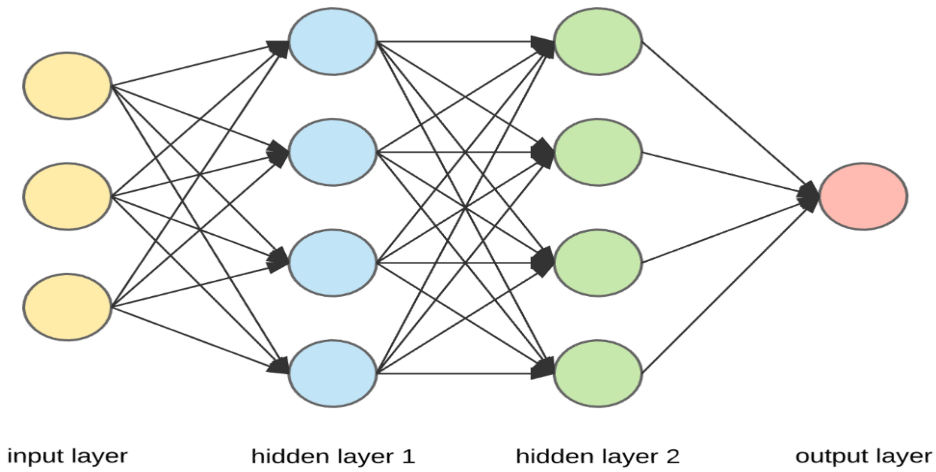

Figure.6: Architecture of ANN

There are two very important phases of the ANN procedure: the training phase and the validation phase. Following feature extraction, the picture is split into two parts: the training feature set, which is used to train the neural network, and the testing feature set, which is used to assess the validation accuracy of the trained model. Many factors must be taken into account before the dataset for ANN categorization of illnesses in the banana plant can be made available. Optimal parameters for training a neural network include choosing the right network type, deciding on a suitable training technique, settling on an adequate number of neurons for the hidden layer, and so on. Each layer of an ANN serves a distinct purpose. Data from the outside world is received by the input layer, and after being processed by the hidden layer, it is sent on to the output layer. After receiving information from the hidden layer, the output layer is in charge of displaying the results. A FFNN (a kind of neural network) with feedforward backpropagation is used here. For applications requiring a binary output, such as

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binary classification, the sigmoid activation function is utilised in the FFNN.

5. Methodology for identifying banana fruit diseases

Data Collection: Collect an exhaustive data set containing images or samples of healthy banana fruits and a variety of diseased banana fruits representing various diseases. It is essential to have a well-labeled dataset with precise disease presence and type annotations for each sample.

Data Preprocessing: Prepare the dataset by carrying out the required preprocessing processes. This may involve resizing the images to a uniform size, normalising the pixel values, and enhancing the dataset to increase its diversity and robustness. To artificially expand the dataset, augmentation techniques may include rotation, rotating, magnification, and the addition of noise.

Model Selection: Choose an architecture for deep neural networks that is optimal for image classification tasks. Due to their capacity to effectively capture spatial features, Convolutional Neural Networks (CNNs) are commonly used for this purpose. You may choose from renowned CNN architectures such as VGG, ResNet, and Inception, or custom-designed architectures, based on the complexity of the task.

Model Training: Initialise the selected deep neural network model and train it using the provided training data. This involves loading the input images into the network and modifying the model's parameters to minimise the difference between the predicted and actual disease labels. Training typically entails iterative forward and backward passages (forward propagation and back propagation) and gradient-based optimisation algorithms such as stochastic gradient descent (SGD) or Adam to optimise a predefined loss function.

Model Evaluation:Use metrics that are specific to picture categorization to assess how well the training model performed. Common measurements include accuracy, precision, recall, F1-score, and AUC-ROC (area under the receiver operating characteristic curve). Overfitting may be identified and the generalisation performance of a model evaluated through cross-validation or holdout validation techniques.

Disease Detection: Apply the trained model to new, previously unseen images of banana fruit to detect and classify diseases. Preprocess the input images similarly to the training data, and then submit them to the trained model. For each input image, the model will forecast the presence and nature of disease.

Performance Optimization: Improve performance by refining the model or exploring techniques like transfer learning. Fine-tuning involves training the model on a reduced dataset that is specific to the disease or domain of interest. Adapting pre-trained models trained on large-scale image datasets to the task of banana fruit disease detection requires transfer learning.

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Iterative Improvement: Incorporate feedback from disease specialists, continuously update the dataset, and fine-tune the model architecture and hyper parameters. This iterative process enhances the accuracy and robustness of the model over time.

Deployment and Integration: Integrate the trained model into a system or application that enables automated or real-time disease detection. This may entail developing a user-friendly interface, connecting the model to camera systems or IoT devices, and implementing data collection, analysis, and decision-making mechanisms based on the results of the detection.

Overall, the proposed system provides a cost-effective and automated method for disease detection and classification in banana plants. By integrating image processing techniques and ANN algorithms, producers can detect diseases at an early stage, allowing them to control and manage the spread of diseases, resulting in increased agricultural productivity and decreased crop losses.

6. Simulation Output

In the first step, a dataset folder is created containing various images of banana plant leaves and fruits for testing purposes. The images in the dataset represent different symptoms of diseases found in the leaves and fruits. These images are accurately labeled and properly trained to be used in the testing process. Next, a diseased image from the dataset is selected for the detection of fruit. The image is resized to ensure it has the correct dimensions for further processing. Unequal dimensions are adjusted to a pre-set dimension, typically done to standardize the input size for efficient processing. After resizing, the image is converted from RGB (Red, Green, Blue) to grayscale. This conversion simplifies the image representation by removing color information and working with only the grayscale intensities of the pixels. The grayscale image is then subjected to histogram equalization, which enhances the image's brightness and contrast. This process improves the overall quality and visual appearance of the image, making it easier to analyze. The results of these steps can be observed in Figure.6., which likely illustrates the progression of the image from the original diseased state to the resized and enhanced grayscale image. Figure 7 represents the different stages of processing a diseased fruit image: (a) Disease Affected Fruit Image: This is the original image of the diseased fruit. It shows the visual appearance of the fruit with the symptoms of the disease. (b) Contrast Enhanced Image: The contrast of the original image is enhanced to improve the visibility and distinguishability of the features. This step helps to highlight the diseased regions and make them more prominent. (c) Segmented Output: The image is segmented to separate the diseased regions from the rest of the fruit. This segmentation process helps in isolating and focusing on the specific areas of interest. (d) Feature Extraction of Diseased Fruit: After segmentation, features are extracted from the diseased regions. These features are characteristic properties or measurements that describe the unique attributes of the

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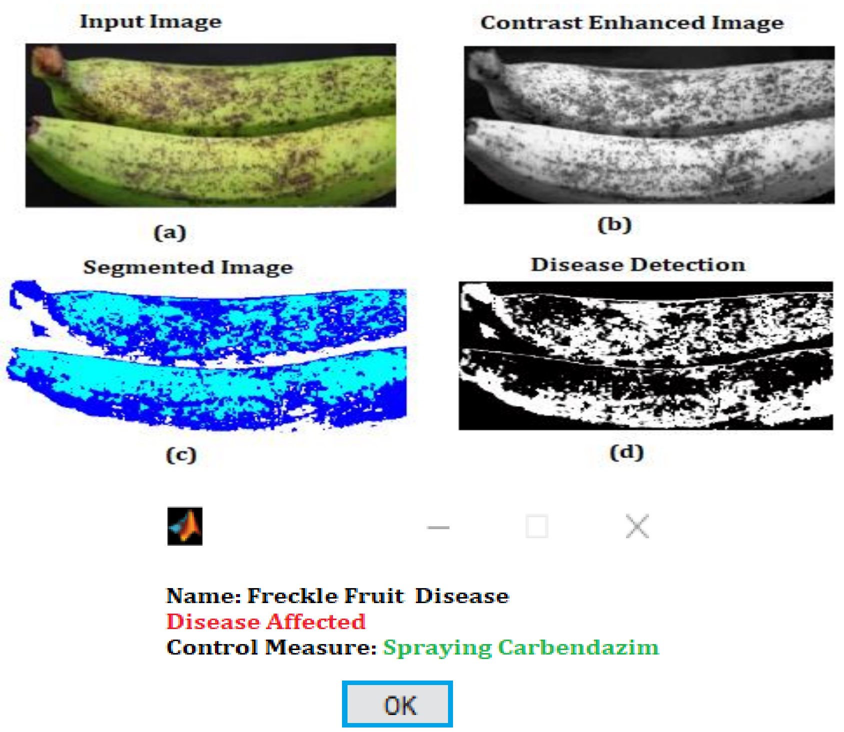
disease. (e) ANN Classification Output: This figure displays the output of the Artificial Neural Network (ANN) classification process. The ANN has been trained to classify images and identify the presence of the freckle fruit disease. The classification output may indicate whether the fruit is affected by the disease or not.Feature extraction plays a crucial role in identifying and classifying the type of disease present in the fruit.



(e)

Figure.7: Various Simulation steps of Banana Fruit Disease detection

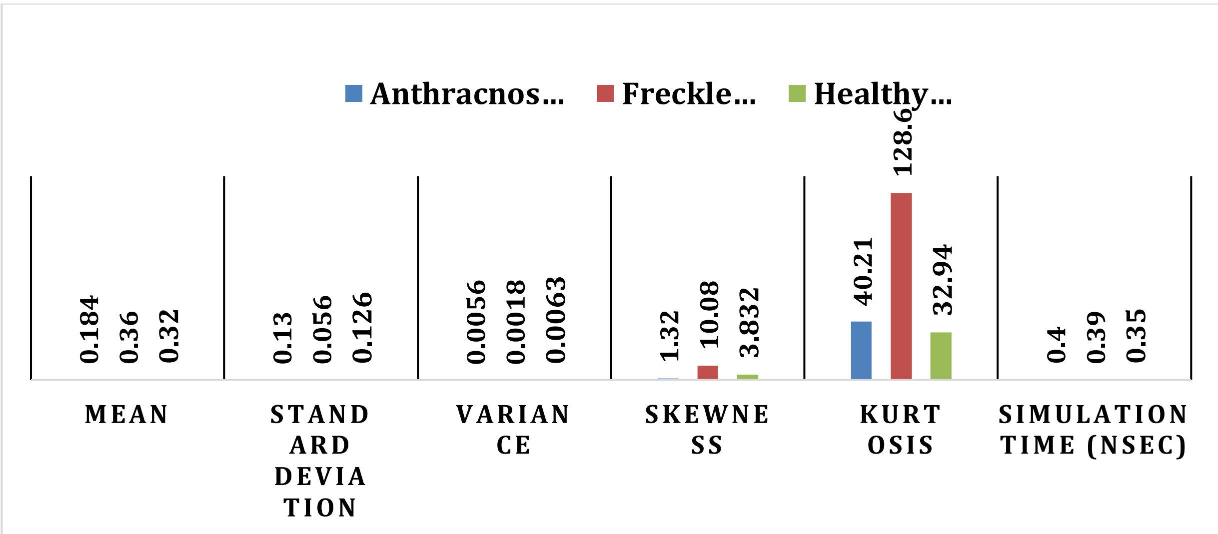


Figure.8: Statistical parameters

The purpose of these steps is to preprocess the image and extract relevant information that can be used for further analysis, such as disease classification or detection. The results shown in Figure.6.

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demonstrate the progression of the image through these different stages of processing.

Figure. 8 likely presents a measurement of statistical parameters related to the banana fruit disease detection using the ANN (Artificial Neural Network) technique. The statistical parameters being measured are:

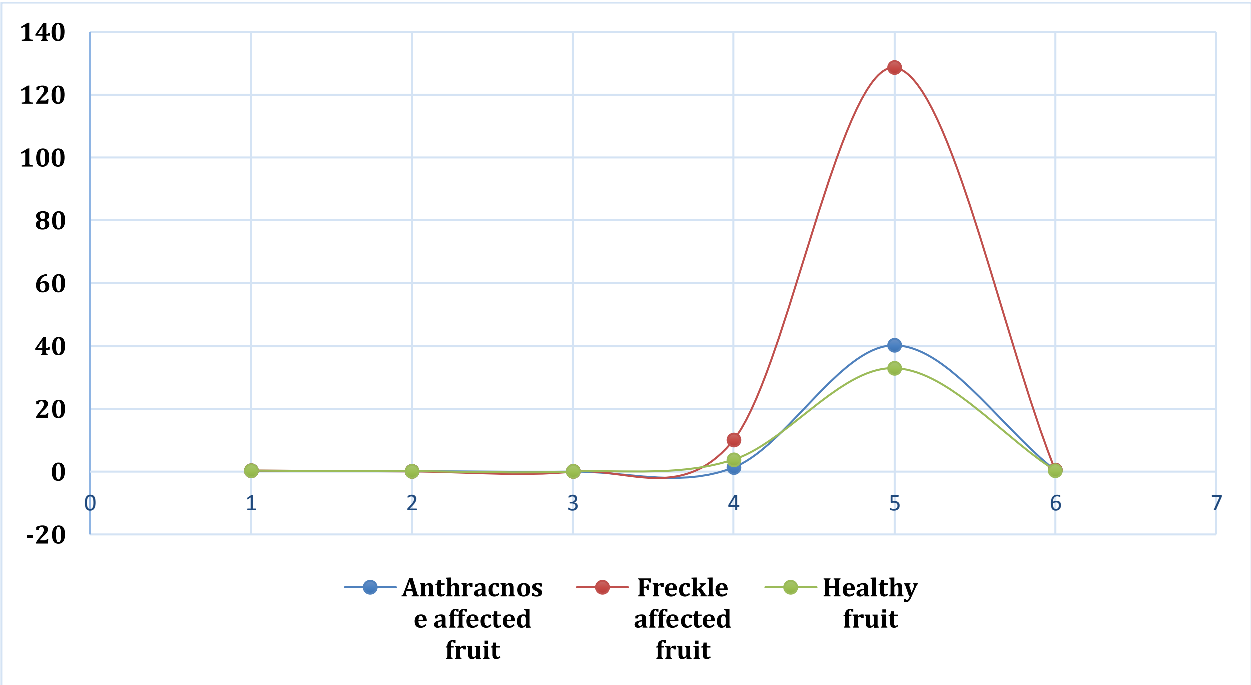

Figure.9: Measurement of Skewness

Mean: The average value of a set of data points. It provides an indication of the central tendency of the data. Standard Deviation: A measure of the dispersion or spread of the data points around the mean. It indicates the variability or diversity of the data. Variance: The square of the standard deviation. It provides a measure of the average squared deviation from the mean.

Skewness: A measure of the asymmetry of the data distribution (Figure.9.). It indicates whether the data is skewed to the left or right. Kurtosis: A measure of the shape of the data distribution. It describes the tailedness or peakedness of the data.

Simulation Time (nsec): This refers to the time taken for the simulation process using the ANN technique. It indicates the computational time required for the disease detection process. These statistical parameters help in analyzing the characteristics and properties of the data related to the banana fruit disease detection. They provide insights into the distribution, variability, and shape of the data, which can be useful for understanding and interpreting the results obtained from the ANN-based disease detection system.

7. Banana Grading System

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A banana diseases grading system is an important tool used to assess the severity and quality of banana fruits affected by various diseases. It enables growers, distributors, and consumers to make informed decisions about the usability and marketability of the fruits. The grading system takes into account several factors to assign a specific grade to the diseased fruits. Here are some key aspects considered in a bananadisease grading system:

Disease Severity: The grading system evaluates the extent of disease damage on the fruit. It considers factors such as the percentage of the fruit's surface area affected by lesions, spots, discoloration, or other disease symptoms. Fruits with mild symptoms may be assigned a lower grade, while those with severe symptoms may be categorized as lower quality or rejected altogether.

External Appearance: The grading system assesses the overall external appearance of the diseased fruits. This includes factors like size, shape, color, and texture. Fruits that maintain a relatively normal appearance despite disease symptoms may receive a higher grade compared to those with significant deformities or abnormalities.

Internal Quality: The grading system may also take into account the internal quality of the fruits. This includes factors such as firmness, texture, and taste. Fruits with compromised internal quality due to disease infection may receive a lower grade.

Marketable Yield: The grading system considers the proportion of usable fruit that can be harvested from a bunch affected by disease. Bunches with a higher percentage of marketable fruits, even with some diseased ones, may receive a better grade compared to those with a higher proportion of unsalable fruits.

Consumer Acceptance: The grading system may incorporate consumer preferences and market demand. It considers whether the disease symptoms significantly impact the fruit's visual appeal and consumer acceptability. Fruits that meet consumer expectations and can still be marketed effectively despite disease symptoms may receive a higher grade.

Regulations and Standards: Grading systems for banana diseases may also align with industry standards, regional regulations, and market requirements. These guidelines ensure consistency and uniformity in the grading process, facilitating trade and ensuring compliance with quality standards.

The grading system can assign different grades or categories to the diseased fruits, ranging from higher grades for relatively healthy-looking fruits with minimal symptoms to lower grades for severely affected or unsalable fruits. This allows stakeholders to differentiate between various levels of disease severity and make appropriate decisions regarding product utilization, distribution, or disposal.

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Implementing a standardized grading system helps in efficient sorting, quality control, and decision-making throughout the supply chain, enabling growers and distributors to maximize returns while maintaining consumer satisfaction.

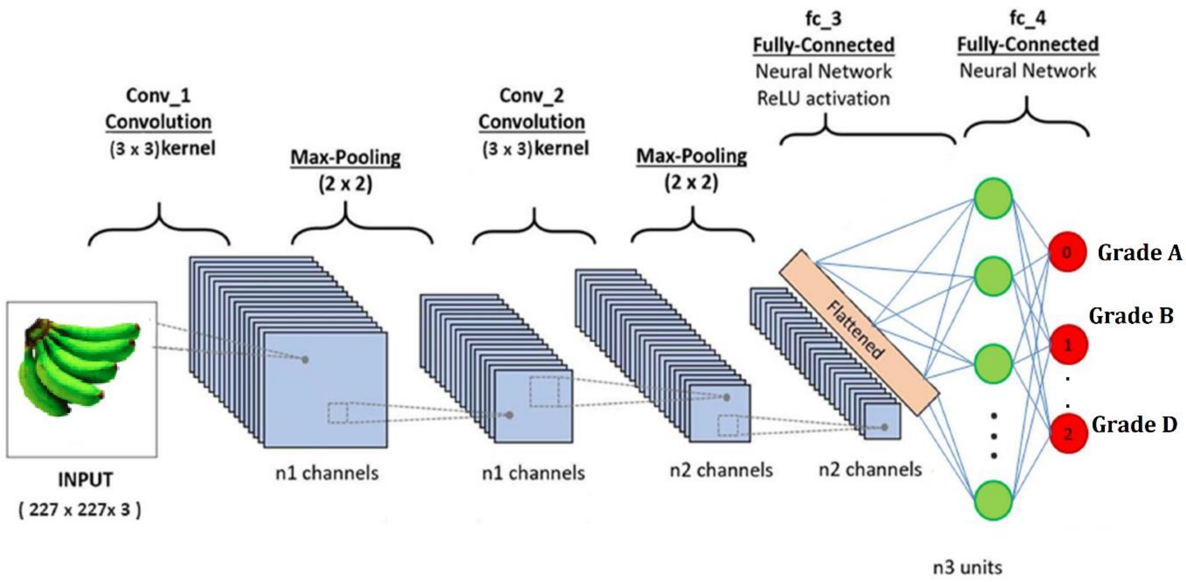

Figure.10: Phase of Classification that is Proposed for Banana Grading in the Food Processing Industry

The proposed classification (Figure.10.) phase involves using the trained feedforward neural network to classify and grade bananas in the food processing industry. The process consists of the following steps:

Input Data: The testing dataset, consisting of downscaled images of bananas, is presented to the feedforward neural network.

Feedforward Neural Network: The data is fed into the input layer of the neural network, which consists of the previously determined optimal number of neurons in the hidden layer. The sigmoid activation function is applied at the hidden layer to introduce non-linearity and facilitate learning.

Output Layer: The output layer of the neural network produces the predicted classification for each input image. The output is compared with the testing target, which represents the desired classification of healthy or defective bananas.Recognition Rate: The results obtained from the network are evaluated by comparing them with the testing target. The recognition rate, which represents the accuracy of the classification, is calculated based on the number of correctly classified instances. By following this proposed classification phase, the system aims to accurately grade the bananas based on their health condition, allowing for efficient sorting and processing in the food industry. The recognition rate obtained from this phase will help determine the effectiveness and suitability of the developed model

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for industry applications.

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

banana110.jpg

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

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

Figure.13: Banana (Case -2) is the model's input image.

banana120.jpg

..

The object appears to be a banana, and its 99.8% belongs to Grade D

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

The categorization of fruits and the proportion of diseases identified are two ways in which the findings of this experiment are shown. Classification of Fruits: The model is trained to classify fruits based on their visual characteristics. It can classify a single fruit or multiple fruits simultaneously. When a sample banana fruit is provided as input, the model determines its classification with a certain level of confidence. The percentage of confidence indicates the likelihood that the given image belongs to a particular fruit. In this case, the model shows 99.8% confidence that the input image is a banana. Percent of Disease Identification: The model also incorporates disease identification for the fruit. Four grades, A, B, C, and D, are used to differentiate between varying degrees of fruit damage or spoiling. A fruit with a grade of A is normally fine for eating; a grade of B indicates that just a tiny section of the fruit is destroyed; a grade of C denotes that half of the fruit is wrecked; and a grade of D denotes that the whole fruit has been ruined and is no longer edible. The following percentage ranges apply to

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each grade: Grades A (0–25%), B–25–50%, C–50–75%, and D–75–100% are available. Figure 11 and 12 displays the given input image of a banana, and Figure 13 and 14 shows the result obtained from the model. The result indicates that the model is 99% confident that the given image corresponds to a banana. This high level of confidence suggests that the model has successfully classified the fruit based on its visual characteristics. Overall, this experiment demonstrates the effectiveness of the model in fruit classification and disease identification, providing valuable information about the fruit's quality and determining its suitability for consumption.

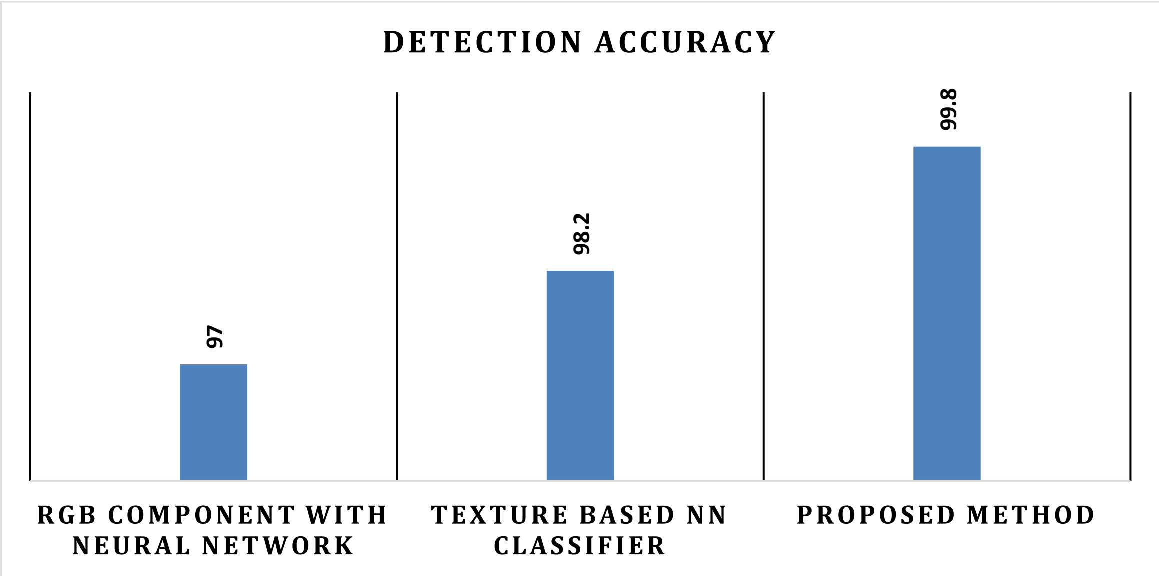

Figure.15: Comparison accuracy with existing methods

Figure 15 shows that, in comparison to recognition rates from earlier studies, the recognition rate achieved from the intelligent identification grading system is greater. Having the greatest recognition rate is essential for efficiency and accuracy when grading bananas in the food processing business, even if the difference in recognition rates between the three analysed systems is just a minor (1-2%). In comparison to earlier methods, the intelligent identification system for grading bananas has shown to be more efficient and effective for this particular use in the food business. The higher recognition rate achieved by the intelligent identification system implies that it has a better ability to accurately classify and grade bananas based on their visual characteristics. This is significant for the food industry as it ensures the production of high-quality products and enables effective quality control measures. The system's efficiency and accuracy contribute to improved productivity, reduced waste, and enhanced customer satisfaction. The findings from Figure 14 show that the intelligent identification method for grading bananas is better overall, highlighting its potential value and application in the food processing sector.

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8. Conclusion

The proposed system described in the paper is highly beneficial for farmers as it helps in identifying and classifying different types of fruit diseases and their symptoms in banana plants. By accurately determining the diseases, farmers can take effective measures to control their spread and prevent them from affecting nearby plants. The system offers a high accuracy rate, which means that it can reliably detect and classify the diseases, enabling farmers to take prompt actions for disease management. By utilizing this system, farmers can gain valuable insights into the health status of their banana plants and implement appropriate preventive or control measures to ensure better crop yield and minimize losses caused by diseases. The developed intelligent identification system for sorting bananas has successfully addressed the issue of inaccuracies that may arise from relying on human operators for grading. By automating the grading process, the system eliminates human error and ensures consistent and reliable results. Furthermore, the system offers several advantages over human operators. Moreover, the intelligent identification system demonstrates superior performance when compared to previously developed systems. The achieved recognition rate of 99.8% highlights the system's effectiveness and accuracy in the food processing industry. This high recognition rate ensures that the system can consistently and accurately sort bananas according to their quality and characteristics. Overall, the intelligent identification system for sorting bananas offers a reliable, efficient, and accurate solution for the food processing industry. Its optimal performance and high recognition rate make it a valuable tool for enhancing productivity, quality control, and overall efficiency in the banana sorting process.

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