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Article

IoT-Assisted Real-Time Detection of Post-Harvest Mango Diseases Using Image Processing, Machine Learning Validation, and an Automated Rotational Imaging System

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Abstract: Mangoes are among the world's most valuable fruit crops, and postharvest disease can have a serious impact on quality, marketability, and storage life. Early detection of these diseases is necessary to diminish loss throughout a mango's lifespan – from the time it is harvested until it is consumed. This research study presents a real-time Internet of Things (IoT)-enabled detection system to find postharvest disease in mangoes utilizing image processing techniques and an automated rotating imaging mechanism. The proposed detection system is comprised of a rotating platform that rotates a camera around the circumference of the mango while capturing images of it from multiple perspectives. This camera setup gives the ability to visually inspect the entire surface of a mango throughout the entire 360° rotation of the ring. In addition to the image acquisition and rotation, the environmental conditions (temperature and humidity). The acquired images will be processed using image processing techniques including image acquisition, image preprocessing, image segmentation, feature extraction, and disease identification. This study focuses on three specific postharvest diseases of mangoes: Anthracnose, Stem-End Rot, and Transit Rot. Image processing is being used as the primary technique for detecting the presence of each disease, while machine learning algorithms are being used to confirm the classification results and provide performance metrics (e.g., accuracy about 91%) for the overall system. When a disease is identified as present via the above processes, the IoT module will generate a real-time notification.

Keywords: Post-Harvest Mango Diseases, Image Processing, IoT, Raspberry Pi, Anthracnose, Stem-End Rot, Transit Rot, Machine Learning, Real-Time Disease Detection

1. Introduction

Post-harvest loss due to rapid biochemistry as well as lack of proper storage facility expansion results in 30% - 40% loss in the mango (Mangifera indica) industry [1]. The mango is a climacteric fruit that has a rapid increase in metabolic rate after harvest; therefore, as metabolic activity ramps up, it causes texture defects, which affects the overall marketability of the fruit.

In addition to rapid fruit development, the development of pathogens within a storage house is comparatively easy when proper temperature and humidity are not controlled. The most significant post-harvest disease affecting mangoes is anthracnose (Colletotrichum gloesporioides), In regions of high humidity, such as those described by [2], approximately 60%–90% of post-harvest diseases occur (Anthracnose). In conditions of extremely high humidity, anthracnose has been shown to develop to up to 100% in relative terms. Visual characteristics of anthracnose are dark, sunken lesions on the surface of fruit, rapid physical deterioration of the fruit tissue, and ultimate preferred decay of the fruit. Moisture and sufficient warmth in the air around tropical fruit trees provide ideal environmental factors for the development of these pathogens. Environmental factors that enable both humidity and warmth are typically many in conjunction with poorly ventilated storage facilities [3]. Fungal pathogens such as Lasiodiplodia theobromae cause the development of stem end rot. Stem end rot often begins at the stem end of fruit and will then spread towards the centre of the fruit assortation causing softening and deterioration of the fruit. In general, stem end rot develops due to improper handling during the harvesting and storage of fruits, especially under high humidity conditions [3]. Black mold rot on mangoes, caused by Aspergillus niger, will develop on the exterior of the mango as a black colour. The likelihood of mangoes exhibiting black mould deterioration is greatly increased in warm, humid environments with little air circulation. The effect of black mould rot on mangoes is economic; the reduced appearance of mangoes caused by black mould will result in a loss of commercial sales due to lower levels of sale.

2. Literature Review

poor post-harvest storage facilities, the rapid biochemical changes associated with increased respiration rates and production of ethylene [1] drastically reduce the time available for sale at retail outlets and lead to softening of mangoes, making them increasingly susceptible to spoilage due to the introduction of fungal pathogens. Additionally, developing countries are particularly challenged due to extensive mango losses occurring during the post-harvest phase of the production cycle which, due to an absence of adequate facilities to provide the required temperature and humidity levels needed to optimize mangoes during post-harvest storage, causes considerable food insecurity on a global scale [4]. The pressure of post-harvest spoilage on the profitability of producing mangoes continues to have a detrimental effect on the amount of food security in countries that produce mangoes. The ability to monitor and control post-harvest spoilage of mangoes must be developed to prevent ongoing post-harvest spoilage of mangoes. Agriculture has seen a dramatic change in the way IoT has changed how Agriculture is done now days. You will have access to real-time information related to crop production management by utilizing IoT [5]. The following are some examples of how farmers can use IoT technology to manage their crop production and care businesses: crop production methods and crop care are just two examples of some of the categories of data that farmers can access using IoT. Based on these references, there are multiple ways that IoT can be used post-harvest; however, there are still few actual instances or evidence of how IoT can provide value to food storage or minimize crop waste. There are multiple opportunities to implement IoT sensors within warehouse-type organizations to continuously monitor their overall operational environment and maintain temperature levels that will assist in mitigating the risk of bacteria developing before significant damage occurs to food stored in warehouses. There have been various studies that have documented a reduction in food waste with IoT-based monitoring, but very few companies have implemented an IoT-based monitoring program thus far because of implementation issues (i.e. cost and existing infrastructure). Edge Computing, or the ability to process data close to where it will be collected, represent a great opportunity in the agricultural context, especially in relation to the fact that so many storage warehouses are in rural areas. By using edge computing devices such as Raspberry Pi, we can process incoming data in real time, allowing us to quickly make decisions pertaining to the data. By doing this, we can reduce the amount of time it takes to receive a critical notification (e.g., outbreak of a disease/death, or sudden environmental change). The literature is full of examples of how edge computing has facilitated low-cost, resilient agricultural monitoring systems that can function in resource-limited environments [6]. One area in which convolutional neural networks (CNNs) have been widely used is the automation of image classification, including the identification of plant diseases from pictures of plants. CNNs can distinguish between healthy/diseased plants automatically based on different sets of features (e.g., texture and colour) that may indicate the health of a given plant [7]. Additionally, CNNs have been used extensively to classify crop images, including tomatoes, apples, and grapes, with a high degree of accuracy [8] However, many CNNs rely on cloud computing to analyze images, which require a steady internet connection and substantial computational resources to accomplish the task. As a result, deploying CNN detection systems on low-power edge computing devices (e.g., Raspberry Pis) can be problematic due to the related hardware.

Table 1: Postharvest Mango Diseases vs Temperature

Disease	**Causal Organism**	**Temperature Range for Development**	**Optimum Temperature**	**Conditions**	**References**
Anthracnose	Colletotrichum gloeosporioides	20–30 °C	25–28 °C	High RH (>90%), latent infection activates during ripening	[9]

Disease	Causal Organism	Temperature Range for Development	Optimum Temperature	Conditions	References
Stem-end rot	Lasiodiplodia theobromae, Alternaria spp.	25–35 °C	28–32 °C	Poor ventilation, high temp storage, stress during ripening	[10],[11]
Aspergillus rot (Black mold)	Aspergillus niger	30–40 °C	33–37 °C	Warm, dry to moderate RH, damaged fruit	[12],[13]

As shown in Table 1, temperature is one of the key factors that initiate disease development in mango after harvest when combined with other inhibiting factors such as high relative humidity and injuries (bruises) to the fruit. The disease anthracnose will start developing on mangoes when they are ripening and are exposed to moderate temperatures (20-30C) (peak activity 25-28C) and high humidity. Stem-end rot begins to develop at moderately higher temperatures (25-35C) than anthracnose (25-30C); however, an ideal temperature range for optimal development is between 28C and 32C. Stem-end rot incidence is closely associated with poor storage conditions and stress on the mango fruit. Black mould (Aspergillus Niger) spore development occurs at elevated temperatures (≥30-40C) with optimum growth at approximately 33-37C on fruits that are being overstressed or have received injury due to a warm environment. Pathogen development will change from Colletotrichum to Lasiodiplodia to Aspergillus as temperatures increase. To minimize the potential for the development of pathogens previously discussed, it is imperative to use proper storage methods including storing at cooler than <13C (but not cold injury) temperatures and controlled humidity levels.

3. Methodology

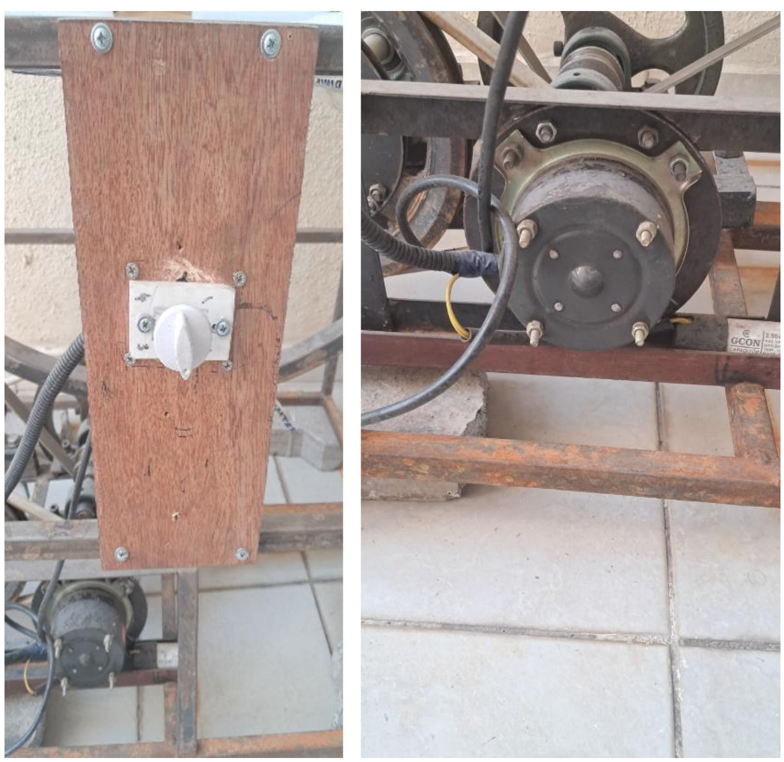

Figure 1: Manufacturing Execution System (MES)

Figure 2: Model for Multimodal Approach to Mango Disease Detection

3.1 Hardware Integration

In Fig 2 Model for Multimodal Approach to Mango Disease Detection motor that offers a hefty one-horsepower rating ensures that its operation is very smooth and steady, and its full 360-degree rotation allows for full coverage of the entire workspace. The imaging system has a fixed angle of 34 degrees, and paired with its rotating capability, can produce an accurate and consistent record of data collected within this space. These two systems together provide a basis for total observation and total analysis. In a Manufacturing Execution System (MES), machines and computers interact to produce motion, energy, and the automatic control of the entire operation of the machine and computer throughout the entire process. The MES system consists of four main components -- a motor with an inverter; a control switch; a belt and pulley drive system; and a Raspberry Pi computer for the collection of real-time data and images of the operation of the MES system. Each of these components has been designed for the purpose of ensuring that the MES system will operate in a smooth, safe manner. In Fig 1 the motor provides the rotational movement; the control switch enables the operator to control both the speed, and the amount of energy supplied to the motor; the belt and pulley systems transfer the movement from one or more components of the MES system; and the Raspberry Pi collects data and images of the MES system. All components of the MES system work together to produce desired results, while providing accurate and reliable records of machine operation for the entire process.

Once acquired, these images will be analyzed using image processing techniques to detect and classify (identify) diseases, and the environmental data will be transmitted to an IoT platform (Internet of Things) for real-time monitoring and evaluation of the overall post-harvest mango quality assessment and disease management systems. The integrated system is a non-destructive, efficient, and intelligent approach to post-harvest quality assessment and management of mango disease.

3.2 Image Preprocessing Technique:

3.2.1Multimodal Approach to Mango Disease Detection:

The proposed system for post-harvest mango disease detection utilizes a multimodal approach, integrating IoT-based environmental monitoring with computer vision. The system is designed to identify key fungal infections—anthracnose, stem-end rot, and Aspergillus niger—by analyzing visual symptoms and storage house conditions. The architecture intentionally utilizes a Raspberry Pi 3 and temperature sensors for edge data collection, while offloading complex image processing to CNN model. Plant disease recognition systems have matured significantly in unimodal setups. However, unimodal approaches often suffer from limitations, including intra-class variation, sensitivity to noise, and difficulty in capturing complex spatial patterns with limited features. To overcome these drawbacks, this study proposes a multimodal framework that combines blob feature-based analysis with raw image processing using convolutional neural networks (CNNs). The multimodal system extracts localized disease indicators (blobs) for baseline classification while simultaneously leveraging full-image hierarchical features learned by CNNs. This hybrid strategy improves robustness and recognition accuracy compared to unimodal systems. Performance scores from both streams are compared, with the image-based CNN stream serving as the primary classifier. The optimization model presented later acts as a post-detection decision-support tool for treatment recommendations.

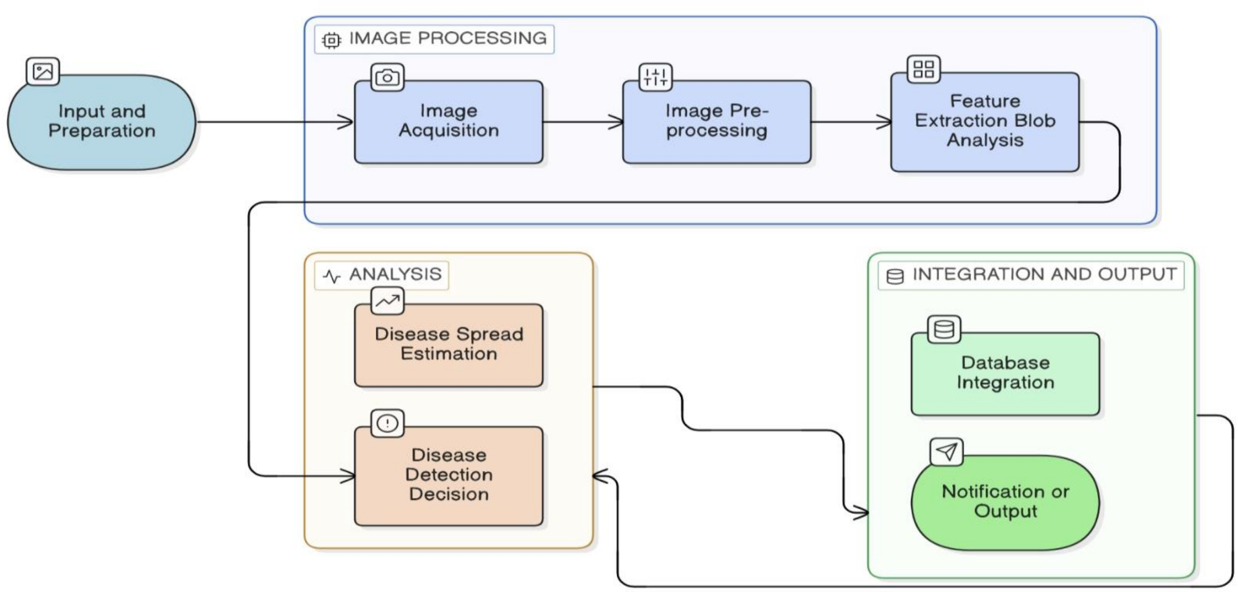

Figure 3: Overall System for detection the diseases after post-harvest

The designed system for detecting post-harvest diseases in mangoes combines image processing usage with the Internet of Things (IoT) to recognize diseased fruits, such as Anthracnose, Stem-End Rot, and Black mould. The whole system is arranged into four modular components: Input & Preparation, Image Processing, Analysis, Integration & Output shown in Fig 3.

1.Input & Preparation

At the start of the process, mango images are captured via a camera placed on a circular rotatable mechanism. The rotating circular base allows for acquiring images of the mangoes from all angles while capturing all the mango's exterior surfaces with images. Additionally, at the same time, the environmental conditions (temperature/humidity) are measured using a DHT11 or DHT22 sensor. The temperature and humidity can have an impact on diseases developing and the way mangoes will store. [14]

2. Image Processing Module

2.1 Image Acquisition

Acquiring images is the first step in the overall processing of images. In this stage, a high-resolution camera is used to take multiple images of mangoes from various angles. The camera produces great-quality photos, so we take several images as the entire system rotates 360 degrees to ensure that any disease signs present on the surface of the fruit will be captured.[15] See Fig 4

2.2 Image Pre-processing:

Figure 4: Image Capture by Model

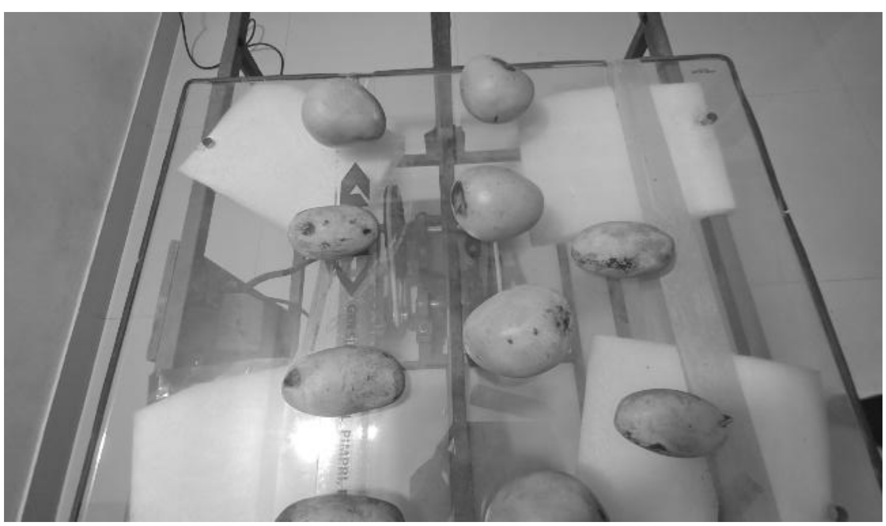

Figure 5: Gray Scale Conversion

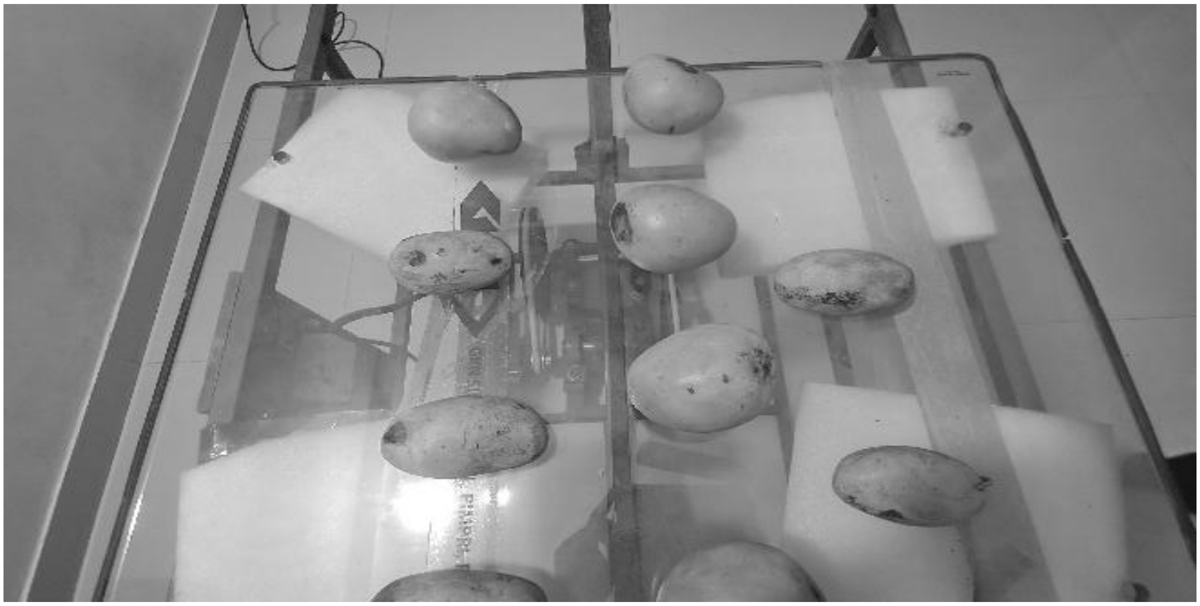

Figure 6: Filter Applied on Gray Scale (Median filter)

Acquired images may have different types of imperfections. Examples include noise, lighting inconsistencies, shadows, and background disturbances. To fix those issues prior to performing any type of analysis on the acquired images, a series of standard shown in Fig 5 & Fig 6 image analysis/preprocessing techniques are applied to help improve the quality of images to derive meaningful results from them. Standard preprocessing techniques include resizing, applying filters to remove noise (such as Gaussian filter and median filter), converting images into gray-scale format, enhancing contrast, standardizing the images, and removing backgrounds [16]. Preprocessing enhances the ability to see infected areas in images and increases the accuracy of any subsequent classification or detection processes used to diagnose or identify diseases found in that infected area [17].

2.3 Feature Extraction and Blob Analysis

Once the image has been pre-processed, the relevant features can be extracted from the image. This process allows us to obtain colour, texture, and shape information about diseased areas (colour features are RGB values, texture features are entropy, contrast, and homogeneity) and shape features (area, perimeter, and circularity) [18] shown in Fig 8. Region of separated as BLOB (Binary Large Object) Shown in Fig 9.

Texture analysis helps identify surface irregularities caused by disease lesions, spots, and decay. Texture features are commonly extracted using the Gray-Level Co-occurrence Matrix (GLCM).

A. Entropy

Entropy measures the randomness or complexity of pixel intensity distribution.

$$\text{Entropy} = -\sum_{i}\sum_{j} P(i,j)\log_2 P(i,j)$$

where:

P(i,j)P(i,j)P(i,j) = Probability value in the GLCM

Interpretation

High entropy → Irregular and diseased surface.

Low entropy → Smooth and healthy surface.

Application: Diseased mango areas often have higher entropy due to uneven color and texture patterns.

B. Contrast

Contrast measures local intensity variations between neighbouring pixels.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P(i,j)$$

Interpretation

High contrast → Significant texture variations.

Low contrast → Uniform texture.

Application: Disease spots create sharp intensity differences, increasing contrast values.

C. Homogeneity

Homogeneity measures the similarity of neighboring pixel values.

$$\text{Homogeneity} = \sum_i \sum_j \frac{P(i,j)}{1+(i-j)^2}$$

Interpretation

High homogeneity → Smooth and uniform surface.

Low homogeneity → Rough and irregular surface.

Blob analysis is then conducted on the infected part of the mango image to determine the connected infected regions within the image. In this way, we can determine the severity of the disease using the size, number, and location of diseased spots [19].

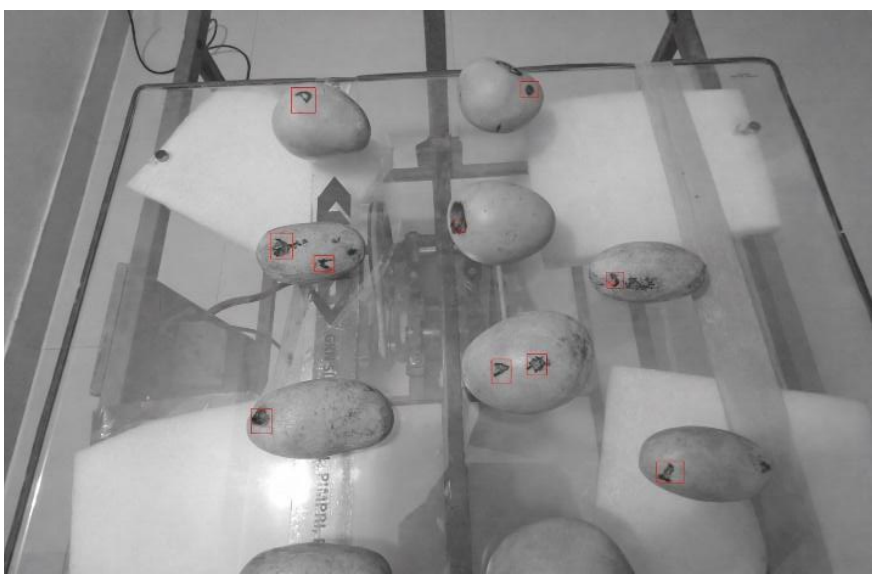

Figure 7: Blob Detection applied on Images

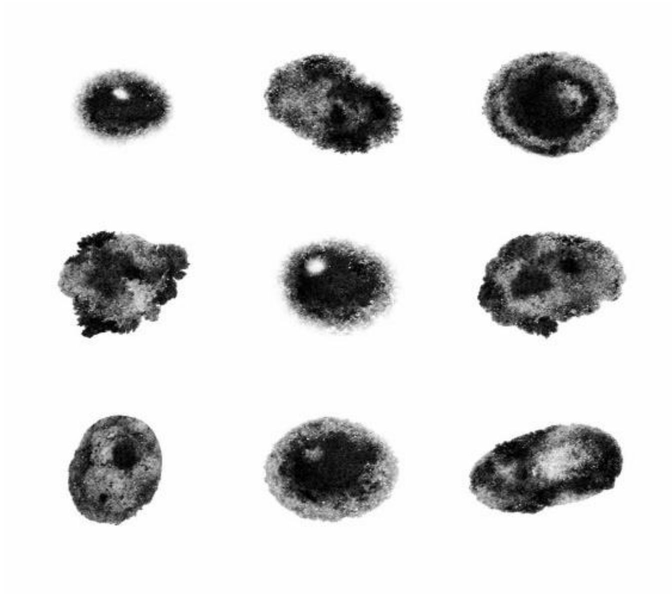

Figure 8: BLOB As separate Image

3. Analysis Module

3.1 Disease Spread Estimation

To calculate the % of infected area on the total fruit surface area, extracted features are then used to estimate the severity of the disease. This assessment of disease severity is an important determinant of fruit quality and marketability [20].

$$\text{Disease Severity (\%)} = \frac{\text{Infected Area}}{\text{Total Fruit Area}} \times 100$$

Based on the calculated severity percentage, the disease can be categorized as mild, moderate, severe, or critical.

3.2 Disease Detection Decision

Module detection decision diseases: this will be done through classification into healthy/infected mangoes and identification of known types of infection (such as Anthracnose, Stem-End Rot, or Transit Rot). The method of classifying the infected mangoes can be achieved by applying various machine learning methodologies (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest, or Convolutional Neural Networks (CNN)) [21].

The output generated from this stage will be sent to the output module for storage/notification purposes.

4. Integration and Output Module

4.1 Database Collection & Integration

Primary Data Base collection has been placed for all three types of diseases. A centralized database stores information about disease identification outcomes, features that were extracted, severity ratings, environmental conditions, and images captured. Using this integrated database will allow for future monitoring of long-term conditions, analysing historical data, and tracing the quality of post-harvest mangoes [22].

4.2 Notification and Output

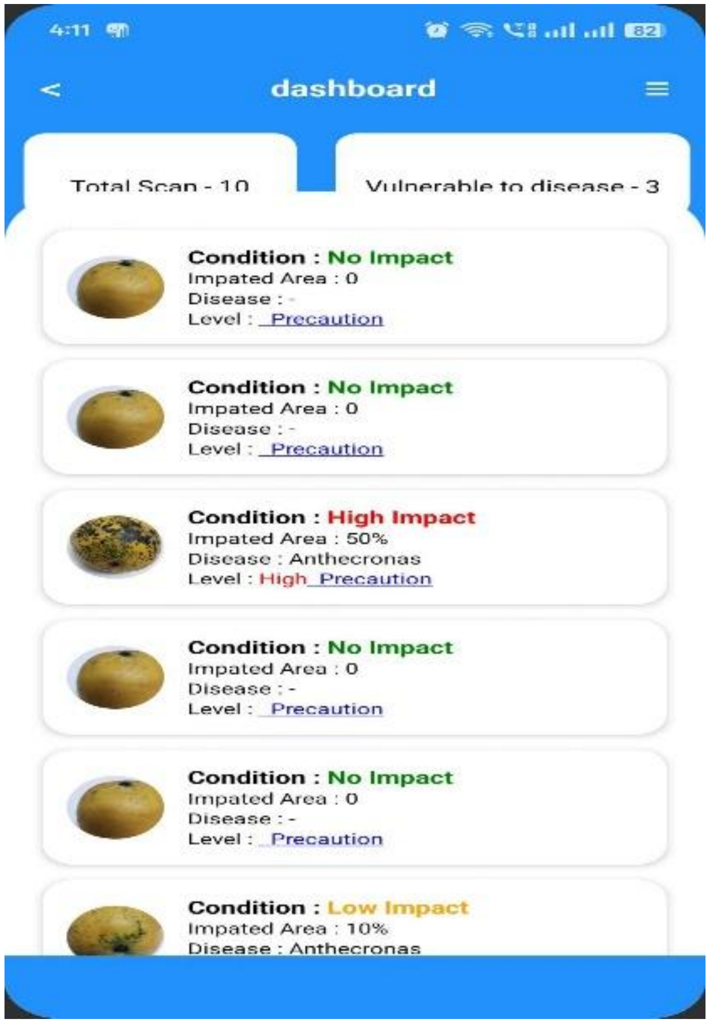

Figure 9: Mobile App for notification

The results of the system will contain type of disease detected, disease severity (percentage), and prescribed actions for treatment. Users will see this information on a web-based dashboard, via a mobile device application or on a Raspberry Pi. Users will also be notified if the severity of their disease exceeds some specified threshold [23]. Mobile application has been created to notify the respective owner of storage house shown in Fig 9.

3.1 Result and Discussion

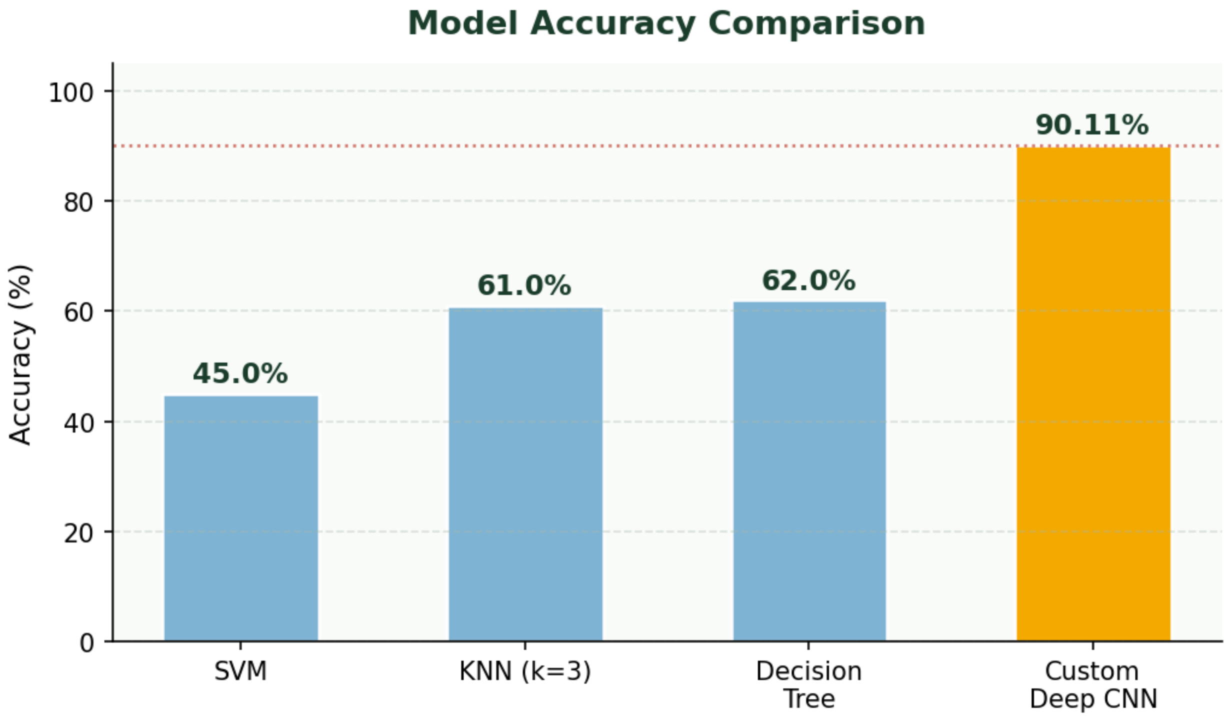

Figure 10: Comparison of different Machine Learning model

Support Vector Machines (SVMs), K-Nearest Neighbors (KNNs), Decision Trees, and a Custom Deep Convolutional Neural Network (CNN) were evaluated for classifying post-harvest disease of mangoes (Anthracnose or stem end rot; and transit rot). The classification accuracy associated with each model is illustrated in the Figure 10.

There was a strong degree of variability in the observed performance of each individual model evaluated in this study. The SVM classifier was most poorly performing overall, achieving 45% classification accuracy on the test set due to the lack of ability of the SVM model to classify the disease classification task based upon the complex and non-linear nature of the disease patterns in the mango images. The K-nearest neighbour (KNN) model (k=3) had 61% classification accuracy on the test set, which is a greater level than the SVM classifier due to KNN's classification methodology of determining the majority class from all neighbouring samples. The Decision Tree classifier obtained an accuracy of 62%, which is slightly better than KNN. The Decision Tree classifier does perform well for feature-based classifications; however, it is subject to overfitting. The Decision Tree classifier had difficulty in handling the complex visual patterns observed in mango images with disease.

With an accuracy of 90.11%, the Custom Deep Convolution Neural Network (CNN) model achieved the highest classification accuracy on the test data and outperformed all the conventional machine learning approaches to the mango disease classification task. The special features of the Custom Deep CNN, which enable the automatic learning of hierarchical image features (colour, texture, and shape) as they pertain to the various mango diseases, substantially contributed to its superior performance compared to the conventional machine learning models.

4. Conclusion

The proposed integration of image preprocessing, feature extraction, severity of disease classification, data management, and notification systems into one automated architecture provides for complete imaging of the mango tree. This automation will allow the use of both image processing and IoT technology to provide real time detection of post-harvest mango disease and reduce the potential for economic losses from post-harvest mango diseases, while contributing to improved management of mango fruit quality .After evaluating various models, the Custom Deep CNN model was ultimately chosen as the final classification model for the proposed post-harvest mango disease detection system, as it achieved the highest accuracy of 90.11%. These results indicate that the proposed deep learning method has made it possible to consistently identify diseases with accuracy and will therefore be usable in real-time IoT-connected mango disease monitoring systems.

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