Mobile-Based Smart Advisory System for Mango Disease Alerts after Harvest

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Abstract. The mango industry suffers heavily from post-harvest losses, especially in tropical agricultural economies. Approximately one-third of the total amount of mangoes that are produced will be lost through the many post-harvest losses associated with fungi that infect the mango crops, as well as other crop types such as grains and seeds. Small and medium-sized producers of mangoes are exposed to many of these pathogens, and many of the efforts put forth by the producers can be completely wiped away if an appropriate preventative action is not taken. Using modern grain and seed production methods, along with new advances in warehouse design, producers of grain and seed do not have any quick and effective means for diagnosing the crop diseases that they experience; therefore, they lose revenue and waste resources. Recently, it has become possible to apply image processing techniques based upon Convolutional Neural Networks (CNNs) to learn to distinguish between the various types of mango fruits based upon the visible symptoms of fungal infection on a mango fruit (for example, Aspergillus niger, stem-end rot and anthracnose). The highest level of accuracy (91%) for a classification system was achieved through the CNN, and the CNN has proven itself to be the most effective in accurately identifying disease.

Keywords: Convolutional Neural Networks, Raspberry Pi, IoT, Diseases.

1 Introduction

The mango delivers much of the revenue of many tropical countries in the world. People appreciate mangoes because they are both delicious and nutritious, while at the same time mangoes constitute a few farmers' cash sources. Post-harvest fungal and bacterial diseases are a significant problem every year for farmers because of the high rates of crop loss due to these infections. Currently, farmers do not have effective tools or pro- cesses for quickly diagnosing or treating post-harvest diseases after harvesting their crops. Diagnostic laboratory tests are expensive and slow, forcing many farmers to make guesses about which mangoes should be harvested, often resulting in mangoes being harvested at an inappropriate time to avoid fungal and bacterial infection. Ac- cording to the Food and Agriculture Organization (FAO) report dated October 3, 2023,

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India is projected to represent about 50% of the total global mango crop by 2023, thereby making them the largest global producer of mangoes. [1] However, certain post-harvest diseases (i.e., anthracnose, stem-end rot, and Aspergillus Niger) thrive un- der hot and humid conditions and in unsatisfactory storage, causing 25% to 40% of harvested mangoes to go to waste. These losses disrupt the supply chain and the capacity for exportation and reduce farmer incomes. The detection of diseases occurring after crop harvest is an area that has not received much focus in the agricultural industry. Farmers, particularly those who are small and medium-scale growers who do not have access to advanced technology or laboratory resources for conducting quality assurance checks (Kumar et al.) [2].

Mobile phone-based smart advisory systems are well-poised to meet this need, given that smartphones have become increasingly affordable and are now widely available, the internet of things (IoT) is expanding rapidly, and there are affordable alternatives to traditional computer servers. These systems use data from environmental sensors, machine learning, and image processing to identify diseases and recommend remedial actions. Chauhan et al. (2022) demonstrated that, using surface properties of mango fruit, including surface properties of mango fruit (CNN). [3]

The proposed system of the research can collect data from a mango storage system using a camera and combined environmental sensors attached to a Raspberry Pi or another similar microcontroller.

The initial field tests of the systems have shown positive results of disease detection rates over 87%, and a significant reduction in fruit wastage due to timely efforts. These systems, based on mobile technologies, could disrupt the current paradigm of post-har- vest handling of mangoes. Farmers will have access to more advanced tools to detect diseases that will occur to their mango. Farmers also have access to data that will allow them to make informed decisions when it comes to growing mangoes.

This research looks at new, innovative, inexpensive ways for smallholder farmers located in developing parts of the world to improve the early identification of post-harvest mango-related illnesses, speed up and increase the accuracy of how quickly they detect illness and/or identify multiple varieties of mango illnesses at once, and improve the ability of mango growers to maintain proper storage and transportation conditions for mangoes throughout their supply chain.

2. Literature Review

Johnson and Hofman (2009) found that the fruit of the mango can be damaged by sap or latex that leaks from a freshly cut stem when cutting very close to the fruit. This latex is acidic due to its low pH and high oil content, which can be harmful to plants when present in large quantities. When the latex meets a mango's skin, it causes burn marks and blemishes on the fruit surface; however, these visible defects reduce the mango's attractiveness and economic value and the shelf life of the product. [4] The latex also contains several chemical compounds (e.g., terpinolene and resorcinol), which are responsible for the observed skin damage in mangoes. When you harvest mangoes, you really want to keep latex from oozing all over the fruit. The best way is to cut the stem at an angle and leave a little bit of it still attached. That way, gravity helps pull the latex away from the mango's skin. Why does this matter? Well, understanding how mango latex affects the fruit is key if we want to keep mangoes fresh after picking and stop unnecessary losses for growers and sellers. Mangoes that are harvested at their peak ripeness typically have a very short post-harvest life, depending upon variety and conditions experienced during harvesting. Under non-refrigerated conditions, mangoes have an average room temperature optimum shelf life of about 4-8 days before going bad after harvest. Mangoes continuously always respire, but with increased respiration rates at high external temperatures (>25-30 degrees Celsius), which can cause them to be at risk for developing anthracnose and various types of fungal infections, and if they don't ripen properly, they will be covered in spots and blemishes. All the conditions present significant obstacles for producers and exporters who wish to sell mangoes be- fore they become unfit for consumption. In contrast, by storing fresh mangoes at lower temperatures (around 13 degrees Celsius), producers could potentially sell their product 1-2 additional weeks before spoilage occurs, as the cooler storage temperature reduces respiration rates significantly. It is worth noting that cold chain facilities may not be available or affordable for most smallholder growers and markets operating within a developing economy. While some smallholders may have limited means to temporarily store mangoes, they do not typically have access to storing mangoes for an extended period optimally for sale. Because the window from harvest to spoilage is so short, exporting mangoes to far-off markets gets tricky. That's why we need better ways to handle mangoes after harvest. We should be looking at new disease management strategies and using tech like modified atmosphere packaging or IoT tools to keep a close eye on fruit during storage and shipping. The goal is simple: keep mangoes fresh longer and get them to more people before they go bad.

The work by G. Corkidi et al. created a user-friendly and accurate way to quantify mango fruit disease damage using digital imaging. Specifically, they concentrated on anthracnose, the result of the fungal pathogen Colletotrichum gloeosporioides. This is one of the most frequently encountered and severe mango post-harvest diseases. Historically, human visual inspection was used to evaluate the presence of disease on fruit. Therefore, subjectivity and lack of precision were common outcomes when lesions were smaller or in an early growth state. Digital image analysis gives researchers additional means to monitor mangoes and provides enhanced precision in terms of accurately calculating the surface area impacted. [5]

The equipment employed for the analysis comprised a combination of simple apparatuses to carry out the image analysis, which involved mounting the mango fruit on a plastic retainer so it could be turned by a stepper motor to take photographs of it at various angles and capturing images of the mango fruit taken with the aid of a CCD RGB TV camera and inspired by a 300-watt incandescent bulb providing strong illumination so that the locations of the disease spots could be more easily seen. The back- ground for these photographs was created using an illuminated white backdrop, which was lit up with the aid of a 60-watt bulb to make the disease spots stand out even more clearly. A control device used a joystick to place the mango at a vertical alignment, allowing the operator to adjust it before scanning to scan in a uniform, repeatable man- ner to obtain consistent results regarding disease severity. Through my review of the work of Gadgile and Chavan (2017) on this novel technique of using X-ray scanning to identify fungal infection in mangoes as part of my research on the technology of non- destructive postharvest quality assessment of fruits, I found that this method is a very effective way of detecting diseases early in mangoes after harvesting, which is of criti- cal importance to the quality control process of many mangoes, particularly for export. [6]

The potential applications for this technology are vast; In addition to reducing spoil- age and damage to traded fruit, exporters and traders would benefit from better systems of quality control, monitoring, and timely action. This paper serves as a crucial resource for my research, which attempts to combine image processing with Internet of Things- based alarm systems for thorough monitoring and classification of mango diseases.

It is well established in the literature that image processing and decision support systems have been shown to be useful in disease detection of horticultural products, such as mangoes. Yacob et al. (2005) conducted a comparison of X-ray and MRI im- aging for postharvest internal disease detection and successfully detected interior wee- vil infestations with edge detection, geometric features, as well as ANN classifiers, but a real-time implementation or auxiliary sensor combination was still not incorporated.

[7] For detecting external disease, Veling et al. developed an image-based system fea- turing GLCM texture features, Fuzzy C-Means segmentation, and SVM classification for the early detection of common mango diseases prior to harvesting; however, they did not include IoT sensor monitoring or real-time feedback. Agriculture program and Philip (ICAR) used rule-based advisory systems to design a web-based intelligent sys- tem, which provided crop diagnosis and recommendations employing symptom-based logic, as well as included much manual input, was missing automation of images, and lacked postharvest knowledge specific to mango. [8] Corkidi et al. (2006) concentrated on measuring the severity of anthracnose in postharvest mango using 3D image analysis and Otsu segmentation, which is accurate when it comes to lesion area measure- ment, though it did not incorporate IoT support or environmental sensing techniques. [5]. In general, the literature indicates an obvious research void in proposing a low- cost, timely IoT-based system to combine image processing with sensor data and intelligent decision support for monitoring and alerting of postharvest mango disease.

2.1 Quality parameters: For consumers to be happy with the fruits, the quality parameters must stay the same. The quality of the fruit after it has been picked can be assessed by physicochemical factors, including firmness, weight loss, color, pH, acid- ity, and soluble solids. The quality and shelf life of the fruit for marketing purposes.

See Table 1. Mango quality and shelf life can be improved during storage with post- harvest treatments. With varying degrees of efficacy, these techniques make use of chemical inhibitors, heat treatments, atmospheric modification, irradiation, and natural coatings:

Table 1. Postharvest Methods for Mango Shelf-Life Extension

Postharvest Method	Conditions / Concentration	Shelf Life (Days)	Reference
Rosmarinus officinalis & *Artemisia persica* essential oils	500 µL/L & 1000 µL/L	15 days	[9]
UV-C Irradiation	2.5 kJ/m²	15 days*	[10]
Hot Water Treatment	55°C for 10 minutes	21 days*	[11]
Modified Atmosphere Storage (O_2, CO_2, N_2)	5–8% O_2, 5–9% CO_2, 86–91% N_2	28 days*	[12]
Chitosan Coating	1.0%	33 days*	[13]
Polyethylene Wrapping	Not specified	18 days	[14]
*Aloe vera*Coating	Not specified	21 days	[14]
Beeswax Coating	3.0%	21 days*	[15]
Moringa oleifera Oil-based Coating	1.5%	12 days	[16]
1-Methylcyclopropene (1-MCP)	1500 ppm	45 days*	[17]

2.2 Natural Essential Oils: With antifungal and antioxidant properties, essential oils from Rosmarinus officinalis and Artemisia persica, at concentrations of 500–1000 µL/L, were successful in prolonging shelf life for up to 15 days. [9].

2.3 UV-C Radiation: The shelf life was increased by up to 15 days, and fungal growth was postponed by UV-C treatment at 2.5 kJ/m². [10]

2.4 Treatment of Hot Water (HWT): By lowering the microbial load, 10 minutes of immersion at 55°C considerably increased shelf life to 21 days. [11]

2.5 Atmosphere Packaging Modified (MAP): A gas mix consisting of 5–8% O_2, 5–9% CO_2, and 86–91% N_2 allowed mangoes to have a longer shelf life of up to 28 days while maintaining their firmness and minimizing deterioration. [12] Several studies have shown that using postharvest control techniques can prolong the shelf life of mango fruit by lowering disease incidence and maintaining quality parameters (Table 1).

3. Methodology

This investigation utilizes a practical and technological approach to create a cost-effective, automated real-time system for identifying postharvest diseases in mangoes. The research utilizes Digital Image Processing (DIP) as well as the implementation of the Internet of Things (IoT) for developing a low-cost solution that automatically detects many types of diseases in mangoes at the earliest possible stages. Musale, S. S., & Patil, P. M. (2014). The five main parts of the method include data acquisition, image pre-processing, algorithm development, system integration, and evaluating the performance. [18] (See Fig. 1.)

3.1 Image Acquisition: To facilitate the image capture of mangoes that are being kept at a facility, pictures of each mango were taken using a camera module that is connected to a Raspberry Pi 3. In terms of cost and portability, the Raspberry Pi met the criteria in addition to compatibility with various types of sensors/devices.

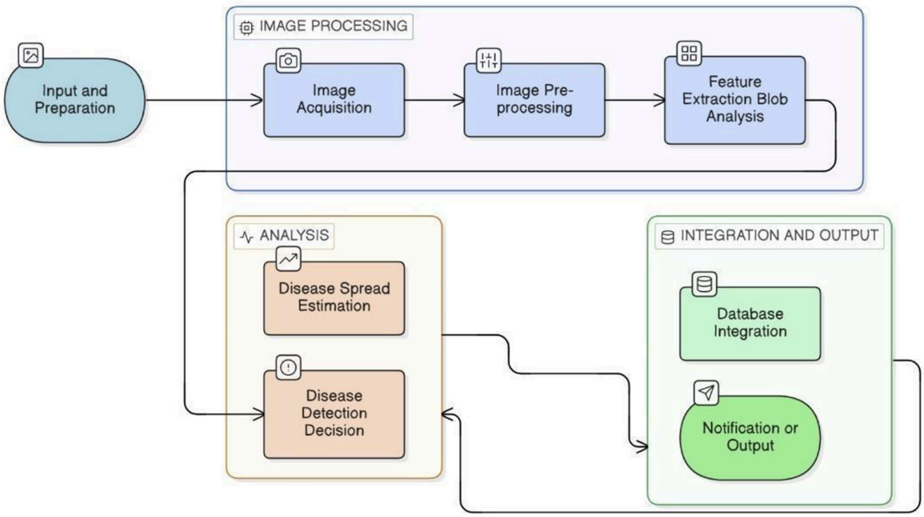

Fig. 1. Complete Overview System

3.2 Image Transfer and Storage: The original images and sensor readings that were obtained from each mango were transferred to a cloud-based platform utilizing wireless networking. Centralizing the ability to access stored images and sensor readings allows farmers and warehouse operators who may live some distance away to view the health status of produce.

3.3 Image Enhancement: At this stage, the system will obtain the stored image file from the processing folder, then begin working with the image(s). This means that as the system loads the image, the details from the image must be completely read into the memory of the system to be maintained for further processing of the image. Before using image data to detect mango diseases, it is important to enhance the image quality before use. The methods used for enhancing images involved resizing, elimination of noise with Gaussian filtering, and improving contrast using histogram equalization. Af- ter enhancement, the RGB image turned into a grayscale image for simpler processing.

3.4 Blob Analysis and Extraction of Features: One of the most important parts of the overall methodology consisted of using blob analysis to determine the area of interest within the mango images. Through the application of blob analysis on the pixels of the mango photo, we were able to discover which portions had varying characteristics from those that were not affected by the mango disease. Shape, size, and colour were used as the measures of these characteristics. Each of the blobs is telling the system different things about the image, so if you are looking for accurate results, then you need to analyze each blob individually.

Additionally, the system will no longer look at the entire image but will focus on the smaller elements. By narrowing in on each element of the image, you can extract much more detailed information from it. While analyzing each blob, you will be looking at the size of each blob, its location in the image, and the colour variations that exist in the blob. The high and low values of colour correspond to the amount of variation that exists in the texture of the blob. The location and the size of the blob also correspond to how you will organize the different pieces of the image. By breaking these details down, you will provide the system with a clear path to convert raw image data into usable information and be able to build your next step from this information, whether it be to further analyze the image or make an informed decision based on what is contained within the image.

— *Classification Algorithms:* (Table 2) We evaluated several machine learning classifiers to automate the process of identifying diseases. These included:

Table 2. Comparison of Algorithms Applied to the data dataset

Sr. no	Name of Algorithm	Description	Accuracy
1	Random Forest	The Random Forest machine-learning technique combines the output of many decision trees to produce a more accurate prediction than each tree can individually produce.	67%
2	K-Nearest Neighbourhood (KNN)	KNN has been chosen primarily due to its simplicity and the ability to explain results to its users.	60%
3	Support Vector Machine (SVM)	According to SVM, the SVM classifier scored the highest for its classification accuracy when being applied to large data sets at a high dimensionality.	(82%)
4	Artificial Neural Networks (ANN)	ANNs enable a more in-depth approach to learning than other models by allowing for the use of multiple layers of neurons to train a neural network.	82%
5	Convolutional Neural Network (CNN)	CNNs are a form of deep learning that allows for automatic detection of spatial information in images through the utilisation of convolution, pooling, and fully connected layers in order to produce high accuracy in classifying im-	91%

3.5. Disease Check: M. D. Yusuf et al. (2018) reported that once the blob attributes have been extracted, the system performs a disease check on the blobs to see if they show any signs of abnormality. Each of the blobs analyzed will be compared against a known disease pattern to identify any abnormalities, including subtle differences in size, colour or texture. The comparison is crucial to differentiate between the regions of healthy plants and those that may indicate disease. A blob that matches any of the records in the Disease Database will be automatically tagged with that specific disease name. By tagging the blob, the areas affected will be clearly identified so that the physician or treatment provider has an accurate reference when planning their diagnosis and treatment for the affected area. The system will use the information contained in the database to reliably identify the disease and minimize the chance of misidentifying a disease, which will result in prompt treatment to manage plant health. [19]

3.6. Database Integration: The database jumps into action the moment a new disease pops up. It logs every detail in one spot, so you don't have to dig around for information later. Need to check how a disease was spotted or compare cases? Knowing that per- centage is important because it provides you with a better understanding of how severe the issue is and therefore what the implications are for mangoes by incorporating easy- to-read descriptions and quantitative measurements, the database offers the user a complete overview. Therefore, the user will be able to make informed choices regarding mango health and take appropriate actions to resolve diseases.

3.7. Disease Spread Calculation: S. Musale et al. (2014) state that the database is used to record systematically the details of the newly identified diseases so that they can be documented in a consistent, organized, and retrievable way, thus giving a precise ac- count of the disease identification process. Furthermore, the centralized storage of dis- ease information facilitates easy accessibility to the entire results of disease identification so that they are properly documented. The database not only records the name of the disease but also records the percentage of the image area covered by the disease. This is essential in determining the level of severity that the disease might have on the plant being inspected. The database is inclusive of all aspects of disease identification, thus ensuring that the entire evaluation of a plant on account of the disease(s) it may be suffering is optimized, thereby making way for more informed decisions on plant health and caring alternatives. [18]

3.8. IoT-Based Alert Mechanism: Based on the results of classification, a notifica- tion system using the Internet of Things (IOT) was developed for subscribers of that system. This application sends users a message via text (SMS) to inform them of an infection, as well as to provide instructions for treatment and prevention of the infec- tion. The application also provides an estimate of how many additional fruits may be- come infected if treatment is not received and how much those numbers could potentially cost. When an analysis of the infection has been completed, the IoT will automatically notify the server that all paired mobile applications receive the notification. Users will receive immediate notification after completion of the analysis so they can access the detailed information about the infection via their paired mobile devices. Sutar, R. M., et al. (2021)] with real-time notifications, the system delivers the process in a much more responsive way so that action can be taken on time. [20] The whole process makes the process of detecting diseases fully automated because images captured are systematically analysed to ascertain that Khalil, H., et al. [21]

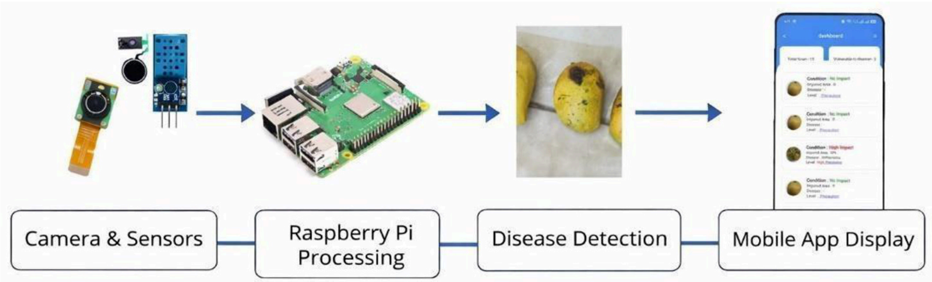

Fig. 2. Overall System Representation

As shown in Fig. 2, an automated and comprehensive flow has been created for the complete post-harvest system (harvesting fruit (Fig. 2) and then processing images and using machine learning (ML)) to enable the processing and post-harvest inspection of mangoes for disease diagnosis using the post-harvest picture of mangoes within the post-harvest inspection system. The results of the classification will be sent wirelessly (using an Internet of Things (IoT) module) for immediate expert assessment (in real time) and used as a method to issue alerts/notifications regarding disease outbreaks.

4. Results and Discussion

4.1 Optimization Model for Mango Diseases: Fungal and bacterial diseases such as anthracnose, stem rot, and Aspergillus Niger can harm mango trees significantly. Farmers must assess the cost-effectiveness of controlling these diseases compared to the costs of controlling them. Our objective is to create a mathematical model to determine the optimal balance between the amount of disease treatment applied and the costs as- sociated with the treatments.

4.2 Mathematical Formulation

4.2.1 **Objective Function:** Minimize total expected loss and treatment. Min $(x_d) \sum_{d \in D} [L_d \,.\, (1 - E_d(x_d)] + C_d \,.\, x_d$ Eq (1)

Where (diminishing returns)

$E_d(x_d) \in [0,1]$, and typically:

$$E_d(x_d) = 1 - e^{-x_d k_d} \quad \text{Eq (2)}$$

4.2.2 **Constraints:** *Budget constraint.*

$$\sum_{(d \in D)} C_d x_d \leq B \quad \text{Eq (3)}$$

Maximum treatment limit (e.g., environmental safety): $x_d \leq x^{max}_d, \forall$ d ∈ D

Non-negativity: $0 \leq x_d \leq 1, \forall$ d ∈ D

4.2.3 **Optimizing the Formula:** Earlier, I formulated the **general optimization prob- lem** like this:

$$\text{Min } (x_d) \ \sum_{d \in D}[L_d . (1 - E_d(x_d)) + C_d . x_d \qquad \text{Eq (4)}$$

where, $E_d(x_d)$: Effectiveness function of treatment x_d, e.g., how much loss is reduced.

- o $E_d(0) = 0$ (no effect if no treatment),
- o $E_d(1) \leq 1$ (maximum possible effect).
- C_d: Cost per unit of treatment for disease d.
- L_d: Expected loss (e.g., in yield or money) if disease d is not treated
- x_d = treatment intensity (decision variable).

This was **abstract and flexible**. Here $E_d(x_d) = 1 - e^{-xdkd}$, I chose this specific function for the following reason:

- It's a standard **diminishing returns curve**: the first bit of treatment gives a big improvement; later doses give less and less.
- It makes the math solvable in closed form and easy to plot.
- It's widely used in biology/agriculture for modelling the effectiveness of pesticides or medicines.

When I plug this into the earlier general formula, it becomes:

$$\boldsymbol{F_d(x_d)} = L_d e^{-x_d{}^k{}_d} + C_d . x_d \qquad \text{Eq (5)}$$

Which will be optimized and plotted. A general theoretical optimization problem (from before). A concrete, worked-out version with exponential effectiveness (now).

Interpretation of terms

- **Disease loss term** ($L_d e^{-x_d{}^k{}_d}$): This decreases exponentially with treatment. At x = 0, the loss is L_d. As x increases, the disease damage reduces rapidly at first and then more slowly.
- **Treatment cost term** ($C_d . x_d$): This increases linearly with treatment. At x=0, cost is zero. At x=1, the cost is maximum.

Together, the curve $\boldsymbol{F_d}(x_d)$ is typically **U-shaped**:

- Left side → dominated by disease losses.

- Right side → dominated by treatment costs.
- Bottom → represents the "sweet spot" of treatment.

Interpretation:

- The first small dose of treatment gives a **big reduction** in disease (steep drop).
- Additional treatment has **smaller incremental effects** (diminishing returns).
- The balance between disease reduction and cost gives an **optimal treatment level**.

Optimizations **without Budget**

$$x_d^* = \min\left\{1, \max\left\{0, \frac{1}{k_d}\ln\left(\frac{L_d k_d}{C_d}\right)\right\}\right\} \quad \text{Eq (6)}$$

Optimization **with Budget**

$$x_d^*(\lambda) = \frac{1}{k_d}\ln\left(\frac{L_d k_d}{C_d(1+\lambda)}\right) \quad \text{Eq (7)}$$

4.2.4 Practical Meaning

- **General model**: Flexible, matches whatever pattern experimental data shows.
- **Exponential model**: Some concrete, biologically realistic example with di- minishing returns.
- **Without budget**: Each disease has its own "sweet spot."
- **With budget**: Treatments must share resources; the λ mechanism ensures fair allocation.

4.2.5 Plotting:

$$\boldsymbol{F_d}(x_d) = L_d e^{-x_d k_d} + C_d \, . \, x_d \quad \text{Eq (8)}$$

for different diseases, where:

- *$X \in [0,1]$ = proportion of treatment,*
- *L_d = baseline loss,*
- *k_d = effectiveness of treatment,*
- *C_d = cost per treatment unit.*

This report presents an optimisation analysis for three major mango diseases: anthracnose, stem rot, and Aspergillus niger. The optimisation problem minimises the total expected loss function:[36]

$$\boldsymbol{F_d}(x_d) = L_d e^{-x_d{}^{k}{}_d} + C_d \, . \, x_d \qquad \text{Eq (9)}$$

where:

L = maximum possible loss without treatment, k = effectiveness rate of treatment, C = cost of treatment, x= = treatment proportion (0 ≤ x ≤ 1).

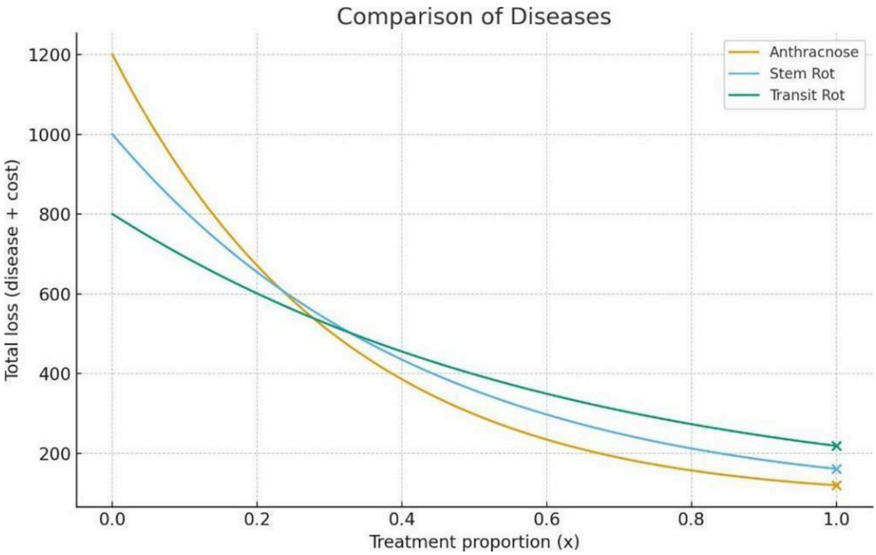

Fig 3: All Diseases in One graph

See Fig. 3. The graph compares total loss f(x) for anthracnose, stem rot, and Aspergillus Niger at different proportions of treatment (x). The total loss on the vertical axis and treatment proportion on the horizontal axis show that with increasing amounts of treat- ment, anthracnose, stem rot, and Aspergillus niger had reduced levels of total loss due to disease because treated fruit had lower disease levels than untreated ones. Initially, the total losses caused by anthracnose were the highest at 1,500. But with treatment, these losses decreased greatly. Thus, treatments are effective for anthracnose. Stem rot had an intermediate total loss of 1,000. Stem rot responded to treatment better than both anthracnose and Aspergillus Niger, and it ended with the lowest total loss after treat- ment. On the other hand, Aspergillus Niger had the lowest total loss with 900 to start the testing, but it did not show much improvement after treatment. Both anthracnose and stem rot showed decreases in total losses over the testing period, while Aspergillus Niger showed very little change after treatment was applied. Therefore, while all three diseases were positively affected by treatment (decreasing total losses), stem rot showed the most benefit. In contrast, Aspergillus Niger showed very little change after treatment.

Table 3: All diseases After Applying the Minimization function

Disease	Max Loss(L)	Effective-ness(K)	Treatment Cost	Optimal x*	Minimized loss f(x*)
Anthracnose	1500.0	3.0	60.0	1.0000	134.6806
Stem rot	1000.0	2.8	50.0	1.0000	110.8101
Aspergillus Niger	9000.0	2.0	30.0	1.0000	151.8018

Table 3 offers a comparison of maximum loss, treatment effectiveness, treatment cost, and minimized loss of three mango diseases (Anthracnose, Stem Rot, and Aspergillus Niger). The greatest amount of potential loss happens from anthracnose at $1500; how- ever, this disease is the easiest to treat. In contrast to anthracnose, stem rot has a maxi- mum loss of $1000 and requires $50 to treat it, which will yield an effectiveness of 2.8 and has the lowest minimized loss at 110.81, making it the most cost-effective way to manage. Aspergillus Niger, on the other hand, has a maximum potential loss of $900 but has an even lower cost of treatment of only $30. Nevertheless, the difficulty of controlling Aspergillus Niger makes it a much riskier option than anthracnose, even when considering the maximum loss associated with both diseases. The effectiveness of treating Aspergillus Niger is also only at 2.0, and its minimized loss is the greatest of the three at 151.80. In summary, anthracnose represents the largest potential loss, but it is by far the most easily manageable disease when treated. Aspergillus Niger may seem to be a less risky option at first, but ultimately, managing Aspergillus Niger will be more difficult and therefore more costly in the long run.

5. Conclusion

Here’s a smarter way for farmers to tackle mango diseases: an optimization framework that blends biology and economics so they can pick the most effective treatments. On top of that, there’s a mobile-based smart advisory system. This isn’t just a tech upgrade; it gives farmers real tools to track and manage mango diseases after harvest. With this, productivity goes up, livelihoods get better, and the whole agricultural sector in tropical regions moves toward real sustainability. In today's world of agriculture becoming increasingly complex and competitive, technology is no longer a ‘nice to have’ for farm- ers who want to succeed as we move forward. In this report, the results of all 5 machine learning techniques are presented. The accuracy for each machine learning technique was evaluated based on the model accuracy reported in Table 2. Of the 5 techniques, Convolutional Neural Networks (CNN) performed best with a total accuracy of 91%

and produced the most accurate models for capturing complex relationships in the dataset. The Support Vector Machines (SVM) also performed well with 82% accuracy, but there is less complexity to the data, and it is not as effective as the CNN. However, the SVM has an excellent ability to generalize its performance across different datasets. The Random Forest (RF) Model has a midrange accuracy rating of 67%, which is greater than both the KNN and the Decision Tree (DT) Models but less than either the CNN or the SVM Models. The KNN and the DT models both have an accuracy rating of 50%, meaning they are not capable of solving the problem addressed in this study. The conclusion reached from the study is that as the complexity of the data increases, the use of deep learning algorithms, such as CNNs, will be more effective in capturing the patterns/trends within high-dimensional/complex data than using traditional algorithms.

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