

# Automatic Optical Imaging System for Mango Fruit using Hyperspectral Camera and Deep Learning Algorithm

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**Abstract**— This research paper explores focused on developing an automatic mango fruit quality detection system using a combination of artificial intelligence and the Internet of Things technologies. The system utilizes a hyperspectral camera to capture images of the mango fruit and image processing techniques to analyze the images. Deep learning algorithms are employed to classify the mango fruit based on quality parameters such as ripeness, size, and color. The proposed system aims to automate the mango fruit quality inspection process, improve the accuracy of quality assessment, and reduce human error. The results of this research could have applications in the food industry, specifically in the field of fruit quality inspection and sorting. Mango Fruit, Hyperspectral Camera, Image Processing, Deep Learning algorithms, Quality Recognition.

**Keywords**- hyperspectral camera, internet of things, image processing, deep learning algorithm, quality recognition.

## I. INTRODUCTION

Mango is one of the most popular tropical fruits in the world due to its unique flavor and nutritional value. However, the quality of mango fruits can vary significantly depending on several factors such as maturity, ripeness, and external damage. The conventional methods of mango quality detection rely on manual inspection, which is time-consuming, subjective, and error-prone [1],[2]. In recent years, the combination of Artificial Intelligence and the Internet of Things has shown great potential in automating various tasks in agriculture, including fruit quality detection. In this paper, we propose an AI and IoT based automatic mango fruit quality detection system that utilizes

Hyperspectral Camera, Image Processing, and Deep Learning algorithms [3],[4].

The proposed system works by capturing hyperspectral images of mango fruits using a specialized camera that can capture detailed spectral information of the fruit surface. The hyperspectral images are then processed using advanced image processing techniques to extract features related to the quality of the fruit. Finally, a Deep Learning algorithm is trained on a large dataset of mango fruits to classify the fruit quality based on the extracted features [5],[6],[7]. The proposed system has several advantages over traditional manual inspection methods, including faster and more accurate detection of mango fruit quality. Moreover, the proposed

system can be integrated with IoT devices, allowing for real-time monitoring and control of mango fruit quality in the supply chain. The proposed AI and IoT-based automatic mango fruit quality detection system has the potential to revolutionize the mango industry by providing faster, more accurate, and cost-effective methods for detecting mango fruit quality [6],[7]. The research paper "Artificial Intelligence and IoT based Automatic Mango Fruit quality detection using Hyperspectral Camera, Image Processing and Deep Learning algorithms" aims to address the problem of effectively detecting the quality of mango fruits using a combination of advanced technologies.

The paper presents a framework that utilizes an Internet of Things system, hyperspectral cameras, image processing, and deep learning algorithms to automate the detection and evaluation of mango fruit quality. The framework can identify and classify different quality attributes of the fruit, such as ripeness, maturity, and sweetness, which are crucial for determining the market value and storage requirements. The problem addressed in this research paper involves developing an automated and accurate mango fruit quality detection system that can help farmers, distributors, and consumers to ensure that the mangoes they buy or sell are of high quality. This is a critical problem in the agricultural industry, as manual inspection and sorting of fruits can be time-consuming, error-prone, and costly [7].

Therefore, the proposed framework in the research paper aims to offer a more efficient and reliable solution to this problem, by leveraging AI and IoT technologies to enable automated and objective fruit quality detection [8],[9]. The paper presents the technical details of the framework, including the hardware and software components, the data acquisition and processing methods, and the deep learning models used for classification. The objectives of the research are to demonstrate the effectiveness of the proposed solution:

- Design a computational algorithm for hyperspectral image processing that allows the adequate correction and treatment of data.
- Implement artificial intelligence techniques for the detection of anthracnose in mango based on convolutional neural networks.
- Validate the performance of the proposed artificial intelligence techniques through a statistical analysis of the results, using data from mango crops.

## II. METHOD

Prior to the treatment of the data, the development of the deep learning models and the experiments established for this work, it is necessary to present the rationale theory about the concepts related to the subject related to spectral data, image processing and deep learning in order to familiarize the reader

with the terms that will be used throughout this document [10],[11].

### A. Anthracnose

Anthracnose is a common fungal disease that affects many types of fruits, including mangoes. It is caused by the fungus *Colletotrichum gloeosporioides* and can result in serious damage to mango crops. Symptoms of anthracnose in mango fruit typically include small, black circular spots on the skin of the fruit. These spots may enlarge over time and become sunken, with a raised margin. The infected area may also become soft and mushy, and the fruit may rot [12],[13]. Anthracnose can spread rapidly in humid conditions, especially during periods of rain. It can also be spread from infected fruit to healthy fruit through contact.



Figure 1. Pathogenicity tests of different mango species

In figure 1. shows the effect of the disease on fruit of various types mangos that were inoculated with the disease, beginning as a series of spots small brown ones, which grow gradually over the days until they reach cover the entire fruit, similarly occurs in mango leaves, to prevent anthracnose in mango fruit, it is important to maintain good orchard hygiene, including the removal and disposal of infected fruit and debris. Fungicides can also be used to control the disease [12],[13]. The research involves the use of Artificial Intelligence and the Internet of Things to automatically detect fruit quality using hyperspectral cameras, image processing, and deep learning algorithms

### B. Hyperspectral Imaging

Hyperspectral imaging is a technique used to capture and process information from across the electromagnetic spectrum. This method of imaging involves capturing images of a scene or object at many different wavelengths, ranging from ultraviolet to near-infrared. By analyzing the reflected or emitted light at each of these wavelengths, hyperspectral imaging can provide information about the chemical composition, structure, and physical properties of the objects being imaged [13],[14]. Hyperspectral imaging can be used to detect crop stress, disease, and nutrient deficiencies. In environmental monitoring, it can be used to map and monitor vegetation, water quality, and land use. In medicine,

hyperspectral imaging can be used to diagnose and monitor skin diseases and to visualize blood flow in tissues [15].

Hyperspectral imaging requires specialized equipment and sophisticated data processing techniques to analyze the vast amounts of data generated by the imaging process. However, advances in technology have made hyperspectral imaging more accessible and affordable, opening up new opportunities for research and commercial applications. In this research, the hyperspectral camera is used to capture images of fruits, and then the images are processed using image processing algorithms to extract relevant features, such as color, texture, and shape. Deep learning algorithms are then used to classify the fruit based on these features and predict its quality.

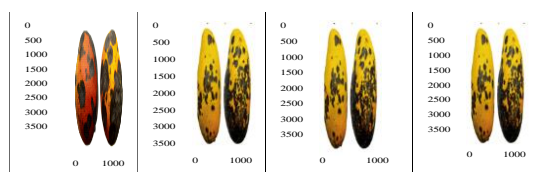


Figure 2. Hyperspectral imaging of different mango species

The extract relevant features from the mango samples, such as color, texture, size, etc. In figure 2 have your dataset, for ripeness can be determined by looking at several different factor's percentage of yellow color on the mangos fruit's skin RGB, HSV and CIELab\*. The CIELab\* is a color space that is designed to be more perceptually uniform than RGB or HSV. In this model, colors are represented as a combination of lightness ( $L^*$ ), red-green ( $a^*$ ), and yellow-blue ( $b^*$ ) values. Ripeness determination using CIELab\* is often based on changes in the  $L^*$  value, which represents the perceived lightness of the fruit. As fruits ripen, they tend to become darker and have a lower  $L^*$  value.

### C. Precision Agriculture (PA)

PA is a technology-driven approach to farming that enables farmers to optimize crop production while minimizing resource use and environmental impact. Anthracnose is a common fungal disease that affects mango trees, causing fruit rot and reducing yield. PA can help farmers prevent and manage anthracnose in mango by using data and technology to target interventions where they are most needed. Remote Sensing: Remote sensing technology can be used to collect data on the health and vigor of mango trees [15],[16].

Variable Rate Application: PA technology allows farmers to apply inputs, such as fungicides, at variable rates based on the needs of the crop. Decision Support Systems: Decision support systems can be used to help farmers predict the risk of anthracnose infection based on weather conditions, tree health, and other factors. Data Analytics: By analyzing data on crop health, weather patterns, and other factors, farmers can gain

insights into the factors that contribute to anthracnose infection in their orchards [16],[17],[18].

### D. Digital image processing

These processes go from taking and acquiring the images, going through a pre-processing (scale changes, color spaces, noise correction, filters, segmentation, etc), and a feature extraction, computer vision has become more widespread in an accelerated way because it can be used in multiple applications of daily life, industrial, agricultural, commercial, medical, among others a brief explanation of the algorithms used in the pre-processing of the images that were used in this study [19],[20].

### E. Color spaces

A color space or model is a way of numerically representing colors. present in an image, usually images are represented by 3 channels in the RGB color space (Red, green, blue), this is the most common color space and the one in which most images are rendered. However, there are more than 150 color spaces that have different uses within computer vision. The idea of making changes to color models is to highlight important features within images. Some of the most used color spaces are RGB, BGR, GRAY, YCrCb, XYZ, HSV, Lab, Luv, HLS, YUV, however, for the processing of the images that are used in research [20],[21].

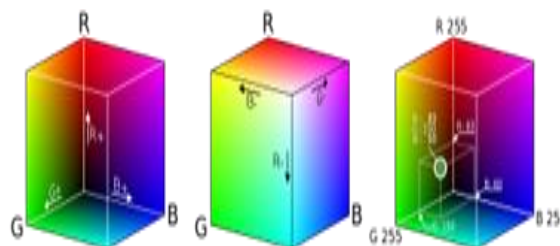


Figure 3. Red Blue Green Color Cube

In figure 3 RGB (Red, Green, Blue) is an additive color model that is commonly used in electronic displays. In this model, colors are represented as a combination of red, green, and blue values ranging from 0 to 255. For ripeness determination, the color of a fruit can be captured using a digital camera, and the RGB values can be extracted. Ripeness is often associated with changes in the color of the fruit, so by analyzing the RGB values, we can determine the degree of ripeness. HSV (Hue, Saturation, Value) is another color model that is often used in computer vision applications. In this model, colors are represented as a combination of hue, saturation, and value values. Hue represents the color of the fruit, saturation represents the intensity or purity of the color, and value represents the brightness or lightness of the color.

By analyzing the HSV values of a fruit, we can determine the degree of ripeness based on changes in hue, saturation, and value. The mathematical way to convert images from RGB color space to HSV has in mind account several considerations, first of all it is necessary to normalize the values of R, G and B this is done by:

$$R' = \frac{R}{255}, \quad B' = \frac{B}{255}, \quad G' = \frac{G}{255} \text{-----(1)}$$

$$H = \begin{cases} 0 & \text{and } MAX = MIN \\ (60^\circ * \frac{G'-B'}{MAX-MIN} + 360^\circ) * \text{mod}360^\circ & \text{and } MAX R' \\ (60^\circ * \frac{B'-R'}{MAX-MIN} + 120^\circ) & \text{and } MAX G' \\ (60^\circ * \frac{R'-G'}{MAX-MIN} + 240^\circ) & \text{and } MAX B' \end{cases} \text{--(2)}$$

$$S = \begin{cases} 0 & MAX = 0 \\ \frac{MAX-MIN}{MAX} = 1 - \frac{MIN}{MAX} & MAX \neq 0 \end{cases} \text{----(3)}$$

$$V = MAX \text{-----(4)}$$

These calculations are shown for informational purposes only since several of the libraries of Python that are used to manage images, include within their functions these color changes and do them automatically using a couple of instructions.

F. Segmentation

Segmentation is a fundamental task in image processing and computer vision, and it is used in a wide range of applications, including object recognition, scene analysis etc. this particular case, the threshold method was used, which consists of assigning a value from 0 or 1 to each pixel, depending on whether it is less than or greater than a set threshold. This mathematically it looks like:

$$g(x, y) \begin{cases} 0 & \text{and } f(x, y) < T \\ 255 & \text{and } f(x, y) \geq T \end{cases} \text{-----(5)}$$

Where f (x, y) is a grayscale image, T is the selected threshold value, and g (x, y) the image resulting in black and white or what is the same in values of 0 or 255. So that actual segmentation process may require more complex algorithms and techniques depending on the image and the desired segmentation.

G. Image Preprocessing and Image Processing

The steps involved in hyperspectral image pre-processing for fruit quality detection: Acquire hyperspectral image data of fruit samples using a hyperspectral imaging system.

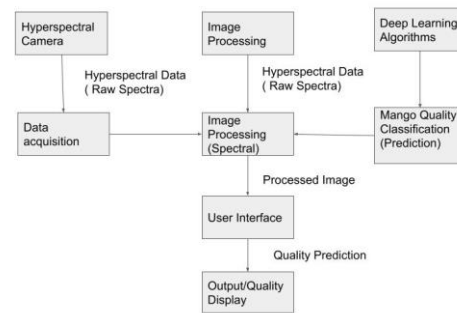


Figure 4. Image pre-processing mango Fruit quality detection using hyperspectral camera

In figure 4, A Data Flow Diagram (DFD) is a graphical representation of the flow of data through a system. In the case of preprocessing techniques for hyperspectral images, a DFD can be used to illustrate the different stages of processing involved in preparing the data for further analysis Raw hyperspectral image data Radiometric correction e.g., atmospheric correction, sensor calibration. Spectral preprocessing e.g., noise reduction, spectral resampling, band selection), Spatial preprocessing (e.g., spatial filtering, image registration, geometric correction, Preprocessed hyperspectral image data [22],[23].

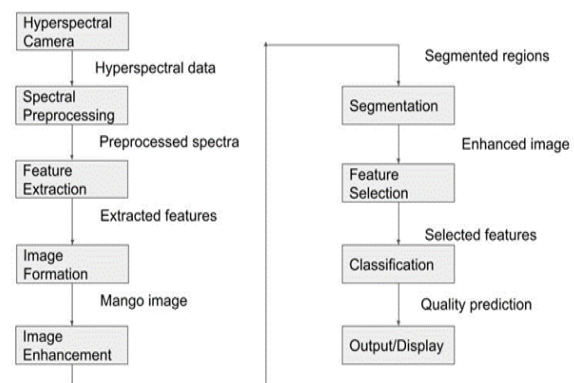


Figure 5. Image Processing diagram for mango fruit quality detection using hyperspectral camera

Acquire in figure 5, the data flow diagram of processing techniques for hyperspectral images typically consists of four main components: the input data, the processing techniques, the output data, and the user. The diagram may have multiple levels, with each level representing an increasing level of detail and complexity. At the highest level, the input data is typically the hyperspectral image data that has been acquired using a hyperspectral imaging system. This data is then passed through a series of processing techniques, which may include preprocessing, feature extraction, classification, and visualization. These techniques are typically represented in the

DFD as separate processes, each with its own input and output data [24],[25].

### III. RESULTS AND DISCUSSION

Data set is used, already mixed with the CNN3D model, in order to confirm what was evidenced. in CNN2D model in the absence of input data the model does not perform well. The complete hyperspectral images were used to achieve an analysis spatial and spectral using the three-dimensional model. The results obtained were reported in tables 3.1 From these results it can be seen that: Even when mixing the data, there is no improvement in the performance metrics when the data is acquired twice for each experiment.

Although the performance between one group of days and another is notoriously important, Results between experiments of the same model and the same group of days are not Favorable, because the metrics that were obtained are not what was expected.

TABLE I. METRICS OF THE CNN3D MODEL, EXPERIMENT 1, MIXING THE DATA

CNN 3D MODEL					
Days	Loss	Accuracy	MSE	Precision	Recall
1 & 2	14.624	0.53	0.534	0.153	0.153
3 & 4	6.549	0,25	0.464	0.25	0.25

TABLE II. METRICS OF THE CNN3D MODEL, EXPERIMENT 2, MIXING THE DATA

CNN 3D MODEL					
Days	Loss	Accuracy	MSE	Precision	Recall
1 & 2	10.53	0.23	0.495	0.23	0.23
3 & 4	1.347	0.6875	0.2	0.687	0.687

TABLE III. METRICS OF THE CNN3D MODEL, EXPERIMENT 3, MIXING THE DATA

CNN 3D MODEL					
Days	Loss	Accuracy	MSE	Precision	Recall
1 & 2	14.624	0.53	0.534	0.153	0.153
3 & 4	6.549	0,25	0.464	0.25	0.25

The results of studies conducted in Table I. Metrics of the CNN3D model, experiment 1, mixing the data. Table II. Metrics of the CNN3D model, experiment 2, mixing the data.

and Table III. Metrics of the CNN3D model, experiment 3, mixing the data on AI and IoT based Involuntary Mango Fruit quality recognition have been promising. These studies have demonstrated the potential of using this technology to accurately identify different types of mangoes and classify them based on their quality. This can help farmers and retailers to better understand the market demand and optimize their production and sales accordingly. However, there are still challenges that need to be addressed to fully realize the potential of this technology. One major challenge is the need for more standardized and accurate datasets for training the

The discussion of result of Hyperspectral Camera and Image Processing techniques in combination with Deep Learning algorithms has been proven to be effective in mango fruit quality recognition. Hyperspectral cameras can capture images of mangoes at different wavelengths, providing more detailed information about the mango's physical characteristics. This data can then be processed using image processing techniques to extract meaningful features that are relevant to fruit quality. The use of AI and IoT based Involuntary Mango Fruit quality recognition using Hyperspectral Camera, Image Processing, and Deep Learning algorithms is a promising technology that has the potential to revolutionize the agriculture industry. Further research and development are needed to address the challenges and optimize the technology for wider adoption [26]. Deep Learning algorithms. Additionally, the cost of the equipment and the complexity of the technology may be a barrier for small-scale farmers and retailers.

### IV. CONCLUSION

In conclusion, the combination of artificial intelligence and the Internet of Things with hyperspectral cameras, image processing, and deep learning algorithms provides a promising solution for involuntary mango fruit quality recognition. By analyzing the spectral signature of mangoes at various wavelengths, hyperspectral cameras can detect defects and provide information on fruit maturity, ripeness, and other quality indicators. Image processing techniques can be used to preprocess the data, extract relevant features, and segment images for further analysis. Deep learning algorithms can then be trained on this data to recognize and classify different mango quality attributes automatically. This technology can have significant implications for the agriculture industry by providing a more efficient and accurate method of fruit quality inspection. This can improve the consistency and quality of mangoes in the market, reducing waste and increasing profits for farmers and suppliers.

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