

AI-Enabled Thermal Imaging Framework for Fruit Quality Assessment

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Abstract - Classifying and identifying fruits and vegetables is still difficult in everyday life and production. The elimination of unfair or fraudulent practices in food processing and the development of innovative methods for the detection of defective products are of utmost importance. The degree of food safety is determined by these methods, hence they must be analytical, precise, and sensitive. The food item's true quality may be lost as a result, and the customer may have health issues. In this, we present an effective fruit classification system based on thermal images that uses convolutional neural networks (CNNs) and deep learning to extract visual features and carry out grading and sorting. We create a database of fruit photos in three categories, including the main varieties found in real life (GOOD: raw, ripe; BAD: rotting). Our categorization algorithm yields an outstanding accuracy rate of 96%, according to experiments done on our own database. Fruits, particularly bananas, are the main focus of this study. The model is trained, tested, and validated using the thermal pictures of the three fruit categories. In the upcoming chapters, the methods and image processing algorithm are covered in detail.

Key Words: Fruit, Vegetables, Adulteration, Image processing, Convolutional Neural Network (CNN), Thermal image, banana.

1. INTRODUCTION

In Asian countries, agriculture is an essential component of their total economic development. For two-thirds of Indians, agriculture is their only source of income. When comparing the advancement of electronics and automobiles to that of agriculture, it is evident that the latter is developing more slowly. Therefore, in order to increase the effect factor of agricultural growth, it is imperative to move towards an innovative design. The market for fruits and vegetables is subjective. Therefore, it is more crucial to verify the fruit's quality before delivering it to the client. Currently, agricultural products are categorized by human experts according to their optical properties.

However, manual inspection degrades the quality of agricultural products by being inaccurate, inconsistent, and inefficient. It is human nature for people to eventually feel weary, bored, or distracted. The enhancement of the fruit quality-based automatic grading method will produce precise, effective, and reliable outcomes. Consequently, it saves time and human labor and will contribute slightly to economic growth. In order to sort fruit more quickly and accurately, an automatic system is therefore required.

1.1 SORTING OF FRUITS

Separating the different types of fruits from fruit lot is called sorting. It depends on

Damage product: The damaged product should be avoided. It should be separated from fruit lot, and the well mature product should be taken.

Diseases: Diseased free fruit and vegetable should be collected from a lot. It is essential for sorting.

Insect cutting products: Insect cutting fruit must be avoided because consumers want good fruit.

Maturing: Mature fruit is delicious. So maturity is very much needed for fruit.

Color: Colours should be lightable. Well-colored fruit should be selected that attract the consumer. Colour also indicates the maturity level of the seed.

Shape: In the case of packaging, the shape is essential. Some type of fruit should be selected for packaging in case of sorting.

Size: Size also an essential matter for sorting fruits from a fruit lot. We should select the same size of the fruit.

The Figure 1 represents the banana with various quality.



Fig-1 Banana with various quality

1.2 INTERNATIONAL GRADES IN SORTING

For the international market, 3 general grades are considered as:

- Extra class.
- Class I.
- Class II.

Extra Class: The extra class is of exceptional quality, has the variety's colors and shapes, and is probably going to change its natural flavor and texture without any internal flaws. Error tolerance is set at 5%. It must be presented with care, taking into account the consistency of the produce's size, color, and condition as well as the appearance of the packing or pre-packing material.

Class I: With the exception of a 10% tolerance, the Extra Class is nearly identical in quality. Individual fruits are permitted to have minor color, shape, and skin flaws as long as they don't detract from their overall appearance or shelf life. The product

does not always need to be organized in the packaging, and the packing may have a larger range of sizes.

Class II: As long as the product is fit for ingestion while it is fresh, it may have some internal or outward flaws. Local or short-distance markets are the ideal fit for this class. Customers who are not very picky and value price above quality will be satisfied by this category.

STAGE	COLOUR
1	Green
2	Green and traces of yellow
3	More green than yellow
4	More yellow than green
5	Green tip and yellow
6	All yellow
7	Yellow , flecked with green

Table 1.1 Different stages of banana

1.3 HEALTH ISSUES OF CONSUMING BAD QUALITY FRUITS

Eating tainted, rotten, or poisoned food can cause food borne illness, also known as food poisoning. Nausea, vomiting, and diarrhea are the most typical signs of food poisoning. If your immune system is weak, you may be more susceptible to food poisoning or experience a more severe reaction. Both short-term and long-term factors can affect your immunity, including:

Age: The immune systems of children under five are still developing. After 65, mature immune systems start to deteriorate.

Pregnancy: Your ability to fend against illnesses is diminished during pregnancy.

Chronic illnesses: Many chronic conditions can affect your immunity, including infections, cancer, immunodeficiency diseases and autoimmune diseases. □

Medications: Corticosteroids and immunosuppressants can repress your immune system and make you more prone to illness.

2. RELATED WORKS

This study [1], By examining physicochemical characteristics such soluble solids, pH, firmness, moisture, and color, thermal imaging was utilized to assess durian ripeness (unripe, ripe, and overripe). Strong prediction accuracy was demonstrated by partial least squares (PLS) regression ($R^2 > 0.94$). The ripeness phases were successfully clustered using principal component analysis (PCA). LDA, kNN, and SVM were among the classification models created; SVM had the best accuracy at 97%. The study shows that a trustworthy non-destructive technique for determining durian ripeness is thermal imaging in conjunction with multivariate analysis.

In this paper [2], Fruits' visual characteristics, such as texture, shape, size, and color, are insufficient to determine their quality and flavor. It is difficult to screen fruit quality at a high level of precision without endangering them. In order to analyze the interior and external characteristics of fruits, this research proposes a non-destructive method based on thermal imaging. The ripening conditions can be accurately identified by

analyzing the thermal characteristics of the fruit's surface. Fruit sorting involves time-consuming human inspection tasks that can be reduced by creating an automated system.

In system [3], It is suggested to use infrared thermal imaging for apple bruise detection in order to find early bruises that may not be visible to the unaided eye and hence cannot be detected by a light camera. In order to increase the range of temperature difference between bruised and non-bruised sections, heating and cooling treatments were used in the active thermal experiment. The suggested system's application uses deep residual learning, or ResNet, to detect and recognize objects. When combined with the YOLO real-time object detection method, this deep neural network offers a skip connection function. It will develop a quick and precise apple-bruised detection method. Lastly, we use the F-measure and confusion matrix approaches to assess the bruise detection result. These are typical measures of an image processing system's performance.

This system [4], New rapid and safe techniques for fruit evaluation are important in agriculture. Traditional grading methods are widely used but are costly and often inconsistent. Automation improves efficiency, reduces labor cost, and minimizes errors in classification. Fruit grading is mainly based on size, shape, color, and texture. This study proposes an automated system using thermal imaging and advanced image processing techniques. A bruise detection system (BDS) is used to identify defects, reducing manual effort and improving sorting speed and accuracy.

Bruising in fruits occurs due to external forces causing physical and chemical changes. This study proposes a system to detect surface and subsurface defects in apples using thermal and digital images. Image processing techniques like contrast stretching, histogram equalization, and Otsu thresholding are used for bruise detection. The bruise area is calculated based on the largest connected component. Apple boundary extraction is performed using median filtering, Canny edge detection, dilation, and hole filling. The system achieves an overall bruise detection accuracy of 94% [5].

This research [6] Bruising is a common mechanical damage during postharvest handling and a major cause of fruit loss. Traditional detection relies on manual inspection, which is slow and error-prone, especially for early bruises. Recent advances in computer vision have enabled automated and real-time bruise detection. Imaging techniques such as hyperspectral, fluorescence, MRI, X-ray, and thermal imaging are widely explored. These methods can detect bruises and estimate their volume more accurately and non-destructively. Future research focuses on integrating these techniques with advanced algorithms and applying them in commercial automated systems.

In this paper [7], Fruit ripening, which can be done artificially with chemicals or naturally with ethylene gas, improves taste, nutrition, and flavor. Calcium carbide (CaC_2) is hazardous and carcinogenic, whereas ethylene-based techniques are harmless. The goal of this study is to utilize machine learning to identify bananas that have been ripened using calcium carbide. To increase the precision and accuracy of detection, a web application is created. Additionally, it offers notifications based on ripening phases and nutritional data. Better food choices and safer consumption are encouraged by the system.

Adulteration in dairy products is a global concern, and near-infrared (NIR) spectroscopy offers a fast, non-destructive detection method. However, building accurate models remains challenging due to issues like overfitting. This study uses an ensemble CNN approach to improve detection of adulterants such as hydrolysed leather protein (HLP) and melamine. An attention-based wavelength selection method enhances model performance and diversity. The proposed method achieves high accuracy with R^2 values of 0.961 and 0.995. Overall, it provides a robust and reliable solution for dairy adulteration detection [8].

3. TECHNOLOGIES USED

In the 1970s, manual techniques of quality control were replaced by computer-based inspection. Manual inspection is expensive and necessitates a large crew under continual supervision. Fatigue and psychological issues are examples of human variables that impair accuracy and cause mistakes. Because various inspectors may classify the same goods differently, inspection results are frequently subjective. It is possible for the same inspector to make different decisions at various periods. Due to these problems, manual inspection is unreliable, slow, and inappropriate for today's needs. Automated systems improve quality assessment efficiency, accuracy, and consistency. In order to assess food quality, digital and thermal imaging methods are employed. Fig 2 shows the image of banana captured using digital camera. Fig 3 shows the image of banana captured using thermal camera.

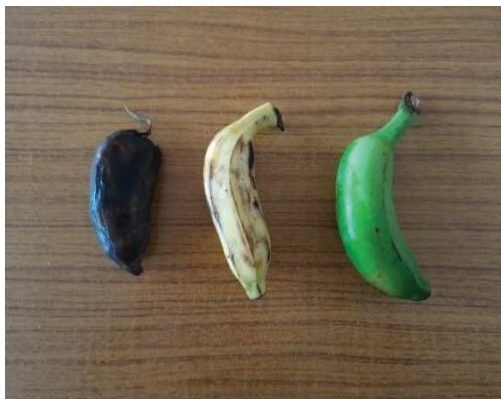


Fig-2 Banana in Digital Camera



Fig-3 Bananas in Thermal Camera (The varying ripeness is depicted in different temperature ranges)

3.1 THERMAL IMAGING

Thermal imaging is a technique that uses thermal energy and infrared radiation to collect data about things and create photographs of them, even in low-light conditions. Over time, this kind of technology has developed a wide range of applications. Because it doesn't rely on visible light, it is an efficient type of night vision technology that can function in complete darkness.

3.2 WORKING OF THERMAL IMAGING

Thermal imaging is a technique that converts infrared radiation (heat) emitted by objects into visible images, representing their temperature distribution. Thermal cameras use sensitive sensors to detect small temperature differences and generate images (thermograms), where variations appear in grayscale or color for better visualization. This method is widely used in applications requiring temperature-based analysis, diagnosis, or evaluation. The captured thermal images reveal heat patterns, which are then processed using feature extraction and analysis for further interpretation.

3.3 CHARACTERISTICS OF THERMAL IMAGES

IR is a form of electromagnetic radiation that has a wavelength-band of 0.78 to 1000 μm (micrometres), which are longer than the wavelength of visible light and shorter than the radio waves. Several characteristics of the infrared radiation are like visible light, such as: the IR radiation can be refracted, focused, reflected, and transmitted. The absorptivity, emissivity, and reflectivity of infrared radiation vary for different objects/ materials. Good absorber objects for the infrared radiation are also good emitters.

Kirchhoff 's law stated the relationship between the absorptivity (η), reflectivity (ζ) and transmissivity (ξ) of an object as follows: $\eta + \zeta + \xi = 1$

At the thermal equilibrium of an object, the absorption is equal to emission. This law can be simplified in several thermographic applications, for opaque objects equation can be expressed as: $\eta + \zeta = 1$ or $\psi + \zeta = 1$ where, ψ = is the emissivity of the object.

In a thermal camera, the infrared sensors receive the total IR radiation emitted from the objects' surface. The total amount of radiation emitted by an object per unit area is directly related to the object's emissivity and its temperature. It is given according to Stefan-Boltzmann law as follows: $E = \sigma \cdot \psi \cdot T^4$

where, E = is the total amount of radiation emitted by an object per square metre, σ = is the Stefan-Boltzmann constant = 5.67×10^{-8} (W m⁻² K⁻⁴)

T= is the temperature of the object in Kelvin (K)

Consequently, the object 's temperature can be calculated if the emissivity of the object and total radiation emitted are known.

In the thermal camera, infrared detectors sense the radiation emitted from the surface of the object in the spectral range of 35 μm (short wave) or 8-12 μm (long wave).

3.4 CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) have gained significant importance in the food industry, which is now among the top sectors adopting this technology. Advances in hardware and software have enabled low-cost and powerful solutions, boosting research in image processing applications. Computer vision involves capturing, processing, and analyzing images for objective and non-destructive evaluation of food quality. It uses sensors and computing systems to perform predefined visual tasks automatically. This technology replicates human vision by electronically interpreting images for decision-making. The CNN model plays a key role in automating such analysis, as shown in the flowchart.

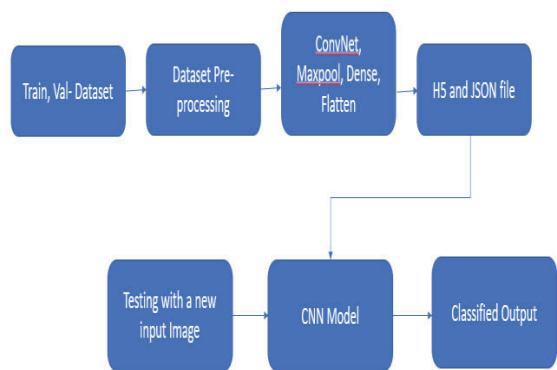


Fig -4 Block Diagram of CNN

CNNs are specialized neural networks created for computer vision tasks. They are made up of convolutional layers, pooling layers, and fully connected layers. In applications like image classification, object identification, and image segmentation, CNNs have proved quite successful. It is a unique kind of deep neural network created primarily for processing and analysing visual data, such as pictures and videos. They are modelled after the human visual system and perform tasks where the spatial relationships between data elements are crucial. The below fig.5 represents the architecture layer of CNN.

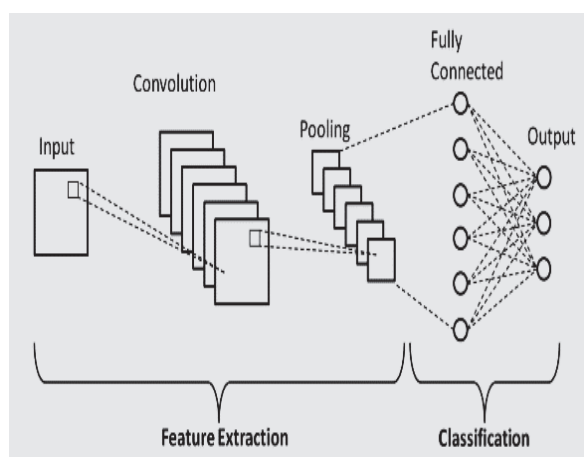


Fig -5 CNN Architecture

Convolutional Layers: Learnable filters (also known as kernels) are used by CNNs to scan the input data using convolutional layers. These filters move through the input, multiplying each element separately, then adding the results to

create feature maps. Local patterns and features found in the input data are captured by convolutional layers. The fig.6 mentioned below indicates that the convolution operation has been implemented on a 5 X 5 input and a 3 X 3 filter.

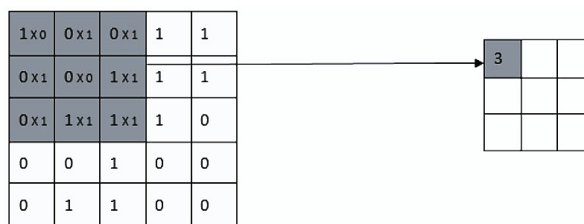


Fig -6 Process of Convolutional layer

Pooling Layers: Pooling layers, such as max-pooling or average-pooling, are used to shrink the feature maps' spatial dimensions while preserving crucial data. By pooling, the network becomes more resistant to changes in the input. The below fig.7 shows how max pooling is performed in CNN technique.

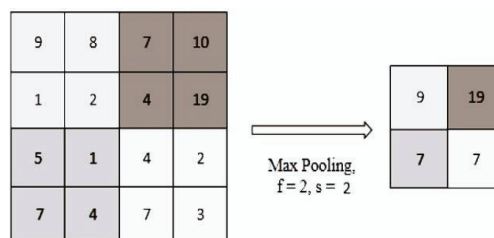


Fig -7 Steps of Max Pooling layer

Activation function: After convolution and pooling layers, non-linear activation functions like ReLU (Rectified Linear Unit) are used for the feature maps. These give the model non-linearity, allowing it to pick up complicated patterns.

Fully Connected Layers (FCLs): Following a number of convolutional and pooling layers, CNNs frequently include one or more FCLs. For final classification or regression, these layers flatten the output of earlier layers and feed it into a conventional feedforward neural network.

Dropout: A regularization method used in CNNs to avoid overfitting is called dropout. During training, it randomly sets a portion of the neurons' outputs to 0, which enhances generalization.

Batch normalization is another method for accelerating training and enhancing the stability of CNNs. Each layer's activations are normalized to have a zero mean and a unit variance.

Strides: To regulate how much the filter moves when scanning the input, convolutional layers might employ strides. Smaller feature maps are produced by a higher stride value.

Padding: Before convolution, padding can be applied to the input to regulate the feature maps' spatial dimensions. "Same" padding keeps the spatial dimensions, while "valid" padding means no padding is added, resulting in smaller feature maps.

Typically, CNNs are built in a hierarchical fashion, with a number of convolutional and pooling layers, to extract progressively complex, and sophisticated characteristics from the input data. Based on the specific work and dataset, the network's architecture may change.

4. PROPOSED SYSTEM

Studies have demonstrated that active thermography (using an energy source) can identify surface flaws in food quality control; these flaws are caused by variations in thermal diffusivity rather than emissivity. There was no need for a light source in this instance. This temperature monitoring equipment's unique feature makes it possible to utilize morphological and statistical analyses (via pattern recognition) to identify food faults resulting from variations in thermal properties.

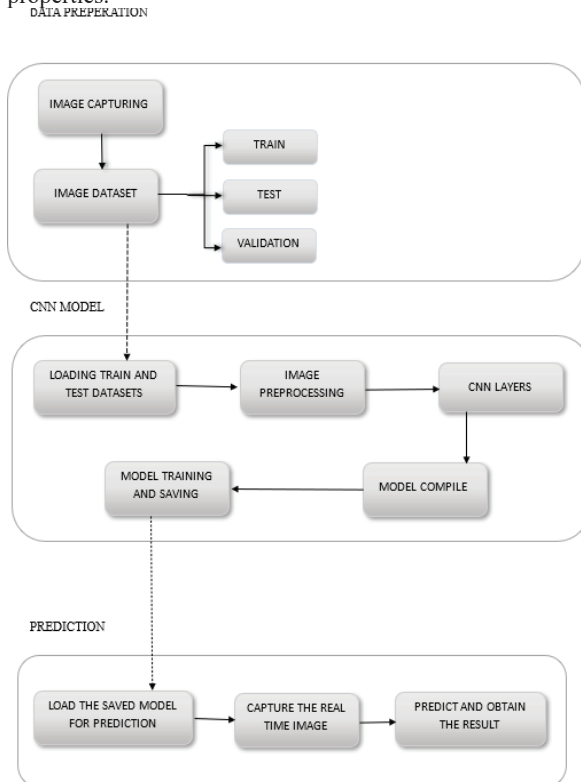


Fig-8 Complete Flow Chart

The working of a CNN can be explained as follows:

- The input image is passed through the input layer, and the convolutional layer applies a set of filters to the image to extract features.
- The ReLU layer applies a non-linear activation function to the output of the convolutional layer, introducing non-linearity into the model.
- The pooling layer downsamples the feature maps to reduce the spatial dimensionality of the output.
- The fully connected layer takes the output of the previous layers and flattens it into a 1D vector.
- The output layer produces the classification output based on the input image.
- During the training phase, the CNN learns the weights of the filters in the convolutional layer and the weights of the neurons in the fully connected layer through backpropagation.

- Backpropagation is an optimization algorithm that adjusts the weights of the model based on the difference between the predicted output and the actual output.
- Once the CNN is trained, it can be used to classify new input images by passing them through the trained model. The output of the model is the predicted class of the input image.
- In summary, a CNN is a deep learning algorithm used for image recognition and classification. It consists of several layers, including convolutional, ReLU, pooling, fully connected, and output layers. The CNN learns the weights of the model through backpropagation during the training phase, and it can be used to classify new input images during the testing phase.

5. RESULTS AND DISCUSSION

The model is tested by using the testcase dataset. The samples and the types of images acquired, and the results given by our CNN model will be discussed in this unit. The inferences are also discussed elaborately in the forthcoming sections.

Image Acquisition

The already categorized and created test_dataset is given as the input to the model and is predicted. The model is then used to predict the images either individually or as a plot of several images within the database.

Let us implement this for a couple cases of singular images and for the whole dataset and check if the results are valid.

```
def mapper(label):
    if label == 0:
        return "Bad Fruit"
    else:
        return "Good Fruit"

image = load_img("C:/Users/viora/OneDrive/Desktop/THERMAL IMAGE/THERMAL IMAGE/BAD FRUIT/IR_00302.jpg", target_size=(640, 480))
image = img_to_array(image)
image = image / 255.0
prediction_image = np.array(image)

prediction_image = np.expand_dims(image, axis=0)
prediction = model.predict(prediction_image)
temp = prediction

if (temp <= 0.4):
    value = 0
else:
    value = 1

move_name = mapper(value)
```

Fig-9 Coding

5.1 Case 1

Consider the following image, "IR_00302.jpg"

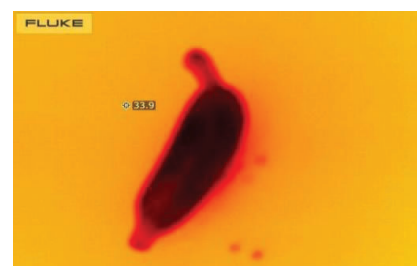


Fig-10 Test image 1

The image is given as input to the CNN model. The output is verified.

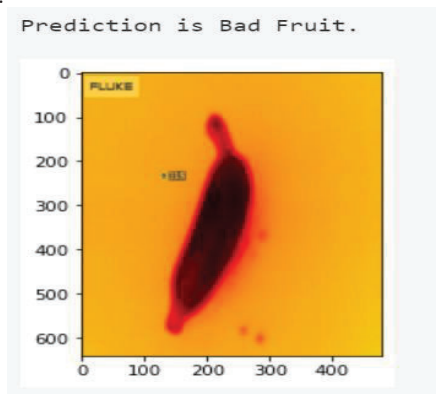


Fig-11 Result of case 1

We can infer from the image that the “Prediction is Bad Fruit” from the output label. Thus, the model has predicted this case accurately.

5.2 Case 2

Consider the following image, IR_00321.jpg

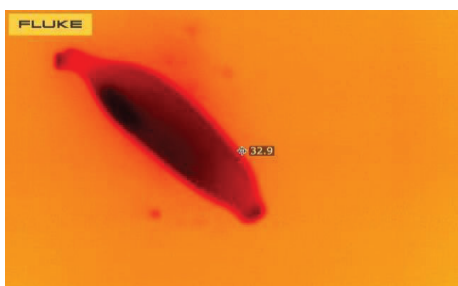


Fig-12 Test image 2

The image is given as input to the CNN model. The output is verified.

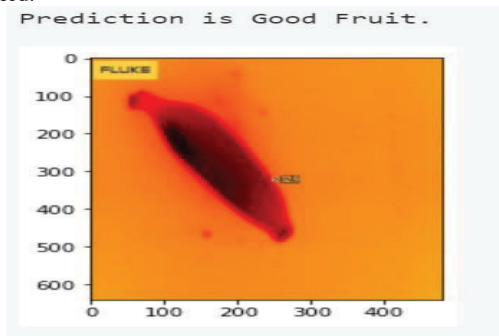


Fig-13 Result of Case 2

We can infer from the image that the “Prediction is Good Fruit” from the output label. Thus, the model has predicted this case accurately.

The model is used to predict the labels in all the images. The results of a few are shown below in figures

5.3 Case 3

Here the whole dataset present in test folder is given as the input. The model is used to predict the labels in all the images. The results of a few are shown below in figures

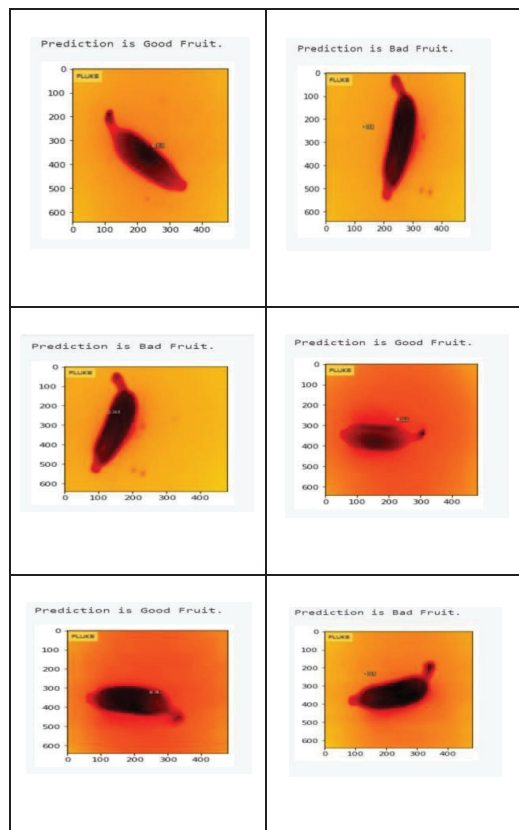


Fig-14 Predicted results for case 3

The outputs obtained from the various cases and test data and their interpretations are displayed successfully. The output of the proposed model is shown in figure 15.

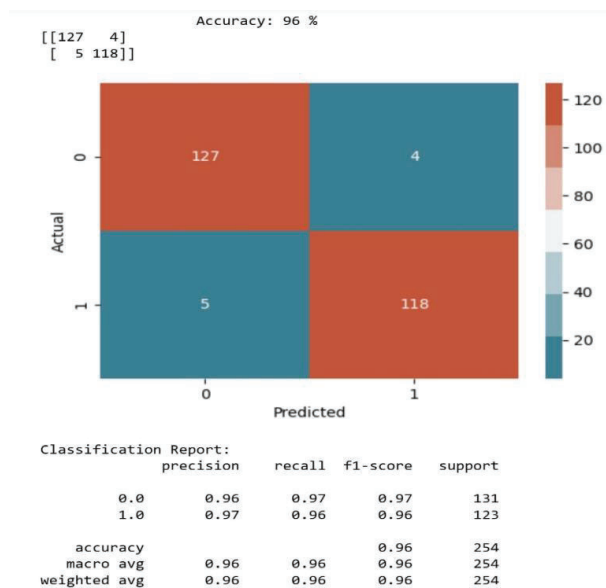


Fig-15 Output of the proposed model

5.4 Comparison with the existing model.

The training time for proposed model is 8 minutes for 15 Epoch whereas for GoogleNet Model it is 4 hours for 50 Epoch. Their accuracy is 96% and 73% respectively.

	Proposed Model	GoogleNet Model
No of Epoch for training	15	50
Training time	8 minutes	4 hours
Accuracy	96%	73%

Table 5.1 shows the comparison between GoogleNet Model and Proposed Model.

CONCLUSION AND FUTURE WORK

The results of the system can be verified through manual inspection of the base data. However, factors such as shadows, shaky images, and similar temperature colors may sometimes lead to incorrect results. Convolutional Neural Networks (CNNs) are highly effective for detecting food quality, especially in fruits. The developed application can be extended to other food products like vegetables, oils, and pulses. This could reduce or even eliminate the need for traditional laboratory setups. The system is low-cost and can run on a personal computer, making it accessible to shopkeepers and consumers. It allows users to easily assess food quality without specialized expertise. The method supports images of varying resolutions, from 640×480 to high-quality images. A single thermal camera is sufficient for multiple models, reducing the need for expensive equipment. This significantly lowers the overall system cost. The approach is practical and scalable for real-world use. The accuracy of the system ranges from 75% to 96%, which is good for a non-contact method. Compared to existing techniques, it offers reliable performance with minimal loss. Further improvements can be achieved by implementing advanced algorithms to enhance CNN efficiency.

In future, the created image processing tool is used to identify the quality of fruits and similar crops. Nonetheless, separate algorithms for identifying adulteration in other food items can also be created and included into the same framework. For instance, thermal imaging and object identification can be used to identify adulterants in peppers, such as when papaya seeds are mixed with good black pepper seeds. This technique can also be used to detect wax covering in apples, look for bruising in other fruits, etc.

Black pepper adulteration (the lighter spots show papaya seeds, and the darker dots show black pepper) Python and TensorFlow libraries are used in the framework's implementation. However, the functionalities of these libraries are occasionally constrained. In this instance, there are several CNN architectures that have been crucial in developing the algorithms that power and will soon power AI. These consist of

- LeNet
- GoogLeNet
- ZFNet
- AlexNet
- ResNet

➤ VGGNet

Other options include MATLAB, Microsoft Visual Studio, and open-source image processing programs like OpenCV that are totally free to use online. If the application is to be made public, this will expand its target user base. Additionally, it provides greater flexibility and room for code optimization. More sophisticated models, including expert systems or machine learning concepts, are not utilized by the algorithms used in this research. For classification, they employ a linear scheme. Non-linear tools can be used in future development.

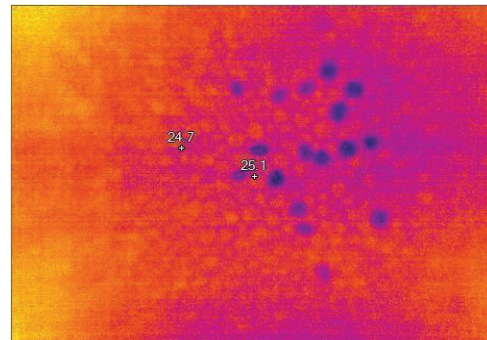


Fig-16 Adulteration in Black Pepper (the darker dots represent Black Pepper and lighter dots represent papaya seeds)

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