Automatic Object Detection using Thermal imaging

A BTP Report

by

E Jaswanth Krishna

S20200020257

A .Gopal Reddy

S20200020248

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY SRICITY

DATE : 30/11/2023
Final Report

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY SRICITY

CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the BTP entitled "Automatic Object detection using Thermal imaging" in the partial fulfillment of the requirements for the award of the degree of B.Tech and submitted in the Indian Institute of Information Technology SriCity, is an authentic record of my own work carried out during the time period from Jan 2023 to Dec 2023 under the supervision of Prof. Dr Raja Vara Prasad Y, Indian Institute of Information Technology SriCity, India.

The matter presented in this report has not been submitted by me for the award of any other degree of this or any other institute.

Jaswanth Krishna
3/12/23

Signature of the student with date

(E Jaswanth Krishna)

A. Gopal Reddy
3/12/23

Signature of the student with date

(A . Gopal Reddy)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

7th Dec 2023

Signature of BTP Supervisor with date

(Dr Raja Vara Prasad Y)

Contents

ABSTRACT	**3**
INTRODUCTION	**4**
RELATED WORK	**4**
PROBLEM STATEMENT	**11**
PROPOSED METHODOLOGY	**12**
EXPERIMENTAL RESULTS	**16**
JUSTIFICATION & CHALLENGES	**22**
CONCLUSION & FUTURE WORK	**22**

ABSTRACT

In today's agricultural landscape, tackling fruit quality and disease identification stands as a big challenge. Despite being underutilized, thermal imaging is a potent solution, offering better distinction in resolving these concerns. Guava serves as a representative for diverse crops. utilizing thermal image data to distinguish heat signature for ripe and unripe classification . When addressing fruit disease identification problems , RGB images excel in capturing intricate color features for precise classification.These are less addressed in the agriculture sector . An innovative approach involves merging RGB and thermal data simultaneously, potentially offering a comprehensive solution that remains effective across diverse weather conditions.

INTRODUCTION

The use of thermal datasets is crucial for fruit ripeness classification due to their ability to capture heat signatures emitted by different fruits. Unlike RGB images, thermal images can differentiate between fruits based on their heat signatures, which are directly related to their ripeness. This makes thermal datasets essential for accurately classifying fruit ripeness, especially when fruits have similar visible appearances or colors, making them difficult to distinguish from one another using traditional RGB images. By incorporating thermal datasets into the training and testing of object detection models, such as those used for fruit ripeness classification, the accuracy of the classification process can be significantly improved.

The utilization of thermal datasets for fruit ripeness classification can lead to more efficient training processes. Thermal images require less training time compared to RGB images, as they capture the heat signatures of fruits directly, eliminating the need for complex color-based distinctions. This efficiency not only saves time but also enhances the overall accuracy of the classification model. Therefore, the thermal datasets in fruit ripeness classification are not only necessary for accurate differentiation between fruits but also for optimizing the training process and improving the overall efficiency of the classification model.

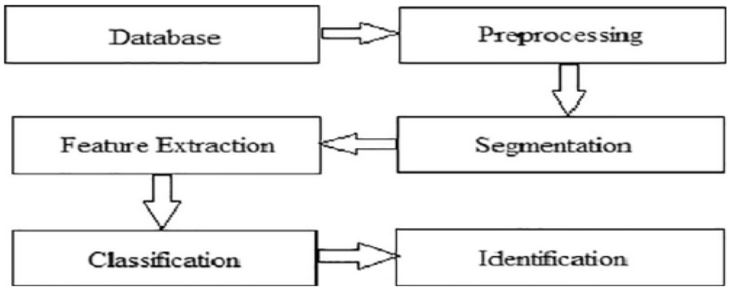
YOLO (You Only Look Once) is a popular real-time object detection system known for its speed and accuracy. It can be utilized for fruit ripeness classification by training it on thermal datasets. Machine learning (ML) models, on the other hand, offer a wide range of algorithms and techniques that can be applied to fruit ripeness classification. These models can be trained on thermal datasets to classify fruit ripeness.Transfer learning is another technique used for fruit ripeness classification. With pre-trained models and adapting them to thermal datasets, transfer learning allows for accurate results.

RGB image datasets were used in both fruits and leaves. For disease detection, fruit diseases, Phytophthora, Scab, Styler, and Root Diseases . To address leaf diseases, Canker, Dot, Mummification, and Rust. By classifying all these diseases we will be able to help the agriculture sector be more effective at cultivation. Technology we create should have a positive ripple effect for a better good.

RELATED WORK

1. Fruits and vegetables quality evaluation using computer vision

Automation Enhances Agricultural Quality and Productivity: Automation in agriculture contributes to increased quality, economic growth, and productivity. The use of astute fruit grading systems employing computer vision algorithms is crucial for consistent and objective sorting and grading of fruits and vegetables. Unlike manual methods, automated systems are not influenced by human subjectivity, making them more reliable, less time-consuming, and cost-effective. This automation is essential for maintaining and improving the quality of agricultural produce, positively impacting the export market and consumer preferences.



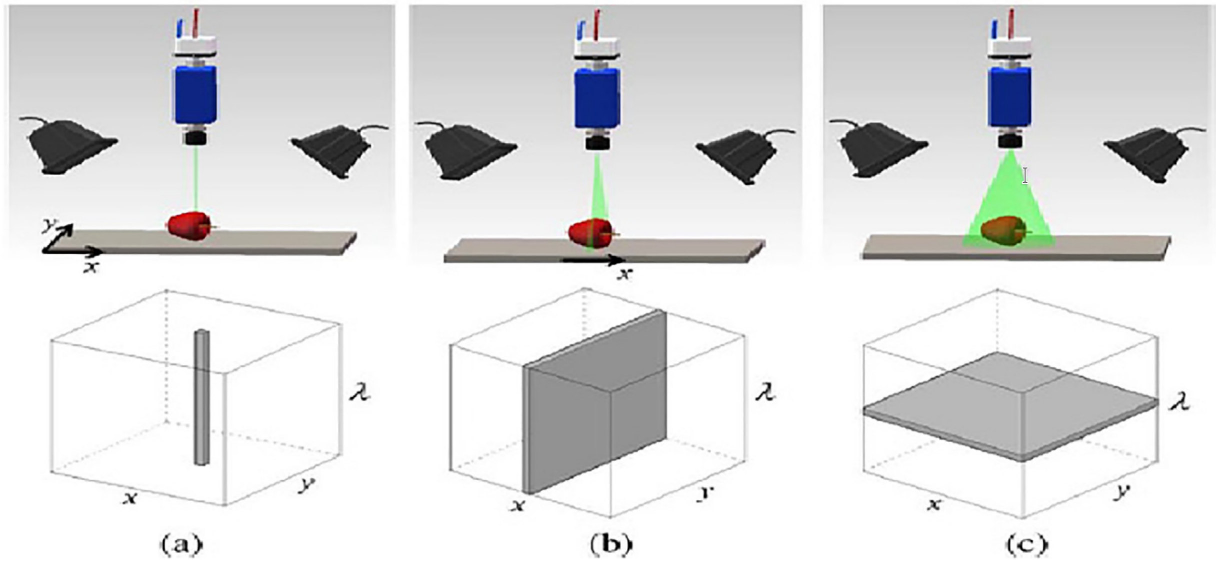


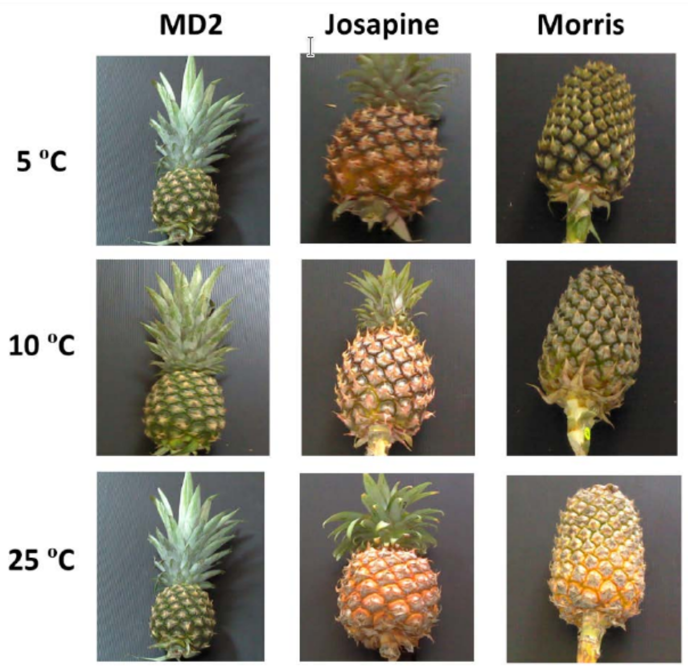
Image processing techniques enable the extraction of relevant features, forming a knowledge base for decision-making in classification algorithms. Various methods, including KNN, SVM, and Deep Learning/CNN, have been developed for this purpose. These algorithms simulate human thinking, allowing for sophisticated and instantaneous judgments. The use of computer vision technology in quality inspection replaces manual methods, providing authentic, equitable, and non-destructive evaluations.

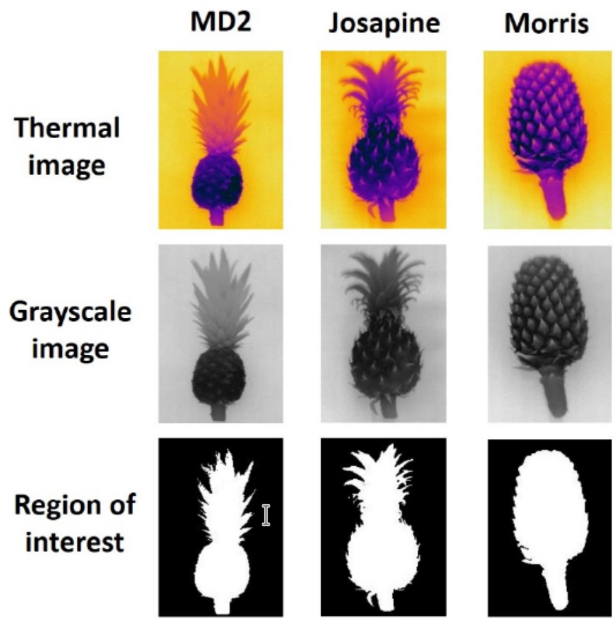
Challenges and Need for Continued Research: Despite advancements in computer vision-based quality inspection, challenges persist, necessitating further research and development. The paper highlights the ongoing need for a robust computer vision system with improved performance in handling the essential quality characteristics of agricultural products, such as size, color, shape, texture, and defects.

2. Characterisation of Pineapple Cultivars under Different Storage Conditions Using Infrared Thermal Imaging Coupled with Machine Learning Algorithms

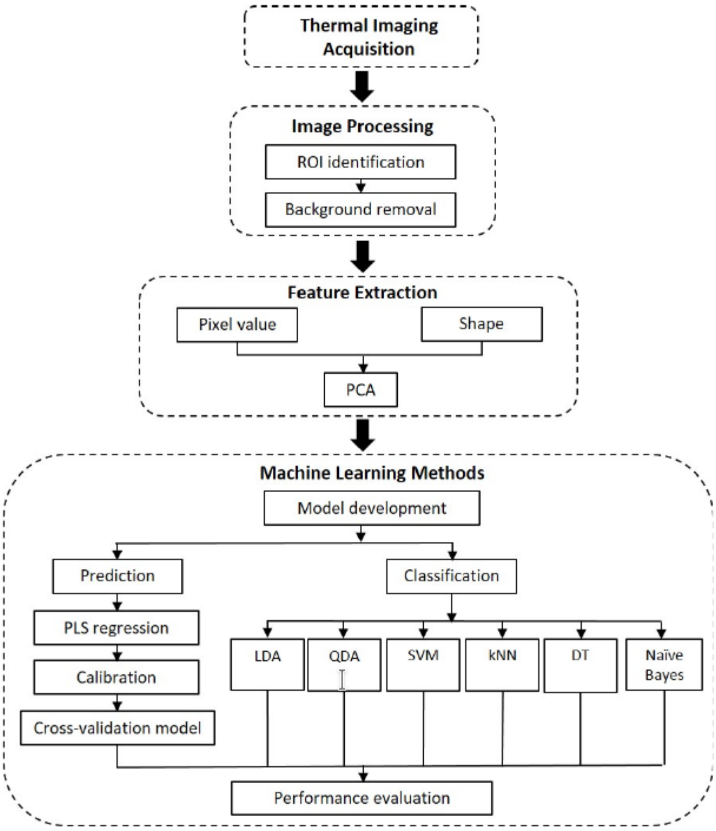
Infrared Thermal Imaging for Pineapple Cultivar Classification: The study utilizes the non-invasive capabilities of infrared thermal imaging to distinguish between different pineapple cultivars (MD2, Morris, and Josapine) subjected to varying storage temperatures. This non-destructive approach offers insights into the thermal characteristics of pineapples, with 14 features extracted from thermal images to capture variations among cultivars. Principal component analysis is employed for feature reduction to enhance classification accuracy, considering the impact of significant differences between selected features.

Image Processing and Segmentation for Cultivar Classification:The research incorporates image processing and segmentation techniques to facilitate the classification of pineapple cultivars based on selected thermal image features. The processing steps involve shadow removal, background noise elimination, and the isolation of the region of interest (ROI) from the image background. The grayscale conversion of thermal images, coupled with Otsu thresholding, enables effective segmentation, maximizing the distinction between the background and the selected ROI. These preprocessing steps contribute to refining the input data for subsequent machine learning-based cultivar classification.





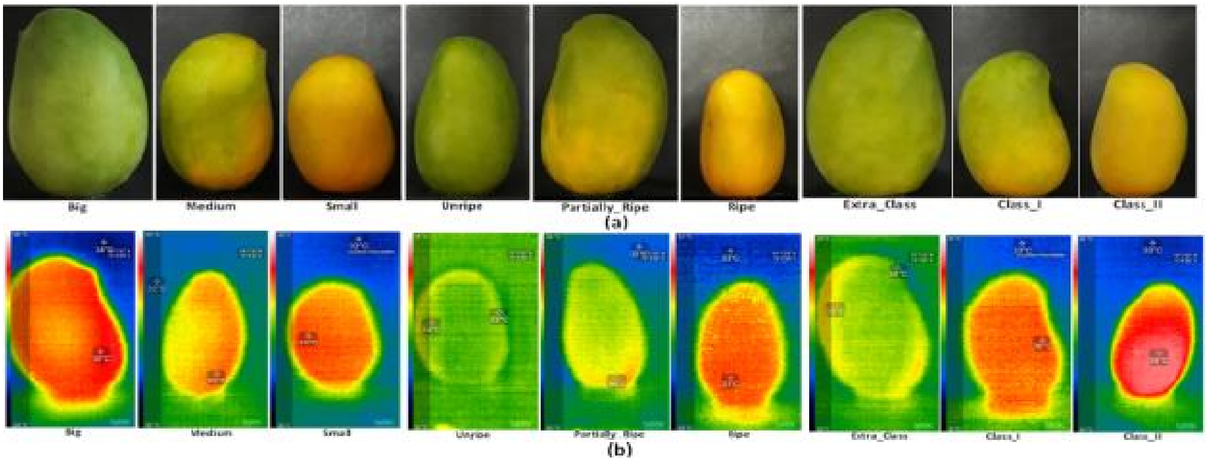
Significant Differences in Image Parameters for Pineapple Cultivars: The investigation reveals notable variations in image parameters among different pineapple cultivars, with statistical significance established at a 95% confidence level. The pixel-count-based analysis indicates distinct characteristics for each cultivar, such as the highest eccentricity and perimeter in the MD2 cultivar and unique values for parameters like area, orientation, and extent in the Josapine cultivar. These findings underscore the potential of thermal image analysis and machine learning algorithms for precise and efficient pineapple cultivar classification, offering valuable insights for quality assessment in the agricultural industry.



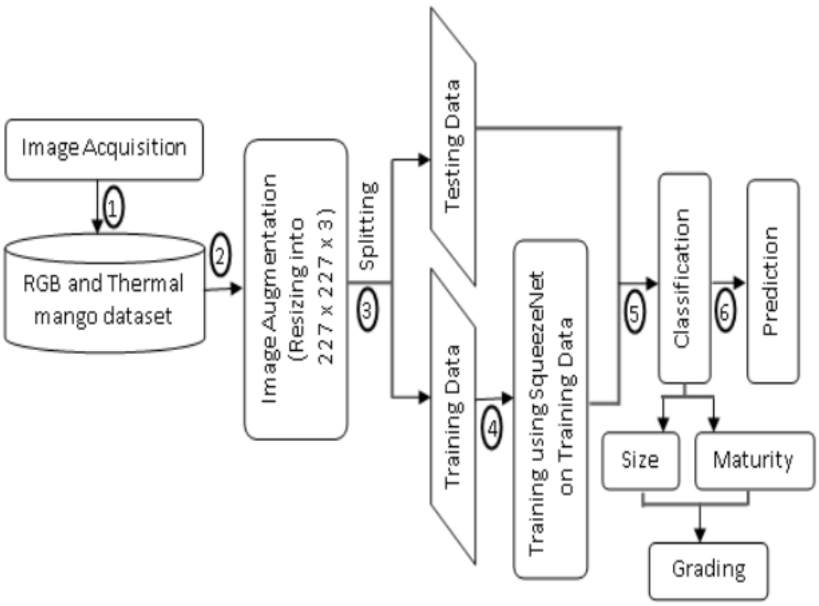
3. Mango Quality Grading using Deep Learning Technique: Perspectives from Agriculture and Food Industry

Importance of Agriculture in India: India, being an agrarian country, relies significantly on agriculture for income, with mango production holding the top global rank among crops. Efficient grading of agricultural products, particularly mangoes, is crucial for the country's commercial development. The implementation of an automatic sorting and grading system without manual intervention is highlighted as a key step in preparing agricultural products for the market.

SqueezeNet Model for Mango Grading:The research introduces a deep learning-centered non-destructive mango sorting and grading system, emphasizing the integration of both hardware and software components. The SqueezeNet model, a Convolutional Neural Network (CNN), is proposed for classifying RGB and thermal images of 'Kesar' mango fruits. The model, with a total of 68 layers and eight fire modules progressively increasing the number of filters, demonstrates its efficacy in predicting size, maturity, and grade of mangoes. The architecture is depicted in Figure 3, illustrating the convolutional layers and fire modules.



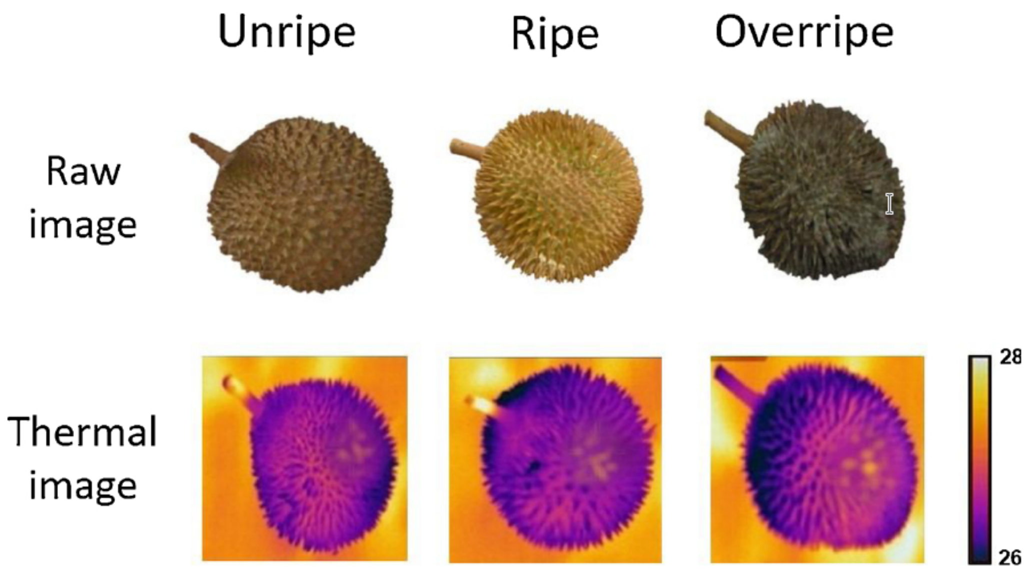
Non-Destructive Techniques for Quality Assessment: The study underscores the impact of factors like bruises, color, and appearance on fruit quality, influencing consumer preferences. To address this, the research focuses on non-destructive techniques, specifically thermal imaging and transfer learning with a pre-trained SqueezeNet model. The proposed automatic mango fruit grading system aims to enhance accuracy in evaluating fruit maturity levels, presenting a modern approach that aligns with current advancements in agricultural technology.



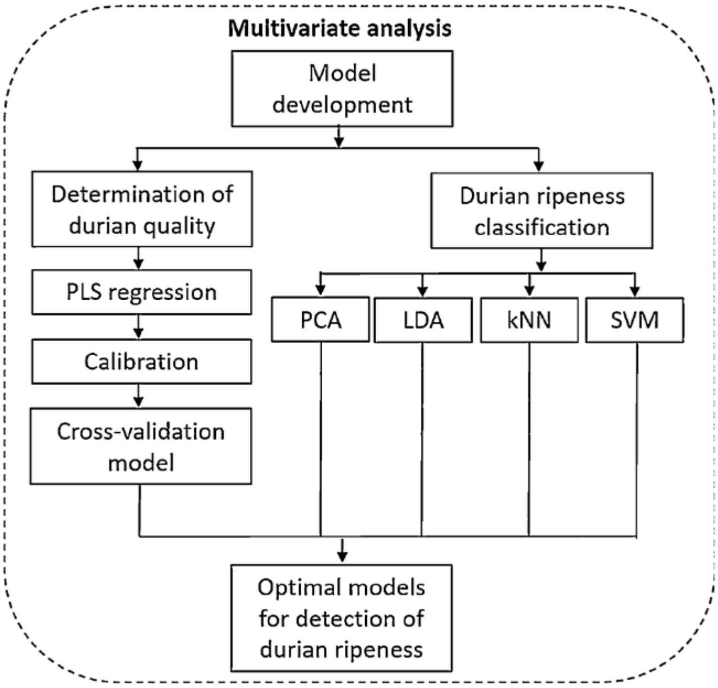
4. ripeness detection using thermal imaging with multivariate analysis

Advancing Durian Ripeness Detection: The study focuses on enhancing the analytical methods for durian ripeness detection, aiming to reduce reliance on routine analysis and human labor skills. Thermal imaging is explored as a tool to evaluate durian ripeness by establishing a relationship between physicochemical properties and thermal image parameters. The research emphasizes the potential of thermal imaging as an innovative approach for non-destructive and efficient durian ripeness assessment, surpassing traditional methods that often involve subjective human judgment.

Technical Details of Thermal Imaging: The study employs an infrared thermal camera with specific technical specifications, including a temperature range from -20 ◦C to +650 ◦C, a resolution of 320 × 240 pixels, and thermal sensitivity less than 0.05 ◦C. The emissivity coefficient of durians is determined for accurate thermal imaging, and calibration checks are performed using known temperature targets or durian samples. The calibration involves the use of a blackbody reference source to ensure accuracy in temperature measurements. These technical details highlight the meticulous approach taken to ensure the reliability and precision of the thermal imaging process.

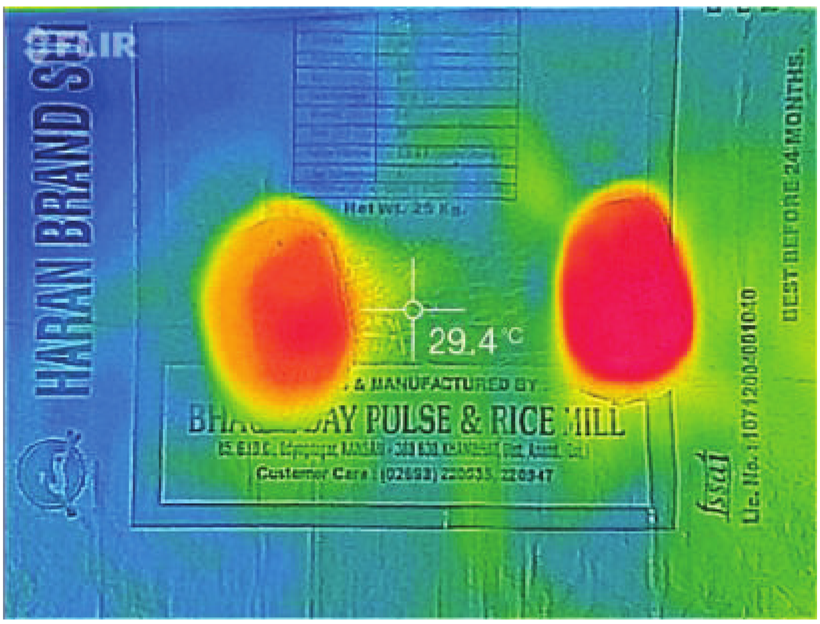


The research concludes by demonstrating the feasibility of thermal imaging for durian ripeness detection across three stages: unripe, ripe, and overripe. Among the various thermal parameters obtained through feature extraction methods, average intensity and min_ROI emerge as optimal parameters for distinguishing durian fruits into ripeness groups.
The study also employs advanced techniques such as Partial Least Squares (PLS) regression, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM) models to achieve accurate and non-supervised ripeness classification. The positive outcomes indicate the potential of thermal imaging as a valuable tool in improving durian quality assessment.

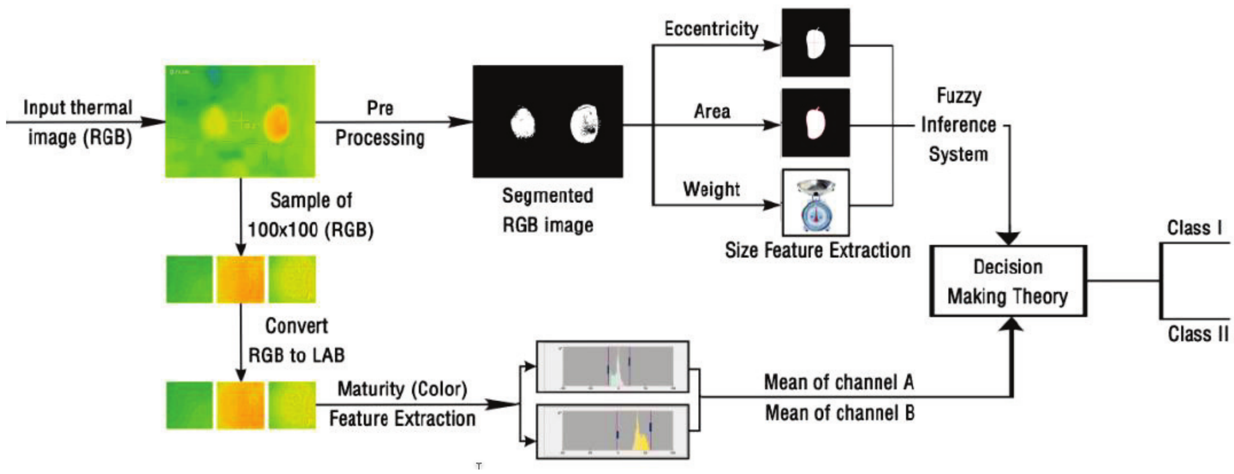


5. Thermal imaging with fuzzy classifier for maturity and size based non-destructive Mango

Advantages of Image Processing in Fruit Grading:The introduction emphasizes the usefulness of image processing in fruit grading, highlighting its potential to reduce manual labor while improving grading quality. By extracting features like shape, color, and size in a non-destructive manner, an automatic grading system can be established with predefined criteria, ensuring faster and more efficient fruit grading. This becomes particularly crucial for meeting the increasing demand for high-quality products within tight timeframes, addressing the need for automation in the agricultural sector.



Advantages of Image Processing in Fruit Grading:The introduction emphasizes the usefulness of image processing in fruit grading, highlighting its potential to reduce manual labor while improving grading quality. By extracting features like shape, color, and size in a non-destructive manner, an automatic grading system can be established with predefined criteria, ensuring faster and more efficient fruit grading. This becomes particularly crucial for meeting the increasing demand for high-quality products within tight timeframes, addressing the need for automation in the agricultural sector.



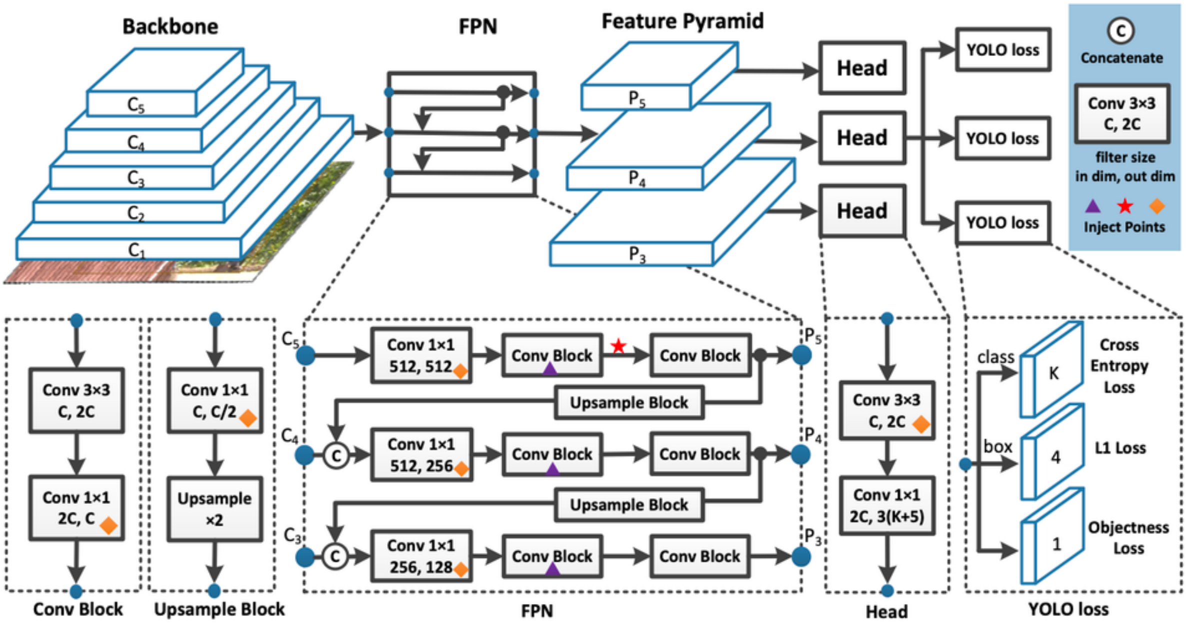
Challenges in Mango Grading and Role of Thermal Imaging: The work section focuses on the challenges posed by mangoes, where skin color remains consistent across different maturity levels, making traditional reflective imaging ineffective. To address this, the study employs a thermal camera, specifically the FLIR ONE, to capture heat signatures and represent them as images. Thermal imaging proves instrumental in predicting the maturity and size of mangoes, offering a novel solution to the limitations of traditional imaging methods, particularly for fruits like mangoes where visual cues are insufficient.

PROBLEM STATEMENT

Design and implementation of fruit quality assessment system using thermal images for ripeness classification and RGB images for disease identification, enhancing agricultural productivity and disease management.

PROPOSED METHODOLOGY

YOLO Architecture:



You Only Look Once (YOLO) version 8, often abbreviated as YOLOv8, is a state-of-the-art object detection architecture designed for computer vision tasks. Object detection involves identifying and locating objects within an image. YOLOv8 improves upon its predecessors by introducing a more streamlined and efficient architecture. In essence, YOLOv8 divides an image into a grid and predicts bounding boxes and class probabilities for each grid cell simultaneously. This allows the model to consider the entire image in one forward pass, making it faster compared to other object detection methods.

The YOLOv8 architecture comprises multiple convolutional layers, forming a deep neural network. These layers are responsible for extracting hierarchical features from the input image. YOLOv8 also incorporates skip connections, enabling the model to combine low-level and high-level features, capturing both fine-grained and contextual information. Another key aspect is the use of anchor boxes, which are predefined bounding box sizes that assist the model in predicting accurate object locations and sizes. YOLOv8 strikes a balance between speed and accuracy, making it suitable for real-time applications such as video surveillance, autonomous vehicles, and various other computer vision tasks.

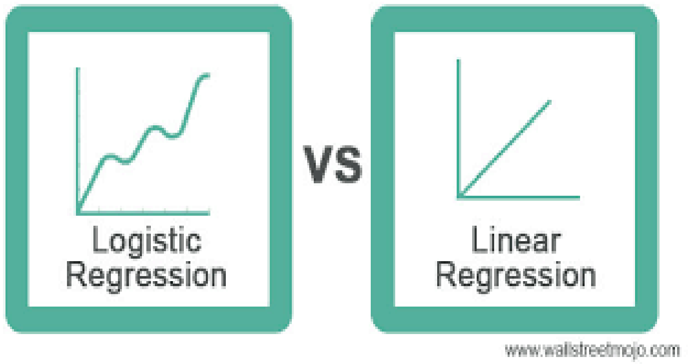
Machine learning :

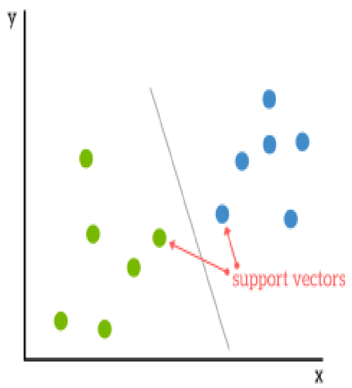
ML algorithms, particularly in the context of deep learning, are adept at automatically extracting hierarchical features from images. Convolutional Neural Networks (CNNs), a popular class of deep learning models for image classification, learn to identify edges, textures, and complex structures as they process layers of the image. These learned features contribute to the model's ability to distinguish between different objects or classes.

During the training phase, the ML model is exposed to a labeled dataset containing examples of various classes. The model adjusts its internal parameters through a process known as backpropagation, minimizing the difference between its predicted outputs and the true labels of the training data. This training allows the model to generalize and recognize patterns that can be applied to unseen images.

Logistic Regression

Logistic Regression is computationally efficient, making it suitable for large datasets and real-time applications.Training a Logistic Regression model is relatively fast compared to more complex algorithms like deep neural networks.Logistic Regression can handle both small and large datasets without a significant increase in computational cost.

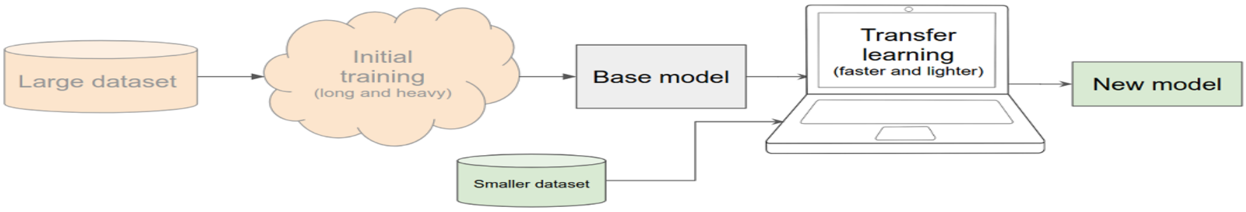




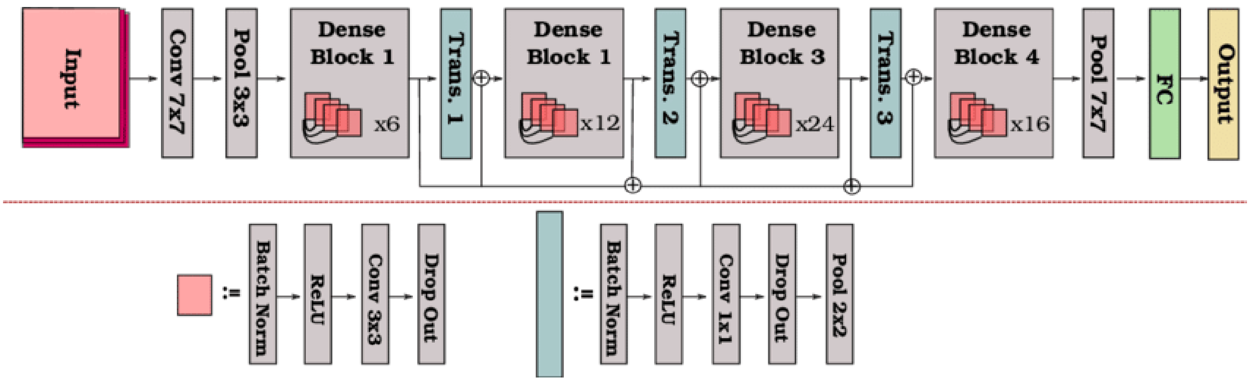
Support Vector Machine

SVMs perform well in high-dimensional feature spaces, making them suitable for problems with many features or complex data.SVMs aim to find the optimal decision boundary that maximizes the margin between classes, leading to good generalization to unseen data.SVMs aim to find the global optimum, ensuring that the chosen decision boundary is the best possible one for the given data and kernel function.

Transfer Learning :



Transfer learning is a machine learning technique where a model trained on one task is adapted for a second related task. In the context of neural networks, it involves taking a pre-trained model, typically on a large dataset for a specific task, and fine-tuning it for another task with a smaller dataset. Transfer learning leverages the knowledge gained from the initial task to expedite learning on the new task. This is particularly useful when labeled data for the target task is limited, as the pre-trained model has already learned general features that can be valuable across tasks. The process involves freezing some layers of the pre-trained model (usually the early layers capturing general features) and training the remaining layers on the new data.



DenseNet Architecture:

DenseNet, short for Densely Connected Convolutional Network, is a neural network architecture known for its dense connectivity pattern. In a DenseNet, each layer receives input not only from the preceding layer but also from all the preceding layers in the network. This densely connected structure encourages feature reuse, strengthens feature propagation, and reduces the risk of vanishing gradient problems. The architecture consists of dense blocks, transition layers, and a global average pooling layer. Dense blocks comprise multiple densely connected layers, and transition layers control the spatial dimensions of the feature maps.

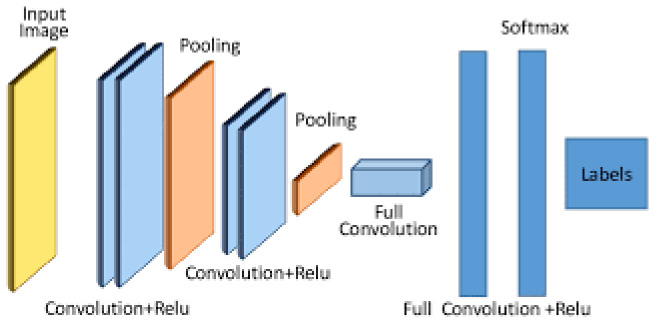
Dense Block:Dense blocks consist of multiple convolutional layers with direct connections between all layers. Each layer takes as input the concatenation of feature maps from all preceding layers within the same dense block. This promotes feature reuse and enhances the flow of information through the network.

Transition Layer:Transition layers connect two adjacent dense blocks. They consist of a batch normalization layer, a 1x1 convolutional layer to reduce the number of channels, and a downsampling operation (typically average pooling) to reduce the spatial dimensions of the feature maps.

Global Average Pooling Layer: Instead of traditional fully connected layers, DenseNet uses a global average pooling layer at the end. This layer computes the average of each feature map, resulting in a single value per channel. This approach reduces the number of parameters in the model and provides a fixed-size output regardless of the input size.

CNN Architecture

Convolutional Neural Networks (CNNs) typically consist of several layers, each serving a specific purpose in the feature extraction and classification process. Here's a simplified explanation of the common layers found in a CNN architecture:



Input Layer: The input layer represents the image or data being fed into the network. For an image, each pixel value serves as an input node. The dimensions of the input layer depend on the size of the input data, such as the height, width, and number of color channels

Convolutional Layer: Convolutional layers are the core building blocks of CNNs. These layers use filters or kernels to slide across the input data, performing element-wise multiplications and summations to extract local patterns or features. The result is a set of feature maps that highlight different aspects of the input, capturing spatial hierarchies.

Activation Layer (ReLU):After convolution, an activation function is typically applied, often Rectified Linear Unit (ReLU). ReLU introduces non-linearity to the model by converting any negative values in the feature maps to zero, allowing the network to learn complex relationships in the data.

Pooling Layer:Pooling layers downsample the spatial dimensions of the feature maps, reducing the computational load and focusing on the most essential information. Max pooling, for example, selects the maximum value from a group of neighboring values in each region, effectively reducing the size of the feature maps.

Fully Connected Layer (Dense Layer):Fully connected layers connect every neuron in one layer to every neuron in the next layer. These layers often follow the convolutional and pooling layers and serve as classifiers. Neurons in this layer analyze the extracted features to make predictions or classifications.

Flatten Layer:Before entering the fully connected layer, the feature maps are flattened into a one-dimensional vector. This step ensures that the output of the convolutional and pooling layers can be fed into the densely connected layers for classification.

EXPERIMENTAL RESULTS

Guava Thermal dataset

Data Augmentation :

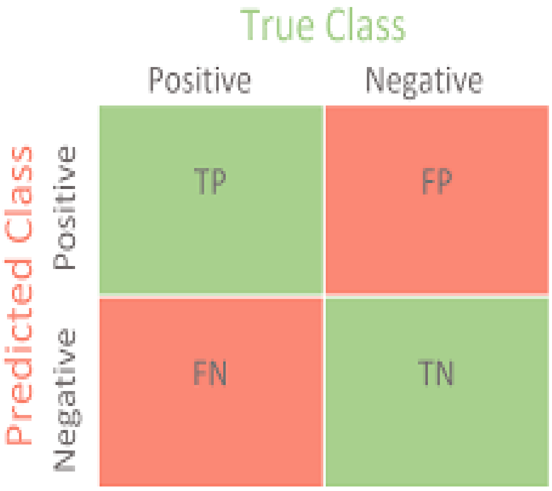
<u>Resize</u>: Stretch to 640x640

<u>Flip</u>: Horizontal, Vertical

<u>90° Rotate</u>: Clockwise, Counter-Clockwise, Upside Down

Dataset	**Images**	**Percentage**
Test	430	87%
Validation	41	8%
Test	26	5%

Accuracy metrics :



F1 SCORE= 2 * (precision * recall) / (precision + recall)

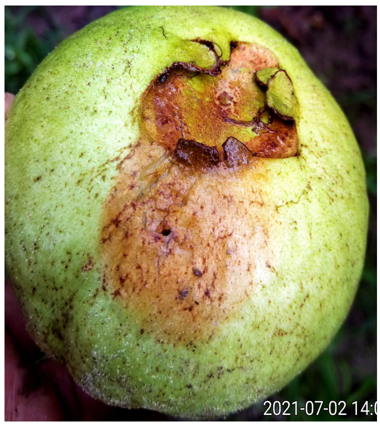
PRECISION= true positives /(true positives + false positives)

RECALL = true positives / (true positives + false negatives)

Guava RGB Fruit disease Dataset

Phytophthora

Scab



Styler and Root

Guava RGB Leaf disease Dataset:

It has 4 types of Diseases and a folder of Normal leaves. I augmented the dataset with factor 6 so there are basically 2300 images.

Canker

Dot

Mummification

Rust

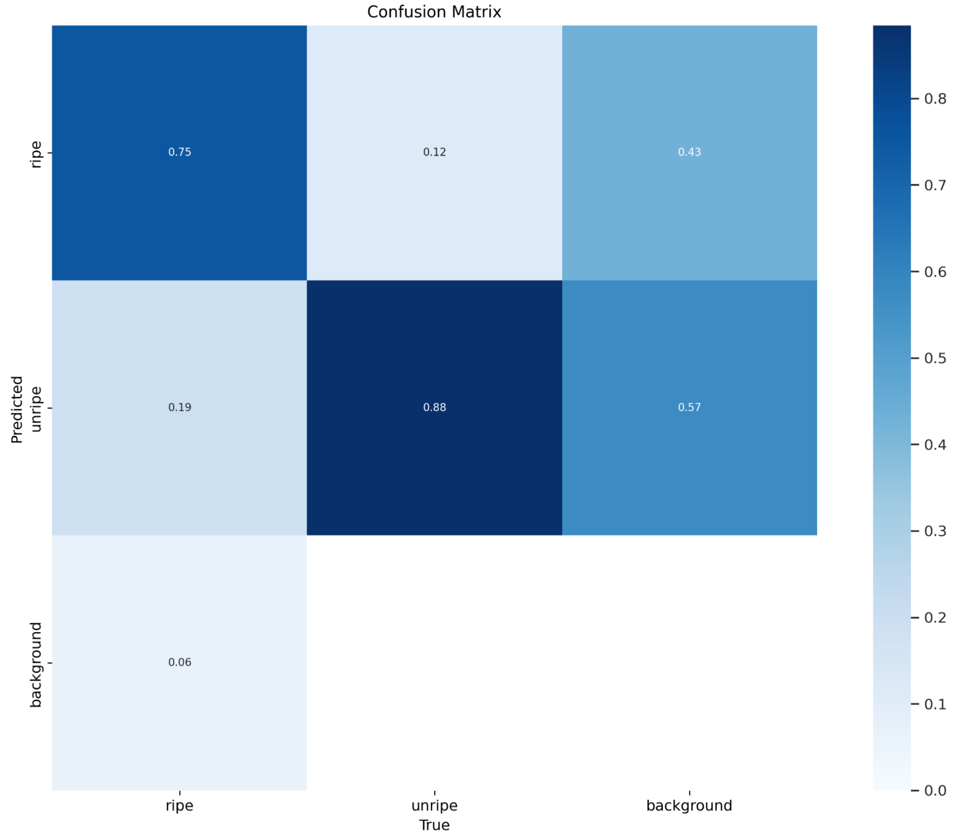
Canker: Canker is a plant disease that causes localized lesions to form on stems or branches. These lesions frequently result in dieback and have an impact on the plant's general health.

Leaf Spot (dot):Dots, also known as leaf spots, are tiny, circular lesions that affect photosynthesis and may result in defoliation, which would be detrimental to the health of the plant.

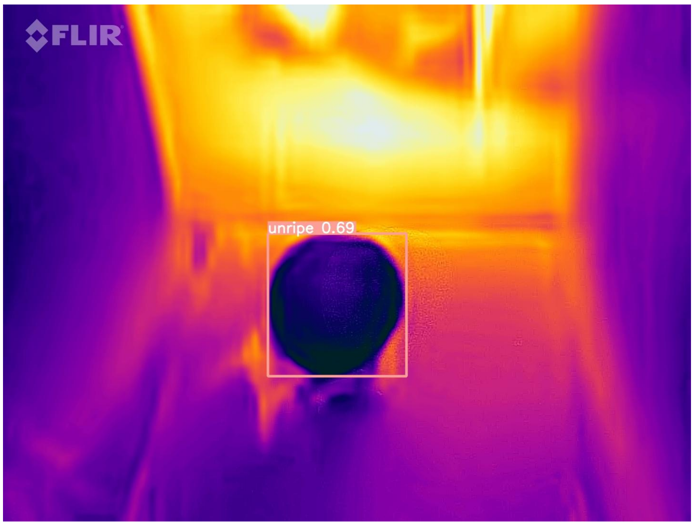
Mummification:The process through which diseased plant tissues shrink and dry out to resemble mummies is known as mummification. Several pathogens can cause this disease, which results in the loss of the afflicted plant parts.

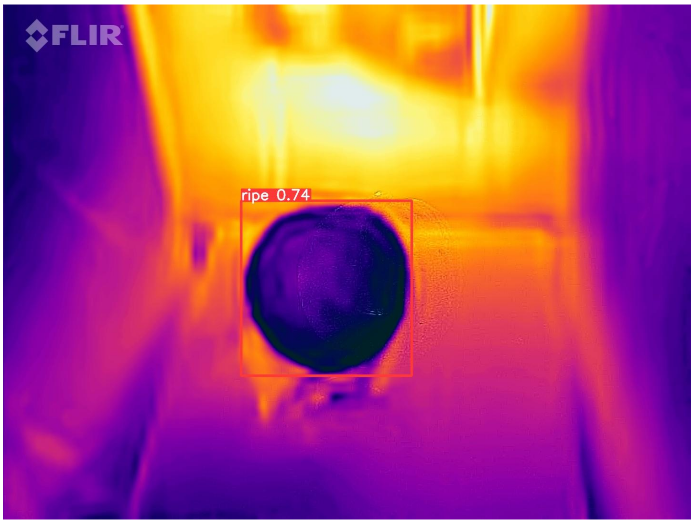
Rust:Rust is a fungal disease that causes orange or reddish-brown powdery spore masses on plant surfaces. This disease reduces the plant's capacity to absorb nutrients and grow.

YOLO V8 object detection results:



Working of Yolo model : it classifies thermal images into ripe or unripe .





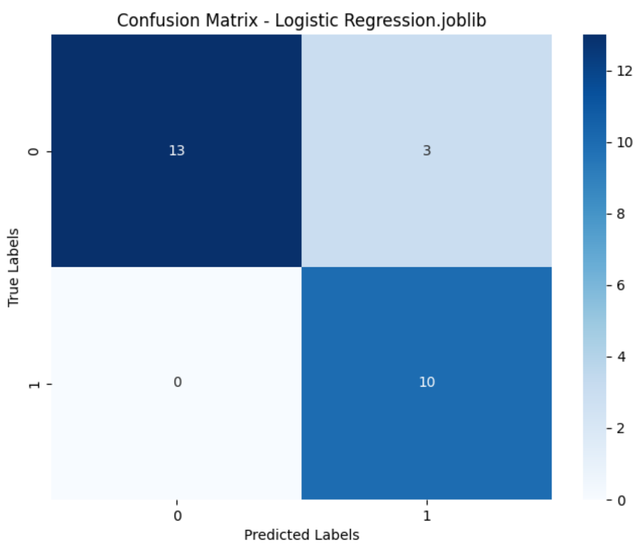
Machine learning algorithms for image classification:

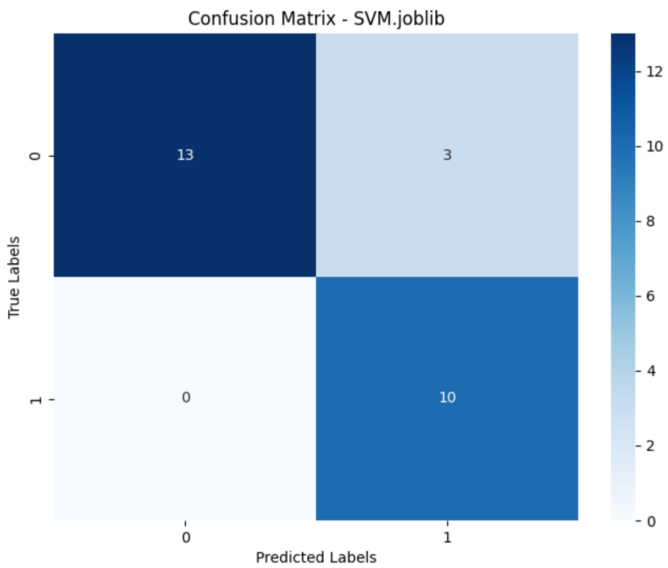
Models	Accuracy(%)	Precision(%)
Logistic Regression	88.4615	91.1243
SVM	88.4615	91.1243
Random Forest	84.6154	85.9890
KNN	80.7692	87.1795
Gradient Boosting	80.7692	81.3054
Naive Bayes	61.5385	63.1868

Despite its ease of use, logistic regression works well for tasks involving binary classification. It works well in image classification when the decision boundary is relatively simple because it effectively captures linear relationships between features and class labels. Because of its simplicity, it can be trained and predicted more quickly, which makes it a practical option in situations where interpretability and computational efficiency are essential.

SVM, which is renowned for its resilience and adaptability, performed exceptionally well in image classification by determining the best hyperplanes to divide various classes. Complex image datasets benefit greatly from its ability to handle high-dimensional feature spaces and nonlinear relationships. The generalization abilities of SVM are enhanced by its margin maximization strategy, which permits precise predictions even in situations with complex decision boundaries.

Confusion matrix of Logistic Regression and State vector machine

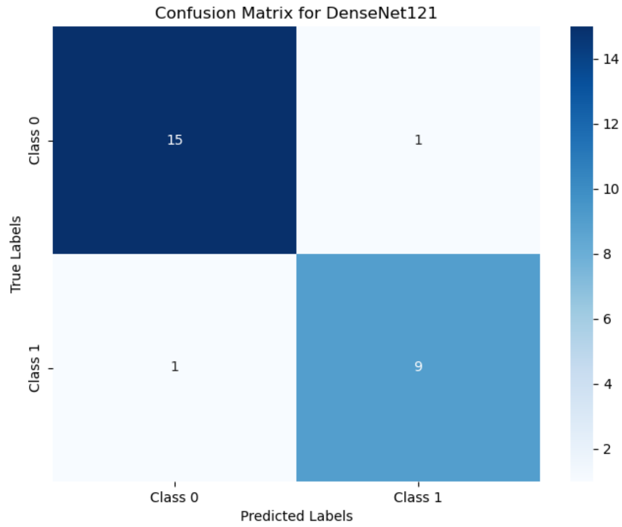




Transfer Learning (Ripeness Classification)results:

Dense net 121 gave the best result with 92% accuracy

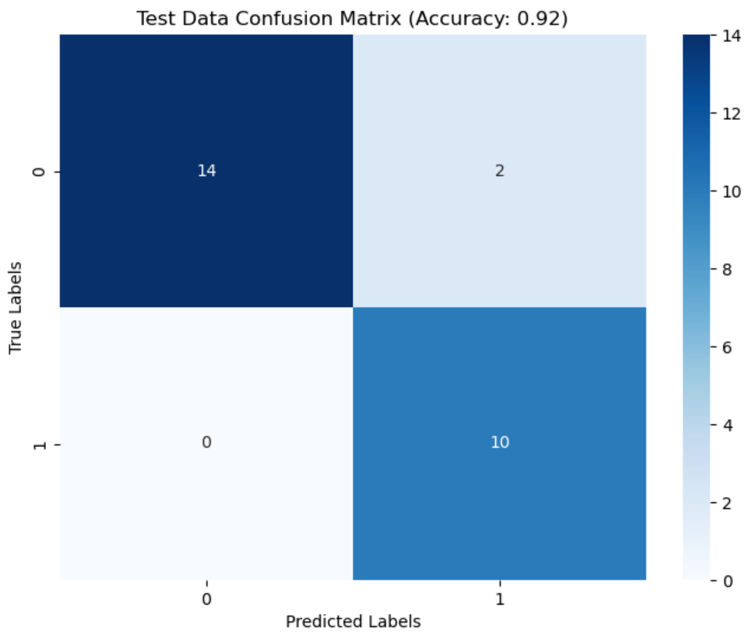
Model	Accuracy(%)
DenseNet121	92.3077
InceptionV3	88.4615
MobileNet	88.4615
ResNet50V2	61.5385
VGG16	38.4615



DenseNet121 is the most accurate ripeness classification model among those examined, demonstrating its ability to manage the intricacies of the ripeness classification task. A convolutional neural network architecture called DenseNet121 is distinguished by its densely connected blocks, which encourage feature reuse and ease information transfer across the network. DenseNet121's architecture makes it possible for it to identify complex patterns and dependencies in the image data, which enhances its ability to distinguish minute variations related to fruit ripeness.

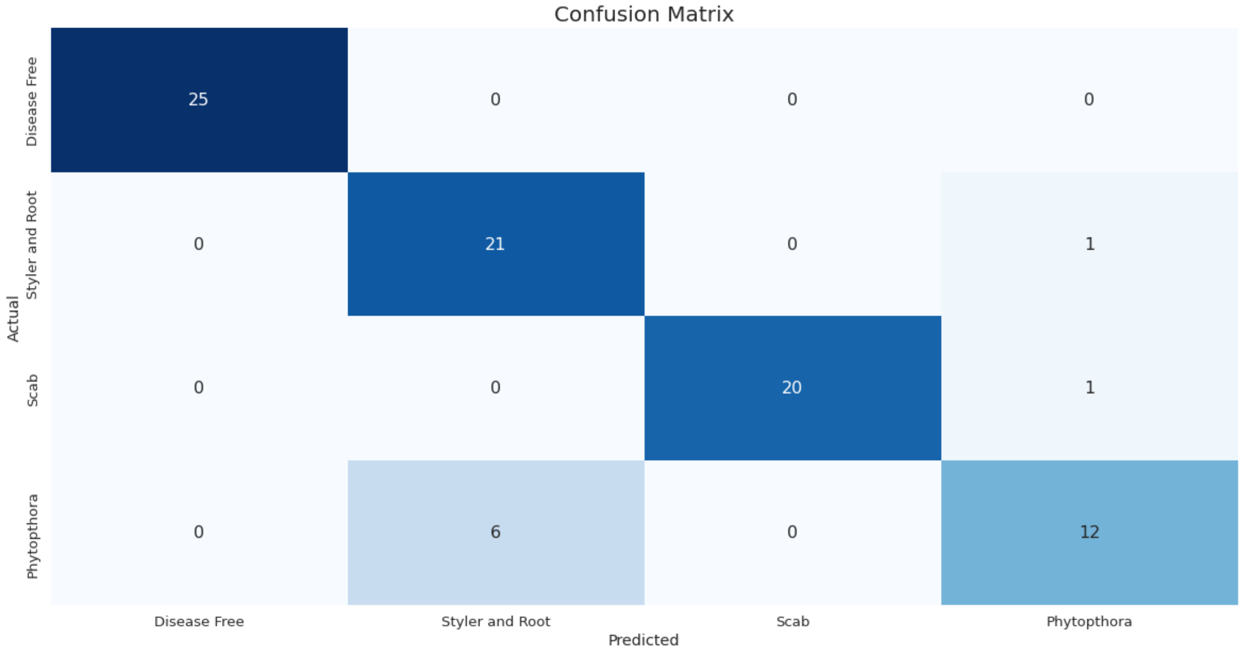
Custom model (Ripeness Classification):

Custom model gave almost the same accuracy . It means we have created a model with less layers which have a less load on hardware .creates less power consumption. There are only 2 instances the model was wrong. Which shows the reliability of the model.



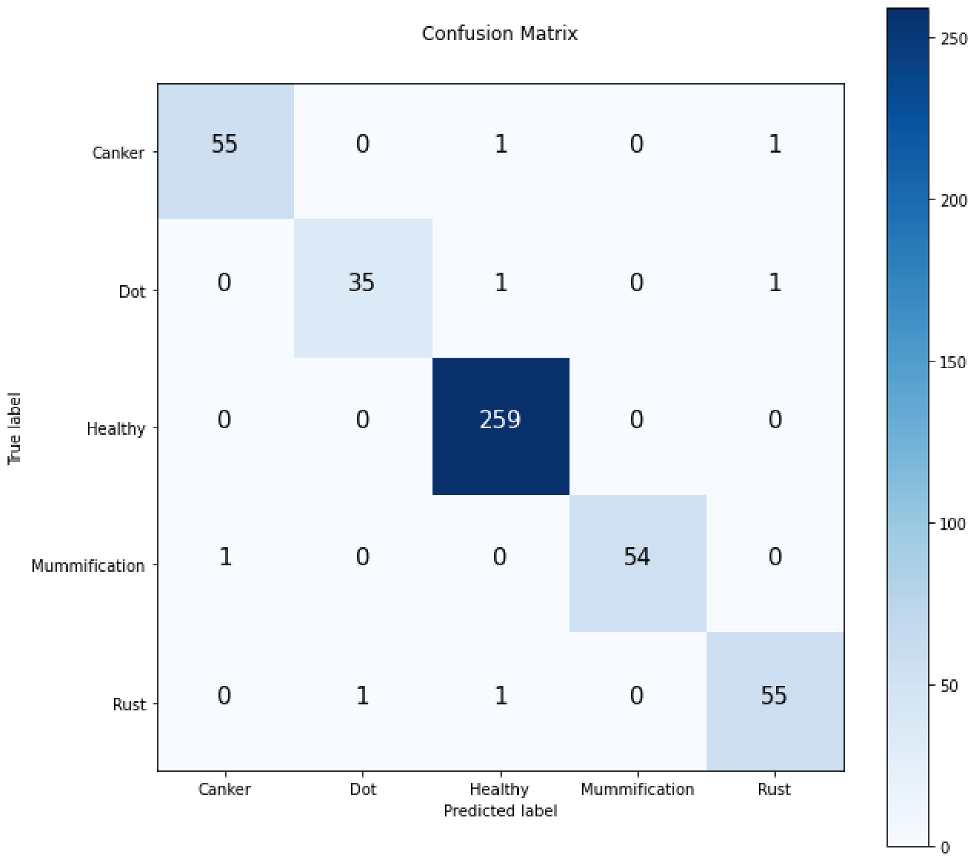
Guava Fruit Disease Classification

We are able to achieve 92% accuracy using a densenet 121 . It helps in classifying a model of the guava disease based on the fruit's health.we have used RGB images for classifying fruit disease classification.



Guava leaf disease classification :

We are able to achieve 98% accuracy using a custom model . It helps in classifying a model of the guava disease based on the leaf health. We have used RGB images for classifying Guava leaf disease classification.there are very few instances which model predicts wrong.



JUSTIFICATION & CHALLENGES

A revolutionary step in agricultural innovation has been made with the integration of technology with farming practices, as demonstrated by the development of three different models for guava farming. A potent toolset has been created to provide farmers with important insights by creating models for the classification of ripe and unripe fruit, guava-specific leaf diseases, and fruit diseases. With the support of deep learning and data analysis, these models help to improve the efficiency of guava farming. In order to maximize harvest, ripeness of the guavas is ensured by classifying them as ripe or unripe.

These models' ability to adjust to different datasets highlights their adaptability and opens up the possibility of customizing them to fit different farming situations and crops. Beyond the immediate benefits to agriculture, the transformative effect promotes a symbiotic relationship between farming practices and technology. There is a chance to improve agricultural yield while also improving technology as farmers adopt these technological solutions. Working together, conventional farming knowledge and state-of-the-art technology not only increases output but also creates opportunities for ongoing improvement and innovation.

Challenges

- It was difficult to use thermal cameras and capture an object's internal details. This constraint makes it more difficult to compile a complete dataset for object detection, especially when fine-grained information is essential to building precise models.

- There aren't many thermal imaging datasets available online. For object detection models that are trained and tested on external datasets, this scarcity presents a major obstacle. The model's capacity to generalize to different scenarios may be impacted by the absence of broad and varied datasets.

- It can be difficult for us to select the best neural network architecture for their particular task and to optimize hyperparameters for efficient training. Students who are not experienced in model tuning may end up with subpar performance. Selecting the proper architecture for the deep learning model and tuning hyperparameters are challenging tasks.

CONCLUSION & FUTURE WORK

In Conclusion ,achieving an accuracy of 92% in classifying fruit ripeness using thermal imaging, coupled with a parallel 92% accuracy in identifying fruit diseases and an 98% accuracy in classifying leaf diseases through RGB imaging, highlights the system's precision in providing comprehensive insights into guava health. This helps the agriculture sector better at identifying diseases and ripeness . The classification is mainly based on the Guava dataset .

For future work , We can customize according to the required fruit . having a custom dataset . Gathering thermal dataset .creating custom datasets for various fruits, expanding the thermal dataset, and augmenting the fruit disease dataset.

REFERENCE PAPERS

1. Mohd Ali M, Hashim N, Abd Aziz S, Lasekan O. Characterisation of Pineapple Cultivars under Different Storage Conditions Using Infrared Thermal Imaging Coupled with Machine Learning Algorithms. Agriculture. 2022 Jul 13;12(7):1013.
2. Naik S, Patel B. Thermal imaging with fuzzy classifier for maturity and size based non-destructive mango (Mangifera Indica L.) grading. In2017 International Conference on Emerging Trends & Innovation in ICT (ICEI) 2017 Feb 3 (pp. 15-20). IEEE.
3. Bhole V, Kumar A. Mango quality grading using deep learning technique: Perspectives from agriculture and food industry. InProceedings of the 21st annual conference on information technology education 2020 Oct 7 (pp. 180-186).
4. Bhargava, A. and Bansal, A., 2021. Fruits and vegetables quality evaluation using computer vision: A review. Journal of King Saud University-Computer and Information Sciences, 33(3), pp.243-257.
5. Ali, M.M., Hashim, N. and Shahamshah, M.I., 2021. Durian (Durio zibethinus) ripeness detection using thermal imaging with multivariate analysis. Postharvest Biology and Technology, 176, p.111517.
6. Yogesh, Dubey, A.K., Arora, R.R. and Mathur, A., 2021. Fruit defect prediction model (fdpm) based on three-level validation. Journal of Nondestructive Evaluation, 40(2), p.45.