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2 Non-Destructive Carabao Mango Sorter and Grader based on Physical Characteristics  
3 using Machine Learning

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5 A Thesis  
6 Presented to the Faculty of the  
7 Department of Electronics and Computer Engineering  
8 Gokongwei College of Engineering  
9 De La Salle University

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11 In Partial Fulfillment of the  
12 Requirements for the Degree of  
13 Bachelor of Science in Computer Engineering

14

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15 by

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20 September, 2025



# De La Salle University

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## THESIS APPROVAL SHEET

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with group number AISL-1-2425-C5 in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Engineering, (BS-CPE)** has been examined and is recommended for acceptance and approval.

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2025

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51

## ABSTRACT

52

to change *Index Terms*—Machine Learning, Carabao Mangoes, Sorting and Grading

53

Mangoes, Machine Vision, Microcontroller.



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## ABBREVIATIONS

229	AC	Alternating Current.....	13
230	GUI	Graphical User Interface .....	49
231	LED	Light Emitting Diode .....	43
232	UI	User Interface .....	49



233

## NOTATION

234	$B(P)$	Bruises Priority .....	63
235	$b(p)$	Bruises Prediction .....	63
236	$R(P)$	Ripeness Priority .....	63
237	$r(p)$	Ripeness Prediction .....	63
238	$S(P)$	Size Priority .....	63
239	$s(p)$	Size Prediction .....	63
240	$D(p, d, f)$	Real World Dimension .....	26
241	$p$	Pixel Dimension .....	26
242	$d$	Distance from Camera to Object.....	26
243	$f$	Focal Length .....	26



## 244 GLOSSARY

245	bruises	The black or brown area of the mango that is visible on the skin of the mango.
246	Carabao mango	A popular variety of mango grown in the Philippines, known for its sweet and juicy flesh.
247	accuracy score	A performance metric that measures the overall proportion of correct predictions made by a machine learning model.
248	confusion matrix	A table that summarizes the performance of a classification model, showing the number of true positives, true negatives, false positives, and false negatives.
249	CNN	A type of deep neural network that is highly effective in analyzing and processing visual data, such as images.
250	F1-Score	A balanced performance metric that is the harmonic mean of precision and recall, taking both into account.
251	machine learning	A subset of Artificial Intelligence that enables systems to learn and improve from data.
252	computer vision	The use of cameras and algorithms to provide imaging-based inspection and analysis.
253	microcontroller	A small computing device that controls other parts of a system such as sensors.
254	Precision	A performance metric that reflects the percentage of instances classified as positive that are truly positive.
255	recall	A performance metric that measures the proportion of actual positive instances that the model correctly identified.



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User Priority-Based Grading

A customizable grading system where users can assign weights to grading factors.



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## LISTINGS



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## **Chapter 1**

259

# **INTRODUCTION**



## 260      **1.1 Background of the Study**

261      Mangoes, also known as the *Mangifera indica*, are a member of the cashew family. This  
262      fruit can often be seen being farmed by countries such as Myanmar, the Philippines, and  
263      India as they have a tropical dry season. Being in a tropical country is an important  
264      aspect for mango cultivation as it ensures proper growth for mangoes. If aspects such as  
temperature and rainfall are not ideal, it may affect the quality of the mango (?). Carabao



265      Fig. 1.1 Carabao Mangoes at Different Ripeness Stages (?)

266      mangoes is a variety of a mango that is found and cultivated in the Philippines. It is known  
267      for its sweet signature taste that was recognized sweetest in the world in the Guinness  
268      Book of World Records in 1995. The mango was named after the national animal of the  
269      Philippines, a native breed of buffalo. On average, it is 12.5 cm in length and 8.5 cm in  
270      diameter, having a bright yellow color when ripe as seen in Figure 1.1. It is often cultivated  
271      during late May to early July (?).

272      As the Philippines is a tropical country, mangoes are a highly valued fruit as it is not  
273      only the country's national fruit but also amongst the leading agricultural exports of the  
274      country, ranking only third below bananas and pineapples. This gives the country the 9th  
275      slot amongst the leading exporters of Mangoes across the world. Attributed to this ranking



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276 is the country's export of both fresh and dried mangoes, as well as low tariff rates. This  
277 allows the country to export a large quantity of the fruit in countries such as Singapore,  
278 Japan, and the USA as they can enter duty free markets provided by the World Trade  
279 Organization and Japan. Due to this, the mangoes have become a major source of income  
280 to an estimated 2.5 million farmers in the country (?).

281 Before mangoes are sold in markets, they first undergo multiple post-harvest processes.  
282 This is to ensure that the mangoes that arrive in markets are utmost quality before being  
283 sold to consumers. Moreover, it ensures that mangoes are contained and preserved properly  
284 such that they do not incur damages and/or get spoiled on its transportation to the market.  
285 Processing of the mango involves pre-cooling, cleaning, waxing, classification, grading,  
286 ripening, packaging, preservation, storage, packing, and transportation (?) (?).

287 Among the processes that mangoes undergo, classification and grading is important as  
288 it allows the manufacturer to separate mangoes with good qualities versus mangoes with  
289 poor qualities. According to a study by (?), size, length, width, volume, density, indentation,  
290 and grooves are aspects that determine the maturity of mangoes. These traits are being  
291 checked along with the ripeness of the mango, sightings of bruise injury, and cracks on the  
292 fruit (?) as these aspects affect the sellability of the fruit as well as the chances of it getting  
293 spoiled sooner.

294 Previous studies have been made to automate the sortation process of the mangoes.  
295 Among these is a research done by ?, which focuses on classification of mangoes using their  
296 texture and shape features. They do this by, first, acquiring an image of the mango using  
297 a digital camera. Then, these images are fed to the MaZda package, which is a software  
298 originally developed for magnetic resonance imaging. Within the MaZda package is the  
299 B11 program, which uses Principal Component Analysis, Linear Discriminant Analysis,



300 Nonlinear Discriminant Analysis, and texture classification to extract features from the  
301 mango, which in this case are the length, width, and texture. This data is then compared to  
302 a database in order to classify any given mango (?).

303 Another study is done by ?, which classifies mangoes based on their color, volume, size,  
304 and shape. This is done by making use of Charge Coupled Devices, Complementary Metal-  
305 Oxide Semiconductor sensors, and 3-layer Convolutional Neural Network. To classify the  
306 mangoes, images are first captured and preprocessed to be used as a data set (?). This data  
307 set is then augmented to be used as a model for the 3-layer Convolutional Neural Network.  
308 After extracting the features of the mango, the 3-layer Convolutional Neural Network  
309 is used as a method for their classification as it can mimic the human brain in pattern  
310 recognition, and process data for decision making. This is important as some mangoes have  
311 very subtle differences which make it difficult to differentiate them.

## 312 1.2 Prior Studies

313 A paper written by ?, designed an automated fruit sorting machine based on the quality  
314 through an image acquisition system and CNN. Furthermore, the results of the paper show  
315 that the image processing detection score was 89% while that of the tomatoes was 92%  
316 while the CNN model had higher validity of 95% for mangoes and 93% for tomatoes.  
317 15%, while the percentage of distinction between the two groups was reported to be 5%  
318 respectively (?). Despite the high accuracy score in detecting mango defects, the fruit  
319 sorting system only sorts based on the mango defects and not on ripeness, and weight.

320 Furthermore, the research paper presented by ? designed an Automated Carabao mango  
321 classifier, in which the mango image database is used to extract the features like size, area



322 along with the ratio of the spots for grading using Naïve Bayes Model. For the results, the  
323 Naïve Bayes' model recognized large and rejected mangoes with 95% accuracy and the  
324 large and small/medium difference with a 7% error, suggesting an application for quality  
325 differentiation and sorting in the mango business industry. Despite the high accuracy of  
326 classifying Carabao mangoes, the researchers used a high quality DSLR camera for the  
327 image acquisition system without any microcontroller to control the mangoes (?).

328 **1.3 Problem Statement**

329 As mangoes are among the top exports of the Philippines (?), assessing the physical  
330 deformities is a necessity. The physical deformities of the Carabao mango can determine  
331 the global competitiveness of the country. Having higher quality exports can often lead to  
332 gaining competitive edge, increase in demand, increase export revenues, and becoming less  
333 susceptible to low-wage competition (?). In order to increase the quality of mango fruit  
334 exports, a key post-harvest process is done, which is sorting and grading. Mango sorting  
335 and grading then becomes important to determine which batches are of high quality and can  
336 be sold for a higher price, and which batches are of low quality and can only be sold for a  
337 low price (?). Traditionally, fruit sorting and grading is inefficient as it is done manually by  
338 hand. Some tools are used such as porous ruler to determine fruit size and color palette for  
339 color grading (?). However, among the problems encountered in the process of manually  
340 sorting and grading mangoes are susceptibility to human error and requiring a number of  
341 laborers to do the task.

342 With the current advancements in technology, some researchers have already taken steps  
343 to automate the process of sorting and grading mangoes. However, these attempts would



344 often only consider some of the aspects pertaining to size, ripeness, and bruises but not all  
345 of them at the same time. Lastly, not all research approaches were able to implement a  
346 hardware for their algorithm, limiting their output to only a software implementation and not  
347 an embedded system. As such the proposed system would assess the export quality of the  
348 Carabao mango based on all the mentioned mango traits, namely size, bruises, and ripeness  
349 while also taking into consideration being non-destructive. These aspects are important  
350 because, as was previously mentioned, there is a need to develop a Carabao mango sorter  
351 that takes into account all these aspects at the same time while being non-destructive.

## 352 **1.4 Objectives and Deliverables**

### 353 **1.4.1 General Objective (GO)**

- 354 • GO: To develop a user-priority-based grading and sorting system for Carabao man-  
355 goes, using machine learning and computer vision techniques to assess ripeness, size,  
356 and bruises. ;

### 357 **1.4.2 Specific Objectives (SOs)**

- 358 • SO1: To make an image acquisition system with a conveyor belt for automatic sorting  
359 and grading mangoes. ;
- 360 • SO2: To get the precision, recall, F1 score, confusion matrix, and train and test  
361 accuracy metrics for classifying the ripeness and bruises with an accuracy score of at  
362 least 90%;



- 363 • SO3: To create a microcontroller-based system to operate the image acquisition  
 364 system, control the conveyor belt, and process the mango images through machine  
 365 learning. ;
- 366 • SO4: To grade mangoes based on user priorities for size, ripeness, and bruises. ;
- 367 • SO5: To classify mango ripeness based on image data using machine learning  
 368 algorithms such as kNN, k-mean, and Naïve Bayes. ;
- 369 • SO6: To classify mango size based on image data by getting its length and width  
 370 using OpenCV, geometry, and image processing techniques. ;
- 371 • SO7: To classify mango bruises based on image data by employing machine learning  
 372 algorithms.

### 373 **1.4.3 Expected Deliverables**

374 Table 1.1 shows the outputs, products, results, achievements, gains, realizations, and/or  
 375 yields of the Thesis.

**TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE**

Objectives	Expected Deliverables
GO: To develop a user-priority-based grading and sorting system for Carabao mangoes, using machine learning and computer vision techniques to assess ripeness, size, and bruises.	<ul style="list-style-type: none"> <li>• To develop a Carabao mango grading and sorting system.</li> <li>• To grade Carabao mangoes into three categories based on ripeness, size, and bruises using machine learning.</li> <li>• To integrate sensors and actuators to control the conveyor belt and image acquisition system.</li> </ul>

*Continued on next page*



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ul style="list-style-type: none"> <li>To make an image acquisition system with a camera and LED light source.</li> <li>To build a flat belt conveyor for moving the mangoes.</li> </ul>
SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.	<ul style="list-style-type: none"> <li>To use a publicly available dataset of at least 10,000 mango images for classification of ripeness and bruises.</li> </ul>
SO3: To create a microcontroller-based system to operate the image acquisition system, control the conveyor belt, and process the mango images through machine learning.	<ul style="list-style-type: none"> <li>To develop an intuitive UI where users can start and stop the system.</li> <li>To implement a priority-based grading system with sliders for ripeness, bruises, and size.</li> </ul>
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<ul style="list-style-type: none"> <li>To utilize a linear combination formula as the overall mango score, where each classification level contributes a grade, weighted by the priority assigned to the three properties.</li> <li>To assign score values for each classification level of the mango.</li> </ul>
SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.	<ul style="list-style-type: none"> <li>To train a machine learning model such as kNN, k-means, or Naïve Bayes capable of classifying mango ripeness based on the image color.</li> <li>To gather a dataset of annotated images with ripeness labels.</li> <li>To obtain an evaluation report of performance metrics of the model.</li> </ul>
SO6: To classify mango size based on image data by getting its length and width using OpenCV, geometry, and image processing techniques.	<ul style="list-style-type: none"> <li>To develop an image processing algorithm capable of determining mango size using OpenCV, NumPy, and imutils.</li> <li>To classify mangoes based on size into small, medium, and large based on measurements.</li> </ul>

*Continued on next page*



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ul style="list-style-type: none"> <li>• To train a machine learning model such as CNN capable of distinguishing bruised and non-bruised mangoes.</li> <li>• To train a machine learning model such as kNN, k-means, and Naïve Bayes capable of assessing the extent of bruising on the mangoes if it is significant or partial.</li> <li>• To gather a dataset of annotated images based on bruises.</li> <li>• To obtain an evaluation report of performance metrics of both CNN and other machine learning models.</li> </ul>

## 1.5 Significance of the Study

Automating the process of sorting and grading mangoes increases efficiency and productivity for the user which would in effect remove human error in sorting and grading and decrease the human labor and time taken to sort and grade the mangoes. This is especially important for farmers with a large amount of fruit such as mangoes and a lesser labor force. A recent study showed that their automated citrus sorter and grader using computer vision can reduce the human labor cost and time to sort and grade when comparing the automated citrus sorter and grader to manual human labor ?.

Another benefit to automating sorting and grading mangoes is the improvement in quality control. This implies that compared to human labor, automating sorting and grading mangoes can uniformly assess the quality of mangoes based on size, color, and bruises, ensuring that the expected grade and high-quality mangoes reach the consumer. By accurately identifying substandard mangoes, the system helps in reducing waste and



389 ensuring that only marketable fruits are processed further.

390 Likewise, the scalability of automating sorting and grading mangoes is simpler, es-  
391 pecially for lower labor force farmers with large volumes of mangoes. Because of the  
392 possibility of large-scale operations by automating sorting and grading mangoes, farmers  
393 can now handle large volumes of mangoes, making them suitable for commercial farms  
394 and processing plants. Moreover, it can be adapted to different varieties of mangoes and  
395 potentially other fruits with minor modifications.

### 396 **1.5.1 Technical Benefit**

- 397 1. The development of an automated Carabao mango sorter would increase the quality  
398 control of classifying Carabao mango based on ripeness, size, and bruising.
- 399 2. The accuracy in sorting Carabao mangoes will be significantly improved while  
400 reducing the errors due to human factors in manual sorting.
- 401 3. The automated Carabao mango sorter carefully sorts the mangoes while ensuring  
402 that they remain free from bruising or further damage during the process

### 403 **1.5.2 Social Impact**

- 404 1. The reduction in manual labor creates opportunities in maintenance and technologies  
405 in the automated Carabao mango sorter.
- 406 2. The automated Carabao mango sorter system improves Carabao mango standards  
407 and enhances the satisfaction of the buyers and the customers through guaranteeing  
408 consistent Carabao mango grade.



- 409        3. Opportunity to increase sales and profit for the farmers through consistent quality  
410                  and grade Carabao mangoes while reducing the physical labor to sort it.

411        **1.5.3 Environmental Welfare**

- 412        1. With the utilization of non-destruction methods of classifying Carabao mangoes  
413                  together with an accurate sorting system, overall waste from Carabao mangoes is  
414                  reduced and the likelihood of improperly sorted mangoes is decreased.
- 415        2. Automation of sorting and grading Carabao mangoes promotes sustainable farming  
416                  practices.

417        **1.6 Assumptions, Scope, and Delimitations**

418        **1.6.1 Assumptions**

- 419        1. The Carabao mangoes are from the same source together with the same variation
- 420        2. The Carabao mangoes do not have any fruit borer and diseases
- 421        3. All the components do not have any form of defects
- 422        4. The prototype would have access to constant electricity/power source.
- 423        5. The Carabao mangoes to be tested would be in the post-harvesting stage and in the  
424                  grading stage.
- 425        6. The image-capturing system would only capture the two sides of the mango which  
426                  are the two largest surface areas of the skin.



427 **1.6.2 Scope**

- 428 1. The prototype would be specifically designed to grade and sort Carabao Mangoes  
429 based on only ripeness, size, and visible skin bruises.
- 430 2. The mangoes used as the subject will be solely sourced from markets in the Philip-  
431 pines.
- 432 3. The Carabao mangoes would be graded into three levels.
- 433 4. The prototype will be using a microcontroller-based system locally stored on the  
434 device itself to handle user interaction.
- 435 5. Computer vision algorithms to be used will include image classification.

436 **1.6.3 Delimitations**

- 437 1. The project would only be able to perform sorting and grading on one specific fruit  
438 which is the Carabao mango and will not be able to sort other types of mangoes.
- 439 2. Additionally, the project prototype will only be able to capture, sort, and grade one  
440 mango subject at a time which means the mangoes have to be placed in the conveyor  
441 belt in a single file line for accurate sorting.
- 442 3. For the bruises, the system will only be able to detect external bruises and may not  
443 identify the non-visible and internal bruises.
- 444 4. The system does not load the mangoes onto the conveyor belt itself. Assistance is  
445 required to put mangoes into the conveyor belt to start the sorting process



- 446        5. The prototype will be powered using Alternating Current (AC) power and will be  
447                plugged into a wall socket which is only suitable for indoor use.

448        **1.7 Overview of the Thesis**

449        There are seven succeeding chapters. To recall, chapter 1 involves the introduction of  
450                the thesis topic containing the background of the study, previous studies, objectives and  
451                deliverables, assumptions, scope, and delimitation, significance of the study, description  
452                of the project together with the methodology, and Gantt chart and budget. Chapter 2  
453                involves the existing articles, the lacking in their approaches, and the summary of chapter 2.  
454                Chapter 3 involves the theoretical considerations of the thesis topic while chapter 4 would  
455                consist of the design consideration involving the thesis topic. Chapter 5 would involve the  
456                research methodology containing the testing procedure and setup. Chapter 6 would involve  
457                the results and discussion based on the methodology while Chapter 7 would involve the  
458                conclusion, recommendations, and future suggestions.



459

## Chapter 2

460

## LITERATURE REVIEW



## 461      **2.1 Existing Work**

462      The research paper written by ? developed a ripeness grader for Carabao mangoes. The  
463      Carabao mango ripeness grade calculated based on object and color detection which were  
464      written in microcontroller. These are the systems designed by the researchers that consists  
465      of Raspberry Pi 4, Arduino Uno, camera, touch screen LCD, MQ3 gas sensor, ventilation  
466      system. The proposed system was able to ascertain an overall reliability of 95%: therefore,  
467      the specified objective of ascertaining the ripeness level of the mangoes was met with  
468      success. However, accuracy and reliability of the software system are there since the  
469      hardware design does not seem to be workable when one must deal with the scores of  
470      mangoes (?). In addition, the design of the hardware does not integrate any form of physical  
471      automating, say like the conveyor belt. Besides, the hardware system only works efficiently  
472      when deciding the ripeness grade of mangoes separately.

473      A study done by ? is another research paper that supports and has relevant information  
474      concerning the topic. The researchers proposed a fully-perovskite photonic system which  
475      has the capability to identify and sort or grade mango based on features such as color,  
476      weight and, conversely, signs of damages (?). Some of the techniques in image processing  
477      that the researchers used included image enhancement, image deblurring, edge detection  
478      using MATLAB and Arduino as well as color image segmentation. By carrying out the  
479      multiple trials on the device they achieved a classification speed of 8.132 seconds and an  
480      accuracy of 91.2%. The proponents' metrics used for the ratings were speed wherein the  
481      results were rated “excellent” while the accuracy rating given was “good”. One of the  
482      limitations of the paper is that the researchers were only limited to the color, texture, and  
483      size of the Carabao mango



484 Furthermore, the research paper presented by ? designed an Automated Carabao  
485 mango classifier, in which the mango image database is used to extract the features like  
486 weight, size, area along with the ratio of the spots for grading using Naïve Bayes Model.  
487 Concerning the quantitative test design, one had to control and experiment with various  
488 methods of image processing that would improve the likelihood of improved classification.  
489 The paper methodology entailed sample collection from 300 Carabao mangoes, picture  
490 taking using a DSLR camera, and feature deconstruction for categorization (?). The  
491 system prototype and the software were designed with the programming language C# with  
492 integration of Aforge. NET routines. The performance of this model was checked with  
493 the help of the dataset containing 250 images, precision, recall, F-score key indicators  
494 were used. The investigation discovered that the Naïve Bayes' model recognized large and  
495 rejected mangoes with 95% accuracy and the large and small/medium difference with a  
496 7% error, suggesting an application for quality differentiation and sorting in the mango  
497 business industry. The limitations in the researchers' paper include the researchers were  
498 able to achieve high accuracy after using a high quality DSLR camera and the fact that the  
499 researchers were not able to incorporate the use of microcontrollers.

500 Another study by ? proposed SVM-based system for classifying the maturity stages of  
501 bananas, mangoes, and calamansi. With the use of 1729 images of bananas together with  
502 711 mango images and 589 calamansi, the researchers were able to achieve a high accuracy  
503 score of above 90% for all fruits. Some pre-processing techniques used to get this high  
504 accuracy are the change in hue, saturation, and value channels in the mango image (?). To  
505 better understand the harvest time of mangoes, the paper by ? examined the association of  
506 the harvest season with seasonal heat units, rainfall, and physical fruit attributes for Haden,  
507 Kent, Palmer, and Keitt mango varieties to establish export and domestic market maturity



508 standards. For the results of the paper, it shows that temperature, rainfall, and physical  
 509 characteristics have a reliable, non-destructive indicators for determining mango maturity  
 510 (?). This shows that physical characteristics and temperature are important when exporting  
 511 fruits such as mangoes.

TABLE 2.1 COMPARISON OF EXISTING STUDIES

Existing Study	Limitations	Accuracy Rating
?	No physical automation, not suitable for large amounts of mangoes, only classifies ripeness and only a sample size of 10 mangoes.	95%
?	Focuses only on color and size.	91.2%
?	Relies on high-quality DSLR cameras, and limited automation due to not integrating microcontrollers.	95%
?	No physical automation implemented. Ripeness, size, and shape-based classification achieved 100%, 98.19%, and 99.20% accuracy respectively on their own. However, errors occurred when taking into account all these aspects together for grading mangoes, causing an accuracy rating deduction.	88.88%

512 Previous studies on mango grading have achieved an accuracy rating of up to 95%, as  
 513 shown in Table 2.1. However, these studies either relied on a small sample size, which  
 514 limits statistical significance, or utilized expensive equipment, which may be impractical.  
 515 In light of this, the researchers have set a target accuracy rating of greater than or equal  
 516 to 90%. This target ensures that the system being developed is comparable to, or better  
 517 than, existing studies that used larger sample sizes or assessed multiple mango traits at the  
 518 same time. Furthermore, this research aims to distinguish itself by not only maintaining or  
 519 exceeding the 90% accuracy rating but also incorporating a graphical user interface (GUI)



520 for selective priority-based mango classification. The system will integrate both software  
521 and hardware components, and it will evaluate a greater number of mango traits for grading  
522 purposes.

### 523 **2.1.1 Sorting Algorithms**

524 In previous studies, researchers have implemented various artificial intelligence algorithms  
525 in order to determine the optimal and most effective method for sorting mangoes. One of  
526 the algorithms that was used in the classification of mangoes was the CNN or Convolutional  
527 Neural Networks. A study done by ? explored the effectiveness of CNN, specifically in  
528 classifying mangoes through image processing. The system that the researchers developed  
529 graded mangoes into four groups which was based on the Chinese National Standard (?).  
530 These mangoes were examined by their shape, color uniformity, and external defects. The  
531 system that was developed had an impressive accuracy of 97.37% in correctly classifying  
532 the mangoes into these grading categories Support Vector Machine was also one of the  
533 classification algorithms that was implemented to detect flaws in mangoes. In that study by  
534 ?, SVM was used in the classification of diseases from mangoes. The study used 4 different  
535 diseases/defects for testing (?). The diseases were Anthracnose, Powdery Mildew, Black  
536 Banded, and Red Rust. and provided 90% accuracy for both the leaves and the fruit

537 In the study done by ?, Simple Linear Regression, Multiple Linear Regression, and  
538 Artificial Neural Network models were all studied and compared for the purpose of size-  
539 mass estimation for mango fruits. The researchers found that the Artificial Neural Network  
540 yielded a high accuracy rating for mass estimation and for mango classification based on  
541 size with a success rate of 96.7% (?). This is attributed to the Artificial Neural Network  
542 model's ability to learn both linear and nonlinear relationships between the inputs and the



543 outputs. However, a problem can occur with the use of the model, which is overfitting.  
544 This issue occurs when the model is overtrained with the data set such that it will start to  
545 recognize unnecessary details such as image noise which results in poor generalization  
546 when fed with new data. With this in mind, additional steps will be necessary to mitigate the  
547 issue. Another research article written by ? implements a method for sorting and grading  
548 Carabao mangoes. This research focuses on the use of Probabilistic Neural Network, which  
549 is another algorithm that is used for pattern recognition and classification of objects. For  
550 this study, the researchers focused on the area, color, and the black spots of the mango  
551 for their Probabilistic Neural Network model (?). Their research using the model yielded  
552 an accuracy rating of 87.5% for classification of the mangoes which means it is quite  
553 accurate for classifying mangoes within the predefined categories. However, problems  
554 were encountered with the use of the model when trying to identify mangoes that did not  
555 fit the predefined size categories of small, medium, and large. This means that the PNN  
556 model may become challenged when presented with a mango with outlying traits or traits  
557 that were very different from the data set.

## 558 2.2 Lacking in the Approaches

559 The majority of past researchers such as ? and ? were able to implement a fruit and  
560 mango sorter together with an accurate AI algorithm to detect the ripeness defects. This  
561 means that none of the previous research papers were able to integrate an interchangeable  
562 user-priority-based grading together with size, ripeness, and bruises using machine learning  
563 for Carabao mango sorter and grader. Our research however would implement an automated  
564 Carabao mango sorter in terms of size, ripeness, and bruises with its own UI, conveyor



TABLE 2.2 COMPARISON OF SORTING ALGORITHM MODELS

Sorting Algorithm Model	Accuracy Rating	Criteria	Problems Encountered
Convolution Neural Network	97.37%	shape, color, defects	Minor blemishes affected the accuracy.
Support Vector Machine	90%	mango defects and diseases	The model is sensitive to noise, which requires intensive image preprocessing.
Artificial Neural Network	96.7%	for mango size and mass	Overfitting
Probabilistic Neural Network	87.5%	for mango area, color, and black spots	Difficulty in identifying mangoes that have outlying features or did not fit the predefined categories

565 belt, stepper motors, and bins for collecting the different ripeness and defect grade of the  
 566 Carabao mango.

### 567 2.3 Summary

568 To reiterate, there is an innovative gap that needs to be filled with regards to the process of  
 569 sorting and grading Carabao mangoes. The traditional methods for conducting this process  
 570 manually by hand, by a porous ruler, by a sugar meter, and by a color palette can be prone  
 571 to human error and expensive costs due to the number of laborers required to do the task.  
 572 On the other hand, although researchers have already taken steps to automate the process  
 573 of mango sorting and grading, there is still a need for an implementation that takes into  
 574 account size, ripeness, and bruises altogether whilst being non-destructive and having its  
 575 own embedded system. The research articles shown above show the different computer



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576 vision and CNN approaches for sorting and classifying mangoes. For example, a system  
577 created by ? was more focused on ripeness detection. ? considered photonic systems  
578 for grading mango fruit based on color and weight. On the other hand, ? implemented  
579 the Naïve Bayes classification model on mangoes with high accuracy, which thereby did  
580 not include any microcontroller. There was an attempt to study each of those parameters  
581 separately and that is why the multifactorial approach was not used. With this in mind, the  
582 system being proposed does exactly what was mentioned, to implement a non-destructive  
583 and automated sorting and grading system for Carabao mangoes that takes into account  
584 size, ripeness, and bruises altogether using machine learning, as well as having its own  
585 embedded system. This system will be mainly composed of a conveyor belt, servo motors,  
586 a camera, microcontrollers, and an LCD display for the user interface. By doing so, the  
587 system should be able to improve the efficiency and productivity of mango sorting and  
588 grading, remove the effect of human error and reduce time consumption. The studies also  
589 provided critical insights regarding the effective algorithms that can be used in classification  
590 stages in image processing. The use of CNN had the most accuracy with manageable  
591 potential challenges. Lastly, by scaling the implementation, the overall export quality of  
592 the Carabao mangoes can be improved.



593

## Chapter 3

594

# THEORETICAL CONSIDERATIONS



### 595      3.1 Introduction

596      Likewise, the purpose of this chapter is to go through the important theories in developing  
 597      the prototype together with training and testing the machine learning model.

### 598      3.2 Relevant Theories and Models

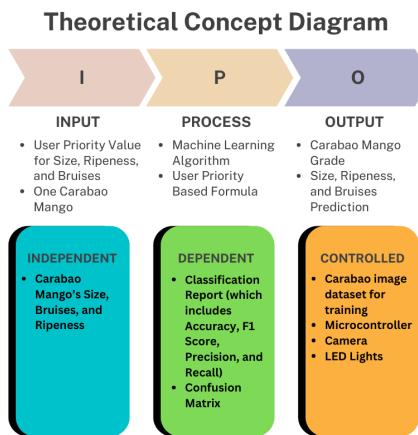


Fig. 3.1 Theoretical Framework Diagram.

599      The theoretical framework seen in figure 3.1 follows the IPO (Input-Process-Output)  
 600      Model for a Carabao Mango Sorting System. The Input section includes user-defined  
 601      priority values for size, ripeness, and bruises, along with a single mango for analysis. The  
 602      Process section highlights the use of a machine learning algorithm and a user-priority-based  
 603      formula to classify the mango. The Output consists of the mango's grade, predicted size,  
 604      ripeness, and bruises. Below the IPO model, the diagram categorizes variables into three  
 605      groups: Independent (mango's size, ripeness, and bruises), Dependent (classification report  
 606      with accuracy, precision, recall, and confusion matrix), and Controlled (image dataset,  
 607      microcontroller, camera, and LED lights).



### 608    3.3 Technical Background

609    At its core, the system will be using machine learning concepts pertaining to CNN and  
610    OpenCV, and may use other algorithms such as Naive Bayes and k-Nearest Neighbors  
611    to supplement the classification tasks, particularly for assessing mango ripeness, bruise  
612    detection, and size determination. The system will be built on an embedded framework,  
613    integrating a Raspberry Pi microcontroller to control the RaspberryPi camera, actuators,  
614    LED lights, and motors. A user-friendly GUI will also be utilized to ensure users can  
615    customize the prioritization of the mango sorting system.

### 616    3.4 Conceptual Framework Background

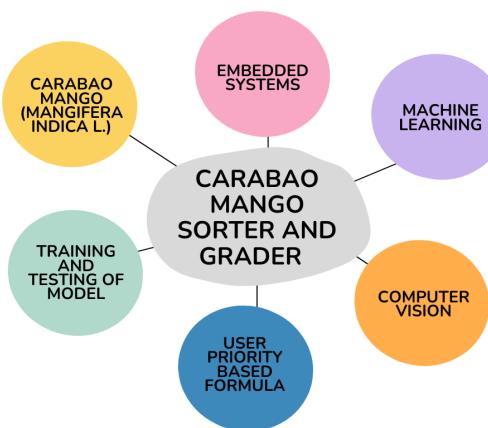


Fig. 3.2 Conceptual Framework Diagram.

617    The conceptual framework seen in figure 3.2 illustrates the key components involved  
618    in the Carabao Mango Sorter and Grader system. At the center, the system is represented  
619    as the core element, surrounded by six interconnected components: Carabao Mango  
620    (Mangifera indica L.), Embedded Systems, Machine Learning, Computer Vision, User



621 Priority-Based Formula, and Training and Testing of the Model. These elements represent  
622 the different technologies, methodologies, and considerations required for the development  
623 and operation of the sorter and grader. The diagram provides an overview of how various  
624 disciplines contribute to the project's functionality.

## 625 **3.5 Software Concepts**

### 626 **3.5.1 Thresholding**

627 Thresholding is a computer vision image segmentation technique that is used to separate  
628 objects from their surroundings by converting a grayscale image to binary. The conversion  
629 is done by choosing a certain threshold intensity value. It is usually done by assigning pixels  
630 with an intensity higher than the threshold are mapped to one value (commonly white),  
631 and pixels with an intensity lower than the threshold are mapped to another (commonly  
632 black). The result of this technique is in a high-contrast image that makes it easy to detect  
633 the object's boundary and shape in the image.

634

635 In this project, two types of thresholding were applied:

- 636 • Absolute Difference Thresholding – This method involves computing the absolute  
637 difference between two images. The first image is one of the object, and the other  
638 of the same background without the object. The result isolates only the pixels that  
639 have changed between the two images, thus isolating the mango from its background  
640 successfully.
- 641 • Binary Thresholding – Once the difference image has been created, binary threshold-



642       ing is used. A threshold value is employed to threshold the difference image into a  
 643       binary image. Values greater than the threshold are made white (foreground), and  
 644       values less than that are made black (background). This creates a clear silhouette of  
 645       the mango, which is appropriate for size estimation and contour detection.

646       **3.5.2 Object Size Calculation**

647       Object size calculation is the calculation of a certain object's true size from image data. This  
 648       is essential in computer vision systems to efficiently process object features in real-time.  
 649       In this research, the size of the Carabao mango is estimated through image measurement  
 650       techniques based on geometric principles and camera calibration.

651       The size of the mango can be determined given:

$$\text{Real World Dimension} = \frac{\text{Pixel Dimension} \times \text{Distance from Camera to Object}}{\text{Focal Length}} \quad (3.1)$$

$$D(p, d, f) = \frac{p \cdot d}{f} \quad (3.2)$$

652       where  $D(p, d, f)$  is the real world dimension of the object,  $p$  is the pixel dimension of  
 653       the object,  $d$  is the distance from the camera to the object, and  $f$  is the focal length of the  
 654       camera.

655       After capture and preprocessing of the image, the binary image so obtained is processed  
 656       with contour detection to find the largest object, which is assumed to be the mango. The  
 657       contour is then bounded with a minimum-area bounding box, and pixel-based length and  
 658       width are calculated using Euclidean distance between the corner points.



659        This size estimation method offers a consistent and efficient way of taking the mea-  
660        surements with only standard camera input, providing consistency in classification and  
661        reducing the necessity for physical measuring devices.

### 662        **3.5.3 Convolutional Neural Network**

663        Convolutional Neural Networks are a class of deep learning models is commonly used in  
664        analyzing visual data. CNNs are particularly effective in image classification tasks due to  
665        their ability to automatically extract and effectively learn the spatial hierarchies of features  
666        directly from the pixels of a given image. This makes it highly suitable for functions such  
667        as object detection and, in the case of this study, image classification.

668        CNN usually applies filters to input images. These filters are designed to detect local  
669        patterns such as edges, textures, and color gradients. The network is able to learn more  
670        patterns as the data goes through the layers. This enables it to recognize effectively the  
671        characteristics that it is looking for.

672        The use of CNNs in this study allows for accurate, automated classification of mango  
673        images which contributes to the development of a reliable, non-destructive grading system  
674        that minimizes human error and ensures consistent quality assessment

## 675        **3.6 Hardware Concepts**

### 676        **3.6.1 Camera Module**

677        The camera module serves as the main image acquisition tool in the mango sorter and  
678        grader system. Its role is to capture clear, high-resolution images of each mango as it moves



679 along the conveyor. These images are critical for analyzing physical traits like ripeness,  
680 bruising, and size through computer vision and machine learning techniques.

681 The camera is directly connected to the Raspberry Pi, which manages both image  
682 capture and processing. It is fixed in position to ensure consistent distance and angle for  
683 all images. It is also paired with a lighting system to provide a consistent lighting for the  
684 images. The system captures images of both the top and bottom sides of each mango to  
685 ensure a more accurate grading. The prototype integrates the Raspberry Pi Camera Module  
686 Version 2. This camera is chosen for its 8MP resolution which is critical in capturing  
687 real-time images. Another reason for integrating this camera is because of its compatibility  
688 with the Raspberry Pi 4, and reliability in capturing detailed images needed for accurate  
689 classification. It is also cost effective and lightweight which is important for the prototype.

### 690 **3.6.2 4 Channel Relay**

691 The relay module in this project is used to control the direction and movement of the  
692 motors that operate the conveyor system and mango sorting mechanism. As an electrically  
693 operated switch, the relay allows the low-power signals from the Raspberry Pi to safely  
694 manage the higher voltage and current required by the DC motors.

695 For the prototype, the relay module is responsible for changing the polarity of motor  
696 connections which enables the motors to rotate in both forward and reverse directions.  
697 This will drive the conveyor belt system. This is essential for moving mangoes along the  
698 conveyor, rotating them for the top and bottom image capture, and directing them to the  
699 appropriate bin based on their grade.



### 700     **3.6.3 Gear Ratio**

701     In this prototype, gear ratios are used to control the rotational speed of the conveyor belts  
702     that move and rotate the mango. A gear ratio of 1:3 was applied, meaning the motor gear  
703     completes one full rotation for every three rotations of the driven gear. This is also done in  
704     order to avoid overspeeding and make sure that the conveyor belt moves in a controlled  
705     manner. This setup slows down one belt relative to the other, creating a differential speed  
706     between the left and right belts. As a result, the mango rotates in place while being moved  
707     forward. This rotation is essential for capturing both the top and bottom views of the mango  
708     for accurate classification and grading.

### 709     **3.7 Summary**

710     Overall, chapter 3 establishes key concepts and theoretical considerations that form the  
711     foundation of the Carabao mango sorter and grading system. It discusses and connects  
712     each component together, explaining how each component such as the RaspberryPi and  
713     DC motors work together to create a system that utilizes machine learning and computer  
714     vision techniques to classify mangoes based on user priority.



715

## Chapter 4

716

# DESIGN CONSIDERATIONS



717 Likewise, the objective of chapter 4 is to describe the researcher's design consideration  
718 when developing and testing the prototype. For an overview of the design of the prototype,  
719 the researchers considered different computer vision models in classifying the ripeness  
720 and bruises together with other algorithms to determine the size of the mango. Likewise,  
721 the hardware design was also taken into consideration where the physical design of the  
722 conveyor belt was taken into account.

## 723 **4.1 Introduction**

724 This chapter discusses the design considerations for the mango sorting and grading system,  
725 focusing on the technical and engineering decisions required for its development. The  
726 design process aims to create a scalable, efficient, and user-friendly system that leverages  
727 machine learning for accurate mango classification.

## 728 **4.2 System Architecture**

729 The system architecture is represented through a block diagram, showcasing modules  
730 such as image acquisition, preprocessing, feature extraction, machine learning model, and  
731 grading output. Each module is described in detail, emphasizing its role in the overall  
732 system. For instance, the image acquisition module uses high-resolution cameras to capture  
733 mango images, while the preprocessing module enhances image quality for better feature  
734 extraction.

735 In figure 4.1 presents the electronic circuit diagram, designed using Proteus. The  
736 diagram illustrates a system where a Raspberry Pi 4 serves as the central control unit,

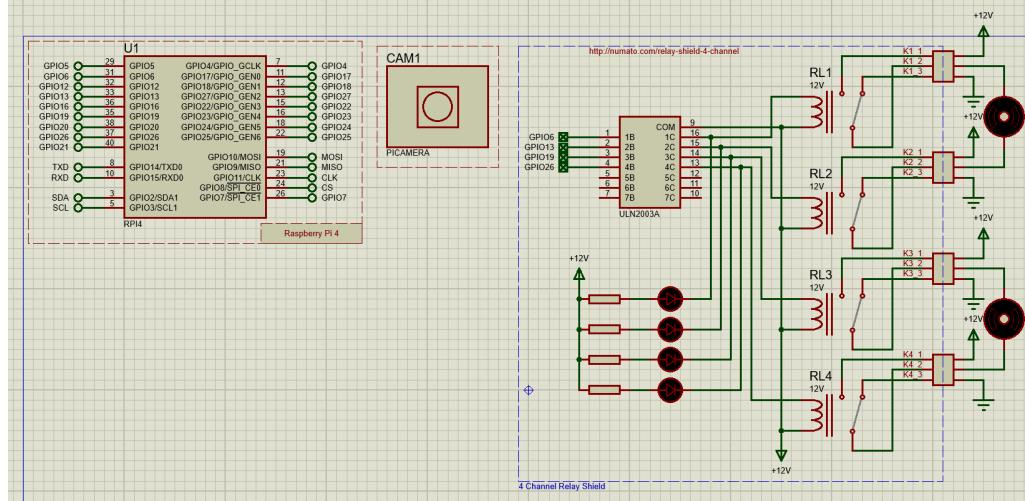


Fig. 4.1 Hardware Schematic

737 managing four motors through a relay mechanism. The Raspberry Pi 4, represented by  
 738 a rectangular box on the left, showcases various pin connections, including GPIO pins,  
 739 power supply pins (5V and 3V3), ground pins (GND), and communication pins (TXD,  
 740 RXD, SDA, SCL).

741 In the center of the diagram, an 18-pin integrated circuit labeled "ULN2803A" is  
 742 depicted. This component, a Darlington transistor array, likely functions as a buffer,  
 743 providing the necessary current to drive the relays. Four relays, designated as RL1, RL2,  
 744 RL3, and RL4, are positioned on the right side of the diagram, each connected to a motor  
 745 (represented by a circle with an "M" inside) and a +12V power source. Additionally, four  
 746 resistors are placed between the ULN2803A and the relays, serving to limit current. The  
 747 circuit section containing these resistors is labeled "4 Channel Relay Driver," indicating its  
 748 purpose.

749 The camera module is labeled "PICAMERA" is located in the top center of the diagram.  
 750 It is represented by a square with a circle inside, symbolizing the camera lens. The camera



751 module is connected to the Raspberry Pi 4 through the CSI (Camera Serial Interface) pins.  
 752 The overall circuit is designed for a 12V system, with the +12V power supply indicated at  
 753 various points. The Raspberry Pi 4's GPIO pins are used to control the relays.

### 754 4.3 Hardware Considerations

755 The hardware components include high-resolution cameras, lighting systems for consistent  
 756 image capture, and microcontrollers like Raspberry Pi or Arduino for system control,  
 757 actuators like DC and stepper motors to move the mangoes. The choice of hardware is  
 758 justified based on cost, performance, and compatibility with the software framework.

#### 759 4.3.1 General Prototype Framework

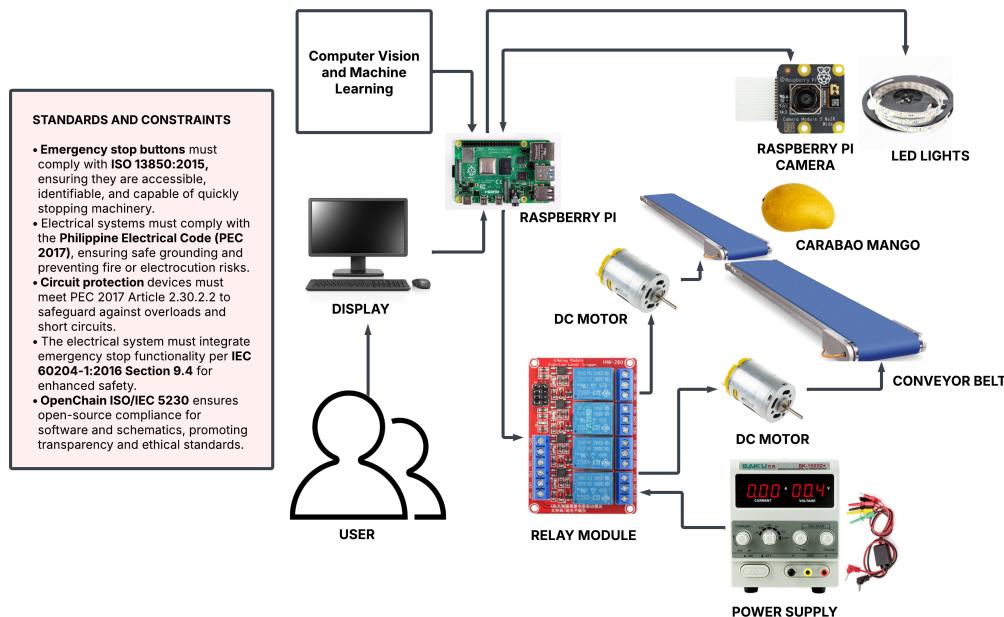


Fig. 4.2 Prototype Framework



760        The Figure 4.2 presents the overall prototype layout of the automated Carabao mango  
761        sorter and grader. The diagram illustrates the flow of operations from mango loading onto  
762        the conveyor belt to sorting them. It illustrates the major elements of the system, that is,  
763        the image acquisition area, lighting system, camera module, Raspberry Pi controller, and  
764        mechanical actuators. The layout illustrates how all the subsystems work together to ensure  
765        mangoes are scanned, processed, sorted based on ripeness, size, and bruises, and eventually  
766        sorted based on the calculated priority score. The layout served as the basis for actual  
767        prototype development.

### 768        **4.3.2 Prototype Flowchart**

769        The flowchart in Figure 4.3 represents the overall operational logic of the mango grading  
770        and sorting system. The process starts with system initialization, where the camera and  
771        lighting modules are switched on and the machine learning algorithms are initialised. The  
772        input of the user priority values as well as the detection of the mango on the conveyor  
773        belt triggers the capture of both the top and bottom cheek of the mango. The captured  
774        image is processed using machine learning algorithms to determine its ripeness, size, and  
775        bruises. Depending on these classifications along with priority weights given by the user,  
776        the system calculates an overall score. Once this calculation is done, the mango is routed to  
777        the respective bin through the respective actuator. Having this logical sequence is important  
778        to know the system's decision-making and automation process.

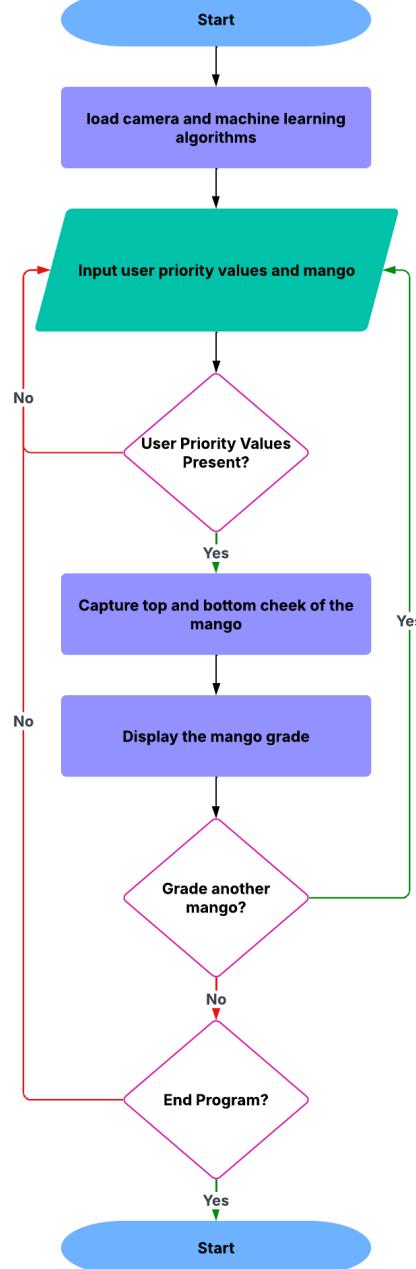


Fig. 4.3 Prototype Main Flowchart



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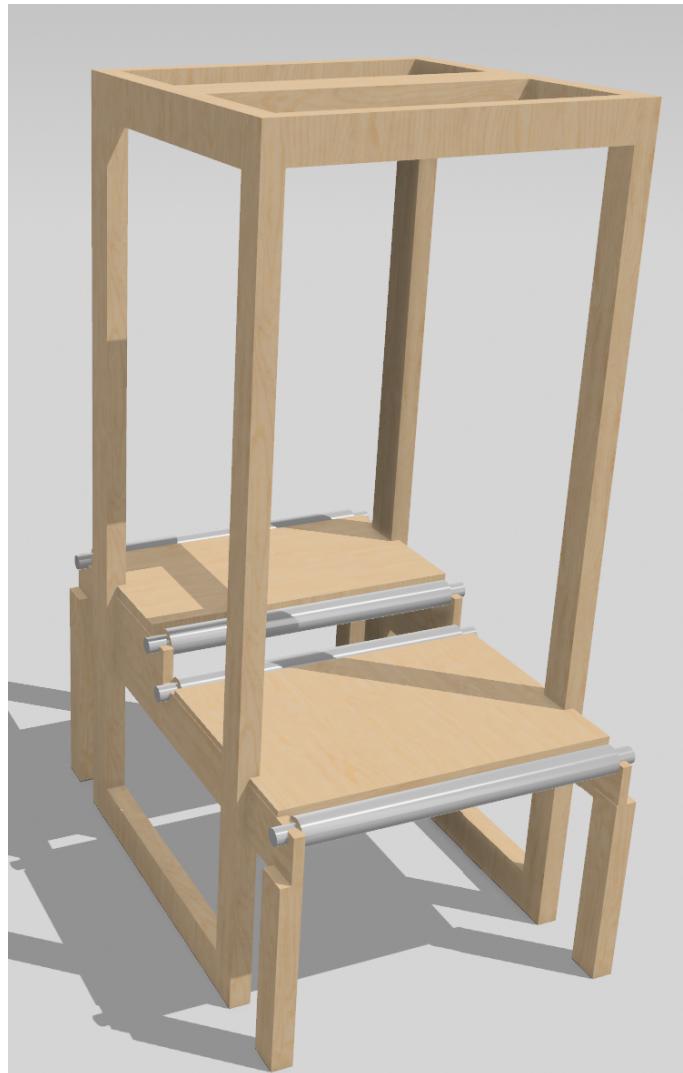


Fig. 4.4 Initial 3D Model of the Prototype



### 779    4.3.3 Prototype 3D Model

780    Figure 4.4 shows the first 3D model of the initial physical prototype developed for the  
781    sorting and grading system. This model shows the skeleton of the system and where  
782    the conveyor system is going to be placed strategically in order to flip the mango for  
783    image acquisition. It is useful for where the hardware components would be arranged  
784    and assembled. This 3D model helped the researchers visualize the spacing, alignment,  
785    and where to mount parts before assembling the prototype making sure all electronic and  
786    mechanical components are effectively integrated.

### 787    4.3.4 Hardware Specifications

#### 788    4.3.4.1 Raspberry Pi



Fig. 4.5    Raspberry Pi 4 Model B

789    Figure 4.5 depicts the Raspberry Pi 4 Model B which is the core of the processing unit



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790 of the prototype. It was selected due to its small size, low cost, and high computing power  
791 for image processing and machine learning. The image depicts the most critical aspects  
792 of the board, such as the GPIO (General Purpose Input/Output) pins for sensor, actuator,  
793 and relay connections, and the USB and HDMI ports for other device connections. Its  
794 capability to support a full operating system makes it suitable for supporting both the user  
795 interface and the control logic of the mango grading system.

796 **Specifications:**

- 797 • SoC: Broadcom BCM2711
- 798 • CPU: Quad-core ARM Cortex-A72 (64-bit)
- 799 • Clock Speed: 1.5 GHz (base, overclockable)
- 800 • RAM: 8GB LPDDR4-3200 SDRAM
- 801 • Wireless: Dual-band 2.4 GHz / 5 GHz Wi-Fi (802.11ac)
- 802 • Bluetooth: Bluetooth 5.0 (BLE support)
- 803 • Ethernet: Gigabit Ethernet (full throughput)
- 804 • USB: 2 x USB 3.0 ports and 2 x USB 2.0 ports
- 805 • Video Output: 2 x micro-HDMI ports (supports 4K @ 60Hz, dual 4K display  
806 capability)
- 807 • Audio: 3.5mm audio/video composite jack
- 808 • Storage: MicroSD card slot (supports booting via SD card or USB)



- 809     • GPIO: 40-pin GPIO header (backward-compatible with older models)  
810     • Camera/Display: CSI (camera) and DSI (display) ports  
811     • Power Input: USB-C (5V/3A recommended)  
812     • Power Consumption: 3W idle, up to 7.5W under load

813     **4.3.4.2 Raspberry Pi Camera**

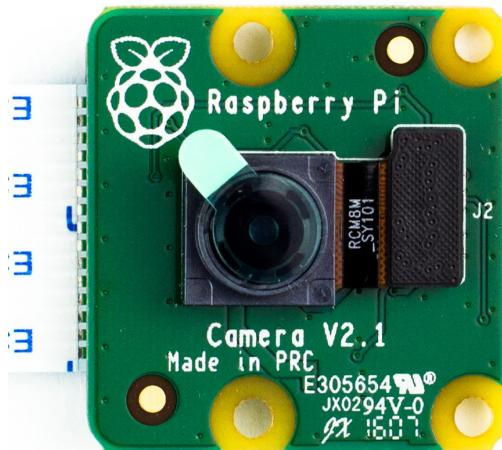


Fig. 4.6 Raspberry Pi Camera Module Version 2

814     The Raspberry Pi Camera Module Version 2 is a high-quality camera module designed  
815     for the Raspberry Pi platform. Likewise, it is capable of capturing still images at 8 megapix-  
816     els, and supports video recording at 1080p @ 30fps, 720p @ 60fps, and 480p @ 90fps.  
817     Moreover, it has a fixed-focus lens with a diagonal field of view of 62.2 degrees, and  
818     an optical format of 1/4 inch. Furthermore, it supports various Python libraries such as  
819     Picamera and OpenCV for image capture and processing. As such, it was selected for its



820 compact size, ease of integration, and ability to capture high-resolution images.

821

822 **Specifications:**

823 • Sensor: Sony IMX219PQ 8-megapixel CMOS sensor.

824 • Still Images Resolution: 8 MP (3280 x 2464 pixels).

825 • Video Resolution: Supports up to 1080p @ 30fps, 720p @ 60fps, and 480p @ 90fps.

826 • Focus: Fixed-focus lens (manual focus adjustment not supported without physical  
827 modification).

828 • Lens Size: 1/4-inch optical format.

829 • Field of View (FoV): Diagonal 62.2 degrees.

830 • Interface: Connected via 15-pin ribbon cable to the Raspberry Pi's CSI (Camera  
831 Serial Interface) port.

832 • APIs/Libraries: Supports Python libraries such as Picamera and OpenCV for image  
833 capture and processing.

834 • Dimensions: 25 mm x 24 mm x 9 mm.

835 **4.3.4.3 DC Motor**

836 The 12 Volt DC Gear Motor is a compact, high-torque, and low-noise motor suitable for a  
837 wide range of applications, including robotics, automation, and industrial control systems.  
838 It features a spur gear design, which provides a high reduction ratio for increased torque  
839 output. The motor is designed for continuous operation and has a low power consumption



Fig. 4.7 12 Volt DC Gear Motor

under standard load conditions. Likewise, it is also capable of withstanding high temperatures and has a high reliability. This motor was selected for its high torque output, low power consumption, and compact size, making it ideal for the conveyor system.

844 **Specifications:**

- 845 • Gearbox Type: Spur gear design
- 846 • Operating Voltage: 12V (operational range: 6-12V)
- 847 • No-load Current Consumption: 0.8A
- 848 • Rated Current Draw: 3A (under standard load)
- 849 • No-load Speed: 282 RPM (maximum)
- 850 • Operating Speed: 248 RPM (under rated load)



- 851     • Torque Output: 18 kg-cm (rated)  
852     • Stall Torque: 60 kg-cm (maximum)  
853     • Power Rating: 50W (maximum)  
854     • Unit Weight: 350 grams

855     **4.3.4.4 MicroSD Card**



Fig. 4.8 SanDisk Ultra MicroSD Card

856     The SanDisk Ultra MicroSD Card is a compact, high-capacity, and secure digital  
857     memory card that is suitable for a wide range of applications, including digital cameras,  
858     smartphones, and tablets. It features a high-speed data transfer rate, making it ideal for  
859     storing large files such as images and videos. This card was selected for its high capacity, se-  
860     cure data protection, and ease of use, making it ideal for the storage system for the prototype.

861  
862     **Specifications:**



- 863     • Capacity: 256GB  
864     • Type: MicroSDXC (Secure Digital eXtended Capacity)  
865     • Form Factor: MicroSD (11mm x 15mm x 1mm)  
866     • File System: Pre-formatted exFAT

867     **4.3.4.5 LED Lights**



Fig. 4.9 LED Light Strip

868     For the Light Emitting Diode (LED), they were used to provide consistent lighting for  
869     image capture, ensuring accurate color representation and feature extraction. The LED  
870     lights were selected for their energy efficiency, long lifespan, and ability to produce a  
871     uniform light output.

872

873     **Specifications:**



- 874     • Power Input: 5V DC (USB-powered, compatible with laptops, power banks, or USB  
875       adapters).
- 876     • Waterproof Design: Suitable for indoor/outdoor use.
- 877     • LED Type: SMD 2835 (surface-mount diodes for high brightness and efficiency).
- 878     • Color Type: White (cool white)
- 879     • Length: 1m
- 880     • Beam Angle: 120°
- 881     • Operating Temperature: -25°C to 60°C.
- 882     • Storage Temperature: -40°C to 80°C.

883 **4.3.4.6 Power Supply**

884 The bench power supply is a versatile and adjustable power source used to provide stable  
885 voltage and current for various electronic projects. It is designed for testing applications,  
886 allowing users to set specific voltage and current levels. This power supply was selected  
887 for its versatility, ease of use, and ability to provide accurate voltage and current control for  
888 the prototype.

889  
890 **Specifications:**

- 891     • Type: SMPS (Switch-Mode Power Supply)
- 892     • Input: 110V AC, 50/60Hz (U.S. Standard)



Fig. 4.10 Bench Power Supply

- 893 • Output Range: 0-30V DC / 0-5A DC
- 894 • Voltage Precision:  $\pm 0.010\text{V}$  (10 mV) resolution
- 895 • Current Precision:  $\pm 0.001\text{A}$  (1 mA) resolution
- 896 • Power Precision:  $\pm 0.1\text{W}$  resolution
- 897 • Weight: 5 lbs (2.27 kg)
- 898 • Dimensions: 11.1" x 4.92" x 6.14" (28.2 cm x 12.5 cm x 15.6 cm)
- 899 • Maximum Power: 195W
- 900 • Power Source: AC input only



Fig. 4.11 4 Channel Relay Module

#### 4.3.4.7 4 Channel Relay Module

The 4 Channel Relay Module is a compact and versatile relay board that allows for the control of multiple devices using a single microcontroller. This module was selected for its compact size, ease of use, and ability to control multiple devices simultaneously. It is designed to be used with microcontrollers such as Arduino and Raspberry Pi, allowing for easy integration into the prototype.

#### Specifications:

- Operating Voltage: 5V DC (compatible with Arduino, Raspberry Pi, and other microcontrollers).
- Number of Relays: 4 independent channels.
- Relay Type: Electromechanical (mechanical switching).



- Max AC Load: 10A @ 250V AC (resistive).
  - Max DC Load: 10A @ 30V DC (resistive).
  - Contact Type: SPDT (Single Pole Double Throw) - NO (Normally Open), NC (Normally Closed), COM (Common).
  - Dimensions: 50mm x 70mm x 20mm
  - Weight: 50-80 grams.
  - Status LEDs: Individual LEDs for each relay (indicates ON/OFF state).
  - Input Pins: 4 digital control pins (one per relay).
  - Output Terminals: Screw terminals for connecting loads (NO/NC/COM).

## 4.4 Software Considerations

The software stack includes Python for programming PyTorch for machine learning and OpenCV for image processing. These tools are selected for their robustness, ease of use, and extensive community support, ensuring efficient system development.

#### 4.4.1 PyTorch

PyTorch is an open-source deep-learning framework used in this project for implementing and running the convolutional neural networks responsible for classifying mango ripeness and detecting bruises. Its dynamic computational graph and GPU acceleration support made it an ideal choice for real-time image classification. Its simplicity and flexibility also



931 allowed for easy integration with the Raspberry Pi which is important as it is the main  
932 processing unit for the system.

933 **4.4.2 OpenCV**

934 Open Source Computer Vision Library or OpenCV is utilized in the system for all image  
935 processing tasks, particularly in preprocessing steps such as background subtraction, thresh-  
936 olding, edge detection, and contour analysis. These operations are essential for calculating  
937 the real-world dimensions of the mango. OpenCV was utilized primarily because of its  
938 diverse set of functions, performance optimization, and ease of use making it a core tool  
939 for enabling accurate and fast computer vision processing within the prototype.

940 **4.4.3 CustomTkinter**

941 CustomTkinter is a modern alternative to the standard Tkinter library, and is used to  
942 build the graphical user interface (GUI) of the system. It provides a more polished and  
943 customizable visual appearance while retaining the simplicity of Tkinter. With features  
944 such as styled buttons, frames, and labels, CustomTkinter allowed for the creation of  
945 a user-friendly interface that supports real-time display of classification results, priority  
946 scoring inputs, and system status updates.

947 **4.5 Security and Reliability Considerations**

948 Potential vulnerabilities, such as data corruption during image capture, are addressed  
949 through redundancy and error-checking mechanisms. Reliability is ensured by implement-  
950 ing fault-tolerant designs and rigorous testing protocols.



## 951    **4.6 Scalability and Efficiency Considerations**

952    The system is designed to handle large volumes of mangoes by optimizing the machine  
953    learning model and using parallel processing techniques. Efficiency is improved through  
954    techniques like model quantization and hardware acceleration.

## 955    **4.7 User Interface**

956    A User Interface (UI) is designed to display grading results, system status. Wireframes  
957    illustrate the layout, ensuring usability and accessibility for operators. Likewise, a Graphical  
958    User Interface (GUI) is also used to allow users to customize the system's grading priorities.

## 959    **4.8 Constraints and Limitations**

960    Challenges include variations in mango appearance due to lighting and environmental  
961    factors. Trade-offs are made between model complexity and real-time performance to  
962    balance accuracy and speed.

## 963    **4.9 Technical Standards**

964    The system adheres to industry standards for image processing and machine learning,  
965    ensuring compatibility and interoperability with other systems.



## 4.10 Prototyping and Simulation

Prototypes are developed using tools like MATLAB and Simulink to simulate the system's performance. These simulations help identify design flaws and optimize the system before deployment.,

## 4.11 Design Validation

The design is validated through testing, including unit testing of individual modules and integration testing of the entire system. Peer reviews and iterative improvements ensure the system meets the desired performance metrics.

## 4.12 Summary

This chapter outlined the key design considerations, including system architecture, hardware and software choices, and validation methods. These decisions are critical for developing a reliable and efficient mango sorting and grading system.



978

## Chapter 5

979

# METHODOLOGY



TABLE 5.1 SUMMARY OF METHODS FOR REACHING THE OBJECTIVES

Objectives	Methods	Locations
GO: To develop a user-priority-based grading and sorting system for Carabao mangoes, using machine learning and computer vision techniques to assess ripeness, size, and bruises.	<ol style="list-style-type: none"> <li>1. Hardware design: Build an image acquisition system with a conveyor belt, LED lights, and Raspberry Pi Camera</li> <li>2. Software design: Coded a Raspberry Pi application to grade and sort the Carabao mangoes</li> </ol>	Sec. 5.2 on p. 54
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ol style="list-style-type: none"> <li>1. Hardware implementation: Design and build an image acquisition system prototype</li> </ol>	Sec. 5.3 on p. 54
SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.	<ol style="list-style-type: none"> <li>1. Performance testing: Train and test the machine learning algorithm for classifying bruises and ripeness</li> <li>2. Data collection: Gather our own Carabao mango dataset together with an online dataset</li> </ol>	Sec. 5.5 on p. 56

*Continued on next page*



*Continued from previous page*

Objectives	Methods	Locations
SO3: To create a microcontroller-based system to operate the image acquisition system, control the conveyor belt, and process the mango images through machine learning.	1. Algorithm development: To develop a code for the image acquisition system 2. Hardware design: To design a schematic for the microcontroller based system	Sec. 5.3 on p. 54
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	1. Formula development: Formulated an equation based on the inputted user priority and the predicted mango classification	Sec. 5.7 on p. 63
SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.	1. Performance testing: Train and test the machine learning algorithm for classifying bruises	Sec. 5.6.3 on p. 60
SO6: To classify mango size based on image data by getting its length and width using OpenCV, geometry, and image processing techniques.	1. Performance testing: Train and test the machine learning algorithm for classifying ripeness	Sec. 5.6.2 on p. 59
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	1. Accuracy testing: Get the percent accuracy testing for getting the length and width of the Carabao mango	Sec. 5.6.4 on p. 62



## 980 5.1 Introduction

981 The methodology for this research outlines the development of the Carabao Mango sorter  
982 using machine learning and computer vision. The sorting system uses a conveyor belt  
983 system which delivers the mangoes into the image acquisition system. This system captures  
984 the image of the mangoes which will then be going through the various stages of image  
985 processing and classification into grades which will depend on the priority of the user.  
986 This methodology ensures that the grading of the mangoes will be accurate while being  
987 non-destructive.

## 988 5.2 Research Approach

989 This study applies the experimental approach for research in order to develop and properly  
990 test the proposed system. The experimental approach of the methodology will allow the  
991 researchers to fine-tune the parameters and other factors in the classification of mangoes in  
992 order to get optimal results with high accuracy scores while maintaining the quality of the  
993 mangoes. This approach will also allow for real-time data processing and classification  
994 which will improve the previous static grading systems.

## 995 5.3 Hardware Design

996 The prototype consists of hardware and software components for automated mango sorting  
997 and grading purposes. The hardware includes the conveyor belt system used to transfer  
998 mangoes from scanning to sorting smoothly. A camera and lighting system are able  
999 to collect high-resolution images for analysis. The DC motors and stepper motors are



1000 responsible for driving the conveyor belt and sorting actuators. The entire system is  
1001 controlled by a microcontroller (Raspberry Pi 4b), coordinating actions of all components.  
1002 Sorting actuators then direct mangoes into selected bins based on their classification to  
1003 make sorting efficient.

## 1004 **5.4 Software Design**

1005 For the programming language used for the prototype and training and testing the CNN  
1006 model, Python was used for training and testing the CNN model and it was also used in the  
1007 microcontroller to run the application containing the UI and CNN model. PyTorch was the  
1008 main library used in using the EfficientNet model that is used in classifying the ripeness  
1009 and bruises of the mango. Likewise, tkinter is the used library when designing the UI in  
1010 Python.

1011 Furthermore, the rest of the software components are of utmost importance to mango  
1012 classification. Image processing algorithms in OpenCV and CNN models extract features  
1013 such as color, size, and bruises that are known to determine quality parameters of mangoes.  
1014 Mangoes are classified based on ripeness and defects by using machine learning algorithms,  
1015 which further enhances accuracy using deep learning techniques. A user interface (UI) is  
1016 designed for users to control and observe the system in real time. Finally, the interface  
1017 programming of the microcontroller provides the necessary synchronization between  
1018 sensors, actuators, and motors throughout the sorting operation scenario.



## 1019    5.5 Data Collection Methods

1020    For the data collection, online available image datasets with Carabao mangoes were used  
1021    together with the captured Carabao mango images. For the setup of the captured Carabao  
1022    mangoes, the height of the camera to the white flat surface is 26 cm which can be seen  
1023    on Figure 5.1. Furthermore, the S24's camera is used for capturing both cheeks of the  
1024    Carabao mango. Initially, the Carabao mangoes would be unripe and green and each day  
1025    the Carabao mangoes would be pictured until they are ripe.



Fig. 5.1 Carabao Mango Image Data Collection

## 1026    5.6 Testing and Evaluation Methods

1027    In a bid to ensure the mango sorting and grading system is accurate and reliable, there is  
1028    intensive testing conducted at different levels. Unit testing is initially conducted on each  
1029    component separately, for instance, the conveyor belt, sensors, and cameras, to ensure that



1030 each of the components works as expected when operating separately. After component  
 1031 testing on an individual basis, integration testing is conducted to ensure communication  
 1032 between hardware and software is correct to ensure the image processing system, motors,  
 1033 and sorting actuators work in concert as required. System testing is conducted to con-  
 1034 duct overall system performance testing in real-world conditions to ensure mangoes are  
 1035 accurately and efficiently sorted and graded.

## 5.6.1 Classification Report

### 5.6.1.1 Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

TABLE 5.2 CONFUSION MATRIX EXAMPLE

1038 A confusion matrix is a table that visualizes the performance of a classification model.  
 1039 For a binary classification problem, it has four components:

- 1041 • True Positives (TP): Cases correctly predicted as positive
- 1042 • True Negatives (TN): Cases correctly predicted as negative
- 1043 • False Positives (FP): Cases incorrectly predicted as positive. (Type I error)
- 1044 • False Negatives (FN): Cases incorrectly predicted as negative (Type II error)

1045 **5.6.1.2 Precision**

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5.1)$$

1046 Precision measures how many of the predicted positives are actually positive. It answers  
 1047 the question: "When the model predicts the positive class, how often is it correct?" High  
 1048 precision means low false positives.

1049 **5.6.1.3 Recall**

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5.2)$$

1050 Recall, which is also called sensitivity, measures how many of the actual positives were  
 1051 correctly identified. It answers the question: "Of all the actual positive cases, how many  
 1052 did the model catch?" High recall means low false negatives.

1053 **5.6.1.4 F1 Score**

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5.3)$$

1054 The F1 score is the harmonic mean of precision and recall. It provides a single metric  
 1055 that balances both concerns. This is particularly useful when you need to find a balance  
 1056 between precision and recall, as optimizing for one often decreases the other.

1057 **5.6.1.5 Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5.4)$$



1058 Accuracy measures the proportion of correct predictions (both true positives and true  
1059 negatives) among the total cases. While intuitive, accuracy can be misleading with imbal-  
1060 anced datasets.

1061 To test system performance, various measures of performance are used to evaluate.  
1062 As seen on equation 5.4, accuracy score is used to measure the percentage of correctly  
1063 classified mangoes to ensure the system maintains high precision levels. Precision as seen  
1064 on equation 5.1 and recall as seen on equation 5.2 are used to measure consistency of  
1065 classification to determine if the system classifies different ripeness levels and defects  
1066 correctly. Furthermore, the F1 score formula as seen on equation 5.3 is used to evaluate the  
1067 performance of the model's classification.

1068 A confusion matrix is used to measure correct and incorrect classification to ensure the  
1069 machine learning model is optimized and that minimum errors are achieved. Throughput  
1070 analysis is also used to determine the rate and efficiency of sorting to ensure that the  
1071 system maintains high capacity without bottlenecks to sort mangoes. Using these methods  
1072 of testing, the system is constantly optimized to ensure high-quality and reliable mango  
1073 classification.

### 1074 **5.6.2 Ripeness Training and Testing**

1075 For the testing of the ripeness classification, the Carabao mangoes are classified into three  
1076 ripeness stages which are Green, green yellow, and yellow. Likewise, The green would  
1077 represent the ripe mangoes while the green yellow would represent the semi ripe while the  
1078 yellow would represent the ripe mangoes. As reference, Figure 5.3 shows the different  
1079 ripeness stages for Carabao/Pico mangoes.



## Annex A

## Stages of ripeness of 'carabao' and 'pico' mango fruits

Stage of ripeness	Peel color	Flesh color
Green	Completely light green	Yellowish white or light yellow green
Breaker	Traces of yellow	Middle area and fruit outline yellowish; other areas, white to yellowish white
Turning	More green than yellow	More yellow than white
Semi-ripe	More yellow than green	Yellow for 'carabao'; yellow orange for 'pico'
Ripe	80-100% yellow ('carabao') or yellow orange ('pico')	Middle area yellow for 'carabao'; yellow orange for 'pico'
Overripe	Yellow for 'carabao'; yellow orange for 'pico'	100% yellow for 'carabao' and yellow orange for 'pico'

Fig. 5.2 Carabao Mango Ripeness Stages

### 5.6.3 Bruises Training and Testing

For the testing of the bruise classification of the Carabao mangoes, it would classified into two categories which are bruised and not bruised. To define what bruise and not bruise mangoes looked like Figure 5.3 is used as reference to categorize which mangoes are bruised and not bruised.

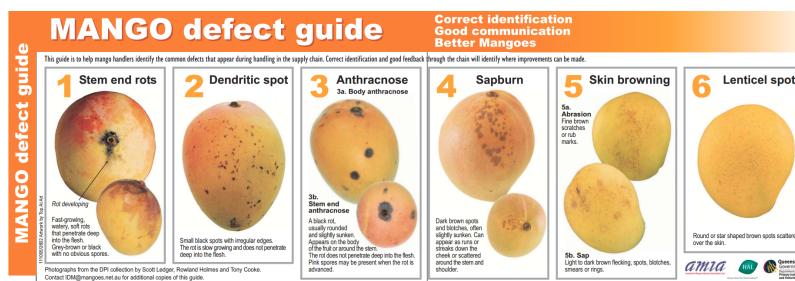


Fig. 5.3 Different Kinds of Mango Defects



1085 **5.6.3.1 Stem End Rots**

1086 Stem end rots are characterized by fast-growing, watery, soft rots that penetrate deeply into  
1087 the flesh. Likewise, it usually appear as grey-brown or black rots starting from the stem  
1088 end, often without obvious spores, that can spread rapidly into the mango.

1089 **5.6.3.2 Dendritic Spot**

1090 Dendritic spots, on the other hand, are small black spots with irregular edges scattered  
1091 across the skin. Furthermore, it grow slowly and do not penetrate into the flesh, remaining  
1092 largely superficial.

1093 **5.6.3.3 Anthracnose**

1094 Anthracnose appears in two forms. First form is through body anthracnose. Body anthrac-  
1095 nose presents as black rots on the fruit surface that are usually round, slightly sunken, and  
1096 located on different parts of the mango. Likewise, the second form is stem end anthracnose.  
1097 Stem end anthracnose occurs around the stem, also presenting as black rots. While these  
1098 rots do not penetrate deeply into the flesh, advanced cases may show pink spores.

1099 **5.6.3.4 Sapburn**

1100 Sapburn appears as dark brown spots or blotches that are often slightly sunken. Likewise,  
1101 damage can occur as runs or streaks down the cheek or as scattered marks around the stem  
1102 and shoulder, resulting from sap exposure.



1103 **5.6.3.5 Skin Browning**

1104 Skin browning may take two forms. First form is abrasion while the second form is sap  
1105 browning. Abrasion is recognized as fine brown scratches or rub marks, while sap-related  
1106 browning appears as light to dark brown flecking, spots, blotches, smears, or rings. These  
1107 types of browning are generally limited to the skin and do not penetrate deeply.

1108 **5.6.3.6 Lenticel Spot**

1109 Lenticel spots are another common defect, appearing as round or star-shaped brown spots  
1110 scattered across the skin surface. Furthermore, these defects are usually cosmetic in nature  
1111 and do not significantly affect the flesh.

1112 **5.6.4 Size Determination**

1113 To get the size of the mangoes, computer vision techniques such as Gaussian Blur and  
1114 Thresholding are used to get the length and width of the mangoes.

1115 **5.6.4.1 Computer Vision**

1116 For the computer vision method of getting the length and width of the mango a foreground  
1117 masking is generated by getting absolute difference between the foreground, that is the  
1118 mango, and the background. Furthermore, image augmentation techniques such as Gaussian  
1119 blur, grayscale, and Canny edge detection are used. After that, the largest contour on the  
1120 foreground masking image is used. Once the largest contour is found then the length and  
1121 width is calculated using equation 3.2.



1122    **5.6.4.2 Object Detection**

1123    For the object detection method, an annotated Carabao mango dataset containing 488  
 1124    images were used. Likewise, the pretrained Faster RCNN model used is the MobileNetV3.

1125    **5.7 Mango Formula with User Priority**

1126    The linear equation used to calculate the Carabao mango grade is shown below. Likewise,  
 1127    the variables  $B(P)$ ,  $R(P)$ , and  $S(P)$  represent the user-defined priority weightings for  
 1128    bruising, ripeness, and size characteristics in the User Priority-Based Grading system.  
 1129    Additionally,  $b(p)$ ,  $r(p)$ , and  $s(p)$  correspond to the machine learning model's predicted  
 1130    values for the bruising, ripeness, and size attributes of the Carabao mango.

$$\text{Mango Grade} = b(P)B(P) + r(P)R(P) + s(P)S(P) \quad (5.5)$$

1131    The machine learning predictions are assigned the following numerical values:

1132    **Ripeness Scores:**

$$r(\text{yellow}) = 1.0 \quad (5.6)$$

$$r(\text{yellow-green}) = 2.0 \quad (5.7)$$

$$r(\text{green}) = 3.0 \quad (5.8)$$

1133    **Bruises Scores:**

$$b(\text{bruised}) = 1.0 \quad (5.9)$$

$$b(\text{unbruised}) = 2.0 \quad (5.10)$$



1134 **Size Scores:**

$$s(\text{small}) = 1.0 \quad (5.11)$$

$$s(\text{medium}) = 2.0 \quad (5.12)$$

$$s(\text{large}) = 3.0 \quad (5.13)$$

1135 

## 5.8 Ethical Considerations

1136 Ethical considerations ensure that the system is operated safely and responsibly. Data  
 1137 privacy is ensured by securely storing and anonymizing extracted images and classification  
 1138 data so that unauthorized access becomes impossible. The system is also eco-friendly  
 1139 through non-destructive testing, saving mangoes while also ensuring that they are of good  
 1140 quality. Safety in operations is also ensured by protecting moving parts to prevent mechani-  
 1141 cal harm and incorporating fail-safes to securely stop operation in case of malfunction.  
 1142 Addressing these concerns, the system is not only accurate and efficient but also secure,  
 1143 eco-friendly, and safe for operators, thus a sustainable solution to automated mango sorting  
 1144 and grading.

1145 

## 5.9 Summary

1146 This chapter explained how to create an automatic Carabao mango sorter and grader using  
 1147 machine learning and computer vision. The system integrates hardware and software  
 1148 resources, including a conveyor belt, cameras, sensors, and actuators, to offer accurate,  
 1149 real-time sorting by ripeness, size, and bruises. Various testing and evaluation processes  
 1150 ensure its performance to offer reliability. Ethical issues are data privacy, environmental



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1151 sustainability, and operation safety. With enhanced efficiency, reduced human error, and  
1152 enhanced quality, this system provides an affordable, scalable, and non-destructive solution  
1153 to post-harvest mango classification in agricultural industries.



1154

## Chapter 6

1155

# RESULTS AND DISCUSSIONS



TABLE 6.1 SUMMARY OF METHODS FOR ACHIEVING THE OBJECTIVES

Objectives	Methods	Locations
GO: To develop a user-priority-based grading and sorting system for Carabao mangoes, using machine learning and computer vision techniques to assess ripeness, size, and bruises.	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully developed a user-priority-based grading and sorting system using machine learning and computer vision which can assess the mangoes' ripeness, size and bruises.</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. More work needs to be done to fine tune the software components to achieve higher accuracy such as changing hyperparameters or using a newer version of EfficientNet</li> <li>2. More work needs to be done to make the hardware component more robust such as by fixing the camera and LED lights in place</li> </ul>	Sec. 6.6 on p. 84
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully integrated a conveyor belt with the image acquisition in order to achieve efficient flow of automated sorting and grading of the mangoes.</li> <li>2. Successfully integrated LED strips to provide optimal lighting for image capturing of the mangoes.</li> <li>3. Successfully fixed the hardware components in place</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully integrated a conveyor belt with the image acquisition in order to achieve efficient flow of automated sorting and grading of the mangoes.</li> <li>2. Successfully integrated LED strips to provide optimal lighting for image capturing of the mangoes.</li> <li>3. Need to fix the hardware components in place</li> </ul>	Sec. 6.4 on p. 79

Continued on next page

## 6. Results and Discussions



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*Continued from previous page*

Objectives	Methods	Locations
<p>SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for ripeness classification of Carabao mangoes</li> <li>2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruises classification of Carabao mangoes</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully achieved at least 93% accuracy for ripeness classification of Carabao mangoes</li> <li>2. Successfully achieved at least 73% accuracy for bruise classification of Carabao Mangoes</li> </ul>	<p>Sec. 6.1 on p. 71</p>
<p>SO3: To create a microcontroller-based system to operate the image acquisition system, control the conveyor belt, and process the mango images through machine learning.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully made a conveyor belt system to move the mangoes through the image acquisition system to the sorting system</li> <li>2. Successfully mounted the image acquisition system on the prototype</li> <li>3. Successfully made the frame for the conveyor belt and image acquisition system to sit on</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully made a conveyor belt system to move the mangoes through the image acquisition system to the sorting system</li> <li>2. Temporarily mounted the image acquisition system on the prototype</li> <li>3. Successfully made the frame for the conveyor belt and image acquisition system to sit on</li> </ul>	<p>Sec. 6.4 on p. 79</p>

*Continued on next page*

## 6. Results and Discussions



# De La Salle University

*Continued from previous page*

<b>Objectives</b>	<b>Methods</b>	<b>Locations</b>
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully grade mangoes based on the user priorities on the physical characteristics of the mango</li> <li>2. Successfully verified with qualified individual the results</li> <li>3. Successfully utilize the weighted equation to evaluate mango grade based on user priorities</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully grade mangoes based on the user priorities on the physical characteristics of the mango</li> <li>2. Successfully utilize the weighted equation to evaluate mango grade based on user priorities</li> <li>3. Need to look for a qualified person to evaluate the graded mango for ground truth</li> </ul>	Sec. 6.3 on p. 78

*Continued on next page*

## 6. Results and Discussions



# De La Salle University

*Continued from previous page*

Objectives	Methods	Locations
<p>SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Achieve at least 90% accuracy on performance metrics</li> <li>2. Obtain performance metrics for kNN, k-mean, and Naive Bayes methods for comparison and show the superior performance of using CNN</li> <li>3. Successfully fine tuned the CNN model to achieve the highest accuracy possible, choosing the best performing among EfficientNet b0-b7, and testing other CNN hyperparameters</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully trained a CNN model using EfficientNet-b0 and Adam Optimizer to detect ripeness based on color</li> <li>2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for ripeness classification of Carabao mangoes</li> </ul>	<p>Sec. 6.1.1 on p. 72</p>
<p>SO6: To classify mango size based on image data by getting its length and width using OpenCV, geometry, and image processing techniques.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Successfully classified mango size using computer vision techniques</li> <li>2. Successfully tuned to have an accurate size with an 80 percent accuracy rating</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully classified mango size using computer vision techniques</li> <li>2. Calculation of mango size is somewhat inaccurate and needs more fine tuning</li> </ul>	<p>Sec. 6.2 on p. 75</p>

*Continued on next page*



*Continued from previous page*

Objectives	Methods	Locations
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<p>Expected Results:</p> <ul style="list-style-type: none"> <li>1. Achieve at least 90% accuracy on performance metrics</li> <li>2. Successfully fine tuned the CNN model to achieve the highest accuracy possible, choosing the best performing among EfficientNet b0-b7, and testing other CNN hyperparameters</li> </ul> <p>Actual Results:</p> <ul style="list-style-type: none"> <li>1. Successfully trained a CNN model using EfficientNet-b0 and Adam Optimizer to bruises</li> <li>2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruise classification of Carabao mangoes</li> </ul>	Sec. 6.1.2 on p. 74

1156

## 6.1 Training and Testing Results of the Model

Model	Accuracy	
	Ripeness	Bruises
EfficientNetB0	89	87
VggNet16	43	54
AlexNet	43	54
ResNet50	87	84
GoogleNet	89	81
MobileNetV2	90	86
DenseNet121	88	84

TABLE 6.2 OVERALL ACCURACY RESULTS OF DIFFERENT CNN MODELS



	Accuracy	
EfficientNet	Ripeness	Bruises
B0	89	87
B1	86	90
B2	92	90
B3	88	91
B4	90	90
B5	92	88
B6	93	88

TABLE 6.3 OVERALL ACCURACY RESULTS OF DIFFERENT EFFICIENTNET VERSIONS

### 6.1.1 Ripeness Classification Results

Add the F1-Score and etc here

EfficientNet Version	Precision	Recall	F1	Test Accuracy
b0	0.9841	0.9838	0.9838	0.98
b1	0.9876	0.9876	0.9876	0.99
b2	0.9802	0.9801	0.9801	0.98
b3	0.9709	0.968	0.9684	0.97
b4	0.9716	0.9699	0.9699	0.97

TABLE 6.4 PERFORMANCE METRICS FOR DIFFERENT EFFICIENTNET VERSIONS

	Precision	Recall	F1	Support
Green	0.95	0.94	0.95	135
Green Yellow	0.77	0.78	0.77	81
Yellow	0.70	0.71	0.71	80
Accuracy			0.83	296
Macro Avg	0.81	0.81	0.81	296
Weighted Avg	0.84	0.83	0.84	296

TABLE 6.5 RIPENESS CLASSIFICATION REPORT USING KNN

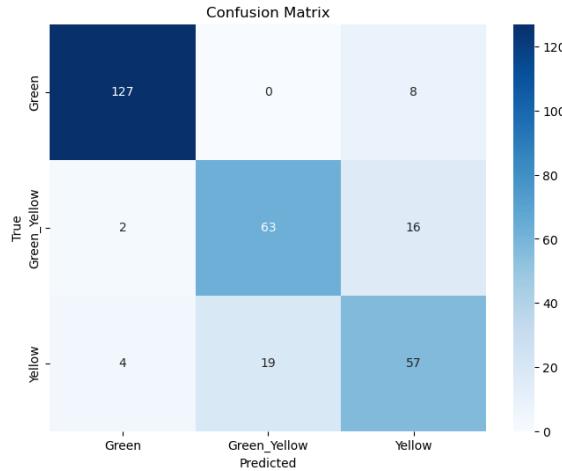


Fig. 6.1 Ripeness Confusion Matrix using kNN

	Precision	Recall	F1	Support
Green	0.96	0.76	0.85	135
Yellow Green	0.75	0.30	0.42	81
Yellow	0.45	0.88	0.59	80
Accuracy			0.67	296
Macro Avg	0.72	0.64	0.62	296
Weighted Avg	0.76	0.67	0.66	296

TABLE 6.6 RIPENESS CLASSIFICATION REPORT USING NAIVE BAYES

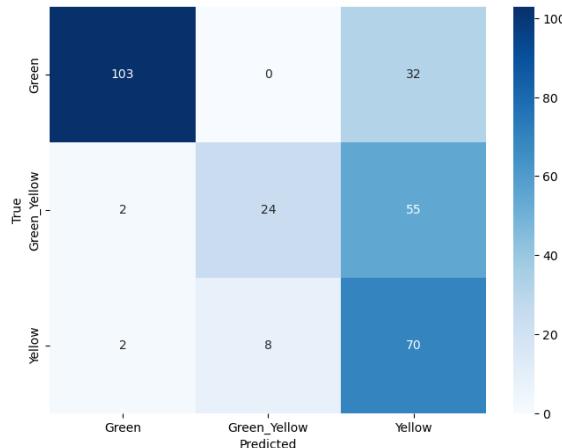


Fig. 6.2 Ripeness Confusion Matrix using Naive Bayes



1159

### 6.1.2 Bruises Classification Results

1160

Add description on how the bruises results were taken and how many images were used.

	Precision	Recall	F1	Support
Bruised	0.97	0.90	0.93	1515
Not Bruised	0.88	0.97	0.92	1146
Accuracy			0.93	2661
Macro Avg	0.93	0.93	0.93	2661
Weighted Avg	0.93	0.93	0.93	2661

TABLE 6.7 BRUISES CLASSIFICATION REPORT USING CNN

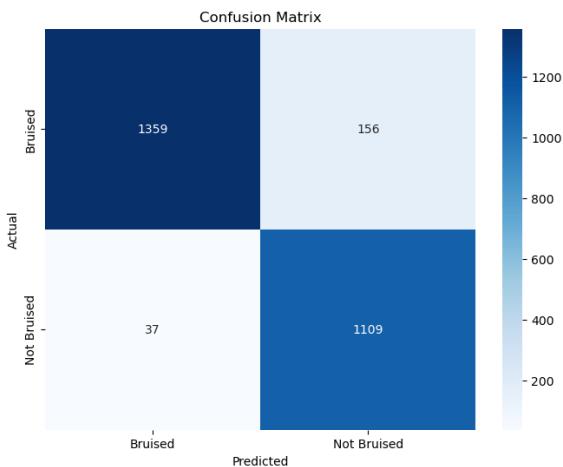


Fig. 6.3 Bruises Confusion Matrix using CNN

Metrics	Results
Precision	0.9318
Recall	0.9275
F1 Score	0.9278

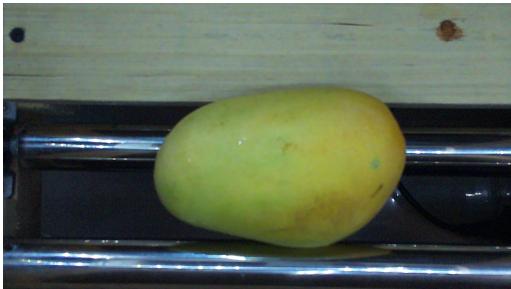
TABLE 6.8 SUMMARIZED CLASSIFICATION REPORT USING CNN



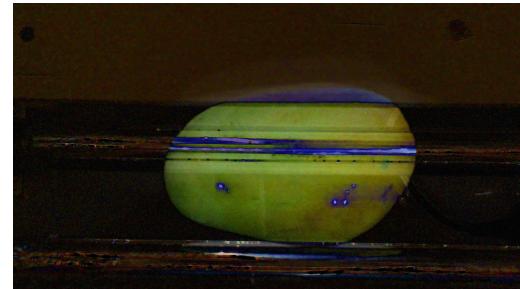
## 6.2 Size Determination Results

### 6.2.1 Method 1: Computer Vision

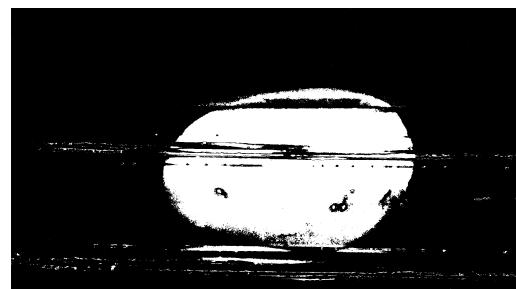
To get the length and width of the mango. An initial image without the mango is taken which would be the background image. After that another image is taken with the mango which would be the foreground image.



(a) Original



(b) Foreground Masking



(c) Thresholding

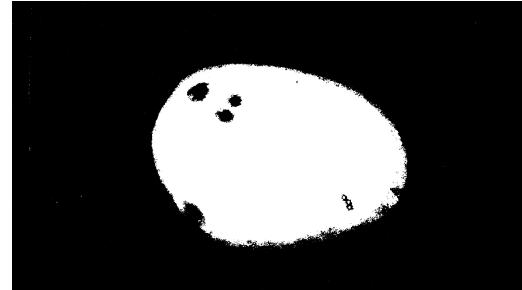
Fig. 6.4 Mango Size with Reflective Material

### 6.2.2 Method 2: Object Detection

For the second method, the researchers train an object detection which is a faster RCNN specifically the MobileNetV3. This was used because of its lightweight properties for the



(a) Original

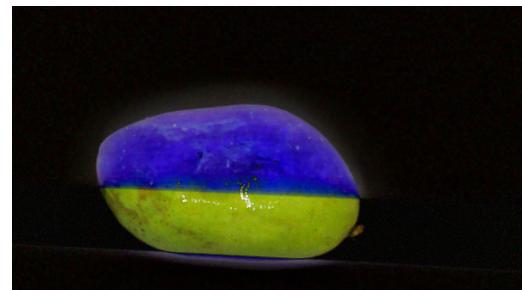


(b) Thresholding

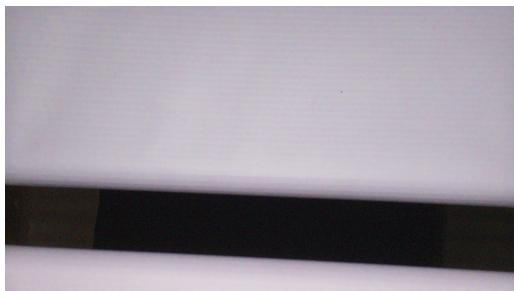
Fig. 6.5 Mango Size Best Case



(a) Original



(b) Foreground Masking

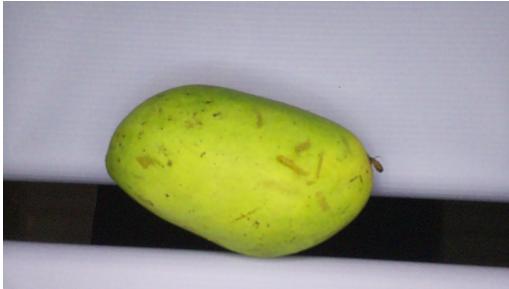


(c) Background

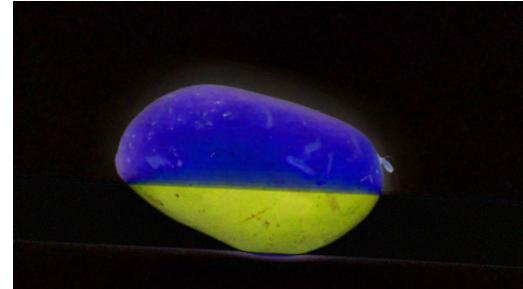


(d) Thresholding

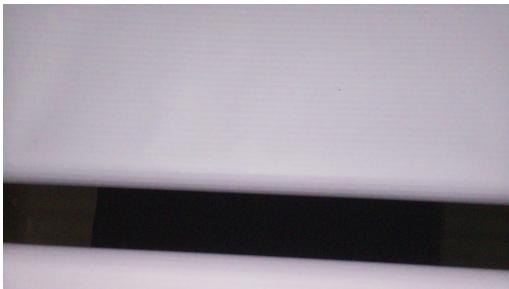
Fig. 6.6 Mango Top Side with White Conveyor



(a) Original View



(b) Foreground Masking



(c) Background



(d) Thresholding

Fig. 6.7 Mango Bottom Side with White Conveyor

1169 Raspberry Pi deployment.

#### 1170 **6.2.2.1 Training and Testing**

1171 For the training of the object detection, the researchers annotated 488 images to detect the  
1172 mango.

#### 1173 **6.2.2.2 Calibration to the Prototype**

1174 To calibrate the model to measure the real world length and width of the mango, the  
1175 researchers calibrated the model using a Philippine peso coin which has a diameter of 2.4  
1176 cm.



1177        self.reference\_box = [815, 383, 999, 556]  
 1178        self.reference\_size\_cm = 2.4



Fig. 6.8 Calibration using Faster RCNN and a Philippine one peso coin

1179        Likewise, the reference box that contain the four coordinate points to the coin and the  
 1180        reference size in cm is added to the prototype's code.

### 6.3 Formula with User Priority

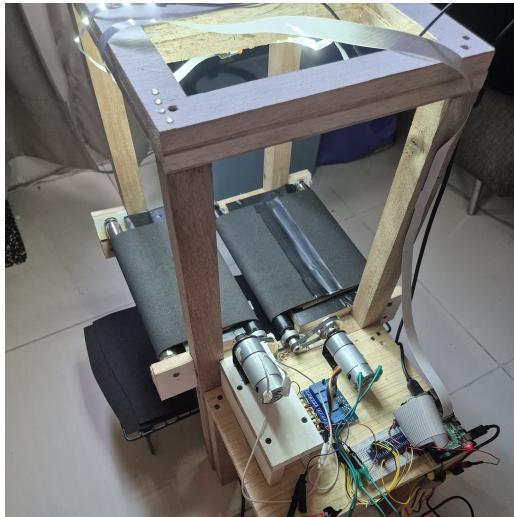
1182         $B(P)$  and  $R(P)$  and  $S(P)$  are the User Priority-Based Grading for bruises, ripeness,  
 1183        and size of the Carabao mango. Furthermore,  $b(p)$  and  $r(p)$  and  $s(p)$  are the machine  
 1184        learning's predictions for bruises, ripeness, and size of the Carabao mango. The formula  
 1185        for the user priority is given by:

$$\text{Mango Grade} = b(P)B(P) + r(P)R(P) + s(P)S(P) \quad (6.1)$$

The machine learning predictions are assigned the following numerical values:



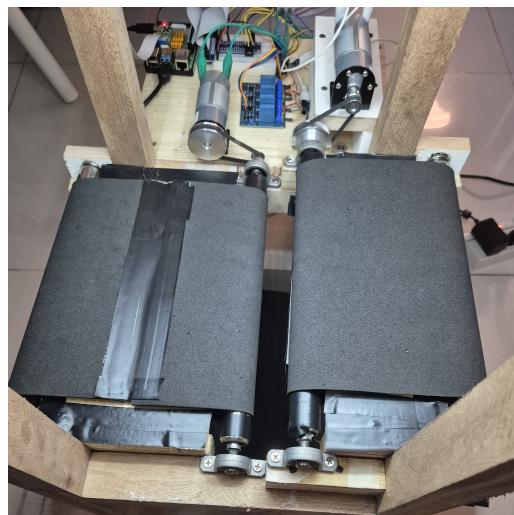
1187	<b>Ripeness Scores:</b>
	$r(\text{yellow}) = 1.0$ (6.2)
	$r(\text{yellow-green}) = 2.0$ (6.3)
	$r(\text{green}) = 3.0$ (6.4)
1188	<b>Bruises Scores:</b>
	$b(\text{bruised}) = 1.0$ (6.5)
	$b(\text{unbruised}) = 2.0$ (6.6)
1189	<b>Size Scores:</b>
	$s(\text{small}) = 1.0$ (6.7)
	$s(\text{medium}) = 2.0$ (6.8)
	$s(\text{large}) = 3.0$ (6.9)
1190	<b>6.4 Physical Prototype</b>
1191	Add pictures of the hardware prototype here with description
1192	<b>6.5 Software Application</b>
1193	Show the raspberry pi app UI and demonstrate it here



(a) Prototype Top View

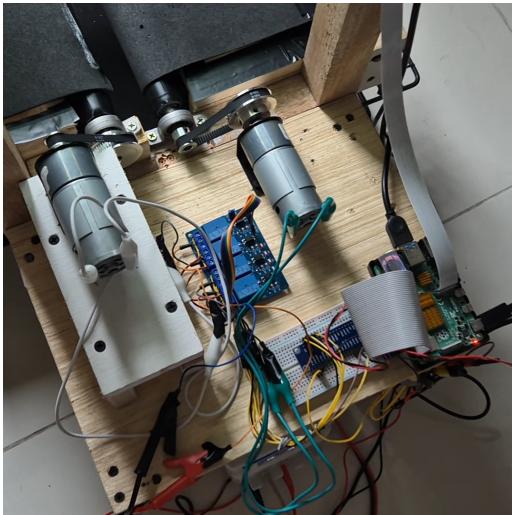


(b) Entrance Conveyor Belt View



(c) Side Conveyor Belt View

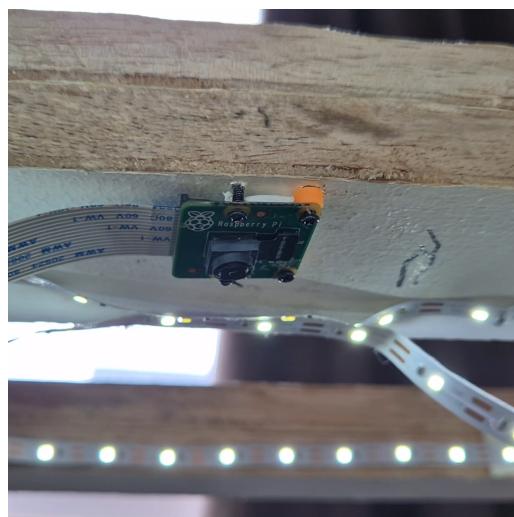
Fig. 6.9 Version 1: Prototype



(a) Prototype Main Hardware



(b) DC Motor and Pulley



(c) LED Lights and Camera Module

Fig. 6.10 Hardware View

## 6. Results and Discussions



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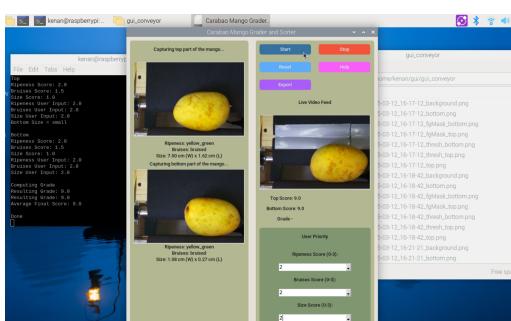


(a) Side View of Improved Prototype

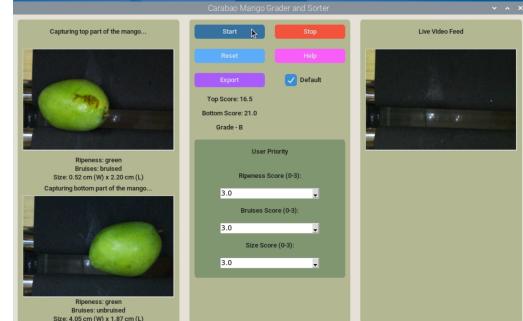


(b) Top View of Improved Prototype

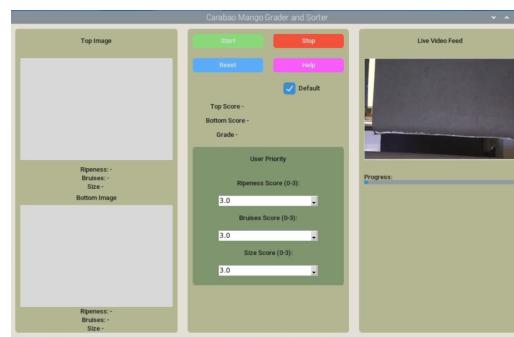
Fig. 6.11 Version 2: Improved Prototype



(a) Version 1



(b) Version 2



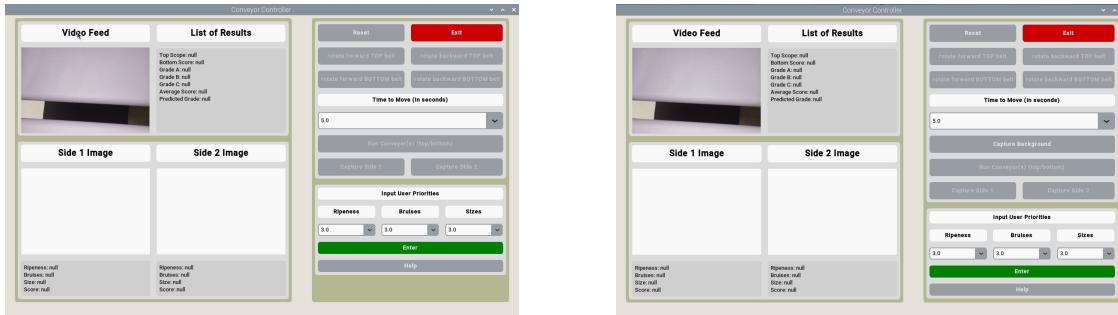
(c) Version 3

Fig. 6.12 Version 1: User Interface of the Raspberry Pi

## 6. Results and Discussions



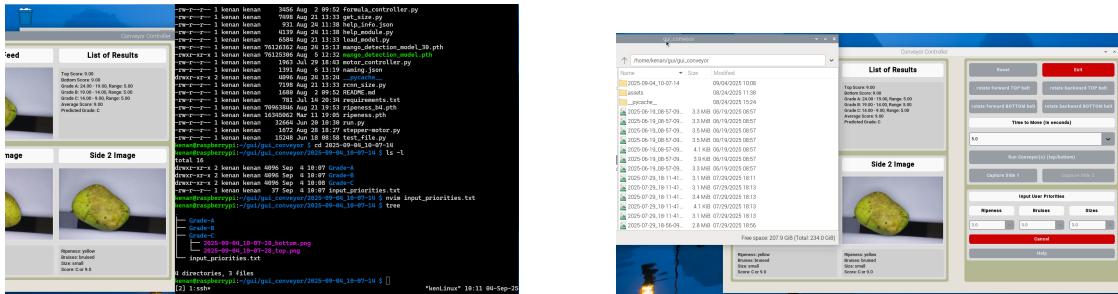
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(a) Version 2.1 with Background Image

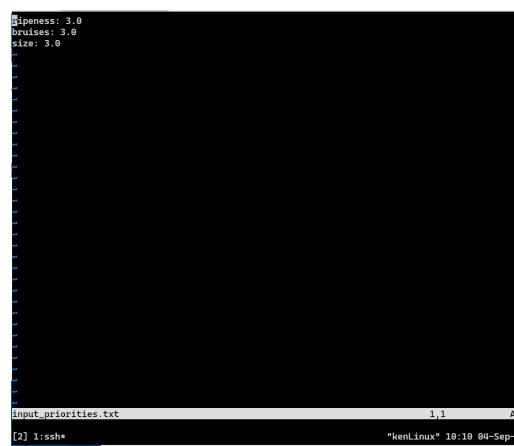
(b) Version 2.2 without Background Image

Fig. 6.13 Version 2: User Interface of the Raspberry Pi



(a) Version 1

(b) Version 2



(c) Version 3

Fig. 6.14 Mango Image Sorted



1194

## 6.6 Summary

1195

Provide the gist of this chapter such that it reflects the contents and the message. This is a

1196

compile test

1197



1198

## Chapter 7

1199

# **CONCLUSIONS, RECOMMENDATIONS, AND FUTURE DIRECTIVES**

1200



## 7.1 Concluding Remarks

In this Thesis, the prototype is successful in grading and sorting Carabao mangoes based on the user priority and machine learning algorithm. More specifically, the prototype is successful in classifying Carabao mangoes based on ripeness (Green, Green Yellow, and Yellow), size (Large, Medium, Small), and bruises (bruised and not bruised).

Likewise, the researchers were successful in getting a training and testing accuracy of at least 90% for ripeness and bruises classification.

## 7.2 Contributions

The contributions of each group member are as follows:

- BANAL Kenan A.: Scrum Master (Project manager in charge of the hardware and software integration)
- BAUTISTA Francis Robert Miguel F.: Front End Engineer (UI/UX Designer in charge of software interface and hardware assistant of the Scrum Master)
- HERMOSURA Don Humphrey L. : Back End Engineer (Software Engineer in charge of the machine learning algorithm and software assistant of the Scrum Master)
- SALAZAR Daniel G.: Product Engineer (Software Engineer in charge of training and testing of the machine learning algorithm)



### 1218    **7.3 Recommendations**

1219    The researchers recommend that the prototype be improved in the optimization of the  
1220    machine learning algorithm and the hardware design. The researchers also recommend that  
1221    the prototype be tested in the actual grading and sorting of Carabao mangoes in the market.

### 1222    **7.4 Future Prospects**

1223    Future researchers may consider the following recommendations for future work:

- 1224    1. User testing of the prototype in the actual grading and sorting of Carabao mangoes  
1225    in the Philippine market.
- 1226    2. Additional of weight measurement to the prototype to improve the grading and  
1227    sorting of Carabao mangoes.
- 1228    3. Integration of a custom PCB to improve the hardware design of the prototype.



1229

Produced: September 4, 2025, 11:22



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1230

## **Appendix A STUDENT RESEARCH ETHICS CLEARANCE**

1231

A. Student Research Ethics Clearance



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1232

RESEARCH ETHICS CLEARANCE FORM <sup>1</sup> For Thesis Proposals	
<b>Names of Student Researcher(s):</b> BANAL, Kenan A. BAUTISTA, Francis Robert Miguel F. HERMOSURA, Don Humphrey L. SALAZAR, Daniel G	
<b>College:</b> GCOE	
<b>Department:</b> ECE	
<b>Course:</b> Computer Engineering	
<b>Expected Duration of the Project:</b> from: January 4 2025 to: January 4 2026	
<b>Ethical considerations</b>  (The <a href="#">Ethics Checklists</a> may be used as guides in determining areas for ethical concern/consideration)	
<b>To the best of my knowledge, the ethical issues listed above have been addressed in the research.</b>  Dr. Reggie C. Gustilo	
<b>Name and Signature of Adviser/Mentor:</b> <b>Date:</b> February 5, 2025	
<b>Noted by:</b>  Dr. Argel Bandala	
<b>Name and Signature of the Department Chairperson:</b> <b>Date:</b> February 6, 2025	

<sup>1</sup> The same form can be used for the reports of completed projects. The appropriate heading need only be used.



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## **Appendix B ANSWERS TO QUESTIONS TO THIS THESIS**

1234



## 1235 **B1 How important is the problem to practice?**

1236 A possible answer to this question is the summary of your Significance of the Study, and  
 1237 that portion of the Problem Statement where you describe the ideal scenario for your  
 1238 intended audience.

1239 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1240 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
 1241 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus  
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 1243 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1244 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1245 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1246 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1247 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

## 1248 **B2 How will you know if the solution/s that you will 1249 achieve would be better than existing ones?**

1250 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1251 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1254 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1255 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1256 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1257 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1258 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

### 1259 **B2.1 How will you measure the improvement/s?**

1260 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1261 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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1267 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1268 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

### **B2.1.1 What is/are your basis/bases for the improvement/s?**

1270 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1271 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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### **B2.1.2 Why did you choose that/those basis/bases?**

1280 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1281 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1288 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

### **B2.1.3 How significant are your measure/s of the improvement/s?**

1290 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1291 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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## **B3 What is the difference of the solution/s from existing ones?**

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### **B3.1 How is it different from previous and existing ones?**

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## **B4 What are the assumptions made (that are behind for your proposed solution to work)?**

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1331 **B4.1 Will your proposed solution/s be sensitive to these assumptions?**

1333 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1334 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
 1335 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus  
 1336 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.  
 1337 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1338 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1339 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1340 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1341 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1342 **B4.2 Can your proposed solution/s be applied to more general cases when some assumptions are eliminated? If so, how?**

1344 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1345 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1348 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1349 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1350 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1351 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1352 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1353 **B5 What is the necessity of your approach / proposed solution/s?**

1355 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1356 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1359 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1360 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1361 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1362 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1363 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1364 **B5.1 What will be the limits of applicability of your proposed so-**  
 1365 **solution/s?**

1366 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1367 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1370 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1371 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1372 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1373 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1374 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1375 **B5.2 What will be the message of the proposed solution to**  
 1376 **technical people? How about to non-technical managers and**  
 1377 **business people?**

1378 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1379 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1382 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla  
 1383 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
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 1385 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1386 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1387 **B6 How will you know if your proposed solution/s**  
 1388 **is/are correct?**

1389 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1390 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1394 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1395 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.



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 1397 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B6.1 Will your results warrant the level of mathematics used  
(i.e., will the end justify the means)?**

1400 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1401 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec  
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 1406 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1407 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1408 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B7 Is/are there an/\_ alternative way/s to get to the  
same solution/s?**

1411 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1412 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec  
 1413 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus  
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 1415 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla  
 1416 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue  
 1417 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1418 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1419 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B7.1 Can you come up with illustrating examples, or even  
better, counterexamples to your proposed solution/s?**

1422 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.  
 1423 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec  
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 1427 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue



1428 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.  
 1429 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit  
 1430 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B7.2 Is there an approximation that can arrive at essentially the same proposed solution/s more easily?**

1433 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1434 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
 1435 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus  
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 1441 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B8 If you were the examiner of your Thesis, how would you present the Thesis in another way? Give your remarks, especially for your methodology and the results and discussions.**

1446 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.  
 1447 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec  
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 1454 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**B8.1 What are the weaknesses of your Thesis, specifically your methodology and the results and discussions?**

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## **Appendix C REVISIONS TO THE PROPOSAL**

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## PRO1 Panel Comments and Revisions – Appendix Z

### PRO1 Panel Comments and Revisions

Zoom Recording:

[https://zoom.us/rec/share/mrn9zBtPz3bJ5laVcy2E8-iBno8A6fBRgOCacMrhmzLPCNO0IDxXBHiK\\_xzdicEb.MzbHGzrD7rL3tVgJ?startTIme=1731326444000](https://zoom.us/rec/share/mrn9zBtPz3bJ5laVcy2E8-iBno8A6fBRgOCacMrhmzLPCNO0IDxXBHiK_xzdicEb.MzbHGzrD7rL3tVgJ?startTIme=1731326444000)

Passcode: +7qL6DZE

Panelist's Comments and Revisions	Action Taken	Page Number
Capture both two sides of the mango and not just one to remove error	The image capturing system would only capture the two sides of the mango which are the two largest surface areas of the skin.	18
How will you get large dataset with sweetness and how will you classify it?	Remove Sweetness in the SO	13
Size and weight are not the same.	Remove Weight in objectives but retained size in the SO4 and SO6	
Specify in the specific objectives that it will be automatic sorting	SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	13
Add what process will be used to get the size classification	SO6: To classify mango size by getting its length and width using OpenCV, geometry, and image processing techniques	13
Add what process the ripeness classification will be	SO5: To classify mango ripeness using kNN or nearest neighbors algorithm	13
Get rid of texture in the general objectives	Texture is removed in the SOs	13
Get rid of CNN in general objectives and replace with machine learning	CNN is removed and replaced with machine learning GO: To develop a user-priority-based grading and sorting system for Carabao mangoes, using machine learning to assess ripeness, size, and bruises.	13
Remove Raspberry Pi on the SO's and generalize to "to create a microcontroller based application"	SO3: To create a microcontroller application to operate and control the prototype.	13
Remove SO4. No need for user testing	Removed user test and the new SO4 is SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	13
Fix IPO to the correct input and output	Input: Two side image of the Carabao Mango and the User Priority Attributes Process: Machine Learning Algorithm, Grading Formula, and CNN model using a microcontroller Output: Size, Ripeness, and Bruises	20

C. Revisions to the Proposal



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## PRO1 Panel Comments and Revisions – Appendix Z

	Classification with its Overall Grade	
Define bruises	The black or brown area of the mango that is visible on the skin of the mango.	6
Dataset should use at least 10,000 images	Added to expected deliverables SO2: To use a publicly available dataset of at least 10,000 mango images for classification of ripeness, and bruises.	14
Add to specific objectives the percentage accuracy	SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.	14
Weight sensor just adds complexity	removed all mention of load sensor, load cell. removed load cell methodology	39,40,41, 42,43,44 previousl y



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## PRO1 Panel Comments and Revisions – Appendix Z

### PRO1 Panel Comments and Revisions

Zoom Recording:

[https://zoom.us/rec/share/mrn9zBtPz3bJ5laVcy2E8-iBno8A6fBRgOCacMrhmzLPCNO0IDxXBHiK\\_xzdicEb.MzbHGzrD7rL3tVgJ?startTim=e=1731326444000](https://zoom.us/rec/share/mrn9zBtPz3bJ5laVcy2E8-iBno8A6fBRgOCacMrhmzLPCNO0IDxXBHiK_xzdicEb.MzbHGzrD7rL3tVgJ?startTim=e=1731326444000)

Passcode: +?qL6DZE

Summary:

- Specific Objectives
- Add:
  - what process will be used to get the sweetness classification
  - what process the ripeness classification will be
  - what process will be used to get the size classification
  - Specify in the specific objectives that it will be automatic sorting
- Remove:
  - get rid of texture in the general objectives
  - get rid of cnn in general objectives and replace with machine learning
  - remove Raspberry Pi on the SO's and generalize to "to create a microcontroller based application"
  - remove SO4. No need for user testing

Comments:

\*[00-00] time stamps from recording

- [15:00] Why only the top side of the mango? Isn't the point of automation to reduce human error? Then what about the bottom side wouldn't that just introduce another error if the mango happens to have defects on the bottom?
- [16:09] What is the load cell for? Size is not the same as weight. If size is taken from the weight wouldn't size be also taken from the image. If size then adding a load cell would just introduce more complexity, if weight then load cell is fine. reminder that size is not the same as weight.
- [17:36] When computer vision, state input and output parameters. Output parameters in this case would be sweetness, ripeness, size and bruising. Input parameters would be images.
- [18:12] No mention of how the dataset would be gathered. Would you be gather your own dataset or using a publicly available dataset
- [21:38] Fix IPO based on mention input and output parameters.
- [21:50] Dataset is lacking. Usually in machine learning at least 10,000 images. can take more than one image per mango. after taking an image of mango can make more out of the image using data augmentations.
- [22:48] Add to specific Objectives the mentioned 80%
- [23:09] Consultant that would grade the mangoes as a third party to remove biases. For both the testing and the training
- [24:55] How do you detect the sweetness of mangoes? Add these to the specific objectives. What are the categories of sweetness? Add these to specific objectives. How do



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### PRO1 Panel Comments and Revisions – Appendix Z

you detect the correct categorization of sweetness? How to automate the classification of the sweetness.

- [33:10] Why is the dataset destructive but the testing non destructive? Clarify this further to avoid confusion.
- [35:09] What is the basis of sweetness using images? Clarify this further.
- [35:35] How would you know if the classifier is correct or not? What is your ground truth (for the sweetness)?
- [38:55] When can you say you are getting the top side of the mango? How would you know if the mango images showing the top side or the bottom side of both cheeks of the mango can be captured? If it doesn't matter then any side can be captured so why is it in the limitations that only the top side can be captured. Clarify the limitations.
- [48:10] What classifier would you use here? What features would you extract from the images?
- [52:07] Does it explain what process will be used to get the sweetness classification? Add it to the specific objectives
- [54:00] How will ripeness be classified? Will it use the same dataset as the sweetness classification did? How was ground truth obtained?
- [55:44] Why not the nearest neighbor? It is more fit in this scenario. Do not specify CNN in the objectives. The embedded systems as well, do not specify the Raspberry pi unless truly sure
- [57:30] Table is just image processing. Is there a specific objective that would describe how ripeness classification will be done? Add this to the specific objectives.
- [59:10] How is the weight obtained? Add it to the specific objectives. Remember that size is not proportional to weight. Size could be obtained from the image as the camera is from a fixed distance. Add to specific objectives how to get the size
- [1:00:00] get rid of texture in the general objectives. get rid of cnn in general objectives and replace with machine learning. as each parameter will use a different method.
- [1:04:00] remove Raspberry Pi on the SO's and generalize to "to create a microcontroller based application"
- [1:04:37] remove SO4. no more user testing
- [1:05:00] The formula used for grading the mangoes, is this used as industry standard? How do they measure the export quality of mango
- [1:07:00] Specify in the specific objectives that it will be automatic sorting

Here are my comments on my end :)

1. Ensure seamless integration between hardware (sensors, motors, etc.) and software (CNNs, Raspberry Pi). You can consider using a modular approach for easier troubleshooting.
2. How do you gather a comprehensive and diverse dataset for training your CNN. This will enhance the model's robustness and accuracy.
3. Make sure that the weight sensors are calibrated correctly to avoid measurement errors.

## C. Revisions to the Proposal



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### PRO1 Panel Comments and Revisions – Appendix Z

4. Implement data augmentation techniques to enhance your image dataset, which can improve model generalization and accuracy.
5. Design an intuitive user interface for the Raspberry Pi application.
6. Besides precision, recall, and F1 score, consider incorporating confusion matrices to better understand model performance and error types.
7. Conduct user testing of the application to gather feedback on usability and functionality. This can lead to improvements in design and user experience. Consider how the system can be scaled or adapted for different fruits or larger processing volumes in the future.

Noted by:

  
\_\_\_\_\_  
**Dr. Donabel de Veas Abuan**  
*Chair of Panel*

Date: November 11 2024

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Note: Keep a copy of this Appendix. It is a requirement that has to be submitted in order to qualify for PRO3 Defense.



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## **Appendix D REVISIONS TO THE FINAL**

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- 1475      Make a table with the following columns for showing the summary of revisions to the  
 1476      proposal based on the comments of the panel of examiners.
- 1477      1. Examiner
- 1478      2. Comment
- 1479      3. Summary of how the comment has been addressed
- 1480      4. Locations in the document where the changes have been reflected

TABLE D.1 SUMMARY OF REVISIONS TO THE THESIS

Examiner	Comment	Summary of how the comment has been addressed	Locations
Dr. Reggie C. Gustilo		1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext  <b>First</b> itemtext  <b>Second</b> itemtext  <b>Last</b> itemtext  <b>First</b> itemtext  <b>Second</b> itemtext	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???

*Continued on next page*



# De La Salle University

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<b>Examiner</b>	<b>Comment</b>	<b>Summary of how the comment has been addressed</b>	<b>Locations</b>
Dr. Donable de Veas Abuan	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext  <b>First</b> itemtext  <b>Second</b> itemtext  <b>Last</b> itemtext  <b>First</b> itemtext  <b>Second</b> itemtext	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???
Engr. Jose Martin Maningo	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext  • First itemtext • Second itemtext • Last itemtext • First itemtext • Second itemtext	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???

*Continued on next page*



*Continued from previous page*

Examiner	Comment	Summary of how the comment has been addressed	Locations
Dr. Alexander Co Abad	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???



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## **Appendix E ARTICLE PAPER(S)**

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# Article/Forum Paper Format

## (IEEE LaTeX format)

Michael Shell, *Member, IEEE*, John Doe, *Fellow, OSA*, and Jane Doe, *Life Fellow, IEEE*

1483

**Abstract—The abstract goes here.** Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

**Index Terms—**Computer Society, IEEE, IEEEtran, journal, L<sup>A</sup>T<sub>E</sub>X, paper, template.

### I. INTRODUCTION

THIS demo file is intended to serve as a “starter file” for IEEE article papers produced under L<sup>A</sup>T<sub>E</sub>X using IEEEtran.cls version 1.8b and later. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

#### A. Subsection Heading Here

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M. Shell was with the Department of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332.  
E-mail: see <http://www.michaelshell.org/contact.html>

J. Doe and J. Doe are with Anonymous University.



Fig. 1. Simulation results for the network.

TABLE I  
AN EXAMPLE OF A TABLE

One	Two
Three	Four

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#### 1) Subsubsection Heading Here: Subsubsection text here.

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### II. CONCLUSION

#### The conclusion goes here.

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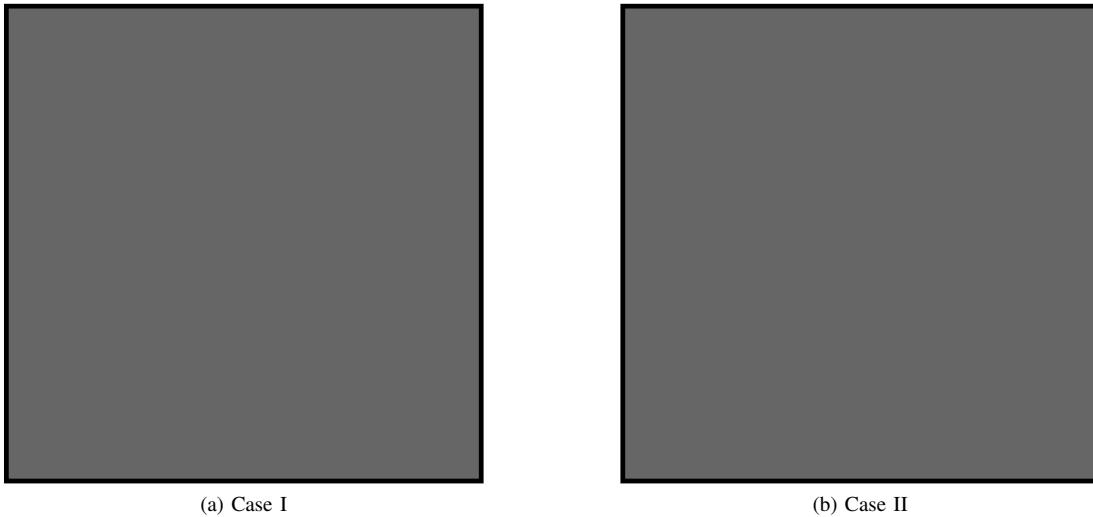


Fig. 2. Simulation results for the network.

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## APPENDIX A PROOF OF THE FIRST ZONKLAR EQUATION

### Appendix one text goes here.

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## APPENDIX B

### Appendix two text goes here. [?].

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## ACKNOWLEDGMENT

The authors would like to thank...