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

4

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

10

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

14

15 by

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20 August, 2025



De La Salle University

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ORAL DEFENSE RECOMMENDATION SHEET

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This thesis, entitled **Non-Destructive Carabao Mango Sorter and Grader based on Physical Characteristics using Machine Learning**, prepared and submitted by thesis group, AISL-1-2425-C5, composed of:

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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 for **ORAL DEFENSE**.

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ABSTRACT

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Carabao Mangoes are one of the sweetest mangoes in the world and one of the major producers of this is the Philippines. However, mangoes go through many screening processes, one of them being sorting and grading during post harvesting which is labor intensive, prone to human error, and can be inefficient if done manually. Previous researchers have taken steps to automate the process, however, their works often focus on only specific traits, and do not try to encapsulate all the physical traits of the mangoes altogether. Furthermore, previous researchers made the grading system static or unchangeable to the user. In this study, the researchers will develop an automated Carabao mango grader and sorter based on ripeness, size, and bruises with an interchangeable mango attribute priority through non-destructive means. Using machine vision, image processing, Machine Learning, microcontrollers and sensors the mangoes will be physically sorted into designated bins via a conveyor belt system which can be controlled and monitored via a graphical user interface. The approach will streamline the post-harvest process and cut down on human errors and labor costs, helping maintain the high quality of Carabao mango exports.

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Index Terms—Machine Learning, Carabao Mangoes, Sorting and Grading Mangoes, Machine Vision, Microcontroller.



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ABBREVIATIONS

215	AC	Alternating Current	13
216	CNN	Convolution Neural Network	14
217	GUI	Graphical User Interface	50
218	LED	Light Emitting Diode	44
219	UI	User Interface	50



220

NOTATION

221	$B(P)$	Bruises Priority	62
222	$b(p)$	Bruises Prediction	62
223	$R(P)$	Ripeness Priority	62
224	$r(p)$	Ripeness Prediction	62
225	$S(P)$	Size Priority	62
226	$s(p)$	Size Prediction	62
227	$D(p, d, f)$	Real World Dimension	27
228	p	Pixel Dimension	27
229	d	Distance from Camera to Object	27
230	f	Focal Length	27



231 GLOSSARY

231	GLOSSARY	
232	accuracy score	A performance metric that measures the overall proportion of correct predictions made by a machine learning model.
233	bruises	The black or brown area of the mango that is visible on the skin of the mango.
234	Carabao mango	A popular variety of mango grown in the Philippines, known for its sweet and juicy flesh.
235	CNN	A type of deep neural network that is highly effective in analyzing and processing visual data, such as images.
236	computer vision	The use of cameras and algorithms to provide imaging-based inspection and analysis.
237	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.
238	F1-Score	A balanced performance metric that is the harmonic mean of precision and recall, taking both into account.
239	machine learning	A subset of Artificial Intelligence that enables systems to learn and improve from data.
240	microcontroller	A small computing device that controls other parts of a system such as sensors.
241	Precision	A performance metric that reflects the percentage of instances classified as positive that are truly positive.
242	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

246

INTRODUCTION



247 **1.1 Background of the Study**

248 Mangoes, also known as the *Mangifera indica*, are a member of the cashew family. This
249 fruit can often be seen being farmed by countries such as Myanmar, the Philippines, and
250 India as they have a tropical dry season. Being in a tropical country is an important
251 aspect for mango cultivation as it ensures proper growth for mangoes. If aspects such as
252 temperature and rainfall are not ideal, it may affect the quality of the mango (Britannica,
nd). Carabao mangoes is a variety of a mango that is found and cultivated in the Philippines.



Fig. 1.1 Carabao Mangoes at Different Ripeness Stages (Guillermo et al., 2019)

253
254 It is known for its sweet signature taste that was recognized sweetest in the world in the
255 Guinness Book of World Records in 1995. The mango was named after the national animal
256 of the Philippines, a native breed of buffalo. On average, it is 12.5 cm in length and 8.5
257 cm in diameter, having a bright yellow color when ripe as seen in Figure 1.1. It is often
258 cultivated during late May to early July (DBpedia, nd).

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



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263 is the country's export of both fresh and dried mangoes, as well as low tariff rates. This
264 allows the country to export a large quantity of the fruit in countries such as Singapore,
265 Japan, and the USA as they can enter duty free markets provided by the World Trade
266 Organization and Japan. Due to this, the mangoes have become a major source of income
267 to an estimated 2.5 million farmers in the country (Centino et al., 2020).

268 Before mangoes are sold in markets, they first undergo multiple post-harvest processes.
269 This is to ensure that the mangoes that arrive in markets are utmost quality before being
270 sold to consumers. Moreover, it ensures that mangoes are contained and preserved properly
271 such that they do not incur damages and/or get spoiled on its transportation to the market.
272 Processing of the mango involves pre-cooling, cleaning, waxing, classification, grading,
273 ripening, packaging, preservation, storage, packing, and transportation (Patel et al., 2019)
274 (Rizwan Iqbal and Hakim, 2022).

275 Among the processes that mangoes undergo, classification and grading is important as
276 it allows the manufacturer to separate mangoes with good qualities versus mangoes with
277 poor qualities. According to a study by (Lacap et al., 2021), size, length, width, volume,
278 density, indentation, and grooves are aspects that determine the maturity of mangoes. These
279 traits are being checked along with the ripeness of the mango, sightings of bruise injury,
280 and cracks on the fruit (Lacap et al., 2021) as these aspects affect the sellability of the fruit
281 as well as the chances of it getting spoiled sooner.

282 Previous studies have been made to automate the sortation process of the mangoes.
283 Among these is a research done by Abbas et al. (2018), which focuses on classification
284 of mangoes using their texture and shape features. They do this by, first, acquiring an
285 image of the mango using a digital camera. Then, these images are fed to the MaZda
286 package, which is a software originally developed for magnetic resonance imaging. Within



287 the MaZda package is the B11 program, which uses Principal Component Analysis, Linear
288 Discriminant Analysis, Nonlinear Discriminant Analysis, and texture classification to
289 extract features from the mango, which in this case are the length, width, and texture. This
290 data is then compared to a database in order to classify any given mango (Abbas et al.,
291 2018).

292 Another study is done by Rizwan Iqbal and Hakim (2022), which classifies mangoes
293 based on their color, volume, size, and shape. This is done by making use of Charge Coupled
294 Devices, Complementary Metal-Oxide Semiconductor sensors, and 3-layer Convolutional
295 Neural Network. To classify the mangoes, images are first captured and preprocessed to
296 be used as a data set (Rizwan Iqbal and Hakim, 2022). This data set is then augmented
297 to be used as a model for the 3-layer Convolutional Neural Network. After extracting the
298 features of the mango, the 3-layer Convolutional Neural Network is used as a method for
299 their classification as it can mimic the human brain in pattern recognition, and process
300 data for decision making. This is important as some mangoes have very subtle differences
301 which make it difficult to differentiate them.

302 1.2 Prior Studies

303 A paper written by Amna et al. (2023), designed an automated fruit sorting machine based
304 on the quality through an image acquisition system and CNN. Furthermore, the results
305 of the paper show that the image processing detection score was 89% while that of the
306 tomatoes was 92% while the CNN model had higher validity of 95% for mangoes and
307 93% for tomatoes. 15%, while the percentage of distinction between the two groups was
308 reported to be 5% respectively (Amna et al., 2023). Despite the high accuracy score in



309 detecting mango defects, the fruit sorting system only sorts based on the mango defects
310 and not on ripeness, and weight.

311 Furthermore, the research paper presented by Guillergan et al. (2024) designed an
312 Automated Carabao mango classifier, in which the mango image database is used to extract
313 the features like size, area along with the ratio of the spots for grading using Naïve Bayes
314 Model. For the results, the Naïve Bayes' model recognized large and rejected mangoes with
315 95% accuracy and the large and small/medium difference with a 7% error, suggesting an
316 application for quality differentiation and sorting in the mango business industry. Despite
317 the high accuracy of classifying Carabao mangoes, the researchers used a high quality
318 DSLR camera for the image acquisition system without any microcontroller to control the
319 mangoes (Guillergan et al., 2024).

320 **1.3 Problem Statement**

321 As mangoes are among the top exports of the Philippines (Centino et al., 2020), assessing
322 the physical deformities is a necessity. The physical deformities of the Carabao mango
323 can determine the global competitiveness of the country. Having higher quality exports
324 can often lead to gaining competitive edge, increase in demand, increase export revenues,
325 and becoming less susceptible to low-wage competition (D'Adamo, 2018). In order to
326 increase the quality of mango fruit exports, a key post-harvest process is done, which is
327 sorting and grading. Mango sorting and grading then becomes important to determine
328 which batches are of high quality and can be sold for a higher price, and which batches are
329 of low quality and can only be sold for a low price (Co., nd). Traditionally, fruit sorting
330 and grading is inefficient as it is done manually by hand. Some tools are used such as



331 porous ruler to determine fruit size and color palette for color grading (Co., nd). However,
332 among the problems encountered in the process of manually sorting and grading mangoes
333 are susceptibility to human error and requiring a number of laborers to do the task.

334 With the current advancements in technology, some researchers have already taken steps
335 to automate the process of sorting and grading mangoes. However, these attempts would
336 often only consider some of the aspects pertaining to size, ripeness, and bruises but not all
337 of them at the same time. Lastly, not all research approaches were able to implement a
338 hardware for their algorithm, limiting their output to only a software implementation and not
339 an embedded system. As such the proposed system would assess the export quality of the
340 Carabao mango based on all the mentioned mango traits, namely size, bruises, and ripeness
341 while also taking into consideration being non-destructive. These aspects are important
342 because, as was previously mentioned, there is a need to develop a Carabao mango sorter
343 that takes into account all these aspects at the same time while being non-destructive.

344 **1.4 Objectives and Deliverables**

345 **1.4.1 General Objective (GO)**

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



349 **1.4.2 Specific Objectives (SOs)**

- 350 • SO1: To make an image acquisition system with a conveyor belt for automatic sorting
351 and grading mangoes. ;
- 352 • SO2: To get the precision, recall, F1 score, confusion matrix, and train and test
353 accuracy metrics for classifying the ripeness and bruises with an accuracy score of at
354 least 90%.;
- 355 • SO3: To create a microcontroller-based system to operate the image acquisition
356 system, control the conveyor belt, and process the mango images through machine
357 learning. ;
- 358 • SO4: To grade mangoes based on user priorities for size, ripeness, and bruises. ;
- 359 • SO5: To classify mango ripeness based on image data using machine learning
360 algorithms such as kNN, k-mean, and Naïve Bayes. ;
- 361 • SO6: To classify mango size based on image data by getting its length and width
362 using OpenCV, geometry, and image processing techniques. ;
- 363 • SO7: To classify mango bruises based on image data by employing machine learning
364 algorithms.

365 **1.4.3 Expected Deliverables**

366 Table 1.1 shows the outputs, products, results, achievements, gains, realizations, and/or
367 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"> • To develop a Carabao mango grading and sorting system. • To grade Carabao mangoes into three categories based on ripeness, size, and bruises using machine learning. • To integrate sensors and actuators to control the conveyor belt and image acquisition system.
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ul style="list-style-type: none"> • To make an image acquisition system with a camera and LED light source. • To build a flat belt conveyor for moving the mangoes.
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"> • To use a publicly available dataset of at least 10,000 mango images for classification of ripeness and bruises.
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"> • To develop an intuitive UI where users can start and stop the system. • To implement a priority-based grading system with sliders for ripeness, bruises, and size.
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<ul style="list-style-type: none"> • 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. • To assign score values for each classification level of the mango.

Continued on next page



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
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"> To train a machine learning model such as kNN, k-means, or Naïve Bayes capable of classifying mango ripeness based on the image color. To gather a dataset of annotated images with ripeness labels. To obtain an evaluation report of performance metrics of the model.
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"> To develop an image processing algorithm capable of determining mango size using OpenCV, NumPy, and imutils. To classify mangoes based on size into small, medium, and large based on measurements.
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ul style="list-style-type: none"> To train a machine learning model such as CNN capable of distinguishing bruised and non-bruised mangoes. 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. To gather a dataset of annotated images based on bruises. To obtain an evaluation report of performance metrics of both CNN and other machine learning models.

368

1.5 Significance of the Study

369

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.

370

371

372



373 A recent study showed that their automated citrus sorter and grader using computer vision
374 can reduce the human labor cost and time to sort and grade when comparing the automated
375 citrus sorter and grader to manual human labor Chakraborty et al. (2023).

376 Another benefit to automating sorting and grading mangoes is the improvement in
377 quality control. This implies that compared to human labor, automating sorting and
378 grading mangoes can uniformly assess the quality of mangoes based on size, color, and
379 bruises, ensuring that the expected grade and high-quality mangoes reach the consumer.
380 By accurately identifying substandard mangoes, the system helps in reducing waste and
381 ensuring that only marketable fruits are processed further.

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

388 1.5.1 Technical Benefit

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



- 395 **1.5.2 Social Impact**
- 396 1. The reduction in manual labor creates opportunities in maintenance and technologies
397 in the automated Carabao mango sorter.
- 398 2. The automated Carabao mango sorter system improves Carabao mango standards
399 and enhances the satisfaction of the buyers and the customers through guaranteeing
400 consistent Carabao mango grade.
- 401 3. Opportunity to increase sales and profit for the farmers through consistent quality
402 and grade Carabao mangoes while reducing the physical labor to sort it.
- 403 **1.5.3 Environmental Welfare**
- 404 1. With the utilization of non-destruction methods of classifying Carabao mangoes
405 together with an accurate sorting system, overall waste from Carabao mangoes is
406 reduced and the likelihood of improperly sorted mangoes is decreased.
- 407 2. Automation of sorting and grading Carabao mangoes promotes sustainable farming
408 practices.
- 409 **1.6 Assumptions, Scope, and Delimitations**
- 410 **1.6.1 Assumptions**
- 411 1. The Carabao mangoes are from the same source together with the same variation
- 412 2. The Carabao mangoes do not have any fruit borer and diseases



- 413 3. All the components do not have any form of defects
- 414 4. The prototype would have access to constant electricity/power source.
- 415 5. The Carabao mangoes to be tested would be in the post-harvesting stage and in the
416 grading stage.
- 417 6. The image-capturing system would only capture the two sides of the mango which
418 are the two largest surface areas of the skin.

419 **1.6.2 Scope**

- 420 1. The prototype would be specifically designed to grade and sort Carabao Mangoes
421 based on only ripeness, size, and visible skin bruises.
- 422 2. The mangoes used as the subject will be solely sourced from markets in the Philip-
423 pines.
- 424 3. The Carabao mangoes would be graded into three levels.
- 425 4. The prototype will be using a microcontroller-based system locally stored on the
426 device itself to handle user interaction.
- 427 5. Computer vision algorithms to be used will include image classification.

428 **1.6.3 Delimitations**

- 429 1. The project would only be able to perform sorting and grading on one specific fruit
430 which is the Carabao mango and will not be able to sort other types of mangoes.



- 431 2. Additionally, the project prototype will only be able to capture, sort, and grade one
 432 mango subject at a time which means the mangoes have to be placed in the conveyor
 433 belt in a single file line for accurate sorting.
- 434 3. For the bruises, the system will only be able to detect external bruises and may not
 435 identify the non-visible and internal bruises.
- 436 4. The system does not load the mangoes onto the conveyor belt itself. Assistance is
 437 required to put mangoes into the conveyor belt to start the sorting process
- 438 5. The prototype will be powered using Alternating Current (AC) power and will be
 439 plugged into a wall socket which is only suitable for indoor use.

440 **1.7 Estimated Work Schedule and Budget**

TASKS	THSCP4A				THSCP4B				THSCP4C			
	Week 1-3	Week 4-6	Week 7-9	Week 10-13	Week 1-3	Week 4-6	Week 7-9	Week 10-13	Week 1-3	Week 4-6	Week 7-9	Week 10-13
Topic Proposal and Defense	BANAL, BAUTISTA, HERMOSURA, SALAZAR				HERMOSURA AND SALAZAR							
Buying and Collecting of Materials					BANAL AND BAUTISTA							
Training and Testing the CNN model						HERMOSURA AND SALAZAR						
Integrating the sensors and actuators to the Arduino Uno						BANAL AND BAUTISTA						
Coding of the Application with CNN model to the Raspberry Pi and connecting it to the Arduino Uno							BANAL AND BAUTISTA					
Polishing and Revising the UI App							BANAL AND BAUTISTA					
Testing and Surviving of the System with the Carabao Mangoes							BANAL, BAUTISTA, HERMOSURA, SALAZAR					
Data Gathering								BANAL, BAUTISTA, HERMOSURA, SALAZAR				

Fig. 1.2 Gantt Chart

441 As seen above, Table 1.2 shows the Gantt Chart together with the assigned task. For
 442 the first part of the THSCP4A, the group would primarily revise and fine tune Chapters
 443 1 and 2 while also preparing for the defense. After that for THSCP4B, the yellow team
 444 which consists of two members, Hermosura and Salazar, would start buying and collecting



445 the materials needed for assembling the prototype. While team yellow is doing that,
446 team purple which consists of Banal and Baustista would start training and validating the
447 Convolution Neural Network (cnn) model based on the Carabao mango image dataset.
448 After that integration of the sensors and actuators together with the integration of the cnn
449 model and beginning of coding of the Application to the Raspberry Pi would be done. Once
450 that cnn model is deployed and the Application works testing of the Carabao mangoes to
451 the prototype would be done. During THSCP4C, data gathering would be done together
452 with polishing and revising of the final paper.

453 1.8 Overview of the Thesis

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



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464

Chapter 2

465

LITERATURE REVIEW



466 **2.1 Existing Work**

467 The research paper written by Adam et al. (2022) developed a ripeness grader for Carabao
468 mangoes. The Carabao mango ripeness grade calculated based on object and color detection
469 which were written in microcontroller. These are the systems designed by the researchers
470 that consists of Raspberry Pi 4, Arduino Uno, camera, touch screen LCD, MQ3 gas sensor,
471 ventilation system. The proposed system was able to ascertain an overall reliability of 95%:
472 therefore, the specified objective of ascertaining the ripeness level of the mangoes was
473 met with success. However, accuracy and reliability of the software system are there since
474 the hardware design does not seem to be workable when one must deal with the scores of
475 mangoes (Adam et al., 2022). In addition, the design of the hardware does not integrate
476 any form of physical automating, say like the conveyor belt. Besides, the hardware system
477 only works efficiently when deciding the ripeness grade of mangoes separately.

478 A study done by Samaniego et al. (2023) is another research paper that supports and
479 has relevant information concerning the topic. The researchers proposed a fully-perovskite
480 photonic system which has the capability to identify and sort or grade mango based on
481 features such as color, weight and, conversely, signs of damages (Samaniego et al., 2023).
482 Some of the techniques in image processing that the researchers used included image
483 enhancement, image deblurring, edge detection using MATLAB and Arduino as well as
484 color image segmentation. By carrying out the multiple trials on the device they achieved a
485 classification speed of 8.132 seconds and an accuracy of 91.2%. The proponents' metrics
486 used for the ratings were speed wherein the results were rated "excellent" while the accuracy
487 rating given was "good". One of the limitations of the paper is that the researchers were
488 only limited to the color, texture, and size of the Carabao mango



489 Furthermore, the research paper presented by Guillergan et al. (2024) designed an
490 Automated Carabao mango classifier, in which the mango image database is used to extract
491 the features like weight, size, area along with the ratio of the spots for grading using
492 Naïve Bayes Model. Concerning the quantitative test design, one had to control and
493 experiment with various methods of image processing that would improve the likelihood
494 of improved classification. The paper methodology entailed sample collection from 300
495 Carabao mangoes, picture taking using a DSLR camera, and feature deconstruction for
496 categorization (Guillergan et al., 2024). The system prototype and the software were
497 designed with the programming language C# with integration of Aforge. NET routines.
498 The performance of this model was checked with the help of the dataset containing 250
499 images, precision, recall, F-score key indicators were used. The investigation discovered
500 that the Naïve Bayes' model recognized large and rejected mangoes with 95% accuracy
501 and the large and small/medium difference with a 7% error, suggesting an application for
502 quality differentiation and sorting in the mango business industry. The limitations in the
503 researchers' paper include the researchers were able to achieve high accuracy after using a
504 high quality DSLR camera and the fact that the researchers were not able to incorporate the
505 use of microcontrollers.

506 Another study by Tomas et al. (2022) proposed SVM-based system for classifying
507 the maturity stages of bananas, mangoes, and calamansi. With the use of 1729 images of
508 bananas together with 711 mango images and 589 calamansi, the researchers were able to
509 achieve a high accuracy score of above 90% for all fruits. Some pre-processing techniques
510 used to get this high accuracy are the change in hue, saturation, and value channels in the
511 mango image (Tomas et al., 2022). To better understand the harvest time of mangoes, the
512 paper by Abu et al. (2021) examined the association of the harvest season with seasonal



513 heat units, rainfall, and physical fruit attributes for Haden, Kent, Palmer, and Keitt mango
 514 varieties to establish export and domestic market maturity standards. For the results of
 515 the paper, it shows that temperature, rainfall, and physical characteristics have a reliable,
 516 non-destructive indicators for determining mango maturity (Abu et al., 2021). This shows
 517 that physical characteristics and temperature are important when exporting fruits such as
 518 mangoes.

TABLE 2.1 COMPARISON OF EXISTING STUDIES

Existing Study	Limitations	Accuracy Rating
Adam et al. (2022)	No physical automation, not suitable for large amounts of mangoes, only classifies ripeness and only a sample size of 10 mangoes.	95%
Samaniego et al. (2023)	Focuses only on color and size.	91.2%
Guillergan et al. (2024)	Relies on high-quality DSLR cameras, and limited automation due to not integrating microcontrollers.	95%
Supekar and Wakode (2020)	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%

519 Previous studies on mango grading have achieved an accuracy rating of up to 95%, as
 520 shown in Table 2.1. However, these studies either relied on a small sample size, which
 521 limits statistical significance, or utilized expensive equipment, which may be impractical.
 522 In light of this, the researchers have set a target accuracy rating of greater than or equal
 523 to 90%. This target ensures that the system being developed is comparable to, or better
 524 than, existing studies that used larger sample sizes or assessed multiple mango traits at the



525 same time. Furthermore, this research aims to distinguish itself by not only maintaining or
526 exceeding the 90% accuracy rating but also incorporating a graphical user interface (GUI)
527 for selective priority-based mango classification. The system will integrate both software
528 and hardware components, and it will evaluate a greater number of mango traits for grading
529 purposes.

530 **2.1.1 Sorting Algorithms**

531 In previous studies, researchers have implemented various artificial intelligence algorithms
532 in order to determine the optimal and most effective method for sorting mangoes. One of
533 the algorithms that was used in the classification of mangoes was the CNN or Convolutional
534 Neural Networks. A study done by Zheng and Huang (2021) explored the effectiveness of
535 CNN, specifically in classifying mangoes through image processing. The system that the
536 researchers developed graded mangoes into four groups which was based on the Chinese
537 National Standard (Zheng and Huang, 2021). These mangoes were examined by their
538 shape, color uniformity, and external defects. The system that was developed had an
539 impressive accuracy of 97.37% in correctly classifying the mangoes into these grading
540 categories Support Vector Machine was also one of the classification algorithms that was
541 implemented to detect flaws in mangoes. In that study by Veling (2019), SVM was used in
542 the classification of diseases from mangoes. The study used 4 different diseases/defects for
543 testing (Veling, 2019). The diseases were Anthracnose, Powdery Mildew, Black Banded,
544 and Red Rust. and provided 90% accuracy for both the leaves and the fruit

545 In the study done by Schulze et al. (2015), Simple Linear Regression, Multiple Linear
546 Regression, and Artificial Neural Network models were all studied and compared for
547 the purpose of size-mass estimation for mango fruits. The researchers found that the



548 Artificial Neural Network yielded a high accuracy rating for mass estimation and for mango
549 classification based on size with a success rate of 96.7% (Schulze et al., 2015). This is
550 attributed to the Artificial Neural Network model's ability to learn both linear and nonlinear
551 relationships between the inputs and the outputs. However, a problem can occur with the
552 use of the model, which is overfitting. This issue occurs when the model is overtrained
553 with the data set such that it will start to recognize unnecessary details such as image noise
554 which results in poor generalization when fed with new data. With this in mind, additional
555 steps will be necessary to mitigate the issue. Another research article written by Alejandro
556 et al. (2018) implements a method for sorting and grading Carabao mangoes. This research
557 focuses on the use of Probabilistic Neural Network, which is another algorithm that is used
558 for pattern recognition and classification of objects. For this study, the researchers focused
559 on the area, color, and the black spots of the mango for their Probabilistic Neural Network
560 model (Alejandro et al., 2018). Their research using the model yielded an accuracy rating
561 of 87.5% for classification of the mangoes which means it is quite accurate for classifying
562 mangoes within the predefined categories. However, problems were encountered with
563 the use of the model when trying to identify mangoes that did not fit the predefined size
564 categories of small, medium, and large. This means that the PNN model may become
565 challenged when presented with a mango with outlying traits or traits that were very
566 different from the data set.

567 2.2 Lacking in the Approaches

568 The majority of past researchers such as Amna et al. (2023) and Guillermo et al. (2019)
569 were able to implement a fruit and mango sorter together with an accurate AI algorithm



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

570 to detect the ripeness defects. This means that none of the previous research papers were
 571 able to integrate an interchangeable user-priority-based grading together with size, ripeness,
 572 and bruises using machine learning for Carabao mango sorter and grader. Our research
 573 however would implement an automated Carabao mango sorter in terms of size, ripeness,
 574 and bruises with its own UI, conveyor belt, stepper motors, and bins for collecting the
 575 different ripeness and defect grade of the Carabao mango.

576 2.3 Summary

577 To reiterate, there is an innovative gap that needs to be filled with regards to the process of
 578 sorting and grading Carabao mangoes. The traditional methods for conducting this process
 579 manually by hand, by a porous ruler, by a sugar meter, and by a color palette can be prone
 580 to human error and expensive costs due to the number of laborers required to do the task.



581 On the other hand, although researchers have already taken steps to automate the process
582 of mango sorting and grading, there is still a need for an implementation that takes into
583 account size, ripeness, and bruises altogether whilst being non-destructive and having its
584 own embedded system. The research articles shown above show the different computer
585 vision and CNN approaches for sorting and classifying mangoes. For example, a system
586 created by Adam et al. (2022) was more focused on ripeness detection. Samaniego et al.
587 (2023) considered photonic systems for grading mango fruit based on color and weight.
588 On the other hand, Guillermo et al. (2019) implemented the Naïve Bayes classification
589 model on mangoes with high accuracy, which thereby did not include any microcontroller.
590 There was an attempt to study each of those parameters separately and that is why the
591 multifactorial approach was not used. With this in mind, the system being proposed does
592 exactly what was mentioned, to implement a non-destructive and automated sorting and
593 grading system for Carabao mangoes that takes into account size, ripeness, and bruises
594 altogether using machine learning, as well as having its own embedded system. This system
595 will be mainly composed of a conveyor belt, servo motors, a camera, microcontrollers, and
596 an LCD display for the user interface. By doing so, the system should be able to improve
597 the efficiency and productivity of mango sorting and grading, remove the effect of human
598 error and reduce time consumption. The studies also provided critical insights regarding the
599 effective algorithms that can be used in classification stages in image processing. The use
600 of CNN had the most accuracy with manageable potential challenges. Lastly, by scaling
601 the implementation, the overall export quality of the Carabao mangoes can be improved.



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Chapter 3

603

THEORETICAL CONSIDERATIONS



604 3.1 Introduction

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

607 3.2 Relevant Theories and Models

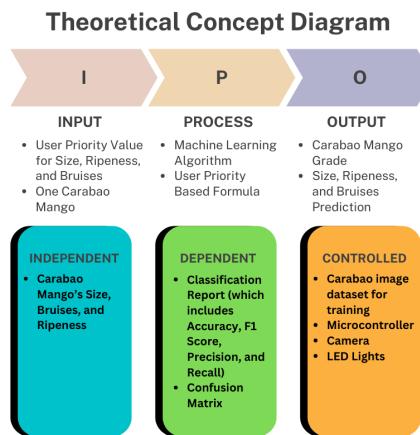


Fig. 3.1 Theoretical Framework Diagram.

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



617 3.3 Technical Background

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

625 3.4 Conceptual Framework Background

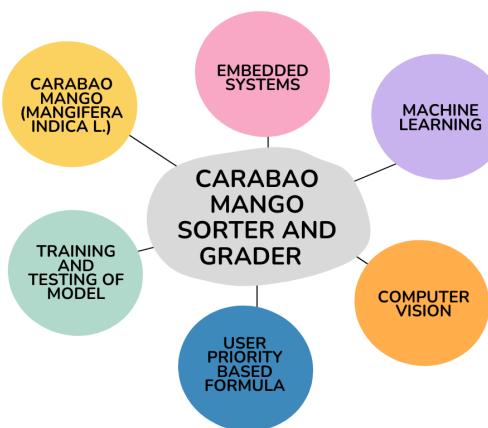


Fig. 3.2 Conceptual Framework Diagram.

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



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

634 **3.5 Software Concepts**

635 **3.5.1 Thresholding**

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

643

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

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



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

655 **3.5.2 Object Size Calculation**

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

660 The size of the mango can be determined given:

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

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

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

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



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

671 **3.5.3 Convolutional Neural Network**

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

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

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

684 **3.6 Hardware Concepts**

685 **3.6.1 Camera Module**

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



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

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

699 **3.6.2 4 Channel Relay**

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

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



709 **3.6.3 Gear Ratio**

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

718 **3.7 Summary**

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



724

Chapter 4

725

DESIGN CONSIDERATIONS



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

732 **4.1 Introduction**

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

737 **4.2 System Architecture**

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

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

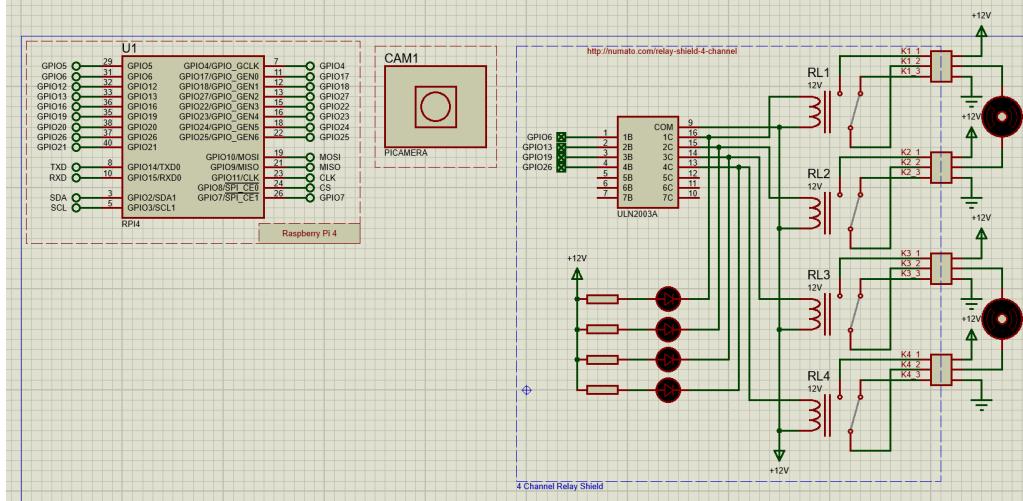


Fig. 4.1 Hardware Schematic

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

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

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



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

763 4.3 Hardware Considerations

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

768 4.3.1 General Prototype Framework

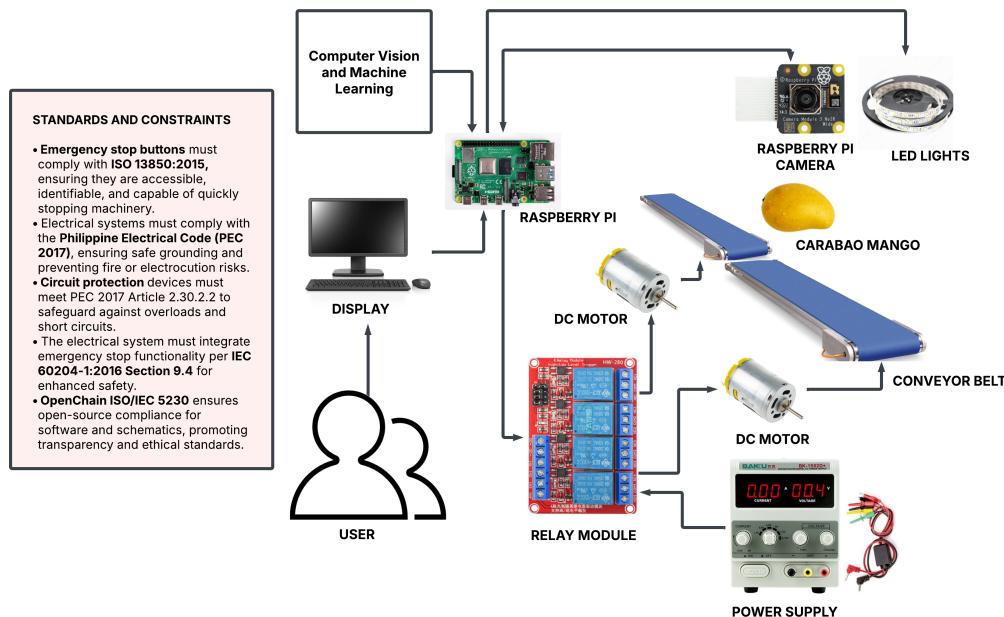


Fig. 4.2 Prototype Framework



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

777 **4.3.2 Prototype Flowchart**

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

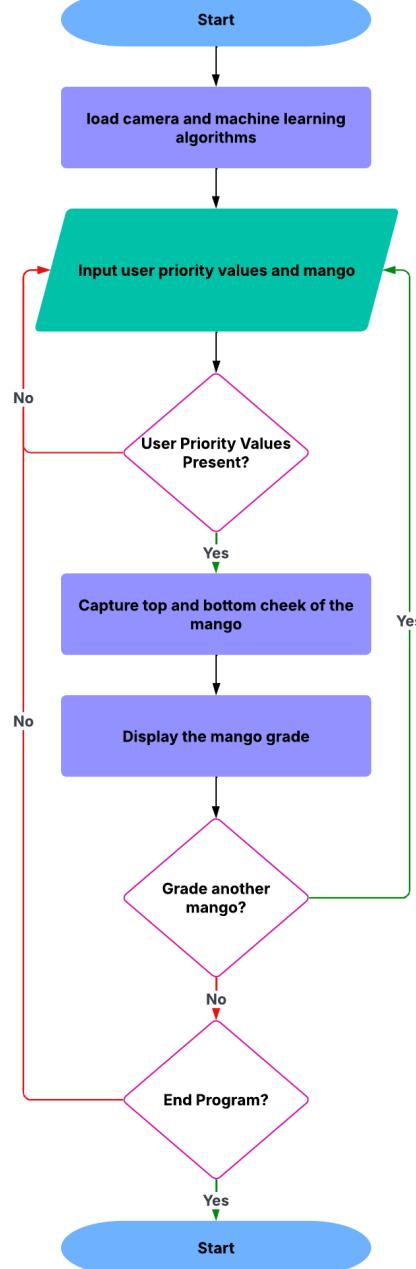


Fig. 4.3 Prototype Main Flowchart



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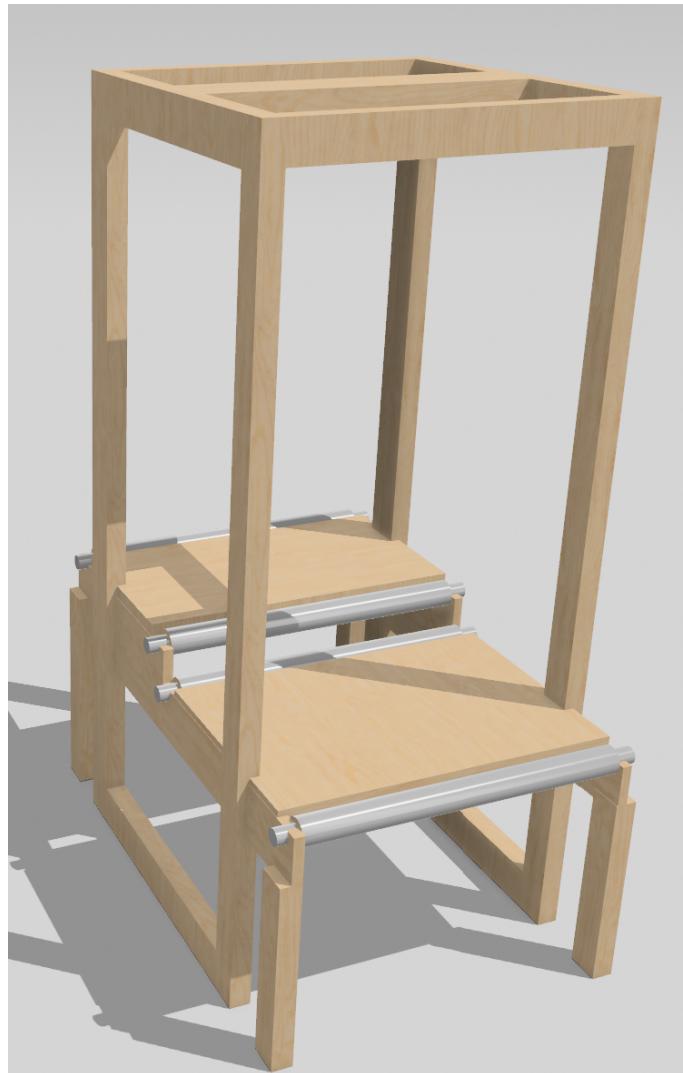


Fig. 4.4 Initial 3D Model of the Prototype



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4.3.3 Prototype 3D Model

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

4.3.4 Hardware Specifications

797 4.3.4.1 Raspberry Pi



Fig. 4.5 Raspberry Pi 4 Model B

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



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

805 **Specifications:**

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



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

822 **4.3.4.2 Raspberry Pi Camera**

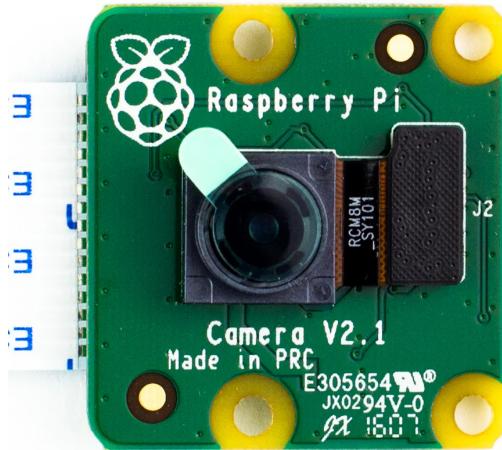


Fig. 4.6 Raspberry Pi Camera Module Version 2

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



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

830

831 **Specifications:**

- 832 • Sensor: Sony IMX219PQ 8-megapixel CMOS sensor.
- 833 • Still Images Resolution: 8 MP (3280 x 2464 pixels).
- 834 • Video Resolution: Supports up to 1080p @ 30fps, 720p @ 60fps, and 480p @ 90fps.
- 835 • Focus: Fixed-focus lens (manual focus adjustment not supported without physical
836 modification).
- 837 • Lens Size: 1/4-inch optical format.
- 838 • Field of View (FoV): Diagonal 62.2 degrees.
- 839 • Interface: Connected via 15-pin ribbon cable to the Raspberry Pi's CSI (Camera
840 Serial Interface) port.
- 841 • APIs/Libraries: Supports Python libraries such as Picamera and OpenCV for image
842 capture and processing.
- 843 • Dimensions: 25 mm x 24 mm x 9 mm.

844 **4.3.4.3 DC Motor**

845 The 12 Volt DC Gear Motor is a compact, high-torque, and low-noise motor suitable for a
846 wide range of applications, including robotics, automation, and industrial control systems.
847 It features a spur gear design, which provides a high reduction ratio for increased torque
848 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.

Specifications:

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



- 860 • Torque Output: 18 kg-cm (rated)
861 • Stall Torque: 60 kg-cm (maximum)
862 • Power Rating: 50W (maximum)
863 • Unit Weight: 350 grams

864 **4.3.4.4 MicroSD Card**



Fig. 4.8 SanDisk Ultra MicroSD Card

865 The SanDisk Ultra MicroSD Card is a compact, high-capacity, and secure digital
866 memory card that is suitable for a wide range of applications, including digital cameras,
867 smartphones, and tablets. It features a high-speed data transfer rate, making it ideal for
868 storing large files such as images and videos. This card was selected for its high capacity, se-
869 cure data protection, and ease of use, making it ideal for the storage system for the prototype.
870

871 **Specifications:**



- 872 • Capacity: 256GB
873 • Type: MicroSDXC (Secure Digital eXtended Capacity)
874 • Form Factor: MicroSD (11mm x 15mm x 1mm)
875 • File System: Pre-formatted exFAT

876 **4.3.4.5 LED Lights**



Fig. 4.9 LED Light Strip

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

881

882 **Specifications:**



- 883 • Power Input: 5V DC (USB-powered, compatible with laptops, power banks, or USB
884 adapters).
- 885 • Waterproof Design: Suitable for indoor/outdoor use.
- 886 • LED Type: SMD 2835 (surface-mount diodes for high brightness and efficiency).
- 887 • Color Type: White (cool white)
- 888 • Length: 1m
- 889 • Beam Angle: 120°
- 890 • Operating Temperature: -25°C to 60°C.
- 891 • Storage Temperature: -40°C to 80°C.

892 **4.3.4.6 Power Supply**

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

898

899 **Specifications:**

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



Fig. 4.10 Bench Power Supply

- 902 • Output Range: 0-30V DC / 0-5A DC
- 903 • Voltage Precision: $\pm 0.010\text{V}$ (10 mV) resolution
- 904 • Current Precision: $\pm 0.001\text{A}$ (1 mA) resolution
- 905 • Power Precision: $\pm 0.1\text{W}$ resolution
- 906 • Weight: 5 lbs (2.27 kg)
- 907 • Dimensions: 11.1" x 4.92" x 6.14" (28.2 cm x 12.5 cm x 15.6 cm)
- 908 • Maximum Power: 195W
- 909 • 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).



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

931 **4.4 Software Considerations**

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

935 **4.4.1 PyTorch**

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



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

942 **4.4.2 OpenCV**

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

949 **4.4.3 CustomTkinter**

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

956 **4.5 Security and Reliability Considerations**

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



960 4.6 Scalability and Efficiency Considerations

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

964 4.7 User Interface

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

968 4.8 Constraints and Limitations

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

972 4.9 Technical Standards

973 The system adheres to industry standards for image processing and machine learning,
974 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.



987

Chapter 5

988

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"> 1. Hardware design: Build an image acquisition system with a conveyor belt, LED lights, and Raspberry Pi Camera 2. Software design: Coded a Raspberry Pi application to grade and sort the Carabao mangoes 	Sec. 5.2 on p. 55
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ol style="list-style-type: none"> 1. Hardware implementation: Design and build an image acquisition system prototype 	Sec. 5.3 on p. 55
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"> 1. Performance testing: Train and test the machine learning algorithm for classifying bruises and ripeness 2. Data collection: Gather our own Carabao mango dataset together with an online dataset 	Sec. 5.5 on p. 57

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.	<ol style="list-style-type: none"> 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. 55
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<ol style="list-style-type: none"> 1. Formula development: Formulated an equation based on the inputted user priority and the predicted mango classification 	Sec. 5.7 on p. 62
SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.	<ol style="list-style-type: none"> 1. Performance testing: Train and test the machine learning algorithm for classifying bruises 	Sec. 5.6.3 on p. 61
SO6: To classify mango size based on image data by getting its length and width using OpenCV, geometry, and image processing techniques.	<ol style="list-style-type: none"> 1. Performance testing: Train and test the machine learning algorithm for classifying ripeness 	Sec. 5.6.2 on p. 60
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ol style="list-style-type: none"> 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



989 **5.1 Introduction**

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

997 **5.2 Research Approach**

998 This study applies the experimental approach for research in order to develop and properly
999 test the proposed system. The experimental approach of the methodology will allow the
1000 researchers to fine-tune the parameters and other factors in the classification of mangoes in
1001 order to get optimal results with high accuracy scores while maintaining the quality of the
1002 mangoes. This approach will also allow for real-time data processing and classification
1003 which will improve the previous static grading systems.

1004 **5.3 Hardware Design**

1005 The prototype consists of hardware and software components for automated mango sorting
1006 and grading purposes. The hardware includes the conveyor belt system used to transfer
1007 mangoes from scanning to sorting smoothly. A camera and lighting system are able
1008 to collect high-resolution images for analysis. The DC motors and stepper motors are



1009 responsible for driving the conveyor belt and sorting actuators. The entire system is
1010 controlled by a microcontroller (Raspberry Pi 4b), coordinating actions of all components.
1011 Sorting actuators then direct mangoes into selected bins based on their classification to
1012 make sorting efficient.

1013 5.4 Software Design

1014 For the programming language used for the prototype and training and testing the CNN
1015 model, Python was used for training and testing the CNN model and it was also used in the
1016 microcontroller to run the application containing the UI and CNN model. PyTorch was the
1017 main library used in using the EfficientNet model that is used in classifying the ripeness
1018 and bruises of the mango. Likewise, tkinter is the used library when designing the UI in
1019 Python.

1020 Furthermore, the rest of the software components are of utmost importance to mango
1021 classification. Image processing algorithms in OpenCV and CNN models extract features
1022 such as color, size, and bruises that are known to determine quality parameters of mangoes.
1023 Mangoes are classified based on ripeness and defects by using machine learning algorithms,
1024 which further enhances accuracy using deep learning techniques. A user interface (UI) is
1025 designed for users to control and observe the system in real time. Finally, the interface
1026 programming of the microcontroller provides the necessary synchronization between
1027 sensors, actuators, and motors throughout the sorting operation scenario.



1028 5.5 Data Collection Methods

1029 For the data collection, online available image datasets with Carabao mangoes were used
1030 together with the captured Carabao mango images. For the setup of the captured Carabao
1031 mangoes, the height of the camera to the white flat surface is 26 cm which can be seen
1032 on Figure 5.1. Furthermore, the S24's camera is used for capturing both cheeks of the
1033 Carabao mango. Initially, the Carabao mangoes would be unripe and green and each day
1034 the Carabao mangoes would be pictured until they are ripe.



Fig. 5.1 Carabao Mango Image Data Collection

1035 5.6 Testing and Evaluation Methods

1036 In a bid to ensure the mango sorting and grading system is accurate and reliable, there is
1037 intensive testing conducted at different levels. Unit testing is initially conducted on each
1038 component separately, for instance, the conveyor belt, sensors, and cameras, to ensure that



1039 each of the components works as expected when operating separately. After component
 1040 testing on an individual basis, integration testing is conducted to ensure communication
 1041 between hardware and software is correct to ensure the image processing system, motors,
 1042 and sorting actuators work in concert as required. System testing is conducted to con-
 1043 duct overall system performance testing in real-world conditions to ensure mangoes are
 1044 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

1047 A confusion matrix is a table that visualizes the performance of a classification model.
 1048 For a binary classification problem, it has four components:

- 1050 • True Positives (TP): Cases correctly predicted as positive
- 1051 • True Negatives (TN): Cases correctly predicted as negative
- 1052 • False Positives (FP): Cases incorrectly predicted as positive. (Type I error)
- 1053 • False Negatives (FN): Cases incorrectly predicted as negative (Type II error)



1054

5.6.1.2 Precision

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

1055

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

1058

5.6.1.3 Recall

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

1059

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

1062

5.6.1.4 F1 Score

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

1063

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

1066

5.6.1.5 Accuracy

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



1067 Accuracy measures the proportion of correct predictions (both true positives and true
1068 negatives) among the total cases. While intuitive, accuracy can be misleading with imbal-
1069 anced datasets.

1070 To test system performance, various measures of performance are used to evaluate.
1071 As seen on equation 5.4, accuracy score is used to measure the percentage of correctly
1072 classified mangoes to ensure the system maintains high precision levels. Precision as seen
1073 on equation 5.1 and recall as seen on equation 5.2 are used to measure consistency of
1074 classification to determine if the system classifies different ripeness levels and defects
1075 correctly. Furthermore, the F1 score formula as seen on equation 5.3 is used to evaluate the
1076 performance of the model's classification.

1077 A confusion matrix is used to measure correct and incorrect classification to ensure the
1078 machine learning model is optimized and that minimum errors are achieved. Throughput
1079 analysis is also used to determine the rate and efficiency of sorting to ensure that the
1080 system maintains high capacity without bottlenecks to sort mangoes. Using these methods
1081 of testing, the system is constantly optimized to ensure high-quality and reliable mango
1082 classification.

1083 **5.6.2 Ripeness Training and Testing**

1084 For the testing of the ripeness classification, the Carabao mangoes are classified into three
1085 ripeness stages which are Green, green yellow, and yellow. Likewise, The green would
1086 represent the ripe mangoes while the green yellow would represent the semi ripe while the
1087 yellow would represent the ripe mangoes. As reference, Figure 5.3 shows the different
1088 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.

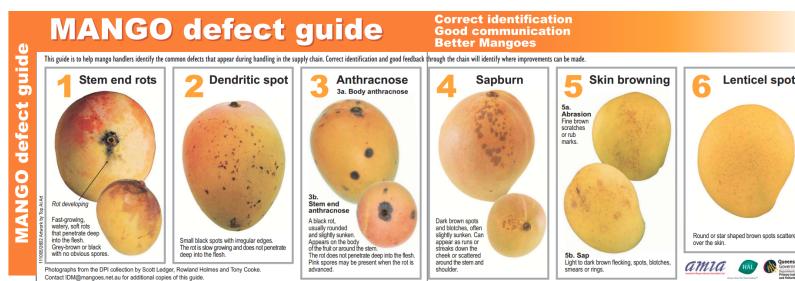


Fig. 5.3 Different Kinds of Mango Defects



1094 5.6.4 Size Determination

1095 To get the size of the mangoes, computer vision techniques such as Gaussian Blur and
 1096 Thresholding are used to get the length and width of the mangoes.

1097 5.7 Mango Formula with User Priority

1098 The linear equation used to calculate the Carabao mango grade is shown below. Likewise,
 1099 the variables $B(P)$, $R(P)$, and $S(P)$ represent the user-defined priority weightings for
 1100 bruising, ripeness, and size characteristics in the User Priority-Based Grading system.
 1101 Additionally, $b(p)$, $r(p)$, and $s(p)$ correspond to the machine learning model's predicted
 1102 values for the bruising, ripeness, and size attributes of the Carabao mango.

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

1103 The machine learning predictions are assigned the following numerical values:

1104 Ripeness Scores:

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

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

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

1105 Bruises Scores:

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

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

1106 **Size Scores:**

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

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

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

5.8 Ethical Considerations

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

5.9 Summary

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



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1123 sustainability, and operation safety. With enhanced efficiency, reduced human error, and
1124 enhanced quality, this system provides an affordable, scalable, and non-destructive solution
1125 to post-harvest mango classification in agricultural industries.



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1126

Chapter 6

1127

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"> 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. <p>Actual Results:</p> <ul style="list-style-type: none"> 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 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 	Sec. 6.6 on p. 77
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"> 1. Successfully integrated a conveyor belt with the image acquisition in order to achieve efficient flow of automated sorting and grading of the mangoes. 2. Successfully integrated LED strips to provide optimal lighting for image capturing of the mangoes. 3. Successfully fixed the hardware components in place <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully integrated a conveyor belt with the image acquisition in order to achieve efficient flow of automated sorting and grading of the mangoes. 2. Successfully integrated LED strips to provide optimal lighting for image capturing of the mangoes. 3. Need to fix the hardware components in place 	Sec. 6.4 on p. 74

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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"> 1. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for ripeness classification of Carabao mangoes 2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruises classification of Carabao mangoes <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully achieved at least 93% accuracy for ripeness classification of Carabao mangoes 2. Successfully achieved at least 73% accuracy for bruise classification of Carabao Mangoes 	<p>Sec. 6.1 on p. 70</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"> 1. Successfully made a conveyor belt system to move the mangoes through the image acquisition system to the sorting system 2. Successfully mounted the image acquisition system on the prototype 3. Successfully made the frame for the conveyor belt and image acquisition system to sit on <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully made a conveyor belt system to move the mangoes through the image acquisition system to the sorting system 2. Temporarily mounted the image acquisition system on the prototype 3. Successfully made the frame for the conveyor belt and image acquisition system to sit on 	<p>Sec. 6.4 on p. 74</p>

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6. Results and Discussions



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Continued from previous page

Objectives	Methods	Locations
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<p>Expected Results:</p> <ul style="list-style-type: none"> 1. Successfully grade mangoes based on the user priorities on the physical characteristics of the mango 2. Successfully verified with qualified individual the results 3. Successfully utilize the weighted equation to evaluate mango grade based on user priorities <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully grade mangoes based on the user priorities on the physical characteristics of the mango 2. Successfully utilize the weighted equation to evaluate mango grade based on user priorities 3. Need to look for a qualified person to evaluate the graded mango for ground truth 	Sec. 6.3 on p. 73

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6. Results and Discussions



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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"> 1. Achieve at least 90% accuracy on performance metrics 2. Obtain performance metrics for kNN, k-mean, and Naive Bayes methods for comparison and show the superior performance of using CNN 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 <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully trained a CNN model using EfficientNet-b0 and Adam Optimizer to detect ripeness based on color 2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for ripeness classification of Carabao mangoes 	<p>Sec. 6.1.1 on p. 70</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"> 1. Successfully classified mango size using computer vision techniques 2. Successfully tuned to have an accurate size with an 80 percent accuracy rating <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully classified mango size using computer vision techniques 2. Calculation of mango size is somewhat inaccurate and needs more fine tuning 	<p>Sec. 6.2 on p. 73</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"> 1. Achieve at least 90% accuracy on performance metrics 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 <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully trained a CNN model using EfficientNet-b0 and Adam Optimizer to bruises 2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruise classification of Carabao mangoes 	Sec. 6.1.2 on p. 73

1128 6.1 Training and Testing Results of the Model

1129 6.1.1 Ripeness Classification Results

1130 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 6.2 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 6.3 RIPENESS CLASSIFICATION REPORT USING KNN

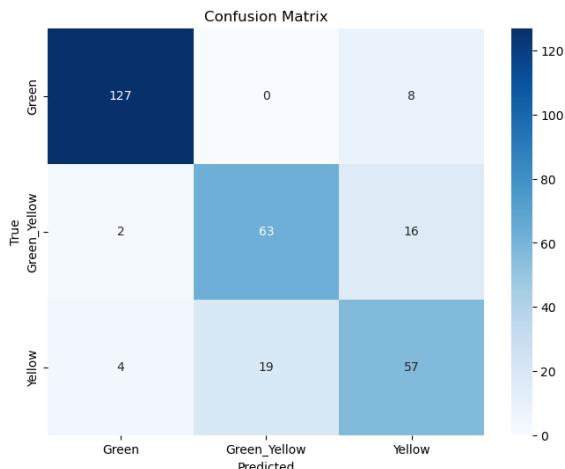


Fig. 6.1 Ripeness Confusion Matrix using kNN

	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 6.4 RIPENESS CLASSIFICATION REPORT USING NAIVE BAYES

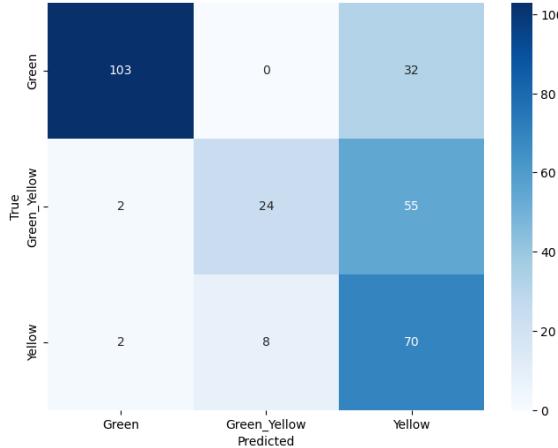


Fig. 6.2 Ripeness Confusion Matrix using Naive Bayes

	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 6.5 BRUISES CLASSIFICATION REPORT USING CNN

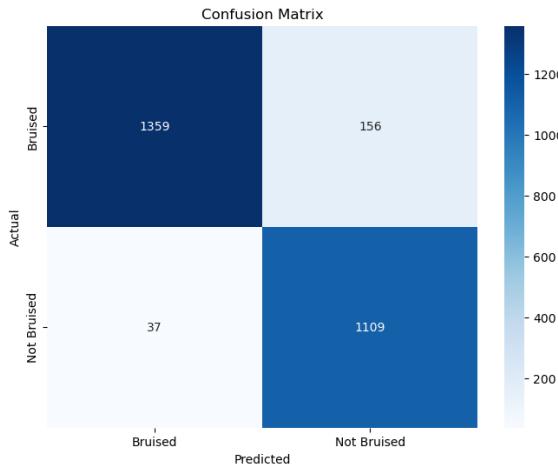


Fig. 6.3 Bruises Confusion Matrix using CNN



Metrics	Results
Precision	0.9318
Recall	0.9275
F1 Score	0.9278

TABLE 6.6 SUMMARIZED CLASSIFICATION REPORT USING CNN

6.1.2 Bruises Classification Results

6.2 Size Determination Results

6.3 Formula with User Priority

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

Ripeness Scores:

$$r(\text{yellow}) = 1.0 \quad (6.2)$$

$$r(\text{yellow_green}) = 2.0 \quad (6.3)$$

$$r(\text{green}) = 3.0 \quad (6.4)$$



1140 **Bruises Scores:**

$$b(\text{bruised}) = 1.0 \quad (6.5)$$

$$b(\text{unbruised}) = 2.0 \quad (6.6)$$

1141 **Size Scores:**

$$s(\text{small}) = 1.0 \quad (6.7)$$

$$s(\text{medium}) = 2.0 \quad (6.8)$$

$$s(\text{large}) = 3.0 \quad (6.9)$$

1142 **6.4 Physical Prototype**

1143 Add pictures of the hardware prototype here with description



Fig. 6.4 Prototype Top View



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Fig. 6.5 Entrance Conveyor Belt View

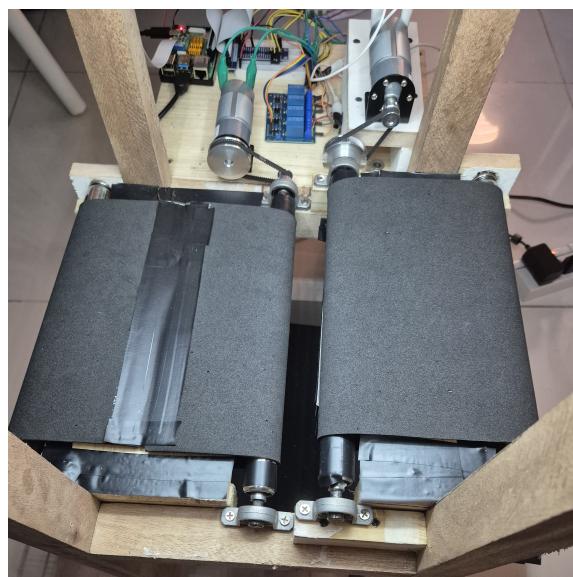


Fig. 6.6 Side Conveyor Belt View

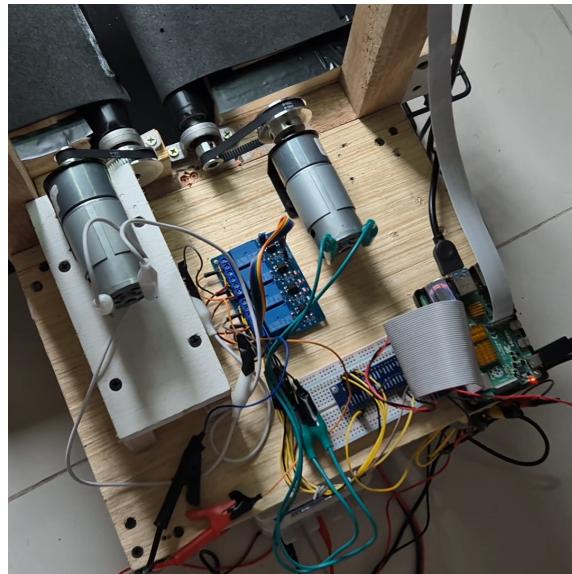


Fig. 6.7 Prototype Main Hardware



Fig. 6.8 DC Motor and Pulley

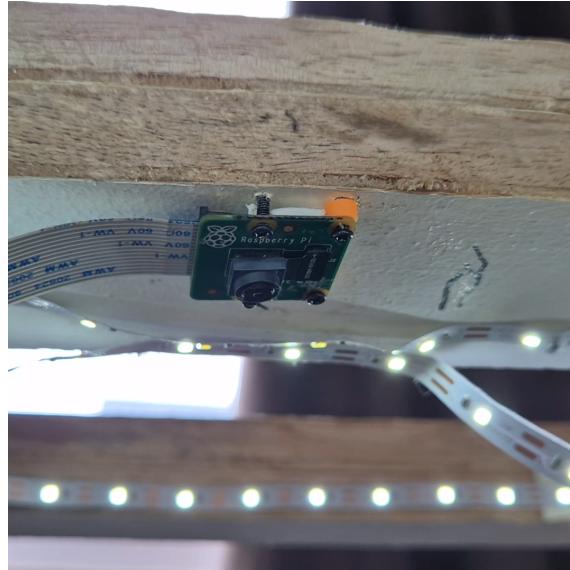


Fig. 6.9 LED Lights and Camera Module

6.5 Software Application

Show the raspberry pi app UI and demonstrate it here

6.6 Summary

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

compile test

1149

6. Results and Discussions



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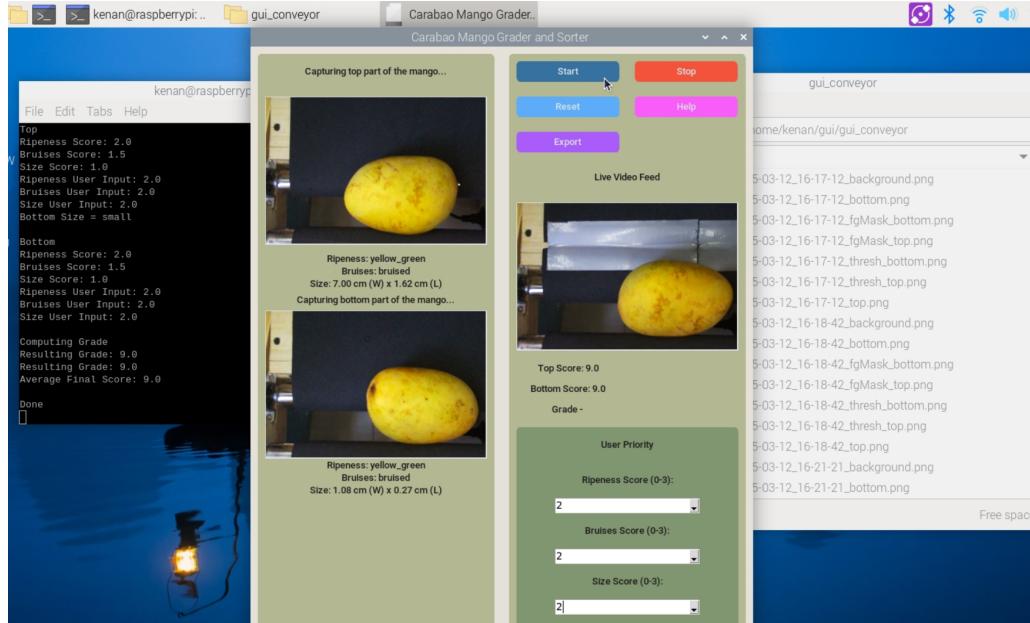


Fig. 6.10 Raspberry Pi App UI Version 1

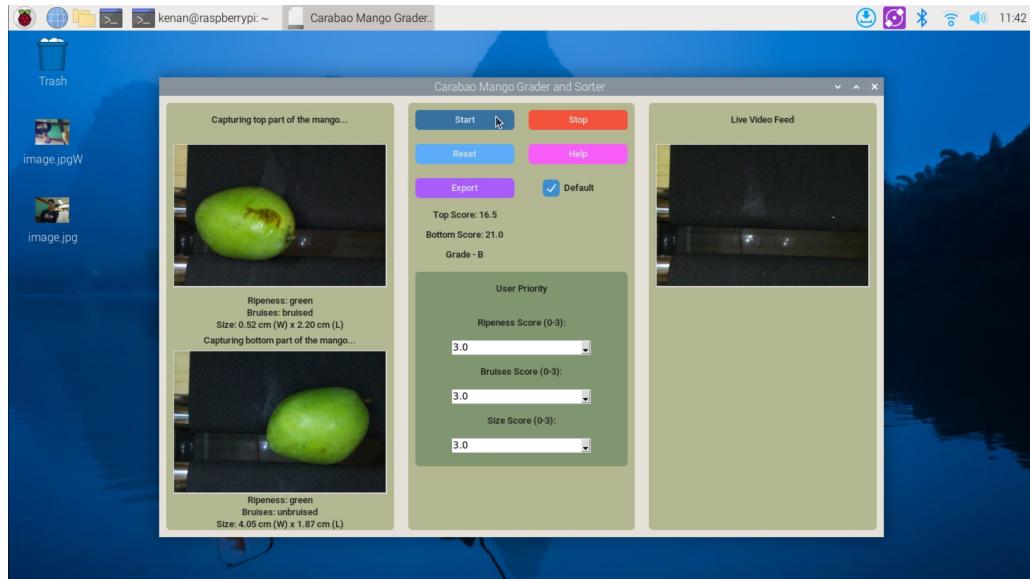


Fig. 6.11 Raspberry Pi App UI Version 2



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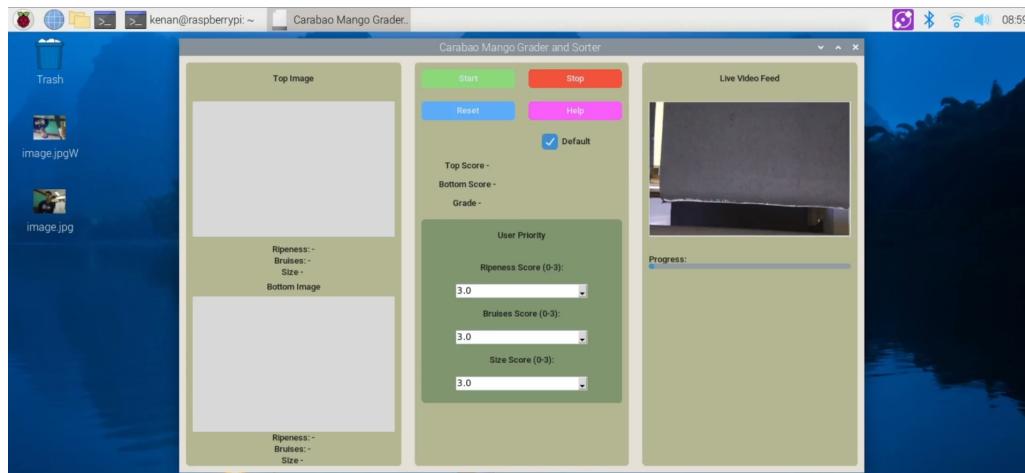


Fig. 6.12 Raspberry Pi App UI Version 3



1150 **Chapter 7**

1151 **CONCLUSIONS, RECOMMENDATIONS, AND**
1152 **FUTURE DIRECTIVES**



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 automatically classifying Carabao mangoes based on ripeness (Green, Green Yellow, and Yellow), size (Large, Medium, Small), and bruises (bruised and not bruised)

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)

7.3 Recommendations

The researchers recommend that the prototype be improved in the optimization of the machine learning algorithm and the hardware design. The researchers also recommend that



1172 the prototype be tested in the actual grading and sorting of Carabao mangoes in the market.

7.4 Future Prospects

1174 Future researchers may consider the following recommendations for future work:

1175 1. User testing of the prototype in the actual grading and sorting of Carabao mangoes

1176 in the Philippine market.

1177 2. Additional of weight measurement to the prototype to improve the grading and

1178 sorting of Carabao mangoes.

1179 3. Integration of a custom PCB to improve the hardware design of the prototype.



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Produced: August 20, 2025, 18:29



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Appendix A

1234

STUDENT RESEARCH ETHICS CLEARANCE

A. Student Research Ethics Clearance



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1235

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

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



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1236

Appendix B ANSWERS TO QUESTIONS TO THIS THESIS

1237



1238 **B1 How important is the problem to practice?**

1239 A possible answer to this question is the summary of your Significance of the Study, and
 1240 that portion of the Problem Statement where you describe the ideal scenario for your
 1241 intended audience.

1242 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1243 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1244 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1245 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1246 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
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 1248 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1249 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1250 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1251 **B2 How will you know if the solution/s that you will 1252 achieve would be better than existing ones?**

1253 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1254 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1257 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
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 1260 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1261 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1262 **B2.1 How will you measure the improvement/s?**

1263 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1264 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1265 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
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1270 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1271 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1273 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1274 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1280 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1281 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

B2.1.2 Why did you choose that/those basis/bases?

1282 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1283 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1289 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1290 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1291 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1292 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1297 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1298 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1299 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1302 **B3 What is the difference of the solution/s from ex-**
 1303 **existing ones?**

1304 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1305 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1310 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1311 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1312 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1313 **B3.1 How is it different from previous and existing ones?**

1314 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1315 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1320 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1321 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1322 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1323 **B4 What are the assumptions made (that are behind
 1324 for your proposed solution to work)?**

1325 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1326 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1327 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
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 1329 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
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 1331 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1332 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1333 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1334 **B4.1 Will your proposed solution/s be sensitive to these assumptions?**

1336 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1337 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1340 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1341 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1342 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1343 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1344 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1345 **B4.2 Can your proposed solution/s be applied to more general cases when some assumptions are eliminated? If so, how?**

1347 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1348 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1354 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1355 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1356 **B5 What is the necessity of your approach / proposed solution/s?**

1358 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1359 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1362 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
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 1364 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1365 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1366 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1367 **B5.1 What will be the limits of applicability of your proposed so-**
 1368 **solution/s?**

1369 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1370 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1376 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1377 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1378 **B5.2 What will be the message of the proposed solution to**
 1379 **technical people? How about to non-technical managers and**
 1380 **business people?**

1381 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1382 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1388 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1389 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1390 **B6 How will you know if your proposed solution/s**
 1391 **is/are correct?**

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 1393 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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1399 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1400 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)?**

1403 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1404 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
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 1410 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1411 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1414 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1415 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
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 1421 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1422 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?**

1425 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1426 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
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 1432 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1433 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?

1436 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1437 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1443 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1444 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.

1449 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1450 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1456 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1457 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?

1458 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1459 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec



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1467 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
1468 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



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Appendix C REVISIONS TO THE PROPOSAL

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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

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

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

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

1477



- 1478 Make a table with the following columns for showing the summary of revisions to the
 1479 proposal based on the comments of the panel of examiners.
- 1480 1. Examiner
- 1481 2. Comment
- 1482 3. Summary of how the comment has been addressed
- 1483 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 First itemtext Second itemtext Last itemtext First itemtext Second itemtext	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???

Continued on next page



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Continued from previous page

Examiner	Comment	Summary of how the comment has been addressed	Locations
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 First itemtext Second itemtext Last itemtext First itemtext Second 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)

1485

Article/Forum Paper Format

(IEEE LaTeX format)

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

1486

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^AT_EX, paper, template.

I. INTRODUCTION

THIS demo file is intended to serve as a “starter file” for IEEE article papers produced under L^AT_EX 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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II. CONCLUSION

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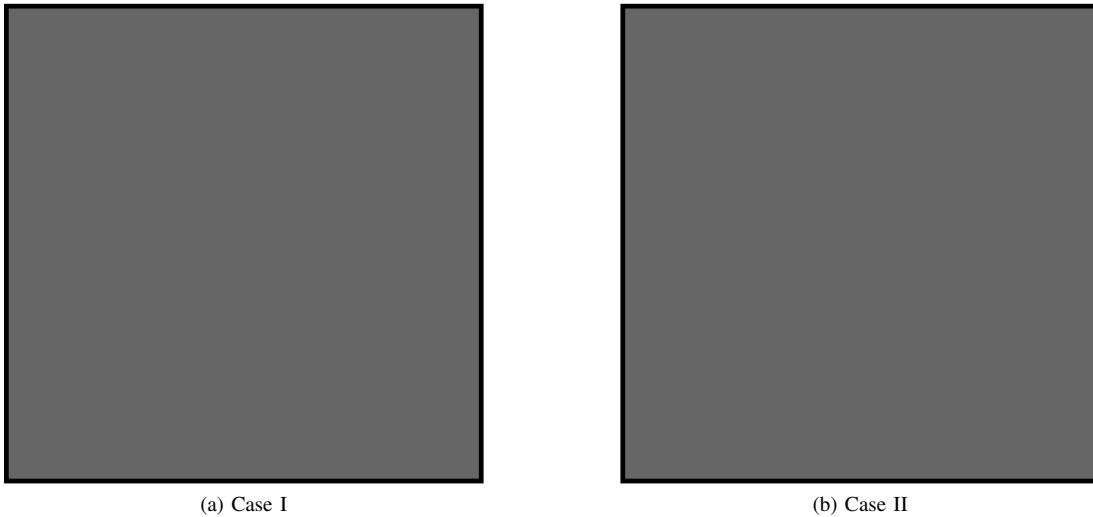


Fig. 2. Simulation results for the network.

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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...