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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

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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 September, 2025



De La Salle University

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THESIS APPROVAL SHEET

22

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51

ABSTRACT

52

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

53

Mangoes, Machine Vision, Microcontroller.



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ABBREVIATIONS

219	AC	Alternating Current.....	13
220	GUI	Graphical User Interface	49
221	LED	Light Emitting Diode	43
222	UI	User Interface	49



223 NOTATION

224	$B(P)$	Bruises Priority	61
225	$b(p)$	Bruises Prediction.....	61
226	$R(P)$	Ripeness Priority.....	61
227	$r(p)$	Ripeness Prediction	61
228	$S(P)$	Size Priority	61
229	$s(p)$	Size Prediction	61
230	$D(p, d, f)$	Real World Dimension	26
231	p	Pixel Dimension	26
232	d	Distance from Camera to Object.....	26
233	f	Focal Length	26



234 GLOSSARY

235	bruises	The black or brown area of the mango that is visible on the skin of the mango.
236	Carabao mango	A popular variety of mango grown in the Philippines, known for its sweet and juicy flesh.
237	accuracy score	A performance metric that measures the overall proportion of correct predictions made by a machine learning model.
238	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.
239	CNN	A type of deep neural network that is highly effective in analyzing and processing visual data, such as images.
240	F1-Score	A balanced performance metric that is the harmonic mean of precision and recall, taking both into account.
241	machine learning	A subset of Artificial Intelligence that enables systems to learn and improve from data.
242	computer vision	The use of cameras and algorithms to provide imaging-based inspection and analysis.
243	microcontroller	A small computing device that controls other parts of a system such as sensors.
244	Precision	A performance metric that reflects the percentage of instances classified as positive that are truly positive.
245	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

249

INTRODUCTION



250 **1.1 Background of the Study**

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



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

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

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



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

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

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

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



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

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

302 1.2 Prior Studies

303 A paper written by ?, designed an automated fruit sorting machine based on the quality
304 through an image acquisition system and CNN. Furthermore, the results of the paper show
305 that the image processing detection score was 89% while that of the tomatoes was 92%
306 while the CNN model had higher validity of 95% for mangoes and 93% for tomatoes.
307 15%, while the percentage of distinction between the two groups was reported to be 5%
308 respectively (?). Despite the high accuracy score in detecting mango defects, the fruit
309 sorting system only sorts based on the mango defects and not on ripeness, and weight.

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



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

318 **1.3 Problem Statement**

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

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



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

342 **1.4 Objectives and Deliverables**

343 **1.4.1 General Objective (GO)**

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

347 **1.4.2 Specific Objectives (SOs)**

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



- 353 • SO3: To create a microcontroller-based system to operate the image acquisition
354 system, control the conveyor belt, and process the mango images through machine
355 learning. ;
- 356 • SO4: To grade mangoes based on user priorities for size, ripeness, and bruises. ;
- 357 • SO5: To classify mango ripeness based on image data using machine learning
358 algorithms such as kNN, k-mean, and Naïve Bayes. ;
- 359 • SO6: To classify mango size based on image data by getting its length and width
360 using OpenCV, geometry, and image processing techniques. ;
- 361 • SO7: To classify mango bruises based on image data by employing machine learning
362 algorithms.

363 **1.4.3 Expected Deliverables**

364 Table 1.1 shows the outputs, products, results, achievements, gains, realizations, and/or
365 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.

Continued on next page



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ul style="list-style-type: none"> 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.
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.

Continued on next page



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ul style="list-style-type: none"> • 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.

366

1.5 Significance of the Study

367

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

374

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



379 ensuring that only marketable fruits are processed further.

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

386 **1.5.1 Technical Benefit**

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

393 **1.5.2 Social Impact**

- 394 1. The reduction in manual labor creates opportunities in maintenance and technologies
395 in the automated Carabao mango sorter.
- 396 2. The automated Carabao mango sorter system improves Carabao mango standards
397 and enhances the satisfaction of the buyers and the customers through guaranteeing
398 consistent Carabao mango grade.



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

401 **1.5.3 Environmental Welfare**

- 402 1. With the utilization of non-destruction methods of classifying Carabao mangoes
403 together with an accurate sorting system, overall waste from Carabao mangoes is
404 reduced and the likelihood of improperly sorted mangoes is decreased.
405 2. Automation of sorting and grading Carabao mangoes promotes sustainable farming
406 practices.

407 **1.6 Assumptions, Scope, and Delimitations**

408 **1.6.1 Assumptions**

- 409 1. The Carabao mangoes are from the same source together with the same variation
410 2. The Carabao mangoes do not have any fruit borer and diseases
411 3. All the components do not have any form of defects
412 4. The prototype would have access to constant electricity/power source.
413 5. The Carabao mangoes to be tested would be in the post-harvesting stage and in the
414 grading stage.
415 6. The image-capturing system would only capture the two sides of the mango which
416 are the two largest surface areas of the skin.



417 **1.6.2 Scope**

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

426 **1.6.3 Delimitations**

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



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

438 **1.7 Overview of the Thesis**

439 There are seven succeeding chapters. To recall, chapter 1 involves the introduction of
440 the thesis topic containing the background of the study, previous studies, objectives and
441 deliverables, assumptions, scope, and delimitation, significance of the study, description
442 of the project together with the methodology, and Gantt chart and budget. Chapter 2
443 involves the existing articles, the lacking in their approaches, and the summary of chapter 2.
444 Chapter 3 involves the theoretical considerations of the thesis topic while chapter 4 would
445 consist of the design consideration involving the thesis topic. Chapter 5 would involve the
446 research methodology containing the testing procedure and setup. Chapter 6 would involve
447 the results and discussion based on the methodology while Chapter 7 would involve the
448 conclusion, recommendations, and future suggestions.



449

Chapter 2

450

LITERATURE REVIEW



451 **2.1 Existing Work**

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

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



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

490 Another study by ? proposed SVM-based system for classifying the maturity stages of
491 bananas, mangoes, and calamansi. With the use of 1729 images of bananas together with
492 711 mango images and 589 calamansi, the researchers were able to achieve a high accuracy
493 score of above 90% for all fruits. Some pre-processing techniques used to get this high
494 accuracy are the change in hue, saturation, and value channels in the mango image (?). To
495 better understand the harvest time of mangoes, the paper by ? examined the association of
496 the harvest season with seasonal heat units, rainfall, and physical fruit attributes for Haden,
497 Kent, Palmer, and Keitt mango varieties to establish export and domestic market maturity



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

TABLE 2.1 COMPARISON OF EXISTING STUDIES

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

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



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

513 **2.1.1 Sorting Algorithms**

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

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



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

548 **2.2 Lacking in the Approaches**

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



TABLE 2.2 COMPARISON OF SORTING ALGORITHM MODELS

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

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

2.3 Summary

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



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



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583

Chapter 3

584

THEORETICAL CONSIDERATIONS



585 3.1 Introduction

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

588 3.2 Relevant Theories and Models

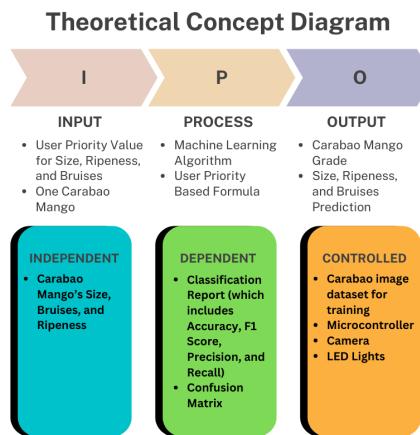


Fig. 3.1 Theoretical Framework Diagram.

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



598 3.3 Technical Background

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

606 3.4 Conceptual Framework Background

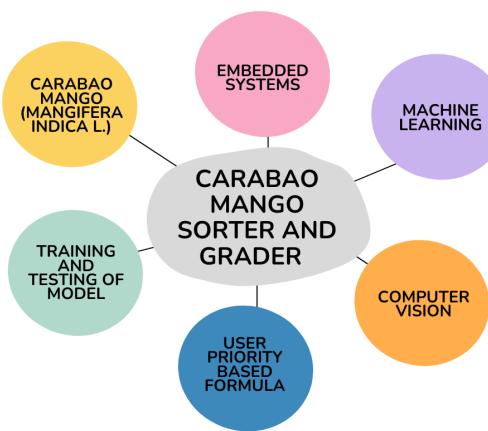


Fig. 3.2 Conceptual Framework Diagram.

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



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

615 **3.5 Software Concepts**

616 **3.5.1 Thresholding**

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

624

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

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



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

636 **3.5.2 Object Size Calculation**

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

641 The size of the mango can be determined given:

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

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

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

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



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

652 **3.5.3 Convolutional Neural Network**

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

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

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

665 **3.6 Hardware Concepts**

666 **3.6.1 Camera Module**

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



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

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

680 **3.6.2 4 Channel Relay**

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

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

**690 3.6.3 Gear Ratio**

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

699 3.7 Summary

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



705

Chapter 4

706

DESIGN CONSIDERATIONS



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

713 **4.1 Introduction**

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

718 **4.2 System Architecture**

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

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

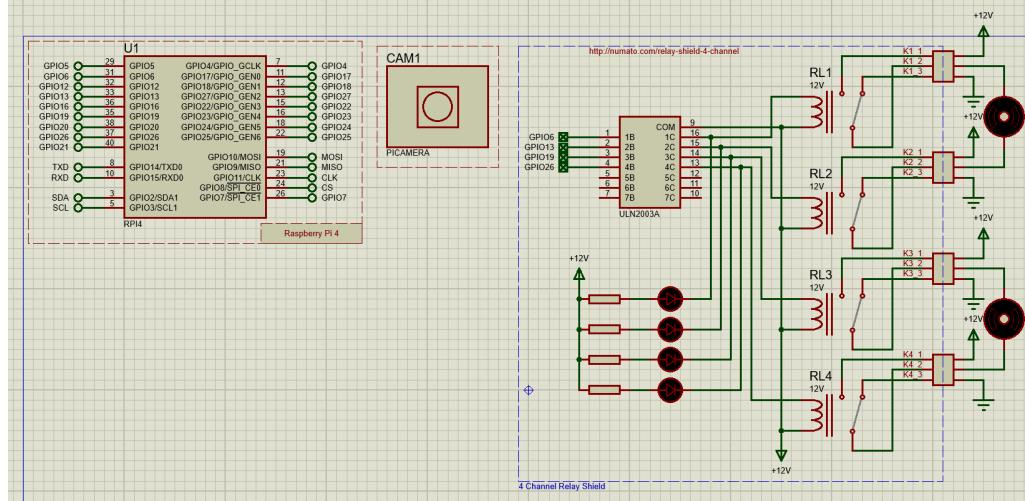


Fig. 4.1 Hardware Schematic

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

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

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



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

744 4.3 Hardware Considerations

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

749 4.3.1 General Prototype Framework

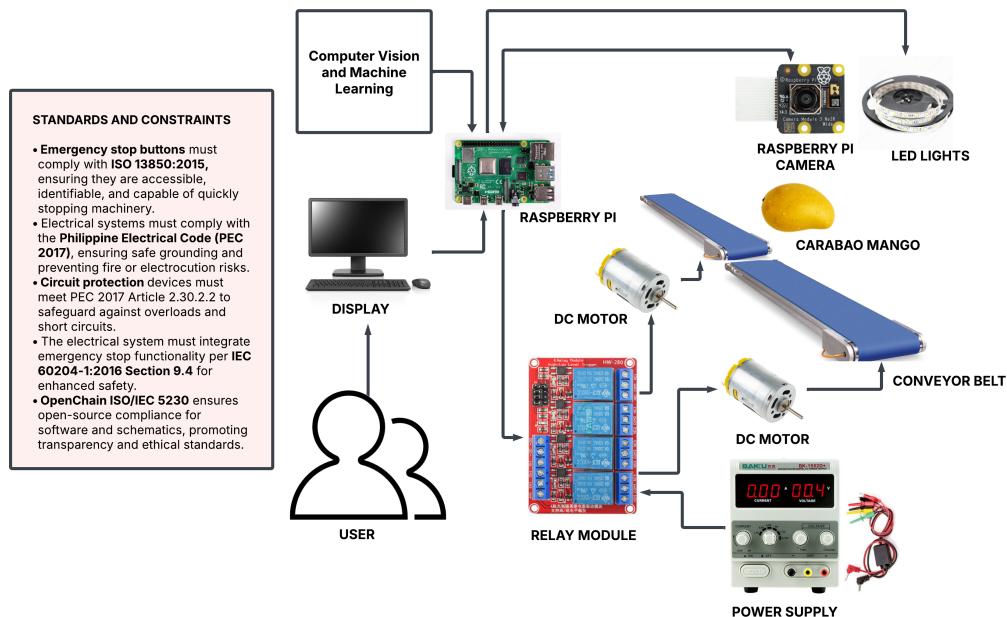


Fig. 4.2 Prototype Framework



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

758 **4.3.2 Prototype Flowchart**

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

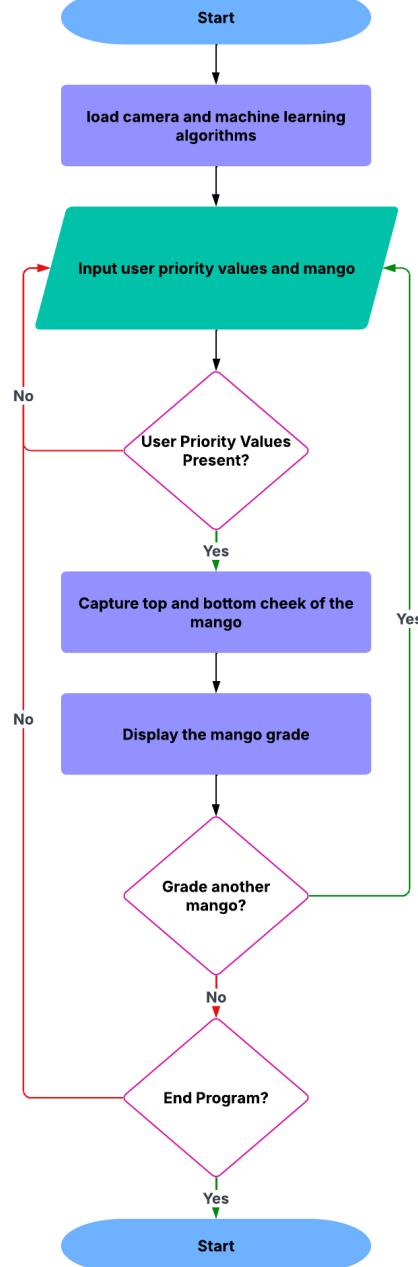


Fig. 4.3 Prototype Main Flowchart



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Fig. 4.4 Initial 3D Model of the Prototype



769 **4.3.3 Prototype 3D Model**

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

777 **4.3.4 Hardware Specifications**

778 **4.3.4.1 Raspberry Pi**

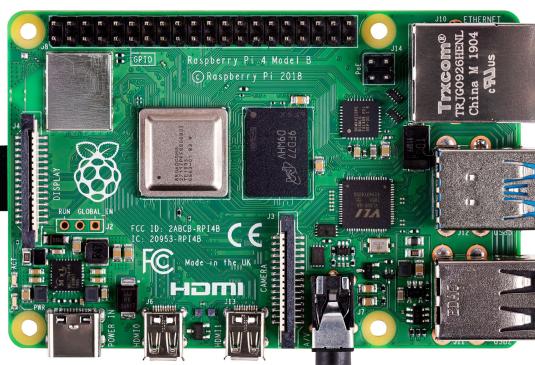


Fig. 4.5 Raspberry Pi 4 Model B

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



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

786 **Specifications:**

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



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

803 **4.3.4.2 Raspberry Pi Camera**

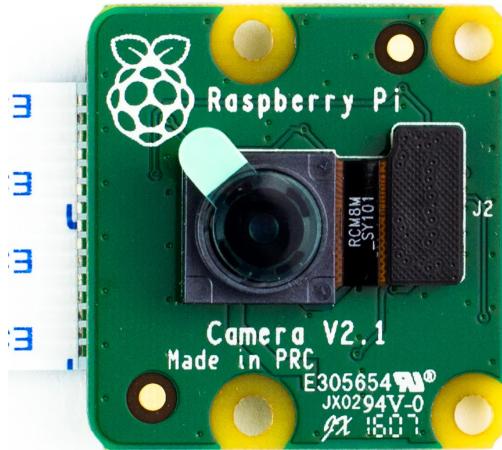


Fig. 4.6 Raspberry Pi Camera Module Version 2

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



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

811

812 **Specifications:**

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

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

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

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

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

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

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

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

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

825 **4.3.4.3 DC Motor**

826 The 12 Volt DC Gear Motor is a compact, high-torque, and low-noise motor suitable for a
827 wide range of applications, including robotics, automation, and industrial control systems.
828 It features a spur gear design, which provides a high reduction ratio for increased torque
829 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.

834 **Specifications:**

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



- 841 • Torque Output: 18 kg-cm (rated)
- 842 • Stall Torque: 60 kg-cm (maximum)
- 843 • Power Rating: 50W (maximum)
- 844 • Unit Weight: 350 grams

845 **4.3.4.4 MicroSD Card**



Fig. 4.8 SanDisk Ultra MicroSD Card

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

851
852 **Specifications:**



- 853 • Capacity: 256GB
854 • Type: MicroSDXC (Secure Digital eXtended Capacity)
855 • Form Factor: MicroSD (11mm x 15mm x 1mm)
856 • File System: Pre-formatted exFAT

857 **4.3.4.5 LED Lights**



Fig. 4.9 LED Light Strip

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

862

863 **Specifications:**



- 864 • Power Input: 5V DC (USB-powered, compatible with laptops, power banks, or USB
865 adapters).
- 866 • Waterproof Design: Suitable for indoor/outdoor use.
- 867 • LED Type: SMD 2835 (surface-mount diodes for high brightness and efficiency).
- 868 • Color Type: White (cool white)
- 869 • Length: 1m
- 870 • Beam Angle: 120°
- 871 • Operating Temperature: -25°C to 60°C.
- 872 • Storage Temperature: -40°C to 80°C.

873 **4.3.4.6 Power Supply**

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

879

880 **Specifications:**

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



Fig. 4.10 Bench Power Supply

- 883 • Output Range: 0-30V DC / 0-5A DC
- 884 • Voltage Precision: $\pm 0.010\text{V}$ (10 mV) resolution
- 885 • Current Precision: $\pm 0.001\text{A}$ (1 mA) resolution
- 886 • Power Precision: $\pm 0.1\text{W}$ resolution
- 887 • Weight: 5 lbs (2.27 kg)
- 888 • Dimensions: 11.1" x 4.92" x 6.14" (28.2 cm x 12.5 cm x 15.6 cm)
- 889 • Maximum Power: 195W
- 890 • Power Source: AC input only

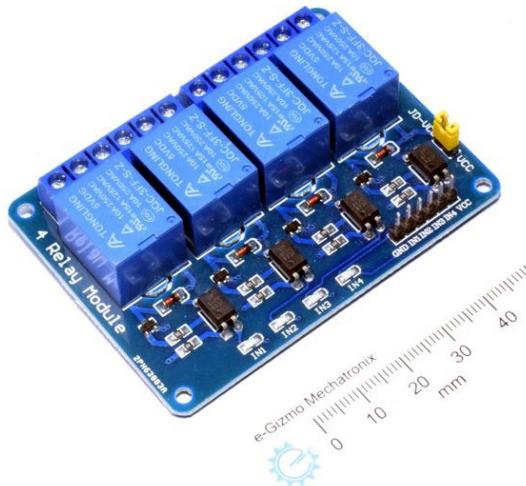


Fig. 4.11 4 Channel Relay Module

891 **4.3.4.7 4 Channel Relay Module**

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

897

898 **Specifications:**

- 899
- 900 • Operating Voltage: 5V DC (compatible with Arduino, Raspberry Pi, and other
microcontrollers).

901

 - 902 • Number of Relays: 4 independent channels.
 - 903 • Relay Type: Electromechanical (mechanical switching).



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

912 **4.4 Software Considerations**

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

916 **4.4.1 PyTorch**

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



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

923 **4.4.2 OpenCV**

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

930 **4.4.3 CustomTkinter**

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

937 **4.5 Security and Reliability Considerations**

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



941 4.6 Scalability and Efficiency Considerations

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

945 4.7 User Interface

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

949 4.8 Constraints and Limitations

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

953 4.9 Technical Standards

954 The system adheres to industry standards for image processing and machine learning,
955 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.



968

Chapter 5

969

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. 54
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. 54
SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.	<ol style="list-style-type: none"> 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. 56

Continued on next page



Continued from previous page

Objectives	Methods	Locations
SO3: To create a microcontroller-based system to operate the image acquisition system, control the conveyor belt, and process the mango images through machine learning.	<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. 54
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. 61
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. 60
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. 59
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. 61



970 5.1 Introduction

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

978 5.2 Research Approach

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

985 5.3 Hardware Design

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



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

994 **5.4 Software Design**

995 For the programming language used for the prototype and training and testing the CNN
996 model, Python was used for training and testing the CNN model and it was also used in the
997 microcontroller to run the application containing the UI and CNN model. PyTorch was the
998 main library used in using the EfficientNet model that is used in classifying the ripeness
999 and bruises of the mango. Likewise, tkinter is the used library when designing the UI in
1000 Python.

1001 Furthermore, the rest of the software components are of utmost importance to mango
1002 classification. Image processing algorithms in OpenCV and CNN models extract features
1003 such as color, size, and bruises that are known to determine quality parameters of mangoes.
1004 Mangoes are classified based on ripeness and defects by using machine learning algorithms,
1005 which further enhances accuracy using deep learning techniques. A user interface (UI) is
1006 designed for users to control and observe the system in real time. Finally, the interface
1007 programming of the microcontroller provides the necessary synchronization between
1008 sensors, actuators, and motors throughout the sorting operation scenario.



5.5 Data Collection Methods

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



Fig. 5.1 Carabao Mango Image Data Collection

5.6 Testing and Evaluation Methods

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



1020 each of the components works as expected when operating separately. After component
 1021 testing on an individual basis, integration testing is conducted to ensure communication
 1022 between hardware and software is correct to ensure the image processing system, motors,
 1023 and sorting actuators work in concert as required. System testing is conducted to con-
 1024 duct overall system performance testing in real-world conditions to ensure mangoes are
 1025 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

1028 A confusion matrix is a table that visualizes the performance of a classification model.
 1029 For a binary classification problem, it has four components:

- 1031 • True Positives (TP): Cases correctly predicted as positive
- 1032 • True Negatives (TN): Cases correctly predicted as negative
- 1033 • False Positives (FP): Cases incorrectly predicted as positive. (Type I error)
- 1034 • False Negatives (FN): Cases incorrectly predicted as negative (Type II error)

1035 **5.6.1.2 Precision**

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

1036 Precision measures how many of the predicted positives are actually positive. It answers
 1037 the question: "When the model predicts the positive class, how often is it correct?" High
 1038 precision means low false positives.

1039 **5.6.1.3 Recall**

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

1040 Recall, which is also called sensitivity, measures how many of the actual positives were
 1041 correctly identified. It answers the question: "Of all the actual positive cases, how many
 1042 did the model catch?" High recall means low false negatives.

1043 **5.6.1.4 F1 Score**

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

1044 The F1 score is the harmonic mean of precision and recall. It provides a single metric
 1045 that balances both concerns. This is particularly useful when you need to find a balance
 1046 between precision and recall, as optimizing for one often decreases the other.

1047 **5.6.1.5 Accuracy**

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



1048 Accuracy measures the proportion of correct predictions (both true positives and true
1049 negatives) among the total cases. While intuitive, accuracy can be misleading with imbal-
1050 anced datasets.

1051 To test system performance, various measures of performance are used to evaluate.
1052 As seen on equation 5.4, accuracy score is used to measure the percentage of correctly
1053 classified mangoes to ensure the system maintains high precision levels. Precision as seen
1054 on equation 5.1 and recall as seen on equation 5.2 are used to measure consistency of
1055 classification to determine if the system classifies different ripeness levels and defects
1056 correctly. Furthermore, the F1 score formula as seen on equation 5.3 is used to evaluate the
1057 performance of the model's classification.

1058 A confusion matrix is used to measure correct and incorrect classification to ensure the
1059 machine learning model is optimized and that minimum errors are achieved. Throughput
1060 analysis is also used to determine the rate and efficiency of sorting to ensure that the
1061 system maintains high capacity without bottlenecks to sort mangoes. Using these methods
1062 of testing, the system is constantly optimized to ensure high-quality and reliable mango
1063 classification.

1064 **5.6.2 Ripeness Training and Testing**

1065 For the testing of the ripeness classification, the Carabao mangoes are classified into three
1066 ripeness stages which are Green, green yellow, and yellow. Likewise, The green would
1067 represent the ripe mangoes while the green yellow would represent the semi ripe while the
1068 yellow would represent the ripe mangoes. As reference, Figure 5.3 shows the different
1069 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.

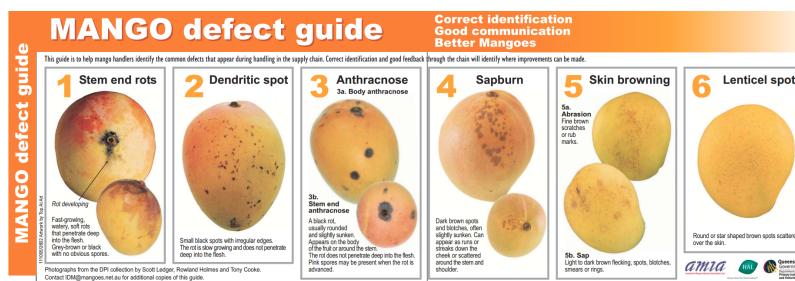


Fig. 5.3 Different Kinds of Mango Defects



1075 5.6.4 Size Determination

1076 To get the size of the mangoes, computer vision techniques such as Gaussian Blur and
 1077 Thresholding are used to get the length and width of the mangoes.

1078 5.7 Mango Formula with User Priority

1079 The linear equation used to calculate the Carabao mango grade is shown below. Likewise,
 1080 the variables $B(P)$, $R(P)$, and $S(P)$ represent the user-defined priority weightings for
 1081 bruising, ripeness, and size characteristics in the User Priority-Based Grading system.
 1082 Additionally, $b(p)$, $r(p)$, and $s(p)$ correspond to the machine learning model's predicted
 1083 values for the bruising, ripeness, and size attributes of the Carabao mango.

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

1084 The machine learning predictions are assigned the following numerical values:

1085 Ripeness Scores:

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

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

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

1086 Bruises Scores:

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

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

1087 **Size Scores:**

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

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

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

1088 **5.8 Ethical Considerations**

1089 Ethical considerations ensure that the system is operated safely and responsibly. Data
1090 privacy is ensured by securely storing and anonymizing extracted images and classification
1091 data so that unauthorized access becomes impossible. The system is also eco-friendly
1092 through non-destructive testing, saving mangoes while also ensuring that they are of good
1093 quality. Safety in operations is also ensured by protecting moving parts to prevent mechani-
1094 cal harm and incorporating fail-safes to securely stop operation in case of malfunction.
1095 Addressing these concerns, the system is not only accurate and efficient but also secure,
1096 eco-friendly, and safe for operators, thus a sustainable solution to automated mango sorting
1097 and grading.

1098 **5.9 Summary**

1099 This chapter explained how to create an automatic Carabao mango sorter and grader using
1100 machine learning and computer vision. The system integrates hardware and software
1101 resources, including a conveyor belt, cameras, sensors, and actuators, to offer accurate,
1102 real-time sorting by ripeness, size, and bruises. Various testing and evaluation processes
1103 ensure its performance to offer reliability. Ethical issues are data privacy, environmental



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1104 sustainability, and operation safety. With enhanced efficiency, reduced human error, and
1105 enhanced quality, this system provides an affordable, scalable, and non-destructive solution
1106 to post-harvest mango classification in agricultural industries.



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1107

Chapter 6

1108

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. 73

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6. Results and Discussions



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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. 69</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. 73</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. 72

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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. 69</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. 72</p>

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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. 72

1109 6.1 Training and Testing Results of the Model

1110 6.1.1 Ripeness Classification Results

1111 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

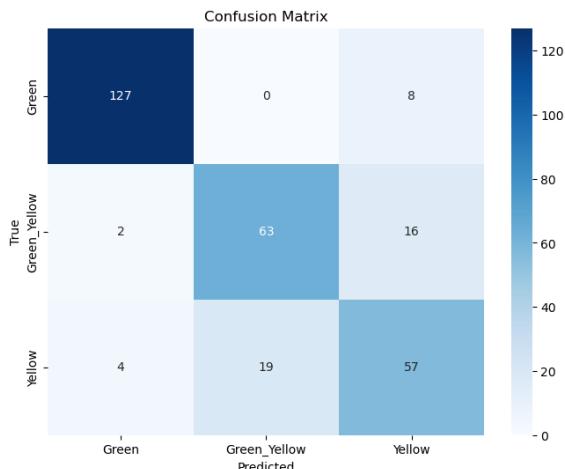


Fig. 6.1 Ripeness Confusion Matrix using kNN

	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

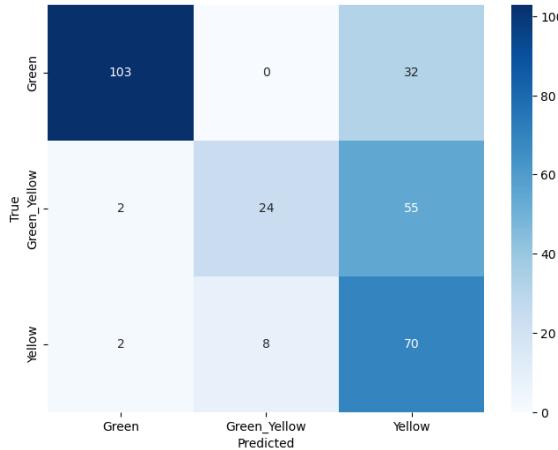


Fig. 6.2 Ripeness Confusion Matrix using Naive Bayes

	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

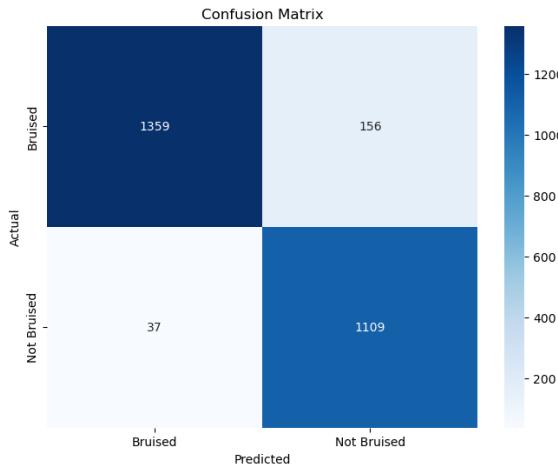


Fig. 6.3 Bruises Confusion Matrix using CNN



Metrics	Results
Precision	0.9318
Recall	0.9275
F1 Score	0.9278

TABLE 6.6 SUMMARIZED CLASSIFICATION REPORT USING CNN

1112 **6.1.2 Bruises Classification Results**

1113 **6.2 Size Determination Results**

1114 **6.2.1 Method 1: Thresholding**

1115 To get the length and width of the mango. An initial image without the mango is taken
 1116 which would be the background image. After that another image is taken with the mango
 1117 with the same background.

1118 **6.2.2 Method 2: Object Detection**

1119 **6.3 Formula with User Priority**

1120 $B(P)$ and $R(P)$ and $S(P)$ are the User Priority-Based Grading for bruises, ripeness,
 1121 and size of the Carabao mango. Furthermore, $b(p)$ and $r(p)$ and $s(p)$ are the machine
 1122 learning's predictions for bruises, ripeness, and size of the Carabao mango. The formula
 1123 for the user priority is given by:

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

1124 The machine learning predictions are assigned the following numerical values:



1125	Ripeness Scores:
	$r(\text{yellow}) = 1.0$ (6.2)
	$r(\text{yellow-green}) = 2.0$ (6.3)
	$r(\text{green}) = 3.0$ (6.4)
1126	Bruises Scores:
	$b(\text{bruised}) = 1.0$ (6.5)
	$b(\text{unbruised}) = 2.0$ (6.6)
1127	Size Scores:
	$s(\text{small}) = 1.0$ (6.7)
	$s(\text{medium}) = 2.0$ (6.8)
	$s(\text{large}) = 3.0$ (6.9)

1128 6.4 Physical Prototype

1129 Add pictures of the hardware prototype here with description

1130 6.5 Software Application

1131 Show the raspberry pi app UI and demonstrate it here



Fig. 6.4 Prototype Top View



Fig. 6.5 Entrance Conveyor Belt View

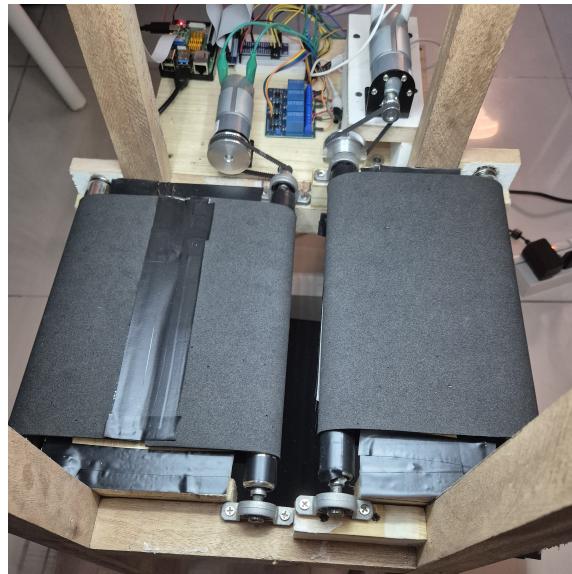


Fig. 6.6 Side Conveyor Belt View



Fig. 6.7 Prototype Main Hardware



Fig. 6.8 DC Motor and Pulley

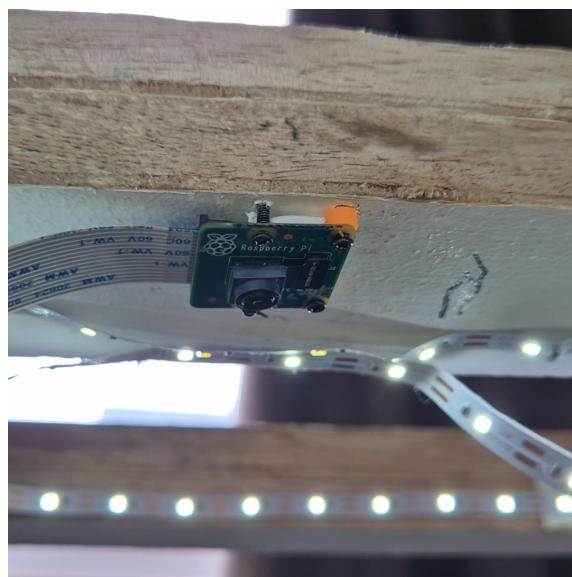


Fig. 6.9 LED Lights and Camera Module



Fig. 6.10 Side View of Improved Prototype



Fig. 6.11 Top View Improved Prototype

6.6 Summary

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

1132

6.6 Summary

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

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

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

1135

6. Results and Discussions



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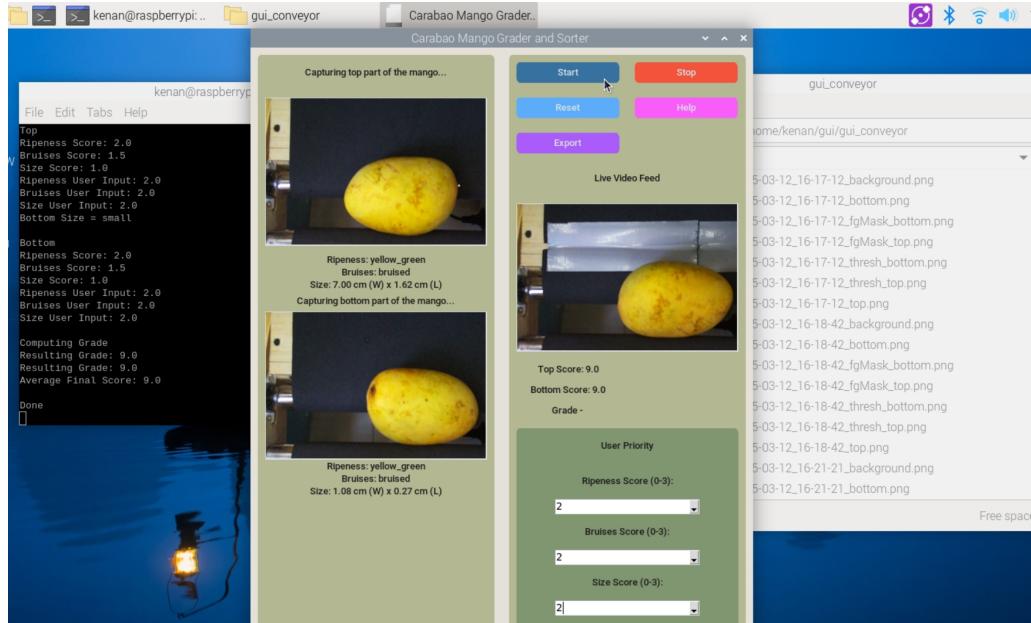


Fig. 6.12 Raspberry Pi App UI Version 1

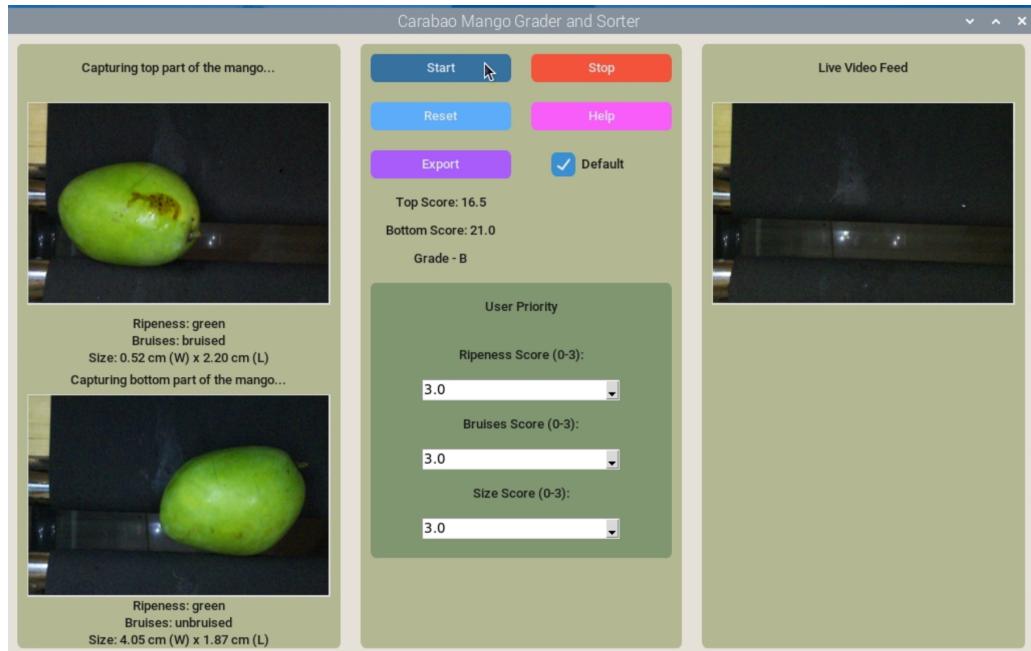


Fig. 6.13 Raspberry Pi App UI Version 2

6. Results and Discussions



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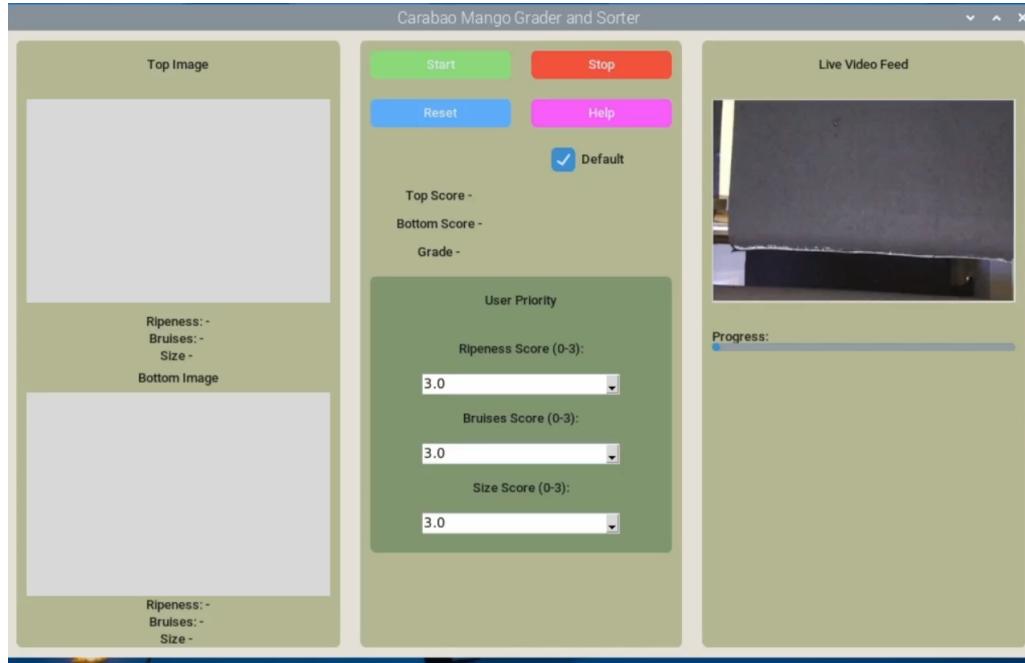


Fig. 6.14 Raspberry Pi App UI Version 3

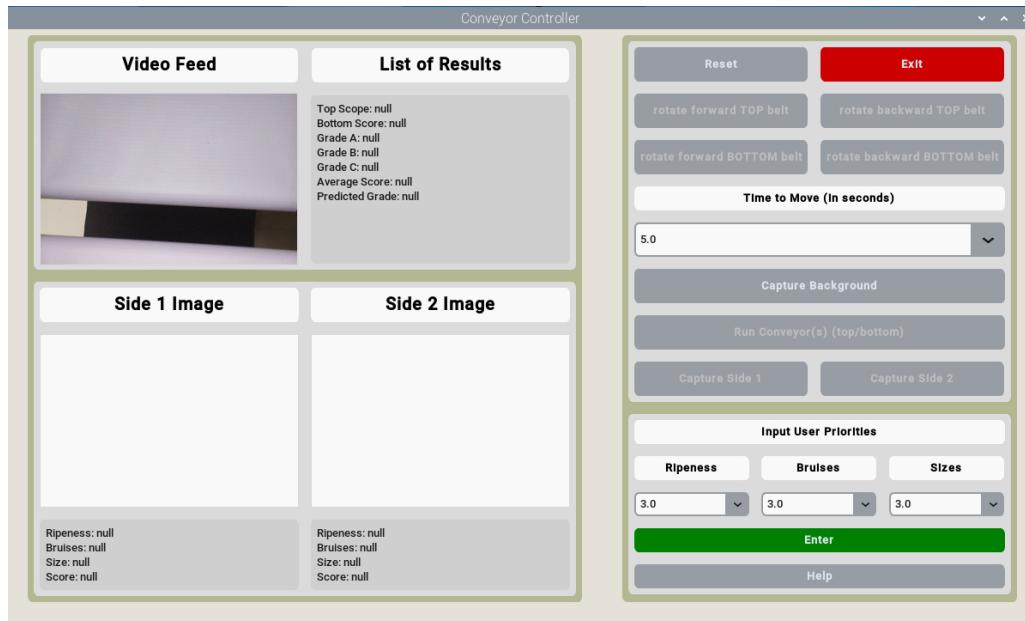


Fig. 6.15 Raspberry Pi App UI Version 4

6. Results and Discussions



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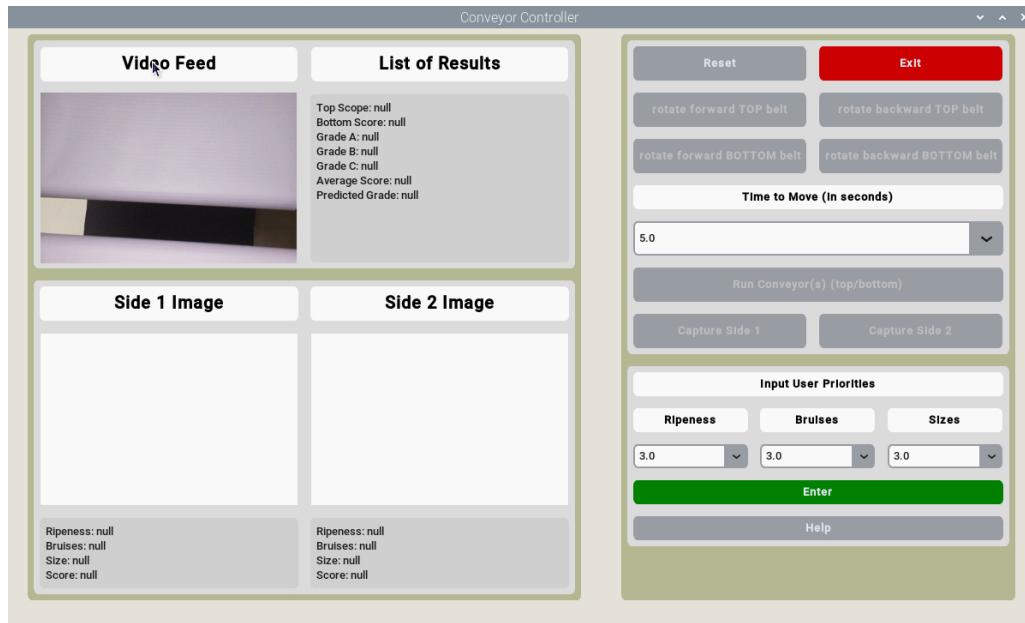


Fig. 6.16 Raspberry Pi App UI Version 5



1136 **Chapter 7**

1137 **CONCLUSIONS, RECOMMENDATIONS, AND**
1138 **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 classifying Carabao mangoes based on ripeness (Green, Green Yellow, and Yellow), size (Large, Medium, Small), and bruises (bruised and not bruised).

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

7.2 Contributions

The contributions of each group member are as follows:

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



1156 7.3 Recommendations

1157 The researchers recommend that the prototype be improved in the optimization of the
1158 machine learning algorithm and the hardware design. The researchers also recommend that
1159 the prototype be tested in the actual grading and sorting of Carabao mangoes in the market.

1160 7.4 Future Prospects

1161 Future researchers may consider the following recommendations for future work:

- 1162 1. User testing of the prototype in the actual grading and sorting of Carabao mangoes
1163 in the Philippine market.
- 1164 2. Additional of weight measurement to the prototype to improve the grading and
1165 sorting of Carabao mangoes.
- 1166 3. Integration of a custom PCB to improve the hardware design of the prototype.

7. Conclusions, Recommendations, and Future Directives



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Produced: September 3, 2025, 13:37



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Appendix A STUDENT RESEARCH ETHICS CLEARANCE

1169

A. Student Research Ethics Clearance



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1170

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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Appendix B ANSWERS TO QUESTIONS TO THIS THESIS

1172



B1 How important is the problem to practice?

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

1173 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1174 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1175 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1176 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1177 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1178 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1179 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1180 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1181 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1182 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1183 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1185 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1186 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1187 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1188 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1189 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1190 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1191 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1192 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
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 1194 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1195 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1196 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1197 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.



1205 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1206 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1208 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1209 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1210 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
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 1212 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1213 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1214 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1215 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1216 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1218 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1219 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1220 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
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 1222 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1223 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1224 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1225 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1226 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1228 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1229 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1230 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
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 1232 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1233 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1234 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1235 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1236 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1237 **B3 What is the difference of the solution/s from ex-**

1238 **existing ones?**

1239 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1240 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1241 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

1242 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.

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1245 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

1246 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

1247 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1248 **B3.1 How is it different from previous and existing ones?**

1249 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1250 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1251 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

1252 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.

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1255 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

1256 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

1257 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1258 **B4 What are the assumptions made (that are behind**

1259 **for your proposed solution to work)?**

1260 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1261 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1262 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

1263 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.

1264 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla

1265 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue

1266 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

1267 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

1268 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1269 **B4.1 Will your proposed solution/s be sensitive to these as-**

1270 **sump tions?**

1271 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1272 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1273 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

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1277 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

1278 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

1279 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1280 **B4.2 Can your proposed solution/s be applied to more general**

1281 **cases when some assumptions are eliminated? If so, how?**

1282 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1283 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1284 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

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1288 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

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.

1291 **B5 What is the necessity of your approach / pro-**

1292 **posed solution/s?**

1293 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.

1294 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec

1295 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus

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1298 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue

1299 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

1300 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

1301 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



1302 **B5.1 What will be the limits of applicability of your proposed so-**
 1303 **lution/s?**

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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 1309 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 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 **B5.2 What will be the message of the proposed solution to**
 1314 **technical people? How about to non-technical managers and**
 1315 **business people?**

1316 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1317 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1318 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1319 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1320 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1321 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1322 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1323 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1324 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1325 **B6 How will you know if your proposed solution/s**
 1326 **is/are correct?**

1327 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1328 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1329 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1330 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1331 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1332 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1333 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.



1334 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1335 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)?**

1338 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
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 1345 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1346 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

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 1350 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
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**B7.1 Can you come up with illustrating examples, or even
better, counterexamples to your proposed solution/s?**

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 1361 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
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B7.2 Is there an approximation that can arrive at essentially the same proposed solution/s more easily?

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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.

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

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1403 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



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Appendix C REVISIONS TO THE PROPOSAL

1405

C. Revisions to the Proposal



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1406

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



1408

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

C. Revisions to the Proposal



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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

1412



- 1413 Make a table with the following columns for showing the summary of revisions to the proposal based on the comments of the panel of examiners.
- 1414
- 1415 1. Examiner
- 1416 2. Comment
- 1417 3. Summary of how the comment has been addressed
- 1418 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	<p>1. First itemtext</p> <p>2. Second itemtext</p> <p>3. Last itemtext</p> <p>4. First itemtext</p> <p>5. Second itemtext</p> <p>First itemtext</p> <p>Second itemtext</p> <p>Last itemtext</p> <p>First itemtext</p> <p>Second itemtext</p>	<p>1. First itemtext</p> <p>2. Second itemtext</p> <p>3. Last itemtext</p> <p>4. First itemtext</p> <p>5. Second itemtext</p>	<p>Sec. ??</p> <p>on p. ??,</p> <p>Sec. ??</p> <p>on p. ??,</p> <p>Fig. ?? on p. ??</p>

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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)

1420

Article/Forum Paper Format

(IEEE LaTeX format)

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

1421

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

The conclusion goes here.

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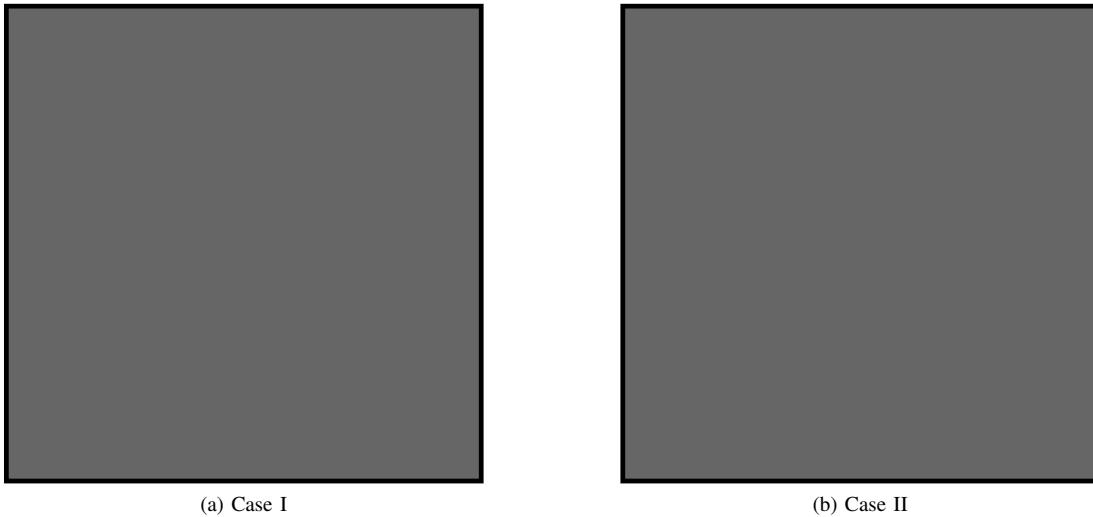


Fig. 2. Simulation results for the network.

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APPENDIX A PROOF OF THE FIRST ZONKLAR EQUATION

Appendix one text goes here.

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APPENDIX B

Appendix two text goes here. [?].

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ACKNOWLEDGMENT

The authors would like to thank...