



1

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

4

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

10

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

14

15 by

16 BANAL Kenan A.
17 BAUTISTA Francis Robert Miguel F.
18 HERMOSURA Don Humphrey L.
19 SALAZAR Daniel G.

20 April, 2025



21

ORAL DEFENSE RECOMMENDATION SHEET

22

23

24

25

26

27

28

29

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

BANAL, Kenan A.

BAUTISTA, Francis Robert Miguel F.

HERMOSURA, Don Humphrey L.

SALAZAR, Daniel G.

30

31

32

33

in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Engineering (BS-CPE)** has been examined and is recommended for acceptance and approval for **ORAL DEFENSE**.

34

35

36

Dr. Reggie C. Gustillo
Adviser

37

April 2, 2025



38

ABSTRACT

39

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

53

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



TABLE OF CONTENTS

55	Oral Defense Recommendation Sheet	ii
56	Abstract	iii
57	Table of Contents	iv
58	List of Figures	viii
59	List of Tables	ix
60	Abbreviations and Acronyms	x
61	Notations	xi
62	Glossary	xii
63	Listings	xiv
64	 	
65	Chapter 1 INTRODUCTION	1
66	1.1 Background of the Study	2
67	1.2 Prior Studies	4
68	1.3 Problem Statement	5
69	1.4 Objectives and Deliverables	6
70	1.4.1 General Objective (GO)	6
71	1.4.2 Specific Objectives (SOs)	7
72	1.4.3 Expected Deliverables	7
73	1.5 Significance of the Study	9
74	1.5.1 Technical Benefit	10
75	1.5.2 Social Impact	11
76	1.5.3 Environmental Welfare	11
77	1.6 Assumptions, Scope, and Delimitations	11
78	1.6.1 Assumptions	11
79	1.6.2 Scope	12
80	1.6.3 Delimitations	12
81	1.7 Estimated Work Schedule and Budget	13
82	1.8 Overview of the Thesis	14



83	Chapter 2 LITERATURE REVIEW	15
84	2.1 Existing Work	16
85	2.1.1 Sorting Algorithms	19
86	2.2 Lacking in the Approaches	20
87	2.3 Summary	21
88	Chapter 3 THEORETICAL CONSIDERATIONS	23
89	3.1 Introduction	24
90	3.2 Relevant Theories and Models	24
91	3.3 Technical Background	25
92	3.4 Conceptual Framework Background	25
93	3.5 Software Concepts	26
94	3.5.1 Thresholding	26
95	3.5.2 Object Size Calculation	27
96	3.5.3 Convolutional Neural Network	28
97	3.5.4 Classification Report	28
98	3.5.4.1 Confusion Matrix	28
99	3.5.4.2 Precision	29
100	3.5.4.3 Recall	29
101	3.5.4.4 F1 Score	30
102	3.5.4.5 Accuracy	30
103	3.6 Hardware Concepts	30
104	3.6.1 Camera Module	30
105	3.6.2 4 Channel Relay	31
106	3.6.3 Gear Ratio	31
107	3.7 Summary	32
108	Chapter 4 DESIGN CONSIDERATIONS	33
109	4.1 Introduction	34
110	4.2 System Architecture	34
111	4.3 Hardware Considerations	36
112	4.3.1 General Prototype Framework	36
113	4.3.2 Prototype Flowchart	37
114	4.3.3 Prototype 3D Model	40
115	4.3.4 Hardware Specifications	40
116	4.3.4.1 Raspberry Pi	40
117	4.3.4.2 Raspberry Pi Camera	42
118	4.3.4.3 DC Motor	43
119	4.3.4.4 MicroSD Card	45
120	4.3.4.5 LED Lights	46



121	4.3.4.6 Power Supply	47
122	4.3.4.7 4 Channel Relay Module	49
123	4.4 Software Considerations	50
124	4.4.1 PyTorch	50
125	4.4.2 OpenCV	51
126	4.4.3 CustomTkinter	51
127	4.5 Security and Reliability Considerations	51
128	4.6 Scalability and Efficiency Considerations	52
129	4.7 User Interface	52
130	4.8 Constraints and Limitations	52
131	4.9 Technical Standards	52
132	4.10 Prototyping and Simulation	53
133	4.11 Design Validation	53
134	4.12 Summary	53
135	Chapter 5 METHODOLOGY	54
136	5.1 Introduction	57
137	5.2 Research Approach	57
138	5.3 Hardware Design	57
139	5.4 Software Design	58
140	5.5 Data Collection Methods	59
141	5.6 Testing and Evaluation Methods	59
142	5.6.1 Ripeness Training and Testing	60
143	5.6.2 Bruises Training and Testing	60
144	5.6.3 Size Determination	60
145	5.7 Formula for User Priority	60
146	5.8 Ethical Considerations	60
147	5.9 Summary	61
148	Chapter 6 RESULTS AND DISCUSSIONS	62
149	6.1 Training and Testing Results of the Model	67
150	6.1.1 Ripeness Classification Results	67
151	6.1.2 Bruises Classification Results	69
152	6.2 Size Determination Results	70
153	6.3 User Priority Formula	70
154	6.4 Physical Prototype	70
155	6.5 Software Application	74
156	6.6 Summary	74



157	Chapter 7 CONCLUSIONS, RECOMMENDATIONS, AND FUTURE DIRECTIVES	76
159	7.1 Concluding Remarks	77
160	7.2 Contributions	77
161	7.3 Recommendations	77
162	7.4 Future Prospects	78
163	References	79
164	Appendix A STUDENT RESEARCH ETHICS CLEARANCE	81
165	Appendix B ANSWERS TO QUESTIONS TO THIS THESIS	83
166	Appendix C REVISIONS TO THE PROPOSAL	92
167	Appendix D REVISIONS TO THE FINAL	98
168	Appendix E VITA	102
169	Appendix F ARTICLE PAPER(S)	103



LIST OF FIGURES

171	1.1	Carabao Mangoes at Different Ripeness Stages (Guillermo et al., 2019)	2
172	1.2	Gantt Chart	13
173	3.1	Theoretical Framework Diagram.	24
174	3.2	Conceptual Framework Diagram.	25
175	4.1	Hardware Schematic	35
176	4.2	Prototype Framework	36
177	4.3	Prototype Main Flowchart	38
178	4.4	Initial 3D Model of the Prototype	39
179	4.5	Raspberry Pi 4 Model B	40
180	4.6	Raspberry Pi Camera Module Version 2	42
181	4.7	12 Volt DC Gear Motor	44
182	4.8	SanDisk Ultra MicroSD Card	45
183	4.9	LED Light Strip	46
184	4.10	Bench Power Supply	48
185	4.11	4 Channel Relay Module	49
186	6.1	Ripeness Confusion Matrix using kNN	68
187	6.2	Ripeness Confusion Matrix using Naive Bayes	69
188	6.3	Bruises Confusion Matrix using CNN	70
189	6.4	Prototype Top View	71
190	6.5	Entrance Conveyor Belt View	71
191	6.6	Side Conveyor Belt View	72
192	6.7	Prototype Main Hardware	72
193	6.8	DC Motor and Pulley	73
194	6.9	LED Lights and Camera Module	73
195	6.10	Raspberry Pi App UI Version 1	74
196	6.11	Raspberry Pi App UI Version 2	75
197	6.12	Raspberry Pi App UI Version 3	75



198 LIST OF TABLES

199	1.1 Expected Deliverables per Objective	8
200	1.1 Expected Deliverables per Objective	9
201	2.1 Comparison of Existing Studies	18
202	2.2 Comparison of Sorting Algorithm Models	21
203	3.1 Confusion Matrix Example	29
204	5.1 Summary of methods for reaching the objectives	55
205	6.1 Summary of methods for achieving the objectives	63
206	6.2 Performance Metrics for different EfficientNet versions	67
207	6.3 Ripeness Classification Report using kNN	68
208	6.4 Ripeness Classification Report using Naive Bayes	68
209	6.5 Bruises Classification Report using CNN	69
210	6.6 Summarized Classification Report using CNN	69
211	D.1 Summary of Revisions to the Thesis	99



212

ABBREVIATIONS

213	AC	Alternating Current	13
214	CNN	Convolution Neural Network	14
215	GUI	Graphical User Interface	52
216	LED	Light Emitting Diode	46
217	UI	User Interface	52



218

NOTATION

219	$B(P)$	Bruises Priority	70
220	$b(p)$	Bruises Prediction	70
221	$R(P)$	Ripeness Priority	70
222	$r(p)$	Ripeness Prediction	70
223	$S(P)$	Size Priority	70
224	$s(p)$	Size Prediction	70
225	$D(p, d, f)$	Real World Dimension	27
226	p	Pixel Dimension	27
227	d	Distance from Camera to Object	27
228	f	Focal Length	27



229 GLOSSARY

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



De La Salle University

241

User Priority-Based Grading

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



De La Salle University

242

LISTINGS



De La Salle University

243

Chapter 1

244

INTRODUCTION



245 **1.1 Background of the Study**

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



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

251
252 It is known for its sweet signature taste that was recognized sweetest in the world in the
253 Guinness Book of World Records in 1995. The mango was named after the national animal
254 of the Philippines, a native breed of buffalo. On average, it is 12.5 cm in length and 8.5
255 cm in diameter, having a bright yellow color when ripe as seen in Figure 1.1. It is often
256 cultivated during late May to early July (DBpedia, nd).

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



De La Salle University

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

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

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

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



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

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

300 1.2 Prior Studies

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



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

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

318 **1.3 Problem Statement**

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



329 porous ruler to determine fruit size and color palette for color grading (Co., nd). However,
330 among the problems encountered in the process of manually sorting and grading mangoes
331 are susceptibility to human error and requiring a number of 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.
SO1: To make an image acquisition system with a conveyor belt for automatic sorting and grading mangoes.	<ul style="list-style-type: none"> • To make an image acquisition system with a camera and LED light source. • To build a flat belt conveyor for moving the mangoes.
SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.	<ul style="list-style-type: none"> • To use a publicly available dataset of at least 10,000 mango images for classification of ripeness and bruises.
SO3: To create a microcontroller-based system to operate the image acquisition system, control the conveyor belt, and process the mango images through machine learning.	<ul style="list-style-type: none"> • To develop an intuitive UI where users can start and stop the system. • To implement a priority-based grading system with sliders for ripeness, bruises, and size.
SO4: To grade mangoes based on user priorities for size, ripeness, and bruises.	<ul style="list-style-type: none"> • To utilize a linear combination formula as the overall mango score, where each classification level contributes a grade, weighted by the priority assigned to the three properties. • To assign score values for each classification level of the mango.

Continued on next page



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.	<ul style="list-style-type: none"> To train a machine learning model such as kNN, k-means, or Naïve Bayes capable of classifying mango ripeness based on the image color. To gather a dataset of annotated images with ripeness labels. To obtain an evaluation report of performance metrics of the model.
SO6: To classify mango size based on image data by getting its length and width using OpenCV, geometry, and image processing techniques.	<ul style="list-style-type: none"> To develop an image processing algorithm capable of determining mango size using OpenCV, NumPy, and imutils. To classify mangoes based on size into small, medium, and large based on measurements.
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ul style="list-style-type: none"> To train a machine learning model such as CNN capable of distinguishing bruised and non-bruised mangoes. To train a machine learning model such as kNN, k-means, and Naïve Bayes capable of assessing the extent of bruising on the mangoes if it is significant or partial. To gather a dataset of annotated images based on bruises. To obtain an evaluation report of performance metrics of both CNN and other machine learning models.

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.

368

369

370



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

374 Another benefit to automating sorting and grading mangoes is the improvement in
375 quality control. This implies that compared to human labor, automating sorting and
376 grading mangoes can uniformly assess the quality of mangoes based on size, color, and
377 bruises, ensuring that the expected grade and high-quality mangoes reach the consumer.
378 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
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.

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.

1.6.3 Delimitations



- 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 Estimated Work Schedule and Budget

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

Fig. 1.2 Gantt Chart

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



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

451 **1.8 Overview of the Thesis**

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



462

Chapter 2

463

LITERATURE REVIEW



464 **2.1 Existing Work**

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

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



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

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



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

TABLE 2.1 COMPARISON OF EXISTING STUDIES

Existing Study	Limitations	Accuracy Rating
Adam et al. (2022)	No physical automation, not suitable for large amounts of mangoes, only classifies ripeness and only a sample size of 10 mangoes.	95%
Samaniego et al. (2023)	Focuses only on color and size.	91.2%
Guillergan et al. (2024)	Relies on high-quality DSLR cameras, and limited automation due to not integrating microcontrollers.	95%
Supekar and Wakode (2020)	No physical automation implemented. Ripeness, size, and shape-based classification achieved 100%, 98.19%, and 99.20% accuracy respectively on their own. However, errors occurred when taking into account all these aspects together for grading mangoes, causing an accuracy rating deduction.	88.88%

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



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

528 **2.1.1 Sorting Algorithms**

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

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



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

565 **2.2 Lacking in the Approaches**

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



TABLE 2.2 COMPARISON OF SORTING ALGORITHM MODELS

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

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

574 2.3 Summary

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



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



600

Chapter 3

601

THEORETICAL CONSIDERATIONS



602 3.1 Introduction

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

605 3.2 Relevant Theories and Models

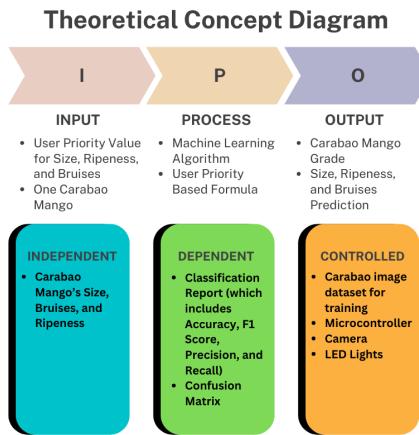


Fig. 3.1 Theoretical Framework Diagram.

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



3.3 Technical Background

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

3.4 Conceptual Framework Background

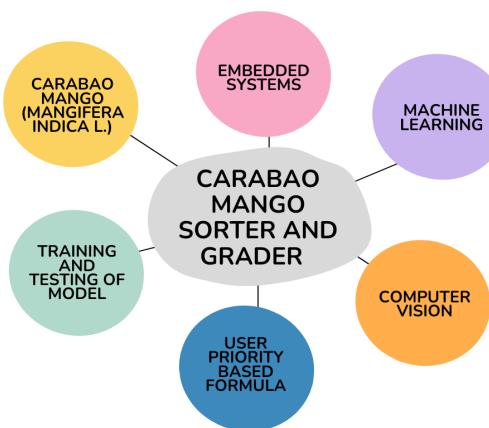


Fig. 3.2 Conceptual Framework Diagram.

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



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

632 **3.5 Software Concepts**

633 **3.5.1 Thresholding**

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

641

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

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



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

653 **3.5.2 Object Size Calculation**

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

658 The size of the mango can be determined given:

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

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

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

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



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

669 **3.5.3 Convolutional Neural Network**

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

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

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

682 **3.5.4 Classification Report**

683 **3.5.4.1 Confusion Matrix**

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

686



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

TABLE 3.1 CONFUSION MATRIX EXAMPLE

- 687 • True Positives (TP): Cases correctly predicted as positive
- 688 • True Negatives (TN): Cases correctly predicted as negative
- 689 • False Positives (FP): Cases incorrectly predicted as positive. (Type I error)
- 690 • False Negatives (FN): Cases incorrectly predicted as negative (Type II error)

691 **3.5.4.2 Precision**

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3.3)$$

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

695 **3.5.4.3 Recall**

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3.4)$$

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

699 **3.5.4.4 F1 Score**

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3.5)$$

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

703 **3.5.4.5 Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.6)$$

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

707

3.6 Hardware Concepts

708

3.6.1 Camera Module

709 The camera module serves as the main image acquisition tool in the mango sorter and
 710 grader system. Its role is to capture clear, high-resolution images of each mango as it moves
 711 along the conveyor. These images are critical for analyzing physical traits like ripeness,
 712 bruising, and size through computer vision and machine learning techniques.

713 The camera is directly connected to the Raspberry Pi, which manages both image
 714 capture and processing. It is fixed in position to ensure consistent distance and angle for
 715 all images. It is also paired with a lighting system to provide a consistent lighting for the



716 images. The system captures images of both the top and bottom sides of each mango to
717 ensure a more accurate grading. The prototype integrates the Raspberry Pi Camera Module
718 Version 2. This camera is chosen for its 8MP resolution which is critical in capturing
719 real-time images. Another reason for integrating this camera is because of its compatibility
720 with the Raspberry Pi 4, and reliability in capturing detailed images needed for accurate
721 classification. It is also cost effective and lightweight which is important for the prototype.

722 **3.6.2 4 Channel Relay**

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

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

732 **3.6.3 Gear Ratio**

733 In this prototype, gear ratios are used to control the rotational speed of the conveyor belts
734 that move and rotate the mango. A gear ratio of 1:3 was applied, meaning the motor gear
735 completes one full rotation for every three rotations of the driven gear. This is also done in
736 order to avoid overspeeding and make sure that the conveyor belt moves in a controlled



737 manner. This setup slows down one belt relative to the other, creating a differential speed
738 between the left and right belts. As a result, the mango rotates in place while being moved
739 forward. This rotation is essential for capturing both the top and bottom views of the mango
740 for accurate classification and grading.

741 **3.7 Summary**

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



747

Chapter 4

748

DESIGN CONSIDERATIONS



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

755 **4.1 Introduction**

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

760 **4.2 System Architecture**

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

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

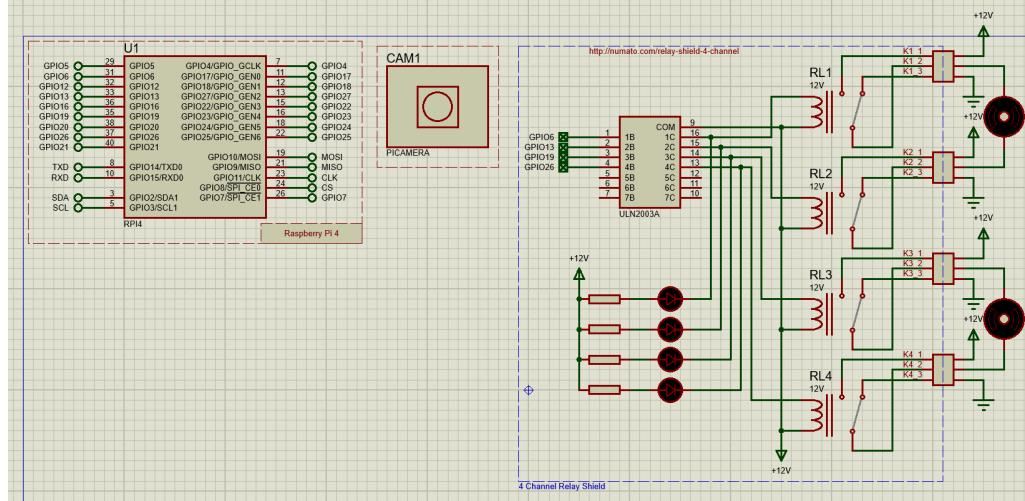


Fig. 4.1 Hardware Schematic

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

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

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



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

786 4.3 Hardware Considerations

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

791 4.3.1 General Prototype Framework

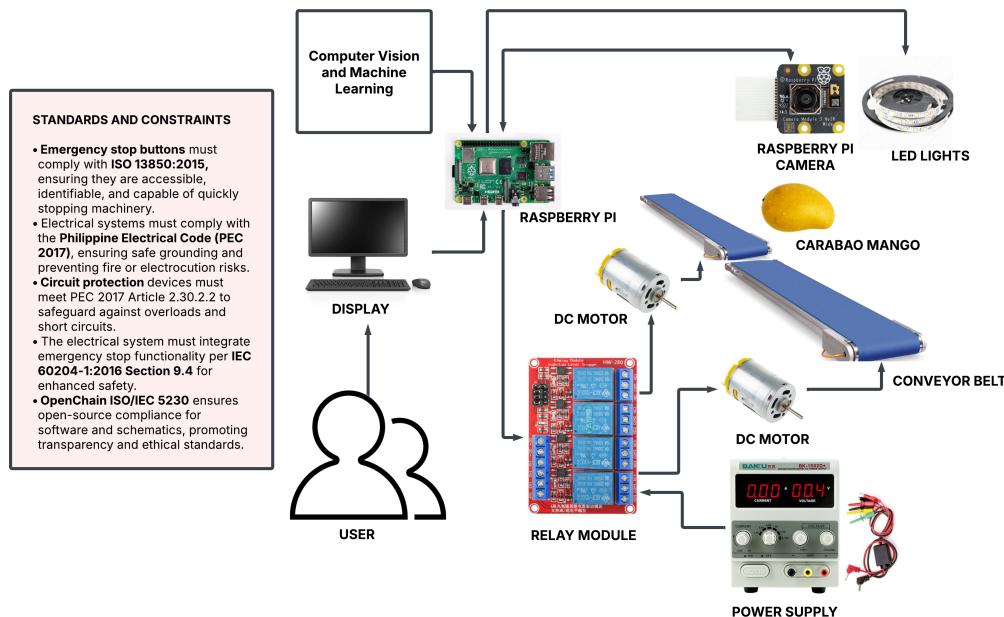


Fig. 4.2 Prototype Framework



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

800 **4.3.2 Prototype Flowchart**

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

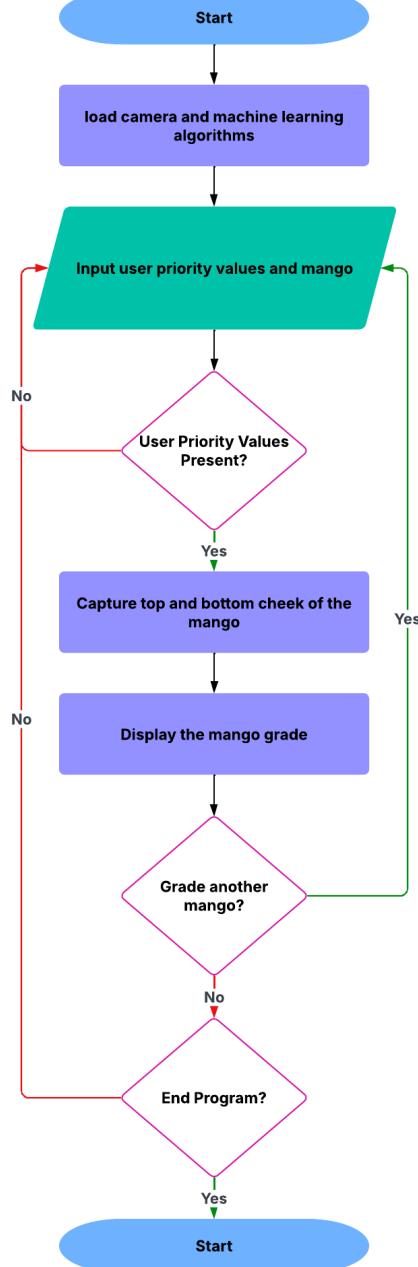


Fig. 4.3 Prototype Main Flowchart



De La Salle University

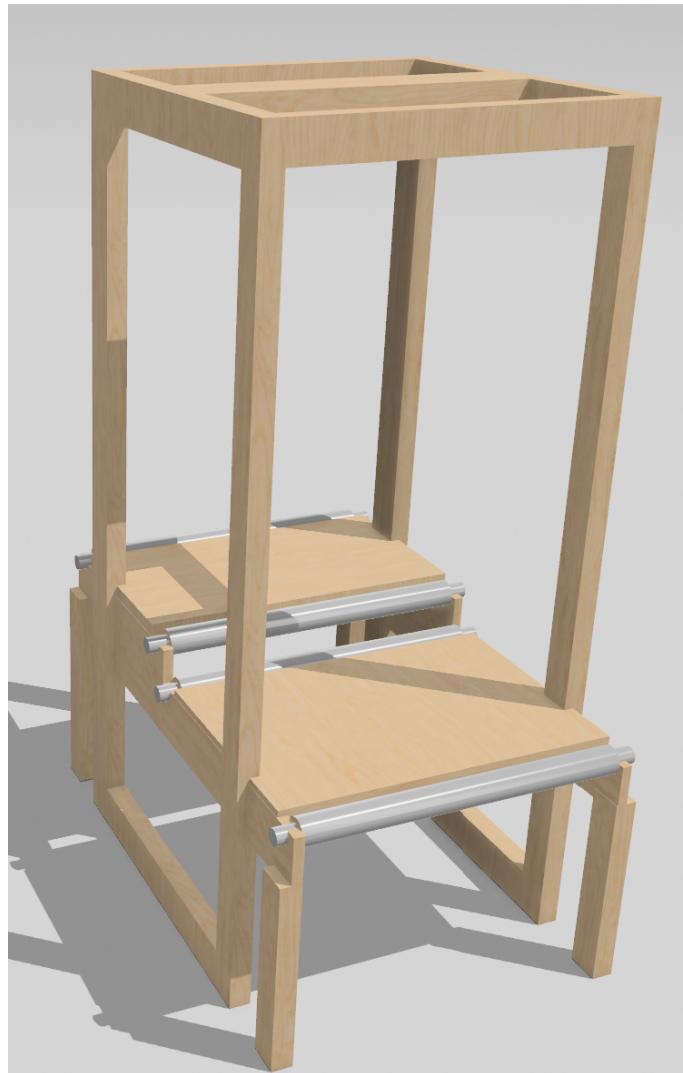


Fig. 4.4 Initial 3D Model of the Prototype



811 **4.3.3 Prototype 3D Model**

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

819 **4.3.4 Hardware Specifications**

820 **4.3.4.1 Raspberry Pi**



Fig. 4.5 Raspberry Pi 4 Model B

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



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

828 **Specifications:**

- 829 • SoC: Broadcom BCM2711
- 830 • CPU: Quad-core ARM Cortex-A72 (64-bit)
- 831 • Clock Speed: 1.5 GHz (base, overclockable)
- 832 • RAM: 8GB LPDDR4-3200 SDRAM
- 833 • Wireless: Dual-band 2.4 GHz / 5 GHz Wi-Fi (802.11ac)
- 834 • Bluetooth: Bluetooth 5.0 (BLE support)
- 835 • Ethernet: Gigabit Ethernet (full throughput)
- 836 • USB: 2 x USB 3.0 ports and 2 x USB 2.0 ports
- 837 • Video Output: 2 x micro-HDMI ports (supports 4K @ 60Hz, dual 4K display
838 capability)
- 839 • Audio: 3.5mm audio/video composite jack
- 840 • Storage: MicroSD card slot (supports booting via SD card or USB)



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

845 **4.3.4.2 Raspberry Pi Camera**

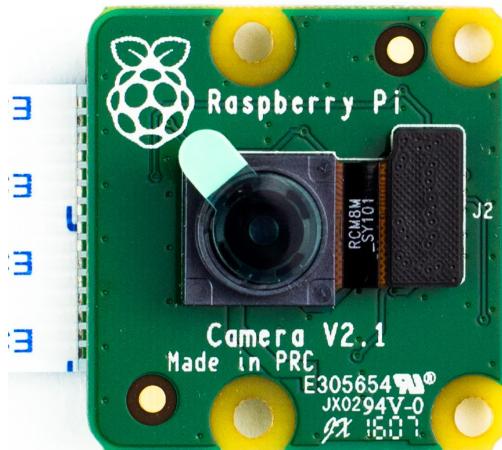


Fig. 4.6 Raspberry Pi Camera Module Version 2

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



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

853

854 **Specifications:**

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

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

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

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

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

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

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

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

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

867 **4.3.4.3 DC Motor**

868 The 12 Volt DC Gear Motor is a compact, high-torque, and low-noise motor suitable for a
869 wide range of applications, including robotics, automation, and industrial control systems.
870 It features a spur gear design, which provides a high reduction ratio for increased torque
871 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.

876 **Specifications:**

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



- 883 • Torque Output: 18 kg-cm (rated)
884 • Stall Torque: 60 kg-cm (maximum)
885 • Power Rating: 50W (maximum)
886 • Unit Weight: 350 grams

887 **4.3.4.4 MicroSD Card**



Fig. 4.8 SanDisk Ultra MicroSD Card

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

893

894 **Specifications:**



- 895 • Capacity: 256GB
896 • Type: MicroSDXC (Secure Digital eXtended Capacity)
897 • Form Factor: MicroSD (11mm x 15mm x 1mm)
898 • File System: Pre-formatted exFAT

899 **4.3.4.5 LED Lights**



Fig. 4.9 LED Light Strip

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

904

905 **Specifications:**



- 906 • Power Input: 5V DC (USB-powered, compatible with laptops, power banks, or USB
907 adapters).
- 908 • Waterproof Design: Suitable for indoor/outdoor use.
- 909 • LED Type: SMD 2835 (surface-mount diodes for high brightness and efficiency).
- 910 • Color Type: White (cool white)
- 911 • Length: 1m
- 912 • Beam Angle: 120°
- 913 • Operating Temperature: -25°C to 60°C.
- 914 • Storage Temperature: -40°C to 80°C.

915 **4.3.4.6 Power Supply**

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

921

922 **Specifications:**

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



Fig. 4.10 Bench Power Supply

- 925 • Output Range: 0-30V DC / 0-5A DC
- 926 • Voltage Precision: $\pm 0.010V$ (10 mV) resolution
- 927 • Current Precision: $\pm 0.001A$ (1 mA) resolution
- 928 • Power Precision: $\pm 0.1W$ resolution
- 929 • Weight: 5 lbs (2.27 kg)
- 930 • Dimensions: 11.1" x 4.92" x 6.14" (28.2 cm x 12.5 cm x 15.6 cm)
- 931 • Maximum Power: 195W
- 932 • Power Source: AC input only



Fig. 4.11 4 Channel Relay Module

933 **4.3.4.7 4 Channel Relay Module**934 The 4 Channel Relay Module is a compact and versatile relay board that allows for the
935 control of multiple devices using a single microcontroller. This module was selected for
936 its compact size, ease of use, and ability to control multiple devices simultaneously. It is
937 designed to be used with microcontrollers such as Arduino and Raspberry Pi, allowing for
938 easy integration into the prototype.939
940 **Specifications:**

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



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

954 **4.4 Software Considerations**

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

958 **4.4.1 PyTorch**

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



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

965 **4.4.2 OpenCV**

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

972 **4.4.3 CustomTkinter**

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

979 **4.5 Security and Reliability Considerations**

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



983 **4.6 Scalability and Efficiency Considerations**

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

987 **4.7 User Interface**

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

991 **4.8 Constraints and Limitations**

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

995 **4.9 Technical Standards**

996 The system adheres to industry standards for image processing and machine learning,
997 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.



De La Salle University

1010 **Chapter 5**

1011 **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. 57
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. 57
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. 59

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. 57
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. 60
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. 5.6.2 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. 5.6.1 on p. 60
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<ol style="list-style-type: none"> 1. Accuracy testing: Get the percent accuracy testing for getting the length and width of the Carabao mango 	Sec. 5.6.3 on p. 60



1012 **5.1 Introduction**

1013 The methodology for this research outlines the development of the Carabao Mango sorter
1014 using machine learning and computer vision. The sorting system uses a conveyor belt
1015 system which delivers the mangoes into the image acquisition system. This system captures
1016 the image of the mangoes which will then be going through the various stages of image
1017 processing and classification into grades which will depend on the priority of the user.
1018 This methodology ensures that the grading of the mangoes will be accurate while being
1019 non-destructive.

1020 **5.2 Research Approach**

1021 This study applies the experimental approach for research in order to develop and properly
1022 test the proposed system. The experimental approach of the methodology will allow the
1023 researchers to fine-tune the parameters and other factors in the classification of mangoes in
1024 order to get optimal results with high accuracy scores while maintaining the quality of the
1025 mangoes. This approach will also allow for real-time data processing and classification
1026 which will improve the previous static grading systems.

1027 **5.3 Hardware Design**

1028 The prototype consists of hardware and software components for automated mango sorting
1029 and grading purposes. The hardware includes the conveyor belt system used to transfer
1030 mangoes from scanning to sorting smoothly. A camera and lighting system are able
1031 to collect high-resolution images for analysis. The DC motors and stepper motors are



1032 responsible for driving the conveyor belt and sorting actuators. The entire system is
1033 controlled by a microcontroller (Raspberry Pi 4b), coordinating actions of all components.
1034 Sorting actuators then direct mangoes into selected bins based on their classification to
1035 make sorting efficient.

1036 **5.4 Software Design**

1037 For the programming language used for the prototype and training and testing the CNN
1038 model, Python was used for training and testing the CNN model and it was also used in the
1039 microcontroller to run the application containing the UI and CNN model. PyTorch was the
1040 main library used in using the EfficientNet model that is used in classifying the ripeness
1041 and bruises of the mango. Likewise, tkinter is the used library when designing the UI in
1042 Python.

1043 Furthermore, the rest of the software components are of utmost importance to mango
1044 classification. Image processing algorithms in OpenCV and CNN models extract features
1045 such as color, size, and bruises that are known to determine quality parameters of mangoes.
1046 Mangoes are classified based on ripeness and defects by using machine learning algorithms,
1047 which further enhances accuracy using deep learning techniques. A user interface (UI) is
1048 designed for users to control and observe the system in real time. Finally, the interface
1049 programming of the microcontroller provides the necessary synchronization between
1050 sensors, actuators, and motors throughout the sorting operation scenario.



5.5 Data Collection Methods

The system acquires high-resolution images of mangoes under pre-specified lighting conditions through systematic acquisition. Apart from that, this corpus of data is based on the real-time images acquired from the camera system, where classification operations are carried out based on real-time data. Pre-processing image operations such as flipping, rotating, resizing, normalization, and Gaussian blur are also carried out in order to enhance image clarity and feature detection. Then, the feature extraction process is carried out, where the intensity of color, shape, and texture are analyzed for the detection of characteristic features in terms of the mango. All these aspects lead to the creation of a reliable dataset for the machine learning algorithm that will allow the system to classify and grade mangoes more accurately.

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 each of the components works as expected when operating separately. After component testing on an individual basis, integration testing is conducted to ensure communication between hardware and software is correct to ensure the image processing system, motors, and sorting actuators work in concert as required. System testing is conducted to conduct overall system performance

testing in real-world conditions to ensure mangoes are accurately and efficiently sorted and graded.



1073 To test system performance, various measures of performance are used to evaluate.
1074 As seen on equation 3.6, accuracy score is used to measure the percentage of correctly
1075 classified mangoes to ensure the system maintains high precision levels. Precision as seen
1076 on equation 3.3 and recall as seen on equation 3.4 are used to measure consistency of
1077 classification to determine if the system classifies different ripeness levels and defects
1078 correctly. Furthermore, the F1 score formula as seen on equation 3.5 is used to evaluate the
1079 performance of the model's classification.

1080 A confusion matrix is used to measure correct and incorrect classification to ensure the
1081 machine learning model is optimized and that minimum errors are achieved. Throughput
1082 analysis is also used to determine the rate and efficiency of sorting to ensure that the
1083 system maintains high capacity without bottlenecks to sort mangoes. Using these methods
1084 of testing, the system is constantly optimized to ensure high-quality and reliable mango
1085 classification.

1086 **5.6.1 Ripeness Training and Testing**

1087 **5.6.2 Bruises Training and Testing**

1088 **5.6.3 Size Determination**

1089 **5.7 Formula for User Priority**

1090 **5.8 Ethical Considerations**

1091 Ethical considerations ensure that the system is operated safely and responsibly. Data
1092 privacy is ensured by securely storing and anonymizing extracted images and classification



1093 data so that unauthorized access becomes impossible. The system is also eco-friendly
1094 through non-destructive testing, saving mangoes while also ensuring that they are of good
1095 quality. Safety in operations is also ensured by protecting moving parts to prevent mechan-
1096 ical harm and incorporating fail-safes to securely stop operation in case of malfunction.
1097 Addressing these concerns, the system is not only accurate and efficient but also secure,
1098 eco-friendly, and safe for operators, thus a sustainable solution to automated mango sorting
1099 and grading.

1100 **5.9 Summary**

1101 This chapter explained how to create an automatic Carabao mango sorter and grader using
1102 machine learning and computer vision. The system integrates hardware and software
1103 resources, including a conveyor belt, cameras, sensors, and actuators, to offer accurate,
1104 real-time sorting by ripeness, size, and bruises. Various testing and evaluation processes
1105 ensure its performance to offer reliability. Ethical issues are data privacy, environmental
1106 sustainability, and operation safety. With enhanced efficiency, reduced human error, and
1107 enhanced quality, this system provides an affordable, scalable, and non-destructive solution
1108 to post-harvest mango classification in agricultural industries.



De La Salle University

1109

Chapter 6

1110

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. 74
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. 70

Continued on next page

6. Results and Discussions



De La Salle University

Continued from previous page

Objectives	Methods	Locations
<p>SO2: To get the precision, recall, F1 score, confusion matrix, and train and test accuracy metrics for classifying the ripeness and bruises with an accuracy score of at least 90%.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> 1. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for ripeness classification of Carabao mangoes 2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruises classification of Carabao mangoes <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully achieved at least 93% accuracy for ripeness classification of Carabao mangoes 2. Successfully achieved at least 73% accuracy for bruise classification of Carabao Mangoes 	<p>Sec. 6.1 on p. 67</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. 70</p>

Continued on next page

6. Results and Discussions



De La Salle University

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. 70

Continued on next page

6. Results and Discussions



De La Salle University

Continued from previous page

Objectives	Methods	Locations
<p>SO5: To classify mango ripeness based on image data using machine learning algorithms such as kNN, k-mean, and Naïve Bayes.</p>	<p>Expected Results:</p> <ul style="list-style-type: none"> 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. 67</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. 70</p>

Continued on next page



Continued from previous page

Objectives	Methods	Locations
SO7: To classify mango bruises based on image data by employing machine learning algorithms.	<p>Expected Results:</p> <ul style="list-style-type: none"> 1. Achieve at least 90% accuracy on performance metrics 2. Successfully fine tuned the CNN model to achieve the highest accuracy possible, choosing the best performing among EfficientNet b0-b7, and testing other CNN hyperparameters <p>Actual Results:</p> <ul style="list-style-type: none"> 1. Successfully trained a CNN model using EfficientNet-b0 and Adam Optimizer to bruises 2. Successfully achieved at least 90 percent accuracy, precision, recall, f1 score for bruise classification of Carabao mangoes 	Sec. 6.1.2 on p. 69

6.1 Training and Testing Results of the Model

6.1.1 Ripeness Classification Results

Add the F1-Score and etc here

EfficientNet Version	Precision	Recall	F1	Test Accuracy
b0	0.9841	0.9838	0.9838	0.98
b1	0.9876	0.9876	0.9876	0.99
b2	0.9802	0.9801	0.9801	0.98
b3	0.9709	0.968	0.9684	0.97
b4	0.9716	0.9699	0.9699	0.97
b5	0.93	0.93	0.93	0.93

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

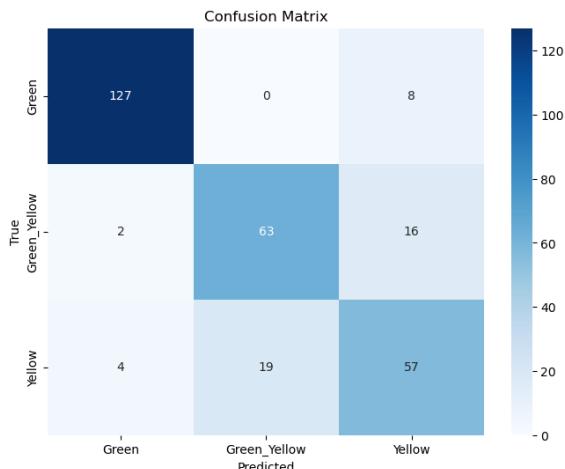


Fig. 6.1 Ripeness Confusion Matrix using kNN

	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

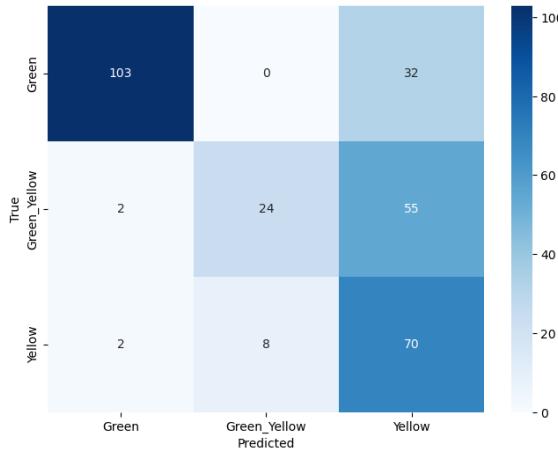


Fig. 6.2 Ripeness Confusion Matrix using Naive Bayes

1114

6.1.2 Bruises Classification Results

	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

Metrics	Results
Precision	0.9318
Recall	0.9275
F1 Score	0.9278

TABLE 6.6 SUMMARIZED CLASSIFICATION REPORT USING CNN

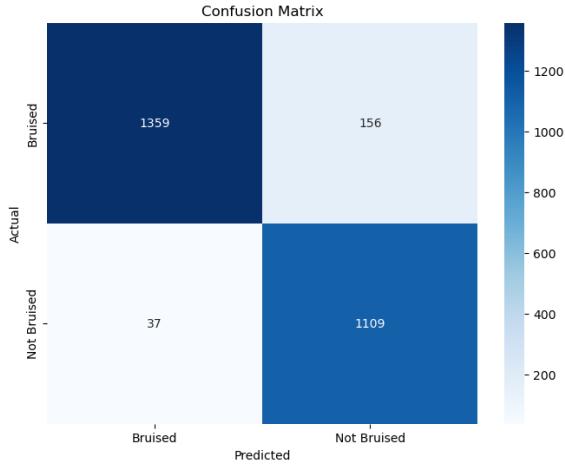


Fig. 6.3 Bruises Confusion Matrix using CNN

6.2 Size Determination Results

6.3 User Priority Formula

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

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

6.4 Physical Prototype

Add pictures of the hardware prototype here with description

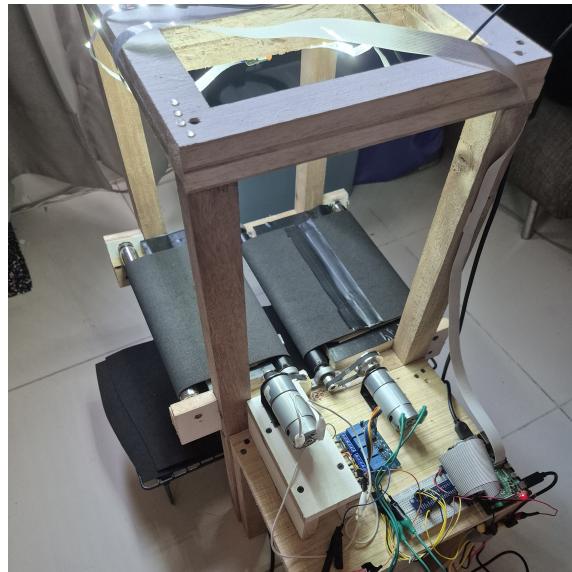


Fig. 6.4 Prototype Top View



Fig. 6.5 Entrance Conveyor Belt View

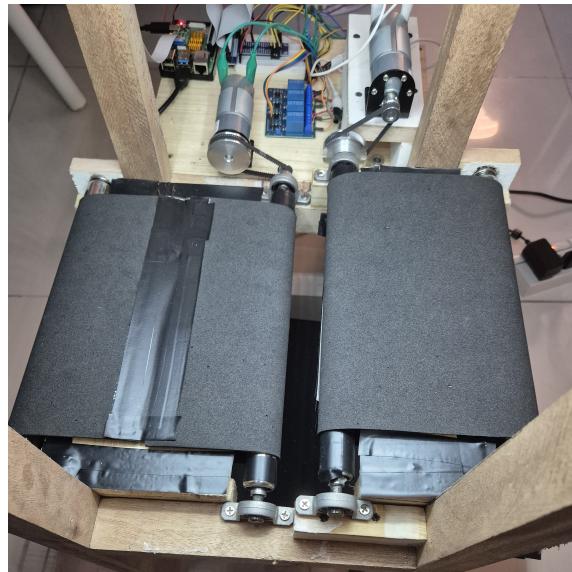


Fig. 6.6 Side Conveyor Belt View



Fig. 6.7 Prototype Main Hardware

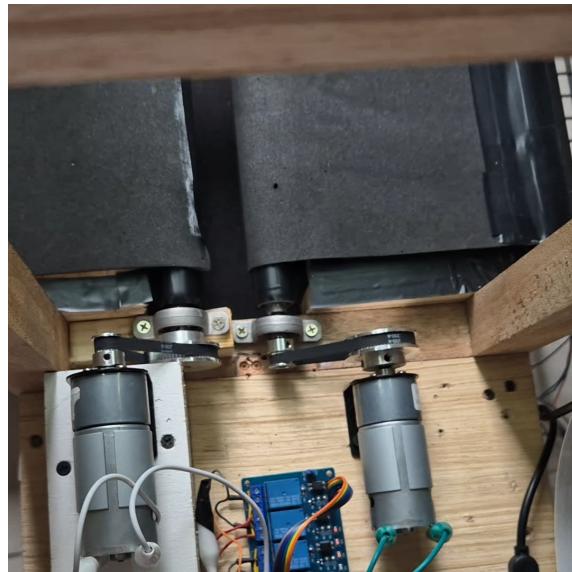


Fig. 6.8 DC Motor and Pulley

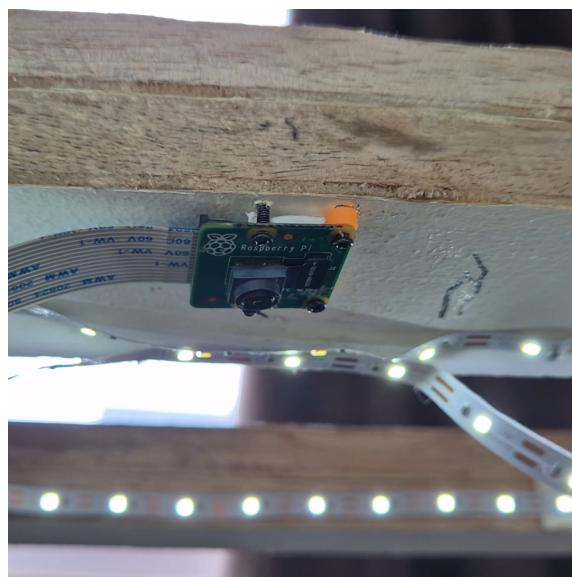


Fig. 6.9 LED Lights and Camera Module



1123 **6.5 Software Application**

1124 Show the raspberry pi app UI and demonstrate it here

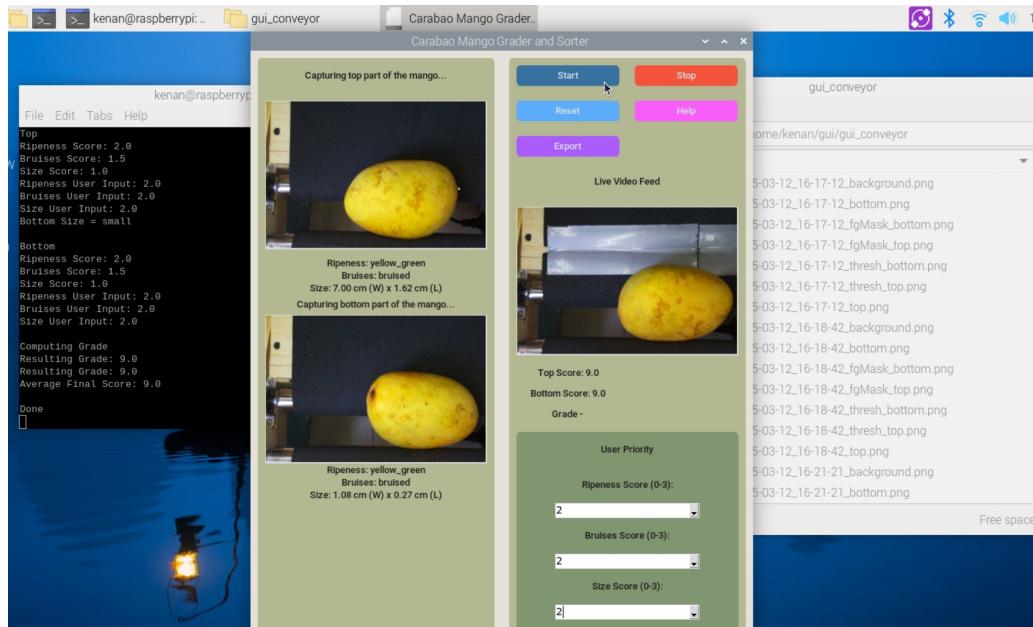


Fig. 6.10 Raspberry Pi App UI Version 1

1125 **6.6 Summary**

1126 Provide the gist of this chapter such that it reflects the contents and the message.

6. Results and Discussions

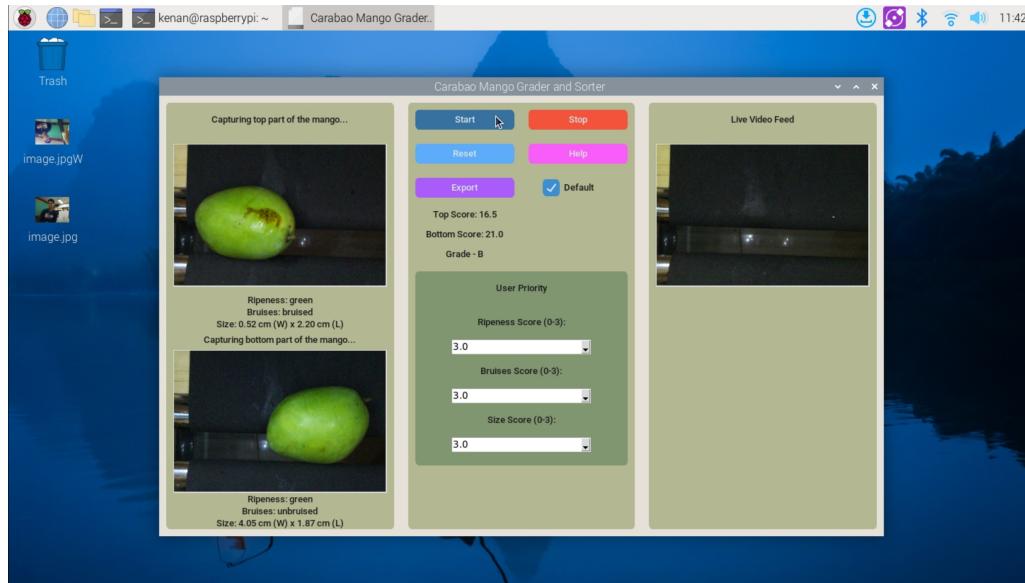


Fig. 6.11 Raspberry Pi App UI Version 2

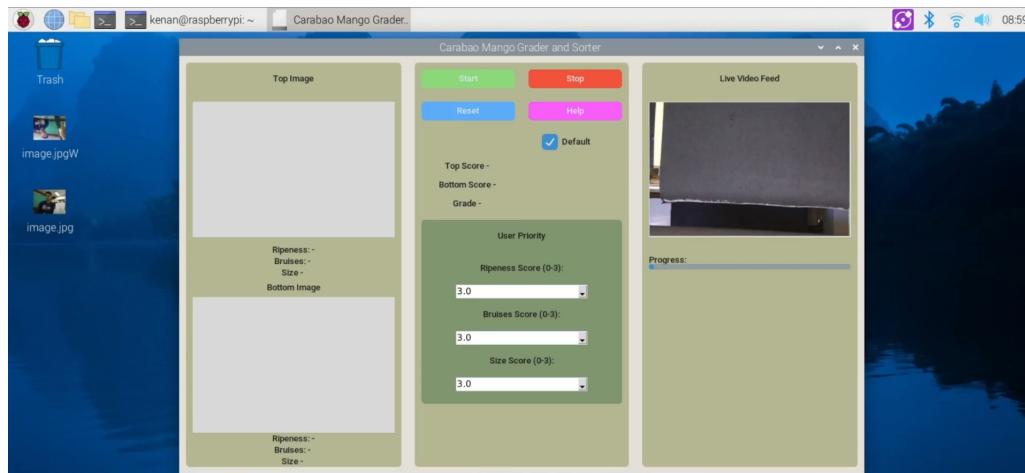


Fig. 6.12 Raspberry Pi App UI Version 3



1127 **Chapter 7**

1128 **CONCLUSIONS, RECOMMENDATIONS, AND**
1129 **FUTURE DIRECTIVES**



7.1 Concluding Remarks

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

7.2 Contributions

The contributions of each group member are as follows:

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

7.3 Recommendations

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



1149 the prototype be tested in the actual grading and sorting of Carabao mangoes in the market.

1150 **7.4 Future Prospects**

1151 Future researchers may consider the following recommendations for future work:

1152 1. User testing of the prototype in the actual grading and sorting of Carabao mangoes

1153 in the Philippine market.

1154 2. Additional of weight measurement to the prototype to improve the grading and

1155 sorting of Carabao mangoes.

1156 3. Integration of a custom PCB to improve the hardware design of the prototype.



1157

REFERENCES

- 1158 Abbas, Q., Niazi, S., Iqbal, M., and Noureen, M. (2018). Mango Classification Using Texture &
1159 Shape Features. *IJCSNS International Journal of Computer Science and Network Security*, 18(8).
- 1160 Abu, M., Olympio, N. S., and Darko, J. O. (2021). Determination of Harvest Maturity for Mango
1161 (<i>Mangifera indica</i> L.) Fruit by Non-Destructive Criteria. *Agricultural Sciences*,
1162 12(10):1103–1118.
- 1163 Adam, J. A. P., Dato, K. S., Impelido, M. C. D., Tobias, R. G., and Pilueta, N. U. (2022). Non-
1164 destructive microcontroller-based carabao mango ripeness grader.
- 1165 Alejandro, A. B., Gonzales, J. P., Yap, J. P. C., and Linsangan, N. B. (2018). Grading and sorting of
1166 Carabao mangoes using probabilistic neural network. page 020065, Bandung, Indonesia.
- 1167 Amna, M. W. A., Guiqiang, L., and Muhammad Zuhair AKRAM, M. F. (2023). Machine vision-
1168 based automatic fruit quality detection and grading. *Frontiers of Agricultural Science and*
1169 *Engineering*, 0(0):0.
- 1170 Britannica (n.d.). Mango history cultivation and facts.
- 1171 Centino, M. F., Castano, M. C. N., and Ebo, J. B. F. (2020). The Current Status of Philippine Mango
1172 in the Global Value Chain.
- 1173 Chakraborty, S. K., Subeesh, A., Dubey, K., Jat, D., Chandel, N. S., Potdar, R., Rao, N. G., and
1174 Kumar, D. (2023). Development of an optimally designed real time automatic citrus fruit grading-
1175 sorting machine leveraging computer vision-based adaptive deep learning model. *Engineering*
1176 *Applications of Artificial Intelligence*, 120:105826.
- 1177 Co., Z. F. I. (n.d.). What is fruit sorting.
- 1178 D'Adamo, G. (2018). The determinants of export quality in the euro area. *Quarterly Report on the*
1179 *Euro Area (QREA)*, 17(1):23–31. Publisher: Directorate General Economic and Financial Affairs
1180 (DG ECFIN), European Commission.
- 1181 DBpedia (n.d.). About: Carabao.
- 1182 Guillergan, G., Sabay, R., Madrigal, D., and Bual, J. (2024). Naive Bayes Classifier in Grading
1183 Carabao Mangoes. *Technium: Romanian Journal of Applied Sciences and Technology*, 22:14–32.
- 1184 Guillermo, M. C. S., Naciongayo, D. S., and Galela, M. G. C. (2019). Determining ‘Carabao’
1185 Mango Ripeness Stages Using Three Image Processing Algorithms.
- 1186 Lacap, A., Bayogan, E. R., Secretaria, L., Joyce, D., Ekman, J., and Goldwater, A. (2021). Bruise
1187 Injury and Its Effect on ‘Carabao’ Mango Fruit Quality. *Philippine Journal of Science*, 150(6B).
- 1188 Patel, K. K., Khan, M. A., Kumar, Y., and Yadav, A. K. (2019). Novel Techniques in Post Harvest
1189 Management of Mango- An Overview. *South Asian Journal of Food Technology and Environment*,
1190 05(02):821–835.



De La Salle University

- 1191 Rizwan Iqbal, H. M. and Hakim, A. (2022). Classification and Grading of Harvested Mangoes
1192 Using Convolutional Neural Network. *International Journal of Fruit Science*, 22(1):95–109.
- 1193 Samaniego, L. A., De Jesus, L. C. M., Apostol, J. D., Betonio, D. C., Medalla, J. D. B., Peruda Jr,
1194 S. R., Brucal, S. G. E., and Yong, E. D. (2023). Carabao mango export quality checker using
1195 matlab image processing. *International Journal of Computing Sciences Research*, 7:2080–2094.
- 1196 Schulze, K., Nagle, M., Spreer, W., Mahayothee, B., and Müller, J. (2015). Development and
1197 assessment of different modeling approaches for size-mass estimation of mango fruits (*Mangifera*
1198 *indica* L., cv. ‘Nam Dokmai’). *Computers and Electronics in Agriculture*, 114:269–276.
- 1199 Supekar, A. D. and Wakode, M. (2020). Multi-Parameter Based Mango Grading Using Image
1200 Processing and Machine Learning Techniques. *INFOCOMP Journal of Computer Science*,
1201 19(2):175–187. Number: 2.
- 1202 Tomas, M. C., Celino, J. P. L., Escalambre, I. E., and Secreto, B. P. (2022). Detection of Overall
1203 Fruit Maturity of Local Fruits Using Support Vector Machine through Image Processing. In *2022*
1204 *12th International Conference on Software Technology and Engineering (ICSTE)*, pages 96–102.
- 1205 Veling, P. S. (2019). Mango Disease Detection by using Image Processing. *International Journal*
1206 *for Research in Applied Science and Engineering Technology*, 7(4):3717–3726.
- 1207 Zheng, B. and Huang, T. (2021). Mango Grading System Based on Optimized Convolutional Neural
1208 Network. *Mathematical Problems in Engineering*, 2021:1–11.

1209

Produced: April 2, 2025, 20:37



De La Salle University

1210

1211

Appendix A STUDENT RESEARCH ETHICS CLEARANCE

A. Student Research Ethics Clearance



De La Salle University

1212

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.



De La Salle University

1213

Appendix B ANSWERS TO QUESTIONS TO THIS THESIS

1214





1247 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1248 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1250 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1251 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1252 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1253 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1254 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1255 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1256 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1257 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1258 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1260 Lorem ipsum dolor sit amet, consectetur 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, consectetur 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.

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

1270 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1271 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1272 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1273 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1274 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1275 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1276 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1277 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1278 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



De La Salle University

B3 What is the difference of the solution/s from existing ones?

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.

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

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.

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

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.



1344 **B5.1 What will be the limits of applicability of your proposed so-**
 1345 **lution/s?**

1346 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1347 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1348 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1349 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1350 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1351 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1352 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1353 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1354 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1355 **B5.2 What will be the message of the proposed solution to**
 1356 **technical people? How about to non-technical managers and**
 1357 **business people?**

1358 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1359 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1360 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1361 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1362 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1363 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1364 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1365 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1366 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1367 **B6 How will you know if your proposed solution/s**
 1368 **is/are correct?**

1369 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1370 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1371 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1372 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1373 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1374 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1375 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.



1376 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1377 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1380 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1381 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
 1382 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1383 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1384 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1385 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1386 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1387 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1388 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1391 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1392 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
 1393 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1394 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1395 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1396 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1397 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1398 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1399 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1402 Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem.
 1403 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdier mi nec ante. Donec
 1404 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1405 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1406 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
 1407 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue



1408 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1409 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1410 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1413 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1414 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1415 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1416 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1417 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1418 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1419 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1420 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1421 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1426 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1427 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec
 1428 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
 1429 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
 1430 Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla
 1431 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
 1432 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
 1433 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
 1434 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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

1435 Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem.
 1436 Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec



De La Salle University

- 1439 ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus
1440 placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor.
1441 Praesent in sapien. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis fringilla
1442 tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue
1443 a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.
1444 Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit
1445 amet ipsum. Nunc quis urna dictum turpis accumsan semper.



De La Salle University

1446

Appendix C REVISIONS TO THE PROPOSAL

1447

C. Revisions to the Proposal



De La Salle University

1448

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



De La Salle University

1449

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



1450

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



1451

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



De La Salle University

1452

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.



De La Salle University

1453

Appendix D REVISIONS TO THE FINAL

1454



- 1455 Make a table with the following columns for showing the summary of revisions to the
 1456 proposal based on the comments of the panel of examiners.
- 1457 1. Examiner
- 1458 2. Comment
- 1459 3. Summary of how the comment has been addressed
- 1460 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. Gustillo	<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. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ??</p>

Continued on next page

D. Revisions to the Final



De La Salle University

Continued from previous page

Examiner	Comment	Summary of how the comment has been addressed	Locations
Dr. Donable de Veas Abuan	<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>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>	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???
Engr. Jose Martin Maningo	<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>1. First itemtext</p> <p>2. Second itemtext</p> <p>3. Last itemtext</p> <p>4. First itemtext</p> <p>5. Second itemtext</p> <ul style="list-style-type: none"> • First itemtext • Second itemtext • Last itemtext • First itemtext • Second itemtext 	Sec. ?? on p. ??, Sec. ?? on p. ??, Fig. ?? on p. ???

Continued on next page



De La Salle University

Continued from previous page

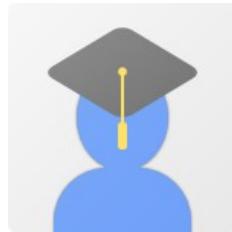
Examiner	Comment	Summary of how the comment has been addressed	Locations
Dr. Alexander Co Abad	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	1. First itemtext 2. Second itemtext 3. Last itemtext 4. First itemtext 5. Second itemtext	Sec. ?? on p. ??, Sec. ??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



1461

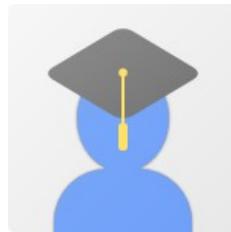
Appendix E VITA

1462



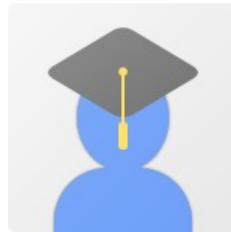
1463 Kenan A. Banal is currently taking up his B.Sc. Computer Engineering studies. He is passionate about software and hardware systems such as Vivado, Arduino, C, and Python.

1464
1465



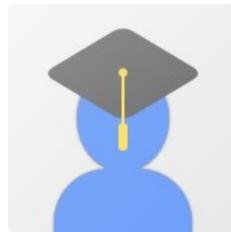
1466 Francis Robert Miguel F. BAUTISTA is currently taking up his B.Sc. Computer Engineering studies. He is passionate about software and hardware systems such as Vivado, Arduino, C, and Python.

1467
1468



1469 Don Humphrey L. HERMOSURA is currently taking up his B.Sc. Computer Engineering studies. He is passionate about software and hardware systems such as Vivado, Arduino, C, and Python.

1470
1471



1472 Daniel G. SALAZAR is currently taking up his B.Sc. Computer Engineering studies. He is passionate about software and hardware systems such as Vivado, Arduino, C, and Python.

1473
1474



De La Salle University

1475

Appendix F ARTICLE PAPER(S)

1476

Article/Forum Paper Format

(IEEE LaTeX format)

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

1477

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

Subsection text 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.

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

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.

1) Subsubsection Heading Here: Subsubsection text 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.

II. CONCLUSION

The conclusion goes here.

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra



(a) Case I



(b) Case II

Fig. 2. Simulation results for the network.

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, consectetuer 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.

APPENDIX A PROOF OF THE FIRST ZONKLAR EQUATION

Appendix one text goes here.

Lorem ipsum dolor sit amet, consectetuer 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, consectetuer 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.

APPENDIX B

Appendix two text goes here. [?].

Lorem ipsum dolor sit amet, consectetuer 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, consectetuer 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.

ACKNOWLEDGMENT

The authors would like to thank...