

DEVELOPMENT OF COMPUTER VISION SYSTEM FOR FRUITS

ABSTRACT

Conventional manual visual inspection of agriculture products in the agriculture industry has been one of the significant difficulties looked at by the farming business because of its difficult nature and irregularity in the grading process. Automatic detection or recognition using computer vision and artificial intelligence has turned into a promising research area in terms of visual examination. A working prototype hardware model of conveyor with PC is to be designed and implemented to analyse the fruit quality. The fruit is subjected to testing into a conveyor system for automatic defect detection and classification. The fruit to be tested is placed on the circular slab and the USB camera captures images and send them to the PC for classification. The classified output is sent from PC to Arduino microcontroller via serial port. The Arduino Microcontroller sends this digital output to PIC Microcontroller for displaying the classified output on LCD. A small door mechanism is fixed on the conveyor system. This door opens when the detected fruit is bad or unripe and rejects the fruit from the conveyor. This door closes when the detected fruit is good or ripe and travels along the conveyor. The machine learning algorithm is used for inspecting the fruit quality whether it is good or bad as well as ripe or unripe. Performance of the developed system has been found higher than the existing methods. In terms of response time and cost, our proposed system is very much feasible. The response time of the system is 5 seconds which is low compared to other systems. Regarding the cost is also it is low because general-purpose microcontrollers were used. So, it will be very suitable and useful for small-scale industries and farmers to growing up their businesses.

Key words: Computer vision, Conveyor, Image processing, ANN,KNN,SVM, Decision Tree, Random Forest

1.INTRODUCTION

The farming industry plays an essential part in the economy of several nations in the world. A significant area of agriculture business is the creation and supply of the new products of the soil to the sellers and markets. The developing interest for successful food creation and fast and safe stock to the market has encouraged the chance of utilizing different innovative advanced technology in this agriculture industry [1]. The innovations like the Internet of Things (IoT) based on strong cultivating have been found helpful in working on the nature of products of the vegetable yields [2]. Also, the utilization of better technologies by medium and large scope ventures has an opportunity to sort, bundle and transport the

37 better quality product to the market [3]. Even though most of the small and medium scale industries have
38 lacked good technologies in automation. the two major reasons are the overall cost of the product and
39 the lack of learning the new technologies Henceforth, there is a rising need to develop minimal expense
40 and simple to-utilize solutions for these agriculture industries so that they can get more advantages with
41 the help of new technologies.

42 The information and data in agriculture essentially begin from visual picture images however
43 numerically to measuring or dealing with visual information, is very challenging. In this manner, advanced
44 image processing techniques assist to analyze visual images. Image processing has different
45 applications in the field of agriculture like distinguishing proof of land [4] assessment of nitrogen
46 recognition plant. Inspection of bug infected regions [5], and discovery of plant illness from shape,
47 surface, and shading [6] As data science is quickly developing, computer vision-based recognition and
48 image processing are developed good techniques for security and quality examination of a few farming
49 applications. Computer vision based system capture the images through external camera ana analysed
50 through the computer compares the impact of the human vision in reviewing nature is accommodated
51 the quality evaluating and arranging.

52 In the recent past, efforts have been made to automate the fruits' classification problem based on
53 their outer appearance or freshness by employing computer vision and machine learning techniques [7].
54 However, in most of these studies, grading has been done using the traditional approach of feature
55 extraction and applying machine learning techniques. For example, in [8] the apples have been classified
56 by using color, texture, and shape feature descriptors, namely Global Color Histogram, Color Coherence
57 Vector (CCV), Local Binary Patterns (LBP), Complete Local Binary Patterns (CLBP), and Zernike
58 Moments (ZM). The extracted features were used individually as well as in combination to train and test
59 the machine learning techniques with the highest accuracy of 95.9% using a combination of CCV, CLBP,
60 and ZM. Further, in [9] both unsupervised and supervised learning algorithms have been used for apples'
61 grading. Initially, K-means clustering was used for the segmentation of defected apples, and in the next
62 stage statistical, textural, and geometric features were extracted from the refined defected regions. These
63 features were used to train, test, and compare the performance of three machine learning techniques
64 namely Support Vector Machine (SVM), MLP, and K-Nearest Neighbor (KNN). The results of this study
65 showed the highest grading results using an SVM classifier with recognition rates of 92.5% for healthy
66 and defected categories and 89.2% for three quality categories (in terms of ranks). In recent research on
67 measuring the ripeness quality on bananas, an artificial neural network (ANN) based framework has been
68 proposed using different features like color, development of brown spots, and Tamura statistical texture
69 [10]. The performance of the ANN model was compared with various other techniques including SVM,
70 naive Bayes, KNN, decision tree, and discriminant analysis. The findings showed that the proposed
71 system has the highest overall recognition rate 97.75%. Similar approaches have been followed for
72 determining the ripeness and maturity level of other fruits including blueberry [11], oil palm fruit [12], and
73 oranges [13]. Though the performance of the machine learning models in these studies is quite good
74 these models are mainly based on the hand-craft feature extraction methods which are mostly time-
75 consuming and dependent on the type of images (fruits) used for training and testing. Moreover, these

76 models have been trained and tested only for small datasets which increases the risk of biased
77 predictions.

78

79 **2. MATERIALS AND METHODS**

80 **2.1. Proposed system**

81 The main aim of the proposed approach is to provide an automated classification system for
82 different fruits and evaluations by classifying them based on defect and color. The proposed system is
83 capable of classifying fruits. The dataset used for this study is based on real sample images of 'fruit
84 varieties, which were collected from local fields. A working prototype hardware model of conveyor is to be
85 designed and implemented in this research work. Computer vision techniques and machine learning
86 algorithms were used for fruit inspection and grading. An USB web camera is used to prepare a dataset
87 using three different fruits like Lemon, Apple, Guava, Orange, Pomegranate, and Tomato. The images of
88 all these fruits are taken in ripe and unripe categories as well as good and rotten fruit categories. Once
89 the preparation of the dataset for all the three different fruits is completed, the fruit is subjected to testing
90 into a conveyor system for automatic detection and classification.

91 The fruit to be tested is placed on the circular slab and the USB camera captures images and
92 send them to PC for classification. For Image feature extraction single-Level 2-D Discrete Wavelet
93 Transform programme is used and five different Machine Learning algorithms are selected namely SVM
94 [14-16], KNN [17,18], ANN [19-21], Random Forest, and Decision Tree for classification. All five
95 algorithms developed are tested on the different fruits and based on the efficiency the best algorithm is
96 recommended. The classified output is sent from PC to Arduino microcontroller via serial port. The
97 Arduino Microcontroller sends this digital output to PIC Microcontroller for displaying the classified output
98 on LCD. The conveyor system operates using five gear motors for different operations.

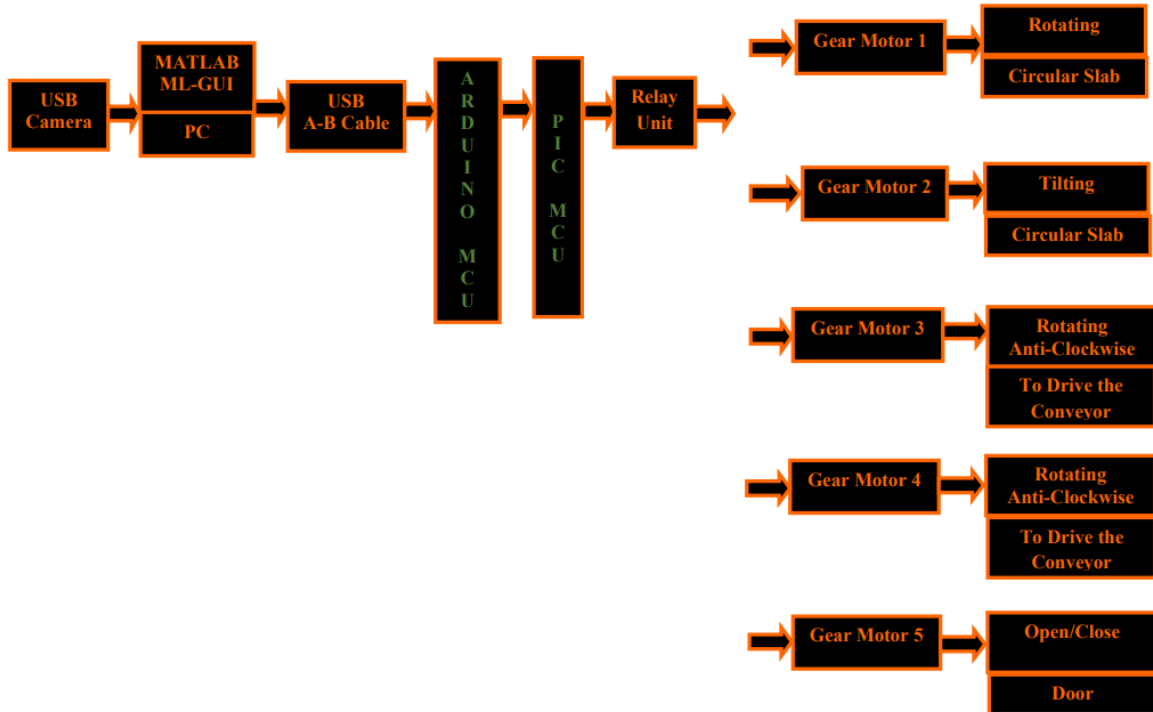
99 The PIC microcontroller operates these motors via the attached relay unit. The two motors are
100 used for tilting and rotating the circular slab. The rotating operation of the circular slab is to take pictures
101 of the fruit placed on the slab. The tilting operation of the circular slab is to drop the fruit into the
102 conveyor. The other two motors drive the conveyor belt and the fifth motor for the door opening and
103 closing mechanism. A small door mechanism is fixed on the conveyor system. This door opens when the
104 detected fruit is bad or unripe and rejects the fruit from the conveyor. This door closes when the detected
105 fruit is good or ripe and travels along the conveyor. A confusion matrix shows a table that is used to
106 calculate the accuracy of a classification model on a set of test data for which the fruits of the true value
107 are known. The results have been shown in the form of a learning curve and confusion matrix that shows
108 the accuracy of the predictive algorithm used.

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110 **2.2 Hardware Model**

111 For real-time testing of the model, a prototype system was developed. The hardware of the
112 prototype system consists of two microcontrollers [22] units Arduino and PIC modules. The classified
113 output is sent from PC to Arduino microcontroller via serial port. The Arduino Microcontroller sends this
114 digital output to PIC Microcontroller for displaying the classified output on LCD. The conveyor system
115 operates using five gear motors for different operations. The PIC microcontroller operates these motors

116 via the attached relay unit. The two motors are used for tilting and rotating the circular slab. The rotating
 117 operation of the circular slab is to take pictures of the fruit placed on the slab. The tilting operation of the
 118 circular slab is to drop the fruit into the conveyor. Hardware Model Diagram is shown in the figure 1.
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 123 The other two motors drive the conveyor [23.24] belt and the fifth motor for the door opening and
 124 closing mechanism. A small door mechanism is fixed on the conveyor system. This door opens when the
 125 detected fruit is bad or unripe and rejects the fruit from the conveyor. This door closes when the detected
 126 fruit is good or ripe and travel along the conveyor

127 **2.2.1 Image Acquisition**

128 An USB camera is connected to the system to capture the fruit which is programmed in MATLAB.
 129 For this, a Quantum QHM495LM web camera which is a high-resolution webcam delivers great video
 130 quality, and imaging quality is selected. The QHM PC Camera (QHM 495 LM) features 6 white lights and
 131 has an image resolution of 25 megapixels. The camera operates on CMOS sensors and has a
 132 potentiometer that switches on the lights when operating in the dark. It supports Automatic Whiteness
 133 Balance that precisely captures true colors even in mixed lighting conditions. The camera is set to an
 134 anti-flicker of either 50 Hz or 60 Hz to get great resolutions while using it outdoors. This webcam
 135 connects to PCs and laptops via a high-speed USB 2.0 interface.

136
 137 **2.3 Conveyer Hardware Setup**

138 The hardware section consists of a belt [25] conveyor used for the classification of fruits and a
 139 rotating circular slab where the fruit is placed and delivered to the belt conveyor. A USB camera is used

140 for taking images. This section also contains an open-close gate for directing the fruits in the specific
141 collecting place based on the classification

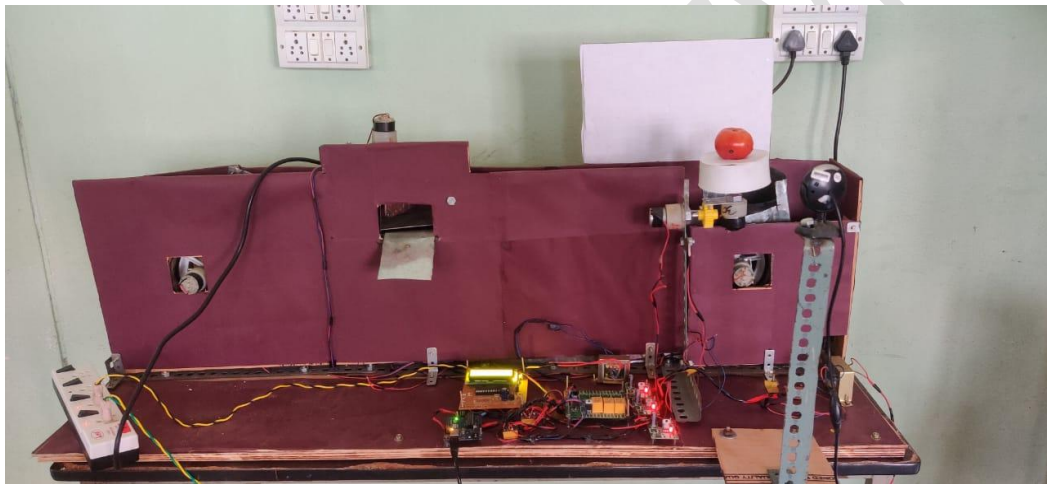
142 Things that are used in designing the conveyor are

- 143 ➤ Belt
- 144 ➤ Gear Motor
- 145 ➤ Pulley

146 A lab model low-cost belt conveyor was designed which could be able to carry a fruit of 250 gm. For this,
147 a Nylon belt was selected. Nylon was an ideal replacement for cotton and was the first polyamide
148 synthetic fiber to be utilized in belting construction which is shown in figure 2. However, it has several
149 positive attributes such as

- 150 1. Brilliant fatigue, impact, and mildew resistance
- 151 2. Good resistance to abrasion
- 152 3. Good resistance to impact fatigue and strength.

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Figure 2: Conveyor Full setup

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157 To develop a lab model conveyor system where a 1M length 3ply nylon belt material would be selected
158 with a width of 4.5 inches where small and medium-size fruits can be handled for classification. the
159 proposed conveyor system could be built with the gear motors. Rotating slab is shown in figure 3.

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Figure 3: Rotating and tilting the circular Tab

162 A total of five gear motors is used in the construction of the conveyor system [26]. Two gear motors are
163 used to rotate the pulleys. One pulley is attached to the open/close gate. Two pulleys are used for
164 rotating circular disc for rotating and tilting action. 12 Volts gear motors are used in developing the
165 system. The 12Volts geared motors are generally simple DC motors with a gearbox attached to them.
166 This can be used in all-terrain robots and a variety of robotic applications. These motors have a 3 mm
167 threaded drill hole in the middle of the shaft thus making it simple to connect it to the wheels or any other
168 mechanical assembly. 12V DC geared motors are widely used for robotics applications.
169 Pulley Wheel is mostly used which is easy to mount, durable and cheap. These wheels have a 6mm hole
170 for a shaft with the screw for fitting making it very easy to mount on motors. This has a smooth surface
171 and is lightweight. Two gear motors are connected to the pulley wheels which are situated at the ends to
172 move the belt. To develop the proposed system pulley wheels of 10 CM in diameter and 4 CM width with
173 a 6mm shaft bore is required to move a belt that can convey fruits of 250gm.

174

175 **2.3.1 Microcontrollers Design**

176 This section is the heart of the proposed system where it acts as a bridge between the hardware section
177 where classification is carried on a belt conveyor and the software section where the software that works
178 for the classification of fruits. The actuating and control system works by receiving signals from relay
179 units. The actuating system consists of Arduino Uno Microcontroller [27], PIC Microcontroller and Relay
180 units, LCD modules, Potentiometer, Transformer, Bridge Rectifier, Electrolytic capacitors, Regulator.

181 The Arduino Uno is a microcontroller board based on the ATmega328 (datasheet). It has 14 digital
182 input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic
183 resonator, a USB connection, a power jack, an ICSP header, and a reset button. It contains everything
184 needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with
185 an AC-to-DC adapter or battery to get started. The Uno differs from all preceding boards in that it does
186 not use the FTDI USB-to-serial driver chip. Instead, it features the Atmega16U2 (Atmega8U2 up to
187 version R2) programmed as a USB-to-serial converter.

188 The PIC microcontroller is interfaced between UNO and relay units. A microcontroller (also MCU or μC) is
189 a functional computer system-on-a-chip. Its getting the input from the computer and Rotate both the
190 pulley motors anti-clockwise direction. Circuit diagram is shown in the figure 4.

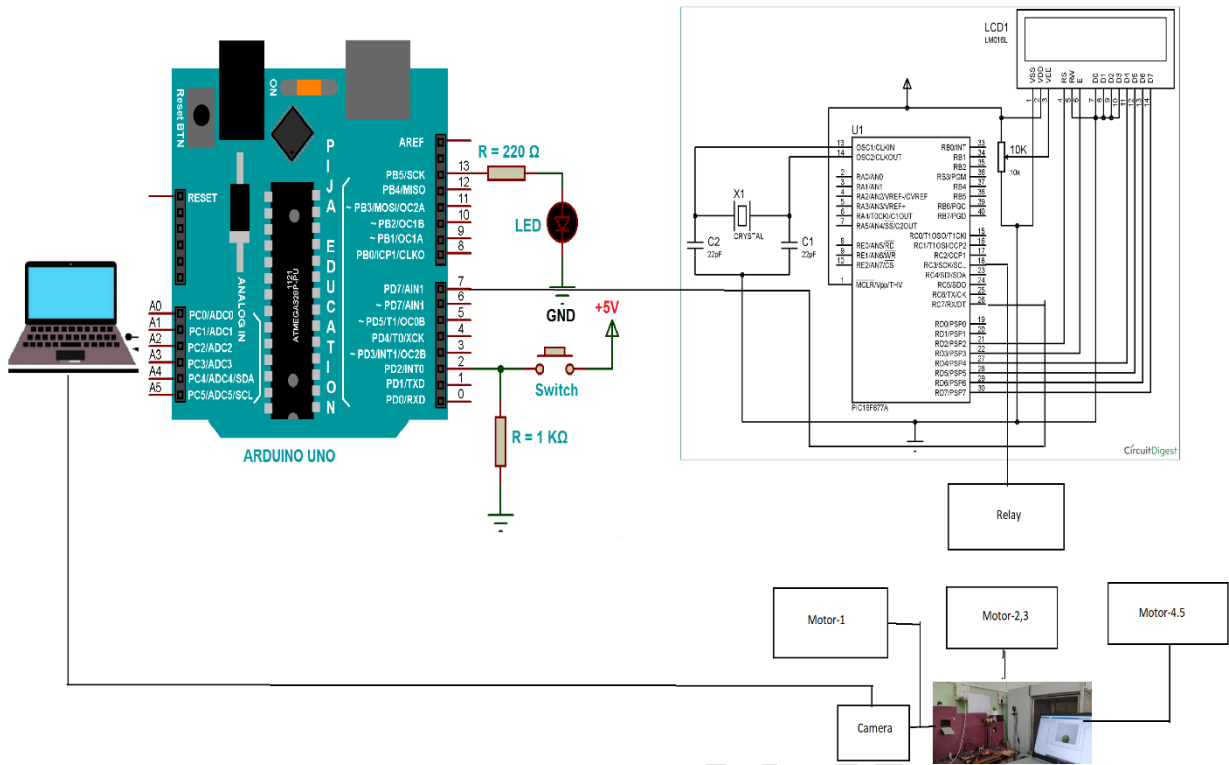


Figure 4: Circuit Diagram

2.3.2 Database creation

A hundred fruits each of mature, immature, and defected were procured from the local market yard (mandis). Where fruits were manually graded by the farmers as matured, immature, and defective. To minimize the noise in the image of fruits could be cleaned from the dust and foreign material before capturing the images. Then data base can be prepared to place each fruit on the circular slab which is an integral part of the conveyor [28,29] belt images will be captured by USB Camera [27]. Creating two separate folders one for matured and the other for defected fruits and then segregating those photos in the respective folders and image capturing is shown in figure 5. For creating the dataset, the captured images from the camera are cropped to 680x420 for all the images and the saved images are renamed in the corresponding folders for further processing.

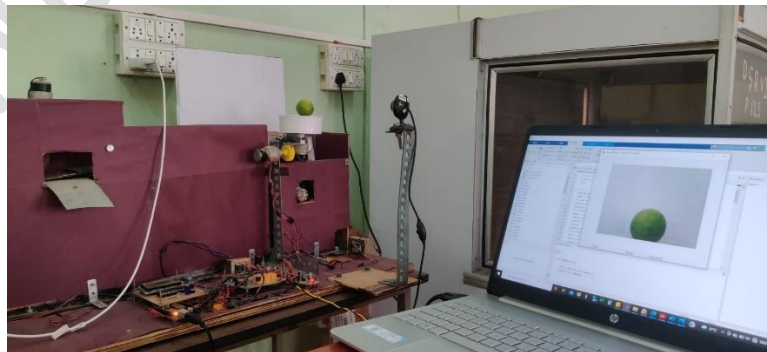


Figure 5: Database creation

208 **2.3.3 Procedure for creating the dataset**

209 Step-1: Take a single fruit and place it on a circular slab.

210 Step-2: The circular slab automatically rotates and images were captured via the USB camera.

211 Step-3: For each fruit, it takes 8 images from different angles.

212 Step-4: As the USB camera is connected to the PC, images need to be saved in the respective Good fruit
213 and Bad fruit folders.

214 Step-5: The same process is repeated for all the 100 images of good and bad fruits

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216 **2.4 Machine learning classification**

217 After the dataset collection. the five machine learning models have been taken for the classification of
218 fruits based on their quality like good or bad and ripe or unripe, All the models are supervised so the
219 training has to be done before the classification and testing is performed to determine the performance of
220 the system. Support vector machine, K-nearest neighbour, Decision tree, Random Forest, and finally
221 Artificial neural network these are five machine learning models. All the models are to be tested for the
222 different fruits with different classification strategies.

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224 **3. RESULTS AND DISCUSSION**

225 This section discusses the distribution of different fruit quality classes, Training, and the performance of
226 the system. Totally five different fruits quality has been analysed. All the fruits have the training data of
227 100 and testing data of 50. Table 1 shows the different number of fruits and the training testing data
228 distribution and Figure 6 shows the data distribution in terms of different quality. The system accuracy
229 was also analysed, Accuracy is the capability to how the system separates the various classes
230 effectively.

231
$$\text{Accuracy} = (Tp + Tn) / (Tp + Tn + Fp + Fn) \tag{1}$$

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Table 1. Data distribution

SI.NO	Fruit	Training	Testing
1	Lemon	100	50
2	Oranges	100	50
3	Tomato	100	50
4	Guava	100	50
5	Pomegranate	100	50
6	Apple	100	50

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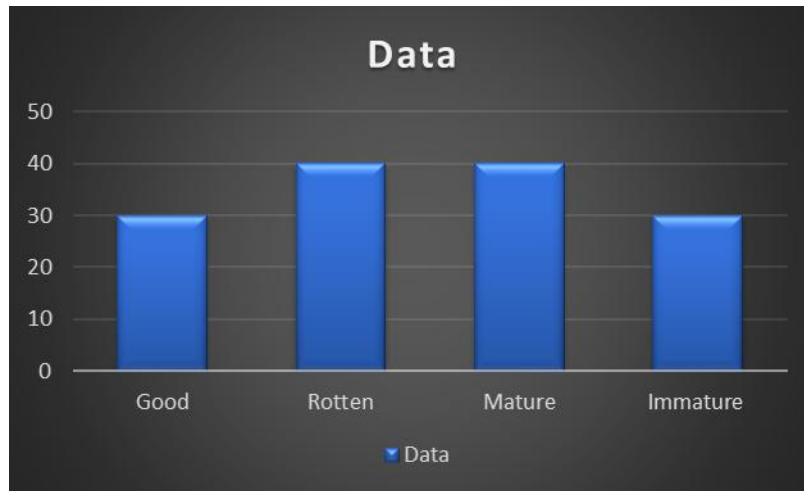


Figure 6: Fruit Quality Classes

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In terms of response time, the system is low. The compact connections make the system perform faster, The rotation time of the fruit is one second which means the controller quickly sends the signal to the motor to capture the input image. It is displayed in Table 2

Table 2 Response Time of the system

SI.NO	Scenario	Time (sec)
1	Rotation	56
2	Tilting	2
3	Open/close	2
4	Total	60

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Regarding the cost of the system no additional specific processor is needed, The general purpose microcontroller Arduino and PIC are needed which is a very low cost. The graphical user interference of the system is displayed here in figure7. It is developed the MATLAB 2019 software.

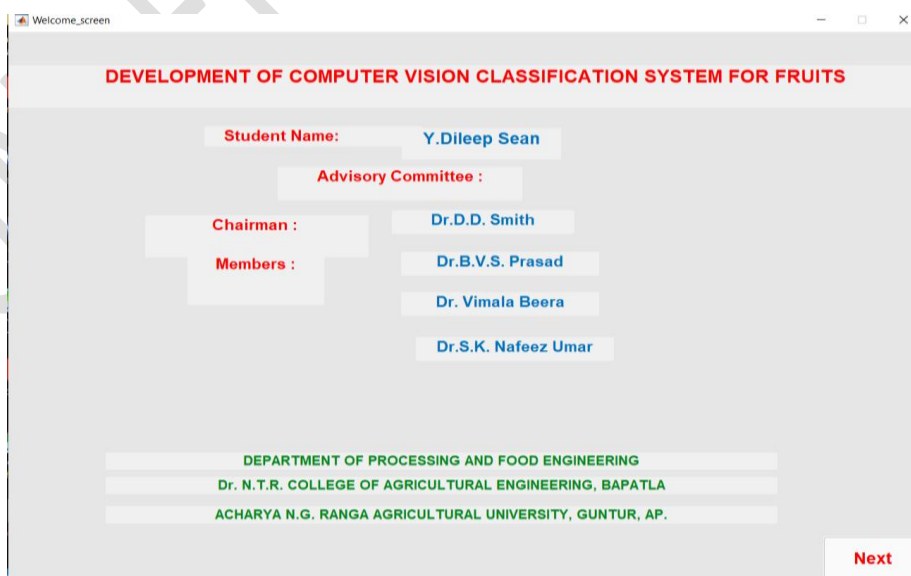
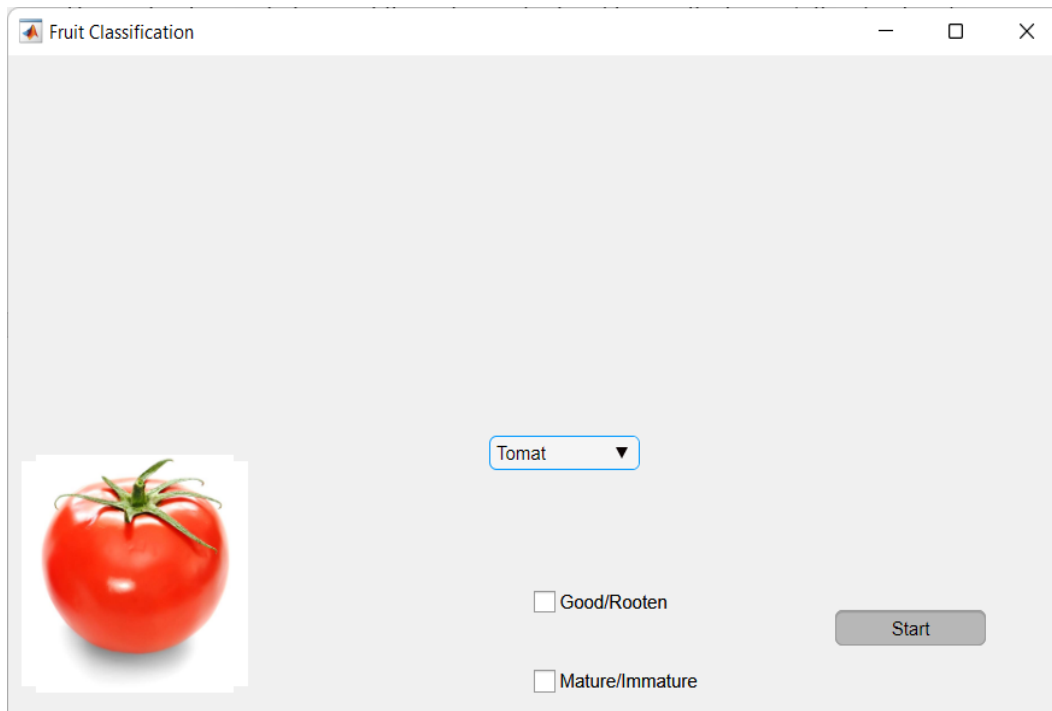


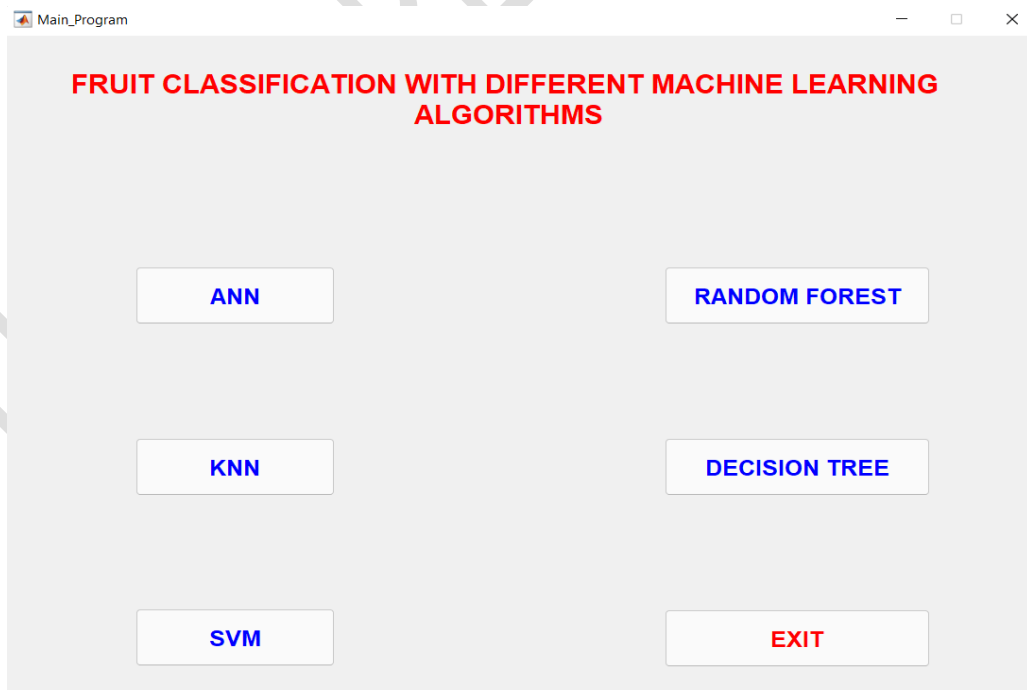
Figure 7: Welcome Screen of the System

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247 The welcome screen only shows the information related to the developer and the Advisory committee
248 members in figure 7
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251 **Figure 8: Different fruit classification Initial Screen**
252 Figure 8 shows the initial screen of the developed system. Here the screen is used to select the different
253 fruits and can check the fruit status Good/Rotten or Mature/Immature.
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256 **Figure -9 Machine learning Method Display Screen**
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Table 3 Comparison of different Methods

Method	Scenario	Time (sec)	Accuracy %
Prabha and Kumar (2013), [30]	Olympus	-	85
Kanade (2014) [31]	Webcam	-	92.6
Yahaya (2015), [32]	LED	-	87.9
Jhawar (2016), [33]	DSC	-	90
Si et al. (2017), [34]	Cannon	-	94
Pereira et al. (2018), [35]	Sony	-	94.7
Our method	Webcam	60	95.6

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Table 3 shows the comparison of different hardware-based systems for image acquisition for fruit classification. Some of the above systems used the light-emitting diode and different types of cameras. The main advantage of our proposed hardware system is the less processing time and good performance in low-resolution images as well. The developed system analyses the quality of the fruit in 60 seconds which is lower compared to other hardware models. So automatically the cost is low no need for any power full expensive camera for image acquisition. So, any small-scale industry can be used the system to analyse the quality of the different fruits even a small farmer can have this portable technology

269 **4.0 CONCLUSIONS**

270 Developed a working prototype hardware model of conveyor with PC is to be designed and implemented
271 to analyse the fruit quality. The fruit to be tested is placed on the circular slab and the USB camera
272 captures images and send them to the PC for classification. The classified output is sent from PC to
273 Arduino microcontroller via serial port. The Arduino Microcontroller sends this digital output to PIC
274 Microcontroller for displaying the classified output on LCD. A small door mechanism is fixed on the
275 conveyor system. This door opens when the detected fruit is bad or unripe and rejects the fruit from the
276 conveyor. This door closes when the detected fruit is good or ripe and travels along the conveyor. The
277 machine learning algorithm is used for inspecting the fruit quality whether it is good or bar as well as ripe
278 or unripe, The response time of the system is 60 seconds which is low compared to other systems.
279 Regarding the cost of construction is low as general-purpose microcontrollers are used. So, it will be very
280 suitable and useful for small-scale industries and farmers to grow up their businesses.

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COMPETING INTERESTS DISCLAIMER:

283 **Authors have declared that no competing interests exist. The products used for this research are**
284 **commonly and predominantly use products in our area of research and country. There is**
285 **absolutely no conflict of interest between the authors and producers of the products because we**
286 **do not intend to use these products as an avenue for any litigation but for the advancement of**

287 **knowledge. Also, the research was not funded by the producing company rather it was funded by**
288 **personal efforts of the authors.**

289

290 REFERENCES

291 [1] Tripathi MK, Maktedar DD. A role of computer vision in fruits and vegetables among various
292 horticulture products of agriculture fields: a survey. *Inf Process Agric* 2020;7:183–203.

293

294 [2] Yan B, Wu XH, Ye B, Zhang YW. Three-level supply chain coordination of fresh agricultural products
295 in the Internet of Things. *Ind Manag Data Syst* 2017;117:1842–65.

296

297 [3] Nukala R, Panduru K, Shields A, Riordan D, Doody P, Walsh J. Internet of Things: a review from Farm
298 to Fork. In: *Proc. Proceedings of 27th Irish Signals and*

299

300 [4] Erdenee, B., Ryutaro, T., Tana, G., 2010, Particular Agricultural Land Cover
301 Classification Case Study Of Tsagaannuur, Mongolia. In: *IEEE International*
302 *Geoscience & Remote Sensing Symposium*, 3194-3197.

303

304 [5] Tewari, V.K., Arudra, A.K., Kumar, S.P., Pandey, V., Chandel, N.S., 2013. Estimation of plant nitrogen
305 content using digital image processing. *Int. Commission Agricu. Biosyst. Eng.* 15 (2), 78–86.

306

307 [6] Krishna, M., Jabert, G., 2013. Pest control in agriculture plantation using image
308 processing. *IOSR J. Electron. Commun. Eng. (IOSR-JECE)* 6 (4), 68–74.

309

310 [7] Nukala R, Panduru K, Shields A, Riordan D, Doody P, Walsh J. Internet of Things: a review from Farm
311 to Fork. In: *Proc. Proceedings of 27th Irish Signals and Systems Conference*. Londonderry, UK; 2016. p.
312 1–6.

313

314 [8] Dubey SR, Jalal AS. Apple disease classification using color, texture and shape features from images.
315 *Signal, Image Video Process* 2016;10:819–26.

316

317 [9] Moallem P, Serajoddin A, Pourghassem H. Computer visionbased apple grading for golden delicious
318 apples based on surface features. *Inf Process Agric* 2017;4:33–40.

319

320 [10] Mazen FMA, Nashat AA. Ripeness classification of bananas using an artificial neural network. *Arab J*
321 *Sci Eng* 2019;44:6901–10.

322

323 [11] Tan K, Lee WS, Gan H, Wang S. Recognising blueberry fruit of different maturity using histogram
324 oriented gradients and colour features in outdoor scenes. *Biosyst Eng* 2018;176:59–72.

325

- 326 [12] Silalahi DD, Rean~ o CE, Lansigan FP, Panopio RG, Bantayan NC. Using genetic algorithm neural
327 network on near infrared spectral data for ripeness grading of oil palm (*Elaeis guineensis* Jacq.) fresh
328 fruit. *Inf Process Agric* 2016;3:252–61.
329
- 330 [13] Sabzi S, Abbaspour-Gilandeh Y, Garcí'a-Mateos G. A new approach for visual identification of
331 orange varieties using neural networks and
332
- 333 [14] Jana S, Basak S, Parekh R. Automatic fruit recognition from natural images using color and texture
334 features. In: *Proc. devLC '17 Proceedings of the 2017 IEEE conference on Devices for Integrated Circuit*,
335 Kalyani, India; 2017. P. 620–4.
336
- 337 [15] Li D, Shen M, Li D, Yu X. Green apple recognition method based on the combination of texture and
338 shape features. In: *Proc. ICMA '17 Proceedings of the 2017 IEEE International Conference on*
339 *Mechatronics and Automation*. Takamatsu, Japan; 2017. p. 264–9.
340
- 341 [16] Purohit S, Viroja R, Gandhi S, Chaudhary N. Automatic plant species recognition technique using
342 machine learning approaches. In: *Proc. CoCoNet '15 proceedings of the 2015*
343
344
- 345 [17] Bolle RM, Connell JH, Haas N, Mohan R, Taubin G. Veggie vision: a produce recognition system. In:
346 *Proc. WACV '96 Proceedings of the 1966 IEEE Workshop on Applications of Computer Vision*, Sarasota,
347 FL, USA;
348 1996. p. 244–251.
349
- 350 [18] Nosseir A, Eldin S, Ahmed A. Automatic identification and classifications for fruits using k-NN. In:
351 *Proc ICSIE '18 Proceedings of the 2018 ACM international conference on software and information*
352 *engineering Cairo, Egypt; 2018. p. 62–67.*
353
- 354 [19] Choi D, Lee WS, Ehsani R, Schueller J, Roka FM. Detection of dropped citrus fruit on the ground
355 and evaluation of decay stages in varying illumination conditions. *Comput Electron Agric* 2016;127:109–
356 19.
357
- 358 [20] Kumar RA, Rajpurohit VS, Nargund VB. A neural network assisted machine vision system for sorting
359 pomegranate fruits. In: *Proc. ICECCT '17 Proceedings of the 2017 Second International Conference on*
360 *Electrical, Computer and Communication Technologies*. Coimbatore, India; 2017.p. 1–9.
361
- 362 [21]Singh N, Dubey SR, Dixit P, Gupta JP. Semantic image retrieval by combining color, texture and
363 shape features. In: *Proc. ICCS '12 proceedings of the 2012 IEEE international conference on computing*
364 *sciences*. Phagwara, India; 2012. p. 116–120.
365

366 [22] Lakooju N. K., Gudla S., and Mantravadi B. S., (2011). AVR-USB Data Acquisition. 2nd National
367 Conference on Information and Communication Technology, 3, 35 - 39.
368

369 [23]Rautu, S. V., Shinde, A. P., Darda, N. R., Vaghule, A. V., Meshram C. B. and Sarawade, S. S.
370 (2017). Sorting of objects based on color, weight and type on a conveyor line using PLC. IOSR Journal of
371 Mechanical and Civil Engineering, e-ISSN: 2278- 1684,p-ISSN: 2320-334X, 4-7.
372

373 [24] Sheela.S, Meghashree. S., Monica. L., Prathima, A., and Shriya, M. K (2016). Automation For
374 Sorting of Objects Using Raspberry PI 3. International Journal of Advances in Electronics and Computer
375 Science, ISSN: 2393.
376

377 [25] DharmannagariVinay Kumar Reddy, Sorting Of Objects Based On Colour By Pick And Place
378 Robotic Arm And With Conveyor Belt Arrangement, International Journal Of Mechanical And Robotics
379 Research, ISSN 2278 – 0149, January 2014.
380

381 [26] Kunhimohammed C. K, MuhammedSaifudeen K. K, Sahna S, Gokul M. S And ShaezUsman
382 Abdulla, Automatic Color Sorting Machine Using TCS230 Color Sensor And PIC Microcontroller,
383 International Journal Of Research And Innovations In Science & Technology, ISSN (Online): 2394-3858,
384 2015
385

386 [27] Prof. NilimaBargal, AdityaDeshpande, RuchaKulkarni, RuchaMoghe, PLC based Object Sorting
387 Automation, International Research Journal Of Engineering & Technology, ISSN (Online): 2395-0056,
388 July 2016
389

390 [28] Sheela S, Shivaram. K. R, Meghashree S, Monica L, Prathima A, Shriya M. Kumar, Low Cost
391 Automation for Sorting of Objects on Conveyor Belt, International Journal Of Innovative Research in
392 Science, Engineering & Technology, ISSN (Online): 2319-8753, May 2016
393

394 [29] Ganesh B. Shinde, Vishal P. Ghadage, Akshay A. Gadhave, Dr. D. K. Shedge, PLC Based Auto
395 Weighing Control System, International Journal Of Engineering And Technical Research (IJETR), ISSN:
396 2321-0869.
397

398 [30] Prabha, D.S., Kumar, J.S., 2013. Assessment of banana fruit maturity by image processing
399 technique. J. Food Sci. Technol.
400

401 [31] Kanade and A. Shaligram, "Development of machine vision based system for classification of Guava
402 fruits on the basis of CIE1931 chromaticity coordinates," 2015 2nd International Symposium on Physics
403 and Technology of Sensors (ISPTS), 2015, pp. 177-180, doi: 10.1109/ISPTS.2015.7220107.
404

405 [32] O. K. M. Yahaya, M. Z. MatJafri, A. A. Aziz and A. F. Omar, "Non-destructive quality evaluation of
406 fruit by color based on RGB LEDs system," 2014 2nd International Conference on Electronic Design
407 (ICED), 2014, pp. 230-233, doi: 10.1109/ICED.2014.7015804
408

409 [33] Jhawar, J., 2016. Orange Sorting by applying pattern recognition on color image. Int. Conf. Inf. Sec.
410 Privacy, 691–697.
411

412 [34] Si, Y., Sankaran, S., Knowles, N.R., Pavek, M.J., 2017. Potato Tuber Length-Width ration
413 assessment using image analysis. Am. J. Potato 94 (1), 88–93.
414

415 [35] Pereira, L.F.S, Jr, S., B., Valous, N.A., Barbin, D.F., 2018, Predicting the ripening of papaya fruit with
416 digital imaging and random forests. Computers and Electronics in Agriculture, 145, 76–82.
417 1.

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