**IMAGED-BASED EMBEDDED SYSTEM FOR DETECTING/CLASSIFYING FRUIT PRODUCTS USING ARTIFICIAL INTELLIGENCE (AI) AND IOT  
  
BY  
  
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# CHAPTER ONE INTRODUCTION

## BACKGROUND TO THE STUDY

The computer vision strategies used to recognize a fruit rely on four basic features which characterize the object: intensity, color, shape and texture. This paper proposes an efficient fusion of color and texture features for fruit recognition. The recognition is done by the minimum distance classifier based upon the statistical and co-occurrence features derived from the Wavelet transformed sub- bands. Recognition system has emerged as a ‘grand challenge' for computer vision, with the longer term aim of being able to achieve near human levels of recognition for tens of thousands of categories under a wide variety of conditions. The fruit recognition system can be applied for educational purpose to enhanced learning, especially for small kids and Down syndrome patients, of fruits pattern recognition based on the fruit recognition result (Seng & Mirisaee, 2010). It can be used in grocery store which makes the customers label their purchases using automatic fruit recognition based on computer vision. A number of challenges had to be overcome to enable the system to perform automatic recognition of the kind of fruit or vegetable using the images from the camera. Many kind of fruits are subject to significant variation in color and texture, depending on how ripe they are. For example, Bananas range from being uniformly green, to yellow, to patchy and brown. Color and texture are the fundamental character of natural images, and plays an important role in visual perception. Color has been a great help in identifying objects for many years. It is often useful to simplify a monochrome problem by improving contrast or separation. The process of color classification involves extraction of useful information concerning the spectral properties of object surfaces and discovering the best match from a set of known descriptions or class models to implement the recognition task (Sahin, 1997). Texture is one of the most active topics in machine intelligence and pattern analysis since the 1950s which tries to discriminate different patterns of images by extracting the dependency of intensity between pixels and their neighboring pixels (Kartikeyan & Sarkar, 1991) or by obtaining the variance of intensity across pixels (Haralick, Shanmugan, & Dinstein, 1973). Recently, different features of color and texture are combined together for their applications in the food industry (Jain & Healey, 1998). Recently, different features of color, size, shape, and texture are combined together for their applications in the food industry. Normally, by increasing the features used, the performance of the methods proposed can be increased. Here, the texture property plays two roles in the recognition procedure. Texture based edge detection has been combined with redness measures, and area thresholding followed by circle fitting, to determine the location of apples in the image plane. It was shown that redness works for red apples as well as green apples. This increased texture contrast helped to identify apples separately from background. Three features analysis methods color-based, shape based and size-based are combined together in order to increase accuracy of recognition (Seng & Mirisaee, 2009). Fruit detection system is primarily developed for robotic fruit harvesting. However this technology can easily be tailored for other applications such as on tree yield monitoring, crop health status monitoring, disease detection, maturity detection and other operations which require vision as a sensor. For fruit harvesting system, it is very necessary to detect the fruit on the tree more efficiently. The vision based fruit harvesting system for the fruit detection basically depend on the contribution of different features in the image. The four basic features which characterize the fruit are: intensity, color, edge and orientation. This paper proposes an efficient multiple features based algorithm for the fruit detection on tree. Color features in image could be successfully used to segment defects on ‘Jonagold’ apples are demonstrated in (Leemans & Destain, 2004). Texture features are found to contain useful information for quality evaluation of fruit and vegetables, e.g., classification of grade of apples after dehydration with the accuracy of 95% (Shigehiko, Tomohiko, Kotaro, Katsunobu, & Naoshi, 2005). Color and texture features are used to locate green and red apples (Blasco, Aleixos, & Molto, 2003). Combining many features and classifiers, where all features are concatenated and fed independently to each classification algorithm. The color and texture features are used for the color recognition. An efficient fusion of color and texture is used for fruit recognition. The recognition is done by minimum distance classifier based upon. the statistical and co-occurrence features derived from the wavelet transformed sub-bands The fusion approach is validated using the multi-class fruit-vegetable categorization task in a semi-controlled environment, such as a distribution center or the supermarket cashier. A machine vision algorithm consists of segmentation, region labeling, size filtering, perimeter extraction and perimeter-based detection, for the recognition of orange fruit is presented in (Hannan, Burks, & Bulanon, 2009). Our work in this paper presents a fruit detection using multiple features based algorithm. A simple feature can not entirely represent the character of the fruit region. Therefore, multiple features analysis is used in the proposed method. For efficient detection of fruit on tree, various types of features like color, intensity, edge and orientation are used. The computed features are then integrated according to their weights. After integrating the feature map, then we obtain the final image map.

## STATEMENT OF PROBLEM

Computer vision alone is not sufficient for detecting the ripeness of fruits.

Regarless of the multi-layer classification techniques used by recent systems, often these systems are unable to accurately predict whether or not a fruit is ripe. Also some fruits are impossible to classify at certain stages of ripeness using computer vision exclusively. Hence, the challenge of quality control, which the manufacturers faces when using the conventional way of classifying/detecting fruit products (which could either be the final products or raw materials) relies solely on human abilities, which leads to errors and due to inadequate technology for detecting/classifying fruit products.

## RESEARCH AIM AND OBJECTIVES

The aim to develop a fruit recognition system will be to increase efficiency and reliability of the detection/classification of fruit products.

The specific objectives are to:

1. Design and train a Convolutional Neural Network (CNN) to classify fruits.
2. Incorporating the camera and sensors with the microcontroller.
3. Making and incorporating a dependable/reliable method of arranging information in the cloud.
4. Testing and validating the image-based embedded system.

## METHODOLOGY OVERVIEW

Towards achieving the aforementioned objectives, the iterative and incremental development was used. This allowed for development of small iterations of the product learning at each version enforcing an optimal final system.

To develop the model, descriptive research of existing systems was done and convergence of what existing systems are was derived. This gave a clear picture of what was to be built. To build the system, Arduino microcontroller and the ESP32 CAM were the major hardware components. The software was based on python and machine learning.

## SCOPE OF THE STUDY

This project is only interested in the detection of fruits and hence cannot be used to detect other food types or objects. It is designed with the sight of overcoming the limitations of closely related systems. Nigeria was considered as a case study.

## SIGNIFICANCE OF THE STUDY

* Robotic fruit harvesting
* Tree yield monitoring
* Crop health status monitoring
* Disease detection
* Fruit maturity detection

## ORGANIZATION OF THESIS

**Chapter Two**: Literature Review - discussed the historical background of the problem, related works, and closely related works

**Chapter Three**: Research Methodology - discussed in detail existing models and proposed model as well as the methods used in attaining the aim and objectives.

**Chapter Four**: Outcomes/Results and Discussions - here, the results of the methods employed and the existing systems are discussed.

**Chapter Five**: Summary, Conclusion and Recommendation - this holds the summary, conclusion limitations and recommendation of the project.

# CHAPTER TWO LITERATURE REVIEW

## 2.1. INTRODUCTION

Fruit recognition is a subset of imag recognition. Image recognition, in the context of machine vision, is the ability of software to identify objects, places, people, writing and actions in images. Computers can use machine vision technologies in combination with a camera and artificial intelligence software to achieve image recognition.

Image recognition is used to perform a large number of machine-based visual tasks, such as labeling the content of images with meta-tags, performing image content search and guiding autonomous robots, self-driving cars and accident avoidance systems.

While human and animal brains recognize objects with ease, computers have difficulty with the task. Software for image recognition requires deep machine learning. Performance is best on convolutional neural net processors as the specific task otherwise requires massive amounts of power for its compute-intensive nature. Image recognition algorithms can function by use of comparative 3D models, appearances from different angles using edge detection or by components. Image recognition algorithms are often trained on millions of pre-labeled pictures with guided computer learning (Rouse, Image Recognition, 2017).

Fruit recognition fundamentally is the ability for software to identify different fruits through the use of enabling hardware components like a camera. This involves the collection, processing, classification and identification of fruit images.

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## 2.2. HISTORICAL BACKGROUND OF THE PROBLEM AREA

A number of studies have been conducted on image categorization. There was an initial attempt to develop a produce recognition system for use in supermarkets. The system could analyze color, texture and density, and thus was able to obtain more information. Density was calculated by dividing weight with the area of the fruit. The reported accuracy was approximately 95% when color and texture features were combined, but the top four responses were used to achieve such result (Bolle, Connell, Haas, Mohan, & Taubin, 1996). The authors approached the multi-class classification problem as a set of binary classification problem in such a way that one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They achieved a classification accuracy of up to 99% for some fruits, but they fused three features, namely, border-interior classification (BIC), color coherence vector (CCV), and unser features, and identified top two responses to achieve them. Their method obtained poor results for some types of fruit and vegetable, such as Fuji Apple.

Fruit detection greatly affects the robot’s harvesting efficiency because it is an unstructured environment with changing lighting conditions. Bulanon et al. enhanced the portion occupied by fruit in images using a red chromaticity coefficient and adopted a circle detection method for classifying individual fruits. To improve fruit visibility, they acquired multiple views from different viewing angles for a portion of a tree canopy. Fruit visibility improved from 50% to about 90% by acquiring multiple views. Date palm fruits are popular in the Middle East and have a growing international presence. Sorting of dates can be a tedious job and a key process in the date palm industry (Bulanon, Burks, & Alchanatis, 2009). Haidar et al. presented a method for classifying dates automatically based on pattern recognition and computer vision. Using an extracted image of an appropriately crafted mixture of 15 different visual features, they tried multiple classification methods. The performance of the methods ranged from 89% to 99% (Haidar, Dong, & Mavridis, 2012). Jimenez et al. developed a method that can identify spherical fruits in the natural environment in which difficult situations are present: occlusions, shadows, bright areas, and overlapping fruits. Range and attenuation data are sensed by a laser range-finder sensor, and the 3-D position of the fruit with radius and reflectance are obtained after the recognition steps.

Thermal imaging is an approach for converting the pattern of invisible radiation of an object into visible images to facilitate the extraction and analysis of features. If temperature differences can be used to assist in the analysis, diagnosis, or evaluation of a product or process, then infrared thermal imaging technology can be successfully applied. The potential use of thermal imaging in the food and agriculture industry includes detecting diseases and pathogens in plants, predicting water stress in crops, predicting fruit yield, planning irrigation scheduling, detecting bruises in fruits and vegetables, evaluating the maturing of fruits, distributing temperature during cooking, and detecting foreign bodies in food material. Vadivambal and Jayas reviewed the application of thermal imaging in the food and agriculture industry and highlighted the potential of thermal imaging techniques in various agricultural processes. The main advantage of using infrared thermal imaging is the non-contact, non-destructive, and non-invasive nature of the technique in finding the distribution of temperature in a short period of time (Vadivambal & Jayas, 2011). Seng and Mirisaee combined different methods that can analyze color, size, and shape to increase the accuracy of recognition. Using the nearest neighbor classifier for the classification, they achieved an accuracy of up to 90% (Seng & Mirisaee, 2009).

## 2.3. RELATED WORKS

FRUIT RECOGNITION FROM IMAGES USING DEEP LEARNING

In this paper, the authors introduced a new, high-quality, dataset of images containing fruits. The paper also present the results of some numerical experiment for training a neural network to detect fruits. Finally, the paper gave justification for the use of fruits by proposing a few applications that could use such classifier (Mures & Oltean, 2018).

CNN TRANSFER LEARNING FOR AUTOMATIC FRUIT RECOGNITION FOR FUTURE CLASS OF FRUIT

Deep fruit recognition model learned on big dataset outperform fruit recognition task on difficult unconstrained fruit dataset. But in practice, we are often lack of resources to learn such a complex model, or we only have very limited training samples for a specific fruit recognition task. This study addressed the problem of adding new classes to an existing deep convolutional neural network framework. We extended our prior work for automatic fruit recognition by applying transfer learning techniques to adding new classes to existing model which was trained for 15 different kind of fruits. Pre-trained model was previously trained on a large-scale dataset of 44406 images. To add new class of fruit in our pre-trained model, there is a need to train a new classifier which will be trained for scratch, on the top of pre-trained model so that the feature learned previously for the dataset can be repurposed (Hussain, Tan, Hussain, & Ali, 2020).

COMPUTER VISION BASED LOCAL FRUIT RECOGNITION

In this paper, the authors performed an in-depth exploration of a computer vision approach for recognizing rare local fruits of Bangladesh. A number of rare local fruits are classified based on the features extracted from their images. For experiment, the paper used a total of 480 images of 6 rare local fruits. The authors performed some preprocessing on the captured image and then expected features are extracted using image segmentation. Classification of the fruits is accomplished using support vector machines (SVMs).

MACHINE VISION BASED FRUIT CLASSIFICATION AND GRADING - A REVIEW

One of the important quality features of fruits is its appearance. Appearance not only influences their market value, the preferences and the choice of the consumer, but also their internal quality to a certain extent. Color, texture, size, shape, as well the visual flaws are generally examined to assess the outside quality of food. Manually controlling external quality control of fruit is time consuming and laborintensive. Thus for automatic external quality control of food and agricultural products, computer vision systems have been widely used in the food industry and have proved to be a scientific and powerful tool for by intensive work over decades. The use of machine and computer vision technology in the field of external quality inspection of fruit has been published based on studies carried on spatial image and / or spectral image processing and analysis. A detailed overview of the process of fruit classification and grading were presented in this paper. Detail examination of each step is done. Some extraction methods like Speeded Up Robust Features (SURF), Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP) were discussed with the common features of fruits like color, size, shape and texture. Machine learning algorithms like K-nearest neighbor (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) were also discussed.

COLOR, DEPTH, AND SHAPE-BASED 3D FRUIT DETECTION

A novel detection algorithm based on color, depth, and shape information is proposed for detecting spherical or cylindrical fruits on plants in natural environments and thus guiding harvesting robots to pick them automatically. A probabilistic image segmentation method is first presented to segment a red–green–blue image as a binary mask. Multiplied by this mask, a filtered depth image is obtained. Region growing, a region-based image segmentation method, is then applied to group the depth image into multiple clusters. Each cluster represents a fruit, leaf, or branch that is later transformed into a point cloud. Next, a 3D shape detection method based on M-estimator sample consensus, a model parameter estimator, is employed to detect potential fruits from each point cloud. Finally, an angle/color/shape-based global point cloud descriptor (GPCD) is developed to extract a feature vector for an entire point cloud, and a support vector machine classifier trained on the GPCD features is used to exclude false positives.

AUTOMATIC CLASSIFICATION OF FRUITS USING GA OPTIMIZED, ROBUST SMRT FEATURES

Automatic classification of fruits using digital image processing techniques has become popular and reliable in automated food packaging industries. In this paper, a computationally efficient fruits classification technique was proposed using Sequency Mapped Real Transform. This technique saves time and is also robust against rotations and illumination changes. First, the input fruit image is preprocessed to enhance its overall visual appearance. The desired fruit region is segmented out from the preprocessed image using Particle Swarm Optimization based segmentation technique. A computationally efficient and robust Sequency Mapped Real Transform (SMRT) is then used to extract feature vectors which uniquely represent fruit images of different categories. The performance of proposed feature vector extraction is studied by testing the extracted feature vectors using various statistical classifiers.

## 2.4. COMPARATIVE STUDY

From the literature study, there are 5 major algorithms employed by fruit detection systems. The table below shows gives a brief comparison of these algorithms.

|  |  |  |  |
| --- | --- | --- | --- |
| Algorithm | Advantages | Disadvantages | Datasets |
| Support Vector Machine(SVM) | It is scalable to high dimensional data. | The error percentage will increase if incorrect support vectors are chosen. | 16400 fruit images were taken as input. |
| Linear Discriminant Analysis(LDA) | It is often used in dimensionality reduction . | Prediction accuracy rate is comparatively low. | 100 images were taken as input. |
| Principal Component Analysis(PCA) | Pre-requisite details about the data is not necessary. | Reduces the overfitting in models. | 1653 images of different categories of fruit were taken as input. |
| Naïve Bayes | Less complex and implementation is easy. | Variables dependency exsist. | 50 images of each fruits were taken as input. |
| Analysis | Prediction is sharp because of the variables. | It is limited in the case of linear relationship. | 3108 images were taken as input. |
| K-NN Classifier | There is no training period for the models generated. | Unscalable when the dataset is massive. | 210 images were taken as input. |

### 2.4.1 REVIEW TABLE

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| S/N | Author(s) | Problem(s) | Methods | Results | Gaps/Limitations |
| 1 | Rabby, M.K.M.,et.al. (2018) | Fruit detection and classification | Modified Canny Edge Detection Algorithm.  Bi-cubic interpolation is used for resizing the images for conversion to gray scale image | Traditional approach may be replaced with MCED for higher computational speed and accuracy | Gray scalling is inapplicaple to certain fruits. |
| 2 | Gonzalez, J.P.B., et.al.(2017) | Estimation of passion fruit using digital images | Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) algorithms were used | The accuracy acquired was above 80% and error rate below 20% | The accuracy depends on the correlation coefficient(R). |
| 3 | Ponce, J.M., et.al.(2019) | Automatic counting of olive fruits | Computer Vision Techniques using regression analysis | The error rates were below 0.80% and 1.05%. | Research is limited to olives. |
| 4 | Kumari, R.S.S., et.al. | Fruit Classification using Statistical Features | Statistical Features in SVM Classifier. The system contains three phases: pre-processing, feature extraction and classification phase | The accuracy was achieved upto 95.3%. | Support vectors imply a more complicated system. |
| 5 | Akin, C., et.al. (2012) | Detection of the pomegranate fruits on tree | Image processing. The system uses local and shape analysis for analysing the color intensity for identifying the desired source | The accuracy rate is 99% | Unripe or problematic pomegranate will not be detected due to the use of color classification |
| 6 | Muhammad, G.,(2014) | Automatic date fruit classification | Local texture descriptors and shape-size features | The system achieved accuracy rate of 97.12% | Only applicable to date fruit |
| 7 | Riyadi, S., et.al.(2008) | Feature extraction technique for fruit shape classification | Wavelet-based feature extraction technique. The algorithm used here is LDA (Linear Discriminant Analysis) | The accuracy achieved is more than 98% | Fruit shape is not efficient alone for classifying fruits |
| 8 | Swati Dewliya et.al. (2015) | Detection and classification for apple fruit diseases | Support vector machine and chain code | Accomplished an accuracy of 95% with low false detection errors. | Training data considered only a small data set as a result of low powered algorithms. |
| 9 | Ronald M. et.al. (2016) | Classification of apple fruit varieties | Naive Bayes | The acquired average values of parameter such as accuracy, sensitivity, precision and specificity were 91%, 77%, 100% and 80%. | Very high quality images are required. This suggests a high graphic process unit |
| 10 | Macanhã P.A. et.al.(2018) | Fruit classification | Handwritten feature descriptor methods | The best feature space computed with this approach reaches 97.54% of correct classification rates. | Classification cannot happen in real time |
| 11 | Zihai Lua,et.al.(2017) | Fruit Sensing and Classification | Fractional Fourier Entropy and Improved Hybrid Genetic Algorithm | The proposed method resulted into an overall accuracy of 89.59% in different categories. | System requires specific hardware, without which the system cannot function |
| 12 | Rocha, A. et.al.(2010) | Automatic fruit and vegetable classification from images | Statistical, structural and spectral approaches with Supervised learning and K-Nearest Neighbors (K-NN) | The implemented solution achieves a classification error less than 2% | Does not have any real-time applications |
| 13 | Akif Birol et.al.(2016) | Olive Fruit Sorting | Color Image Processing | The optimum parameters and results were attained in response to the five different belt speeds (0.518, 0.691, 0.749, 0.806 and 0.864 m/s) | Image processing using only color features is not ideal as an olive colored ball would be sorted as an olive. |
| 14 | Raja Sekar et.al.(2018) | Fruit Classification | Artificial Neural Network, Adaptive Neural Fuzzy Interference &SVM | SVM (Support Vector Machine) gave highest accuracy, but ANFIS (Adaptive Neuro Fuzzy Interference System) showed the best result out of these techniques | SVM and ANFIS are not easily implemented. Implementing Fuzzy interference produces low accuracy. |
| 15 | Nandi, C.S. ,et.al.(2014) | Sorting of Harvested Mangoes | A Machine Vision-Based Maturity Prediction | Accuracy in classification phase was obtained up to 96%. | Requires an enormorse data set |

# CHAPTER THREE RESEARCH METHODOLOGY

## 3.1 INTRODUCTION

This chapter gives insight into the design methodology adopted for this research project in a deliberate attempt to address the aim and objectives. This chapter contains the System Development Life Cycle Model, Unified Modelling Language (UML) diagrams.

## 3.2 METHOD OF PRELIMINARY STUDY

In this project, a descriptive research process was adopted as multiple information was collected to reduce predictions and elucidate the subject. Rapid Application Development (RAD) model was chosen as the System Development life cycle.

### 3.2.1 ITERATIVE AND INCREMENTAL DEVELOPMENT

Iterative and incremental development which falls under the parental category of agile development techniques describes a method of software development that heavily emphasizes miniature versions or the system and iterative delivery. Learning comes from both the development and use of the system, where possible key steps in the process start with a simple implementation of a subset of the software requirements and iteratively enhance the evolving versions until the full system is implemented (Farcic, 2014).

**3.2.1.1 Steps in Rapid Application Development**

Incremental development divides the system functionality into increments. In each increment, a little portion of functionality is delivered, from the requirements to the deployment. Increments are divided into 4 key phases: inception, elaboration, construction, and transition. Each of these phases may be associated with one or more iterations.

**Inception**: During this initial phase, the engineer develops to a rough project scope and system requirements, detailed enough that the work can be estimated.

**Elaboration**: This delivers a working architecture that suggests reduced risks and and fulfils the non-functional requirements.

**Construction**: This phase is where most of the actual application coding, testing, and integration takes place, it comes after the requirements have been collected. The Construction phase is repeated as often as necessary, as new components are required or alterations are made to meet the needs of the project.

**Transition**: The final phase allows the development team time to move components to a live production environment, where any necessary full-scale testing can take place. It is similar to the final tasks in the Software Development Life Cycle (SDLC) implementation phase.

**Iterative Development**

Where abnormal state necessities are set up in the establishment stage to be investigated and change more subtleties amid improvement in the period of investigation and building a key system. To develop the key methods are from an abnormal state thought, to a conveyed item and gradually. Iterative improvement cycles are short and comprise of a few stages. These are as per the following –

* Identifying targets for the proposed framework
* Planning to meet those targets.
* Evolving any targets amid advancement.
* Testing the answer to the check objective has been accomplished.

**Modeling**

It is a connected idea. A model is dependably a sort of model however a model might be or might be not a model. A model is a lot of graphs, for example, bound together demonstrating dialect (UML). After finishing a model then prototyping is begun in the improvement stage. Demonstrating sees how to build up a necessity.

## 3.3 METHOD OF SYSTEM ANALYSIS

This is the first phase of the process model. It involves the study of the system and the gathering of the requirements. The requirements Data gathered were then analyzed for their validity in the design used for this research project, the requirements, which are set of functionalities, and constraints that the final users of the system expect from the system.

### 3.3.1 REQUIREMENTS ANALYSIS

Requirements analysis, also called requirements engineering, is the process of determining user expectations for a new or modified product. These features, called requirements, must be quantifiable, relevant, and detailed (Rouse, requirements analysis (requirements engineering), 2007). Requirement analysis is the study and identification of the functionalities to be performed by a system to be developed. The requirements of any system are the functionalities or services provided by a system and its operational constraints that reflect the needs of customers for a system that helps solve problems. Requirements of a system can be categorized into the two:

* User Requirements
* System Requirements

**USER REQUIREMENTS**

The user requirements of any system are the actions or functions that a user of the system can perform. The user requirements of a fruit recognition system are:

1. The user can install the system.
2. The user can issue commands to detect a fruit.
3. The user can issue commands to check the maturity of a fruit.
4. The user can view the result of the commands.

**SYSTEM REQUIREMENTS**

The system requirements describe the services offered by the system. The system requirements are a description of the functionalities of the system as a whole. The system requirements can be further divided into functional and non-functional requirements.

**FUNCTIONAL REQUIREMENTS**

The functional requirements of a system are the description of functions of the system. They indicate everything the designer needs to put in place to convey accurately the concept of the system. The functional requirements of this system are:

1. The system should be able to be installed on a compatible configuration.
2. The system should be able to identify fruits.
3. The system should be able to check the maturity fruits.
4. The system should be able to display results.

**NON-FUNCTIONAL REQUIREMENTS**

Non-functional requirements of a system do not ordinarily express the particular usefulness of the system. They characterize the system properties and imperatives on capacities performed or benefits offered by the system. The non-useful prerequisites of the proposed system are:

1. Response Time: this is the time taken for a message to be sent and accepted. An opportunity to process supplies, points of interest ought to as fast as could be expected under the circumstances.
2. Efficiency: the system ought to have the capacity to work in the most extreme conditions, subsequently meeting the expressed point and goals of the users.
3. Reusability: the system ought to have the capacity to use already given assets within the previous system and utilize them, in this way meeting the expressed point and goals of the users.
4. User Friendliness (User Interface): the system ought to be composed in a way that it can be utilized and controlled by the planned clients effortlessly without stress. The system interface ought to be planned in such a way that it will be easy to use.

## 3.4 METHODS OF THE MODEL

Towards achieving the first objective, the requirements analysis and preliminary research have motivated the formulation of a model for the fruit recognition system.

### 3.4.1 PROPOSED MODEL

The proposed model comes with newer modules such as:

**Resistance Testing Module:** All fruits have different resistances when they are ripe and unripe. This module is dedicated to checking for the ripeness using the resistance values.

**Gas Detection Module:** This is quality check support module. Many fruits give off methane gas and different cycles (unripe, ripe, spoiled). The system analyses the gas and predicts to a good degree of accuracy the condition of the fruit.

**\*ESP32 – Arduino Interface Module:** As opposed to connecting the ESP32 directly to the computer and programming it, this module further improves the relevance of the ESP32 Cam by buffering it with the Arduino chip and configuring it using Arduino libraries.

Figure 3.1 - Proposed Model. Circuit diagram of the system

## 3.5 METHOD OF IMPLEMENTATION

Implementation is the execution of the application, model, design, and algorithm. After the development of the system, it must be implemented on-site. Usually, implementation will require conversion from the old system to the new system but this project employed a type of implementation known as Parallel Run.

**Parallel Run:** The parallel run method of implementation involves operating both systems (old and new) together for a period. This allows any major problems with the new system to be encountered without the loss of data. The user inputs go into both systems (Wainwright, 2009).

This project adopted the parallel run to satisfy the needs of users that have already familiarized themselves with the old system and during this run, they can learn to use the new system.

### 3.5.1 SYSTEM DEVELOPMENT ENVIRONMENT

The system development environment refers to the collection of hardware and software tools used by a engineer to build a system (Dart, Ellison, Feiler, Habermann, & Fritzson, 2000). This implies all processes and tools used to realize a system. Software development is done through coding with a programming language on an integrated development environment while hardware devepoment is done by configuring and assembling the components physically.

#### 3.5.1.1INTEGRATED DEVELOPMENT ENVIRONMENT (IDE)

This software provides facilities for software development. This project made use of visual studio code (VS code) as well as the Arduino console. VS code was used for all the python programming and the Arduino console was used for programming the hardware.

#### 3.5.1.2PROGRAMMING LANGUAGES

**Python**: This is one of the leading languages for machine learning and artificial intelligence. It is a high-level and general purpose language. It is used for logical programming for small and large scale projects.

### 3.5.2 TESTING

After all the designing and programming, the final phase is set and then test the system for its functionality as the software is created and added to the developing system, this is performed to ensure that the designed and developed system is working correctly and efficiently. This system was designed and tested on several operating systems.

Debugging has to do with fixing of errors encountered during program execution. System testing deals with the real-life testing of the system, to ascertain how far it has gone in carrying out the expected task. This was carried out in two phases. Phase one is the source code and circuit testing which examines the logic of the program. Secondly, the specification testing which involves the examination of the system as regards to what it should do and how it should be done given specific conditions. This includes inputting data, collecting its output and comparing it with the output of the old system and assessing it to see if it can replace the old system.

#### 3.5.2.1TESTS TO BE DONE

* **Unit Testing**: Unit testing will be performed for testing the explicit usefulness of every module of the entire system in line with the framework.
* **Integration Testing**: Integration testing will be performed by consolidating all modules or parts of this framework and testing it as a gathering to guarantee that this framework is working legitimately.
* **Acceptance Testing**: Acceptance testing will be performed for confirming that this framework has met all client prerequisites and the framework is prepared to convey.
* **Performance Testing:** Performance testing will be performed to gauge this current framework's effectiveness. Execution testing will distinguish this present framework's reaction against the client's desire.

#### 3.5.2.2TESTING ENVIRONMENT

Necessary tools required for proper testing states below:

* Full configured PC with an operating system installed.
* Web browsers such as Mozilla, Google chrome, etc.
* Internet connection.
* Some fruits.

## 3.6 METHOD OF EVALUATION

This project employs the use of small increments for its evaluation. However, these increments follow a descriptive evaluation technique.

**Descriptive evaluation techniques**: These are used to describe the status and the actual problems of the system in an objective, reliable, and valid way. The project adopted usability testing as its approach.

**Usability Testing**: This is understood to be a combination of behavior-based evaluation that record user behavior while working with the system. These procedures include observational techniques and opinion based measures with some amount of experimental control, usually chosen by an expert. Observe that all descriptive evaluation techniques require some kind of prototype with several users.

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