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Smart Refrigerator Model for Food Safety and Health promotion using YOLOv10

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Abstract

According to the United Nations (UN), a significant amount of food waste comes from household refrigerators, necessitating a refrigerator that can detect food spoilage and monitor its contents. Current solutions include basic alert mechanisms for expiration dates and temperature monitoring, but they fall short in detecting actual spoilage and lack comprehensive content monitoring and user-friendly interfaces for real-time updates. This paper introduces the development of a smart refrigerator that uses object identification in images via a neural network model to inform users about products nearing exhaustion through a mobile application. The prototype features a smart food quality monitoring system to detect spoilage and ensure freshness, collects data on dietary patterns to offer health recommendations, and measures water consumption levels, prompting users to drink more water if they fall short of the recommended intake for a healthy lifestyle.

Keywords: Smart Fridge; Object Identification and recognition; Deep learning; IoT; Android; YOLO

1. Introduction

Through progressions in IoT, the study and advancement of smart houses have stepped onto another level [1]. There are numerous examples of homes fitted with intelligent technologies that have been constructed within recent years. In terms of speed, comfort and effectiveness, Smart houses are going to play a great role in future times. To achieve the concept of smart homes, we must create smart appliances. Devices like automated lights, fans, refrigerators, garage doors, air conditioners, etc. are just a few examples of appliances that would greatly simplify our lives [2]. The refrigerator is the most frequently utilized kitchen appliance and plays a crucial role in preserving and maintaining the freshness of food items within the household. According to a study conducted by the United Nations Environment Program, each year, over 1. 3 billion tons of food is discarded. The majority of the waste consists of expired food products and spoiled fruits and vegetables that have been stored in refrigerators. Therefore, it is crucial to ensure that the perishable items in the refrigerator are consumed before their expiration dates or they go bad. As technology advances at a rapid pace, numerous companies have provided innovative ideas for the creation of smart refrigerators.

However, these refrigerators are costly and, as a result, are not widely favored by middle-class families. Modern smart refrigerators employ a combination of RFID (radio-frequency identification) technology, which is managed through a desktop application that monitors the contents of the refrigerator and alerts the user when any item is nearing its expiration date. The challenge with using RFID is that all products must be equipped with an RFID tag. Not all products may have the option to be tagged. Companies like Samsung and LG have these refrigerators were not very successful as they were very expensive (they costed around $20,000 USD) for the problems they solved. Therefore, consumers were not interested in buying them. In this paper, we present a solution to this problem by introducing a smart refrigerator that utilizes open-source, cost-effective hardware design. The proposed framework can be incorporated into current refrigerators.

Our framework incorporates a camera that takes a picture of the inside of the refrigerator. By analyzing this image, we can identify the various products and their respective quantities. The suggested system incorporates multiple sensors that aid in identifying the presence and quantity of various products. In addition to our plans, we are considering integrating a food quality monitoring module that aids in minimizing the waste produced by the refrigerator. Additionally, the framework includes an Android application that lets users easily check a list of essential needs from their mobile devices. A variety of Machine Learning (ML) algorithms can be applied to analyze the data [5] gathered by the IoT-based refrigerator. This analysis can be used to determine dietary patterns of the user.

The paper consists of three sections. The first section discusses the previous technologies available and different frameworks put forward by different authors over the years. It also discusses the flaws and drawbacks of these frameworks. The second section talks about the proposed system to eliminate some of the drawbacks mentioned above. It also discusses the design of the model and its working. The concluding section provides an analysis of the developed model. It talks about the different results got and also about some of the fallacies. It also discusses the future improvements that can be made to the system.

2. Literature Survey

In [6], a novel approach is proposed to detect and recognize food and beverages in images. Their approach is based on a new convolutional neural network (CNN) [22,25] architecture known as NutriNet. The model was trained using a dataset that has 225,953 images each measuring 512 × 512 pixels of 520 different products. The input to the recognition model is an image containing a food item or drink. The hybrid CNN-GRNN (general regression neural network) model that is efficient in the case of small samples was developed in [7, 8]. For this purpose, during training and testing phases, we could get features from the image using CNN model. The classification phase is when GRNN takes place during the testing periods. This results in a better identification precision as well as wider applications for CNN because GRNN possesses a higher function approximation capability. The algorithms and parameters used for training Convolutional Neural Networks based on a set of aerial pictures in order to enable efficient and automatic detection of objects on land are presented. To do this, they adapted YOLO (You Only Look Once) software for CNN adaptation and testing. The work reported in [9] presented an efficient classification system for fruits and vegetables based on CNN model which extracts the required features from images used for classification purposes. The classification process is done using Visual Geometry Group (VGG) model which trains the items. The detecting accuracy of the system for over 26 categories of fruit and vegetables in this experiment was 95.6%. In [10], they developed a system that can identify the contents inside without opening the refrigerator. Here, the type, quantity and freshness of these items are all available to the user. They employed the Single Shot Multi-Box Detector (SSD) algorithm to detect foodstuff. VOC2007 dataset was used for training the assessment tool. Gao et al. [11] deal with some ways of measuring fruit quality without destroying it. These include nuclear magnetic resonance (NMR) detection, optical property detection, acoustic vibration detection, machine vision detection, electrical property detection, computed tomography (CT) detection, and lastly electronic nose detection. In [12], a modular electronic nose has been fitted in refrigerators to check if food spoils or not, Beer mentioned that users shall receive notices regarding spoiled food through an LCD display unit. This system works by detecting gases and chemicals such as CO2, acetone, ethanol etc. that are created when food items decompose These inputs are fed into the microcontroller where they are analyzed and sent as signals to the Bluetooth module for transmission. They have utilized an ATMega2561 microcontroller. In reviewing the use of quartz crystal microbalance (QCM) based gas sensors for identifying fruit freshness, Liu and Zhang [13] have provided support. They are inexpensive and they can be adjusted to detect various Volatile Organic Compounds by changing the composition of the sensitive membrane.

Viswanath et al. [14] have invented a low power wireless system which measures the amount of water in a tank using ultrasonic sensors. They employed an Artificial Neural Network (ARM) based spatio-temporal memory (STM) 32 as microcontroller while communicating with the server using a Global System for (Mobile) 32 module. The printed circuit board hosts the microcontroller and other components. When the ultrasonic sensor emits the wave form, the software starts a timer which continues until this same wave form comes back. This arrangement is positioned on top of the tank. By determining distance, it is possible to infer how much water is present within its confines. The server receives this value from GSM module which can be seen on computer screen. A proposal of a cost-effective automatic pump system that turns on the pump when water level in tank drops below a certain percentage was made in [15]. The liquid level is tracked by an ultrasonic sensor that is installed within the tank. The electric circuit uses the sensor's input to regulate the pump's operation. In [16] a capacitive sensing device to detect any liquid levels in containers has been developed. They used comb electrode for detecting levels. Significant change occurs in equivalent capacitance gradient as soon as large areas of comb electrode are reached by liquid levels. The capacitance increases with the area of electrode covered by the liquid. An automated system based on the level and proper placement of corks has been developed by Vargas et al. [3]. As these sensors are good for opaque and flat surfaces - laser and information retrieval (IR) sensors have been discarded. Hence ultrasonic technique is used. By knowing echo–signals time we could check whether our measurement value is correct or not. Nasir et al [2] developed smart refrigerator that informs people about food condition through SMS or email. Their prototype consists of three sub-modules i.e. the sensing module, the control module and transmission module. Sensing module consists of MQ3 sensor which is used to detect rotting fruits and vegetables. DHT11 sensor is utilized to monitor temperature and humidity along with measuring freshness of the fruits. We use Mos D1 R2 board as microcontroller while ThingSpeak system is utilized as Internet of Things platform for connecting refrigerator with mobile phone. Pushbullet application helps in sending notifications to user. In [17] two different methods are used for identifying food; RFID for packaged food identification and camera for both raw and processed foods thus making use of a camera to recognize their quality and quantity respectively.[11]. A Convolutional Neural Network (CNN) model was utilized in identification of foods. The model was trained using Inception V3 weights from Google and Kaggle’s Food 101 dataset [13]. In [1], a low-cost smart refrigerator was made using Raspberry Pi boards. It contains two sensors; IR proximity sensor and a light sensor connected to it along with two cameras which are placed one inside it while another outside it honoring that all connections are made through Raspberry Pi unit.A trigger of internal camera takes place when door opens while external camera responds whenever any object comes near it. A mobile android application was designed enabling users see what is in their fridge regardless of time or location.

Lately, the existing refrigerators’ item counting systems are not efficient. They are relying on expensive RFID tags in detecting any item. Moreover, they do not possess a liquid measure device for beverages in glass containers. It is common that almost all the available stock counting systems are manual input based. To add onto this problem there is no known system which has effectively integrated food quality monitoring and counting mechanisms simultaneously. Hence this is what our proposed model offers to the market.

3. Proposed Framework

A smart refrigerator module has been designed by us to be both cost-effective and based on open-source hardware. You can even install it in your existing refrigerator without needing another one since it is very cool. The system includes a camera that takes a picture of what’s inside the fridge; from this image we are able to identify its contents and their quantities. Moreover, our system features numerous sensors which enable that track presence as well as amount of different products. We are developing even a feature for food quality monitoring which will help avoid food waste. Additionally, it has an Android app where you can easily look through your groceries while still holding on to your phone.

The smart refrigerator module lets you communicate with an external device via mobile phone. Image processing will enable determining what is in the refrigerator and counting each item inside it. For this purpose, YOLOv10 algorithm is used because of its speediness and suitability for real-time applications. Every time a product goes into or comes out of the refrigerator she snaps a photo capturing all its contents. Passive Infra-red Sensor (PIR) motion sensors monitor this movement. The ultrasonic sensor on top of the bottle measures gap between cap and liquid thus its quantity; whereas it is capable to detect rotten fruits gas with help from gas sensor. These details get stored on database update regularly intended for access through app interface. When amounts of goods fall below specified minimum amount mobile app receives notification about them.

3.1. System Model

A simplified visual representation of the proposed system model is displayed in Fig. 1. The main module has two microcontrollers, namely the Node Microcontroller Unit (MCU) and the Raspberry Pi 3. The Node MCU is coupled to the temperature, gas, and ultrasonic sensors. The Raspberry Pi is connected to the PIR motion sensor and the pi camera. The real-time database called Firebase is utilized to hold the information gathered by the sensors. The raspberry pi provides 5 V power supplies that are required by all sensors except for one, which is the temperature sensor that is powered using 3.3V output from Node MCU whenever, thus when it's switched on.

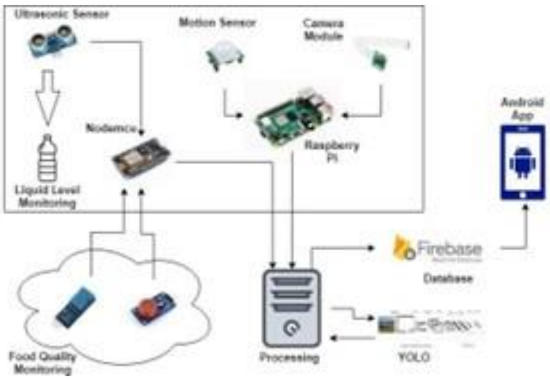


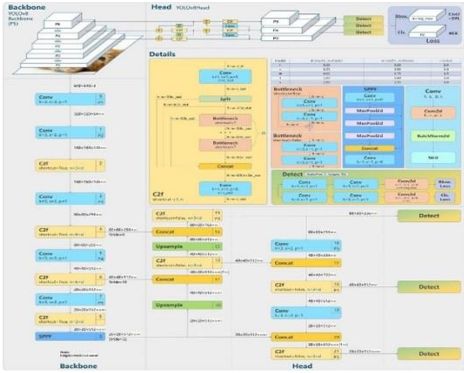
Fig. 1. Proposed System Model

3.2. Product Sensing Module

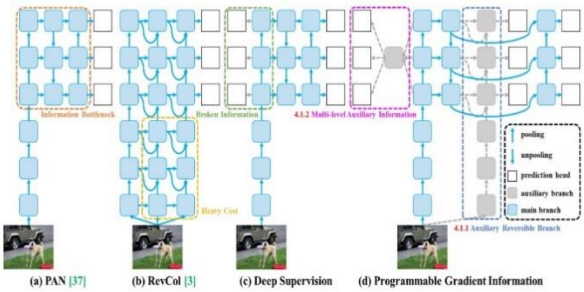
The jobs of this module are recognizing if an item exists in refrigerator, taking count of them and updating database. It contains a pi camera that is installed on raspberry pi. When someone go to refrigerator to put something inside or take out something, camera will take a picture of objects inside it. YOLO algorithm helps in identifying these objects and showing their total number being counted by this module which also has an ultrasonic sensor placed close to the rack containing bottles. Through this sensor one can find out how much liquid is within a given bottle thus this value gets updated into databank.

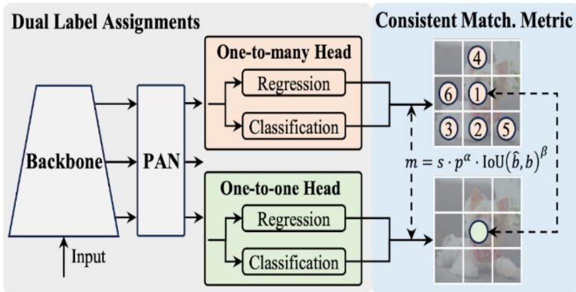
3.2.1 YOLO

Similar algorithms to several object detection techniques such as R-CNN (Region based Convolutional Neural Networks), SSD (Single Shot Detectors) or DPM (Deformable part model). On the contrary, YOLO is light and fast. YOLO-You Look Only Once is a neural network that can identify objects from an image with only one pass [18]. It can recognize various items in the same picture. For every object, it has a bounding box. It performs object detection in one shot. Object identification is done via regression. The model begins by predicting the location of the object and assigning it bounding boxes. Afterwards, the class of the particular object within each bounding box are predicted respectively. YOLO looks at the image only once. The YOLO model was inspired by Google Net. YOLO is one of the popular algorithms in object detection used by the researchers around the globe. The YOLO algorithm is very helpful in identifying skin cancer. It is accurate even when trained with only a few images. There are currently 10 versions on YOLO, v1-v10. V10 being the latest.



(a) YOLOv8 [19]





(b) YOLOv9 [20] (c) YOLOv10 [21]

Fig. 2. Architecture of different versions of YOLO

YOLOv8 has the same architecture as of its predecessor, YOLOv5 and it uses c2f module which is a advanced version of CSPNet. It comes with improved anchor-free detection system and it also changes convolutional blocks used in the model. Applied throughout training, mosaic augmentation was disabled prior to the last ten epochs. For Classification loss, DFL and CloU loss functions were used. These all features have improved the object detection up to a very good extent especially for small objects [19]. Fig. 2(a) shows the architecture of YOLOv8.

YOLOv9 is an improvement of its previous version. It introduced a new approach to overcome loss challenge in DNN. With the help of PGI and its GELAN architecture, the model has a improved learning capacity. It also ensures retention of peculiar points throughout the detection process. The model uses Information Bottleneck Principle, which means the chances of information loss increases when data passes through layers of a network.

The model overcomes this limitation by using PGI which helps in conserving data in all layers resulting in better efficiency and performance [20]. Fig. 2(b) shows the architecture of YOLOv9.

YOLOv10 is the latest version of YOLO. This is the version used in this project. YOLOv10 uses a more powerful backbone network. Fig. 2(c) shows the architecture of YOLOv10. It uses NMS-free training which lowers inference latency. Now, Moving away from traditional anchor boxes, YOLOv10 uses anchor-free detection techniques, which simplifies the model and reduces computation. It also incorporates attention mechanisms, such as SE (Squeeze-and-Excitation) blocks, helps the model focus on important features, improving detection accuracy. Four coordinates are predicted for each bounding box, Here, Xi and Yi indicate the coordinates pertaining to the center of a bounding box, while Wi and Hi are its width and height respectively. Furthermore, both Wi and Hi refer to the predicted dimensions, whereas 1ij shows if during cell I there exists a jth box that is held responsible for such estimations [21]. Denoting bounding box regression, confidence loss, class probability loss by L_{Box}, L_{conf} and L_{Class} respectively, the total loss L_{total} is given by

$$L_{Total} = L_{Box} + L_{Conf} + L_{Class} \tag{1}$$

Performance of different versions of YOLO are shown in Fig. 3.

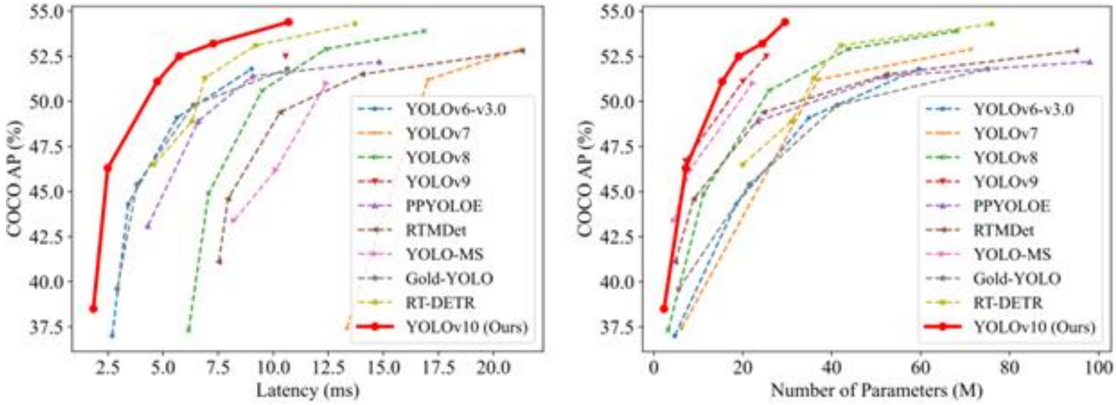


Fig. 3. Accuracy comparisons between other state-of-the art detectors [21].

3.2.2 Microsoft VoTT

Before each image can be used for training, the objects in the image and their bounding box information have to be fed to YOLO. This is done using Visual Object Tagging Tool (VoTT). There are other software that can be used but VoTT is free and user friendly. Microsoft VoTT [23] [24], Visual Object Tagging Tool, is an open-source tool that is used for annotating and labeling images and videos. This software has been used to annotate the images before training (Fig. 4). It also gives the user support for the creation of datasets and for validation of object detection models which use videos or images.

Fig. 4. Annotating images in VoTT

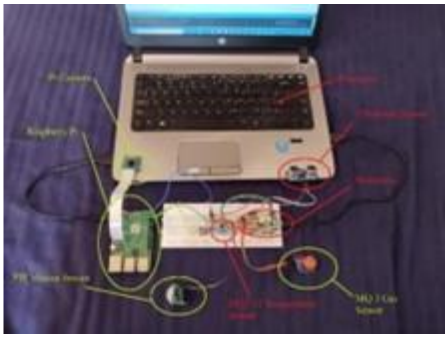


Fig. 5. Product sensing and quality sensing modules

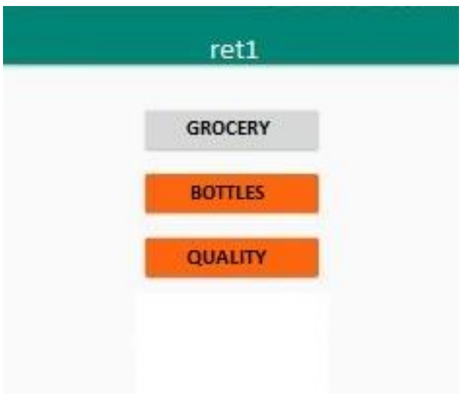


Fig. 6. (a) Category of items

Fig. 6. (b) List of items

3.3. Product Quality Measuring Module

This module focuses on detecting food spoilage early including for fruits and vegetables since they help in avoiding stomach problems from rotten ones. For instance, alcoholic smell can be detected using gas sensors in rotting fruits which release different gases. This quality monitoring module, which has a temperature humidity sensor and a gas sensor, is controlled by a node MCU. These sensors help to measure some important parameters which will help us know whether the fruits and vegetables are fresh or not. Figure 5 shows the prototype developed. The sensors have minimum operating temperatures of approximately -20 degrees Celsius. This makes them suitable for monitoring drugs and vaccines requiring cold storage.

3.4. Android Application

Designed for showing the group and enumeration of things that can be found inside the fridge, this Android application (see Fig. 6). It also allows each user to assign a minimum level of particular items in their fridges. Once the amount of specific product drops below given limit, a warning will be sent by the application.

4. Implementation

4.1. Data Flow of the System

A diagram showing the flow of data within a system is illustrated below (Fig. 7). The information collected from the sensors are sent either to NodeMCU or Raspberry Pi nodes. In this regard, the NodeMCU forwards this information directly to a database (Fig. 8). For image data, it is sent to a processor in the raspberry pi, whereupon detection of objects occurs using YOLO algorithm followed by updating of the database. Firebase is a real time database which means it will be easily updatable whenever a change occurs, and it is easy to use. It also uses end to end encryption and provides many ways to support confidentiality. All the stored data remains encrypted. App that runs on an Android device to access data from a database like shown in Figure 9.

4.2. Image Processing

Inside this main processor (here, the laptop), object detection and identification are completed. A client server architecture sends pictures taken with pi camera to processor. In this case raspberry Pi serves as server while processor serves as client in their relationship. Pi Camera produces distinct images that can be utilized to capture images for medicine labels. For identifying objects, there is a use of YOLO.

4.3. Product Sensing

The PIR motion sensor's output is linked to General-Purpose Input Output (GPIO) pin 23 of the Raspberry Pi. A picture of what is in the refrigerator is taken whenever there is any movement detected. These images are then sent to the processor using a socket connection

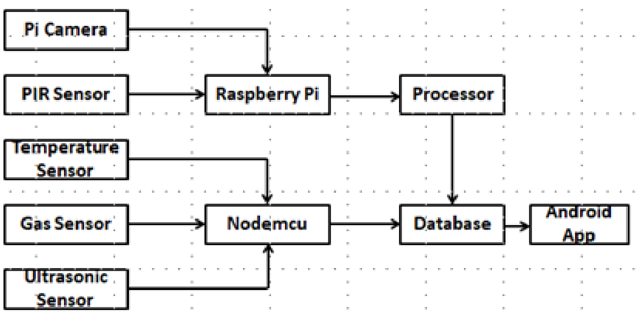


Fig. 7. Flow of Data through the system

```python
if GPIO.input(23):
    print("Motion Detected...")
    time.sleep(4)
    camera.capture(stream, 'jpeg')
    # Write the length of the capture to the stream an
    # ensure it actually gets sent
    connection.write(struct.pack('<L', stream.tell()))
    connection.flush()
    # Rewind the stream and send the image data over t
    stream.seek(0)
    connection.write(stream.read())
```

Fig. 8. Python code for capturing image

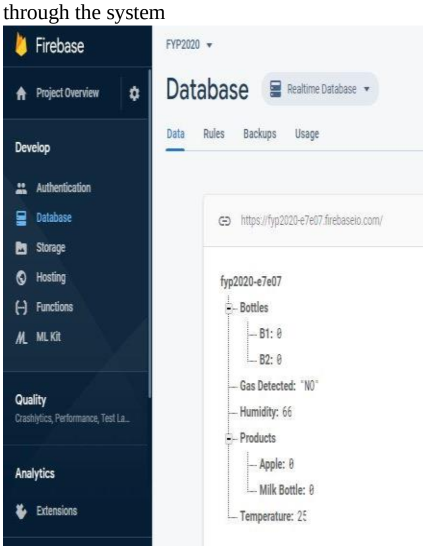
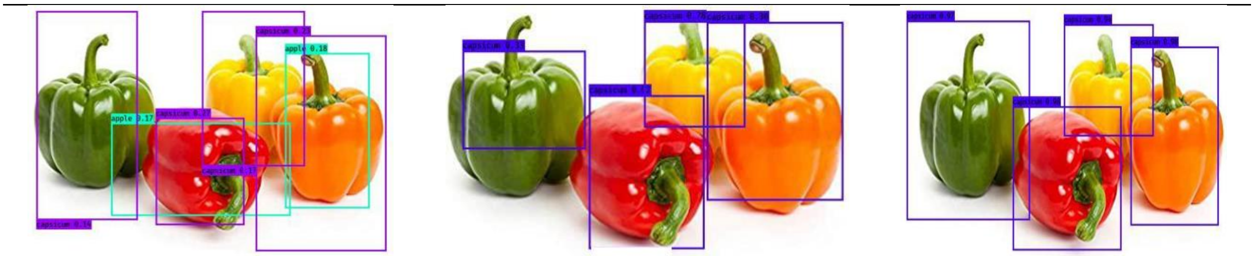


Fig. 9. Sample database snapshot

5. Results and Discussion

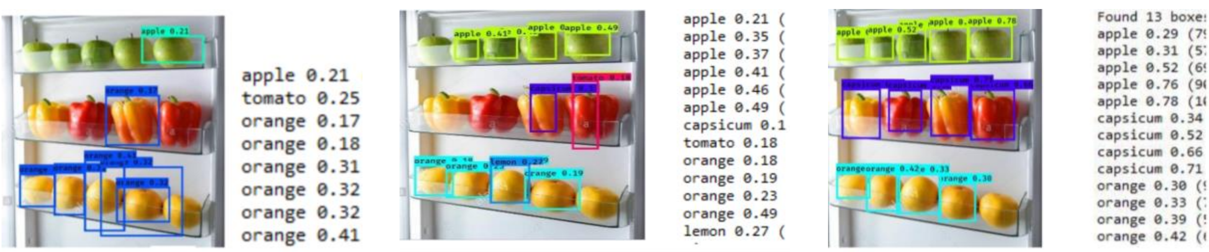
5.1. Object Detection

Figure 10 shows a total of 4 capsicums. For instance, by using 100 training images to train the YOLO model, its result is shown in figure (10 a). It is observed from the image that besides the four capsicums, there are some other extra detections. Figures 10 (b) and 10 (c) are the same images but tested on models that were trained using 200 images and 500 images respectively. All the four capsicums have been detected while no other fruits or vegetables have been detected.



(a) Trained using 100 images (b) Trained using 200 images (c) Trained using 500 images

Fig. 10. Detection of images after training for different number of images



(a) Using 100 images (b) Using 200 images (c) Using 500 images

Fig. 11. Images inside a refrigerator with different number of training images

Figure 11 represents the view from the inside of a refrigerator. The results of utilizing 100 training photos to train the YOLO model are shown in Figure 11(a). In this image, it is seen that most of the apples and capsicums have not been picked up by the model; moreover, one capsicum has been erroneously categorized into an orange. These results are compared with those of Figure 11(b), which employs the same image on a model trained with 200 pictures. All but one of the apples have been detected now but only one capsicum was observed that also made two misclassifications. For instance, Figure 11(c) indicates similar graphics that were tested on a model that was trained with 500 photographs. There remains no orange left undetected among all fruits enabled interceptions or no other categories were wrongfully dated at all.

Table 1. Measures of accuracy of the system with no. of images for training

Number of images utilized for training	True Detection	Failed or false detection	Accuracy
100	35	5	87.5%
200	37	3	92.5%
500	39	1	97.5%

The model training analysis is displayed in Table 1. At present, the accuracy of the model is approximately 95%. The model was fed ten randomly chosen images, out of a total of 100, 200, and 500 images used for training. All ten of the accompanying photos had 40 objects. The accuracy was determined by use the subsequent equation:

$$Accuracy = \frac{\text{Number of items detected correctly}}{40} \times 100 \tag{2}$$

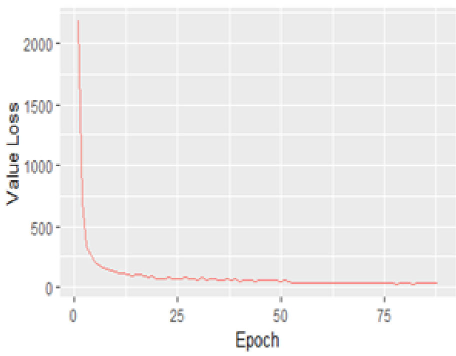


Fig. 12. Graph showing the change in loss with respect to epochs

Figure 12 shows a graphic representation of the number of epochs vs the loss following each epoch. 80 epochs were used in training the model.

5.2. Quality and Quantity Measurement

Output from Quality and liquid Quantity measuring systems is illustrated by figure 13. The first picture is of an empty bottle which measures 21cm while the second one has partly filled with water (9cm, 10 cm,11cm).Hence, it follows that ultrasonic sensor can be employed to gauge how much liquid there is in a bottle. Ultrasonic sensors can measure liquid level without coming in contact with the liquid. This is very useful when the liquid that has to be measured must be sterile. Therefore, it can be used to measure blood level, hazardous liquids and to monitor drug administration.

6. Modifications for Healthcare

The developed model can be further modified to make it more useful in the field of healthcare. The Module can be modified to maintain stock in pharmacies and cold storages for vaccines. Barcode scanners can be added to maintain stock of medicines stored in the fridge, for example insulin bottles. The image detection program can also be trained to maintain stock of these. Using Data collected by the fridge, the users' dietary patterns can be identified, and recommendations can be made for a healthier diet.

```
Current humidity = 73%  temperature = 33 C
Centimeter : 21
1024
Current humidity = 73%  temperature = 33 C
Centimeter : 21
1024
Current humidity = 73%  temperature = 33 C
Centimeter : 21
1024
```

(a)

```
Current humidity = 74%  temperature = 33 C
Centimeter : 9
1024
Current humidity = 73%  temperature = 33 C
Centimeter : 10
1024
Current humidity = 73%  temperature = 33 C
Centimeter : 10
1024
Current humidity = 73%  temperature = 33 C
Centimeter : 11
1024
```

(b)

Figure 13: (a) Empty bottle measurement (b) Partially filled bottle measurement

7. Conclusions and Future Scope

In this write-up, a clever fridge module has been proposed which can aid an individual to know things present in the refrigerator without being at home. It sends notifications when you're almost home reminding you about missing items. There are numerous benefits of using the smart device .One does not need to travel back home and open the refrigerator; just know what they are lacking and buy them elsewhere .Saving yourself time and extra trips is possible this way. Time and fuel are saved. The gasses from decaying fruits can be detected by this product quality monitoring module. The user's awareness of the existence of spoiled fruits or vegetables in the refrigerator is one crucial characteristic. The completed design would then create a healthy meal plan based on one's eating preferences whilst keeping track of their hydration level by observing how much water they drink.

To improve accuracy, more training can be administered (the adequate size for high precision is roughly thousand images per product. More image recognition methods can also come on board here in order to distinguish rotting food items. Furthermore, it is possible to inspect fruits and vegetables for any abnormalities on their surfaces within the context of image processor technology. Further techniques like load cells for weight measurement could be employed instead of measuring liquid amounts with ultrasonic sensor methods. In addition to elliptical images from a pi camera, other cameras should be added for more clarity because their field of vision is smaller. For better efficacy, this system can be linked with an online shopping site so that it can place orders automatically when stock runs low.

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