



## Application of Edge Impulse and ESP32-CAM in Smart Freezer Systems for Object Recognition

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### Abstract

The increasing need for efficient refrigeration solutions, especially in food storage and pharmaceutical industries, highlights the importance of advanced monitoring systems. This study presents the development of an IoT-enabled multi-power source freezer system incorporating image recognition for item quality monitoring. The system combines a Vapor Compression Refrigeration System with machine learning-based object detection, utilizing ESP32-CAM and Edge Impulse to classify and track stored items in real time. A dataset of 395 images was gathered and categorized into 272 training samples across five distinct classes: Onion, Tomato, Watermelon, Leaves, and a non-food item (Fan). The trained model achieved an accuracy of 98.1%, while testing accuracy fluctuated between 71% and 99%, depending on object positioning. Compared to previous research, the model demonstrated enhanced precision and reliability. With a cooling capacity of 3,471 BTU/h, the freezer effectively monitored stored items by displaying recognition results via the Arduino IDE Serial Monitor. This research contributes to improved food quality monitoring, inventory management, and storage accountability in refrigeration systems. Future enhancements should focus on integrating image recognition into the user interface to improve accessibility and user experience.

**Keywords:** Internet of Things (IoT), Multi-Power Source Freezer, Image Recognition, Edge Impulse, ESP32-CAM, Machine Learning.

## I. INTRODUCTION

The refrigeration industry is crucial for the storage of food and beverages. Refrigerated warehouses are commonly used to store large amounts of fresh food at ideal temperatures, usually around 0°C, to ensure the preservation of quality.

(Padmaja et al., 2021). Wasting food is like depriving the poor and hungry. Often, food stored in refrigerators spoils because people neglect to check the expiry dates of packaged items and fail to monitor the freshness of vegetables. Furthermore, due to a lack of attention to these household appliances, food is not consumed in time, leading to spoilage, waste, and eventual disposal, contributing to food wastage. (Bonaccorsi et al., 2017).

A neural network is a computational model based on the structure and operation of biological neural networks in the human brain. It plays a crucial role in machine learning and artificial intelligence (AI), commonly applied in tasks such as pattern recognition, classification, and prediction. (Mohammad et al., 2020). Edge Impulse is a cloud-based platform for machine learning operations (MLOps) that supports the development of embedded and edge AI systems. It enables the creation and deployment of machine learning models on devices such as microcontrollers, sensors, and IoT devices. The platform allows developers to build AI applications that run directly on devices without relying on cloud infrastructure. (Hymel et al., 2022).

The IoT-enabled Multi-Power Source Freezer System with Image Recognition offers significant advantages in food preservation, inventory tracking, and pharmaceutical storage. By leveraging real-time object detection, it enhances

monitoring accuracy, reducing food wastage and ensuring proper item organization. In the food industry, the system helps maintain product freshness by identifying and categorizing perishable goods for timely use. Similarly, in pharmaceutical storage, it ensures medicines are stored correctly and remain easily trackable. With its ability to streamline inventory management, minimize spoilage, and enhance storage accountability, this advanced refrigeration system proves to be a valuable asset across multiple sectors.

## II. REVIEW OF LITERATURE

Jessica Velasco, *et al* (2019) presented research that the refrigerator starts with collection of data by the Arduino Uno using the sensor network and camera installed within it. The data captured will be transferred to the Arduino Yun and will then be uploaded to the Dropbox which shall serve as the cloud storage of the research. The Dropbox is linked with Android application which shall display all the uploaded data for the user to see it wherever the user is. They limited the technology by using two micro-controllers instead of multiplexed, they also only considered Grid electricity as the source of power to the freezer.

Zhongxu Dong *et al* 2020 work involved the use of AI, IoT, machine vision, and deep learning algorithms for real-time temperature monitoring inside a refrigerator. It also included identifying barcodes, expiration dates, and fruit categories, uploading the data to the Thing Network, and using Ubidots for messaging and dashboard display. However, the project did not consider a mobile application and relied solely on grid electricity as the power source for the freezer.

Shaji Sidney *et al* (2021) The study tested a solar-powered milk chiller in Chennai, India, using thermal energy storage. Across seasons, average daily ice production was 3.61 kg (monsoon), 19.75 kg (winter), and 27.97 kg (summer), sufficient to chill 10 liters of milk twice daily. There need of additional power source for continuous operation in the monsoon season. The component should be reduced (the milk chiller had two separate refrigerant circuits with refrigerator's component of the same dimensions and material, to reduce cost and complexity.

Bharj *et al* (2021) determined the novel designed of a portable solar hybrid vapor compression refrigerator. This hybrid energy operated DC refrigerator was tested with four load conditions on sunny days. It evaluates the energy consumption, solar energy production and feasibility of the hybridization of renewable energy and grid utility. The lead-acid battery had enough capacity to run the refrigerator without solar energy for 2.5 days at 90% load condition. The designed presented shows battery life span may not be longer, they also did not consider IoT, it was used only Solar as source of power.

Gabriele *et al* 2023 explores the potential of the Edge Impulse platform, a low-code machine learning (ML) tool, to facilitate object recognition tasks. Using a dataset of images of computer mice, the platform achieved high initial accuracy (97.9% during training and 89% on testing), highlighting possible overfitting issues. The tool demonstrated ease of use for non-technical users, making it a viable option for beginners in ML. Adjustments to the dataset and exposure methods are recommended to improve performance and reduce false positives, particularly for complex applications.

## MATERIAL AND METHODS

The list of major components/materials used in this research are listed at the table 3.1 below

**Table 3.1: Lists of components/materials**

S/N	Device Name	Material used	Quantity/Unit
1	Micro-controller	ESP-Wroom-32 ESP32-CAM	1 1
2	Temperature Sensor	DHT 22	1
3	Liquid Crystal Display (LCD)	RoHS 16 x 2	1
4	Serial Communication	8574T-I2C	1
5	Buck Converter (DC-DC Converter)	LM 2596S	2
6	Relay	T90-12-C-6P	1
7	Lithium Ion Battery (power bank)	4S5P (18.8V/10A)	1
8	Battery Management System	JH 996040-4S	1
9	Freezer Cabin	Stainless Steel	1mm
10	Insulation Material	Polyurethane	20mm
11	Compressor	BD35F	1

**3.1 ESP-Wroom-32:** The ESP-WROOM-32 is a multi-functional MCU module powered by the ESP32-D0WDQ6 chip, featuring Wi-Fi, Bluetooth, and Bluetooth LE. It includes dual CPU cores with adjustable clock speeds and a low-power co-processor, making it ideal for both low-power sensor networks and high-performance applications like music streaming. With built-in connectivity and support for various peripherals such as sensors, SD card interface, Ethernet, and communication protocols, it enhances functionality and ensures reliable long-range internet access and seamless device interaction. (About This Guide, 2018)

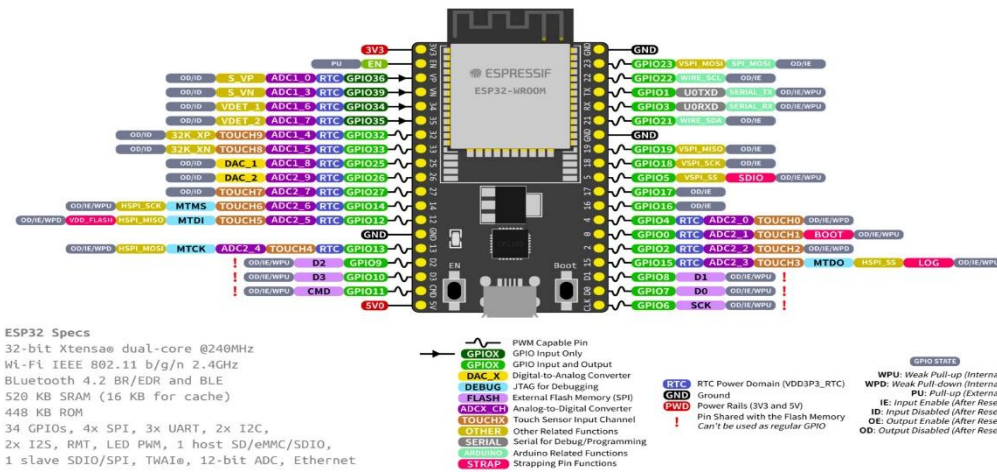


Fig 3.1: ESP-WROOM-32 (About This Guide, 2018)

**3.2 ESP32-CAM:** The ESP32-CAM is an affordable, compact development board designed for IoT projects, prototyping, and DIY applications. It features dual 32-bit LX6 CPUs with adjustable frequencies (80-240 MHz) and integrates Wi-Fi, Bluetooth, and BLE connectivity. The board includes sensors such as Hall and temperature sensors and supports Wi-Fi 802.11b/g/n/e/i and Bluetooth 4.2. It can function as a standalone network controller or enhance other devices by adding networking capabilities. (ESP32-CAM Development Board, n.d.).



Fig 3.2: ESP32-CAM (ESP32-CAM Development Board, n.d.).

**3.3 Temperature Sensor (DHT11):** The DHT11 (also called AM2302) is a digital sensor commonly used for measuring temperature and humidity. Recognized for its accuracy and dependability, it is a popular option in IoT applications, weather stations, and environmental monitoring. (DHT22-DIGITALER-TEMPERATUR-UND-LUFTFEUCHTESENSOR, n.d.), 2018.

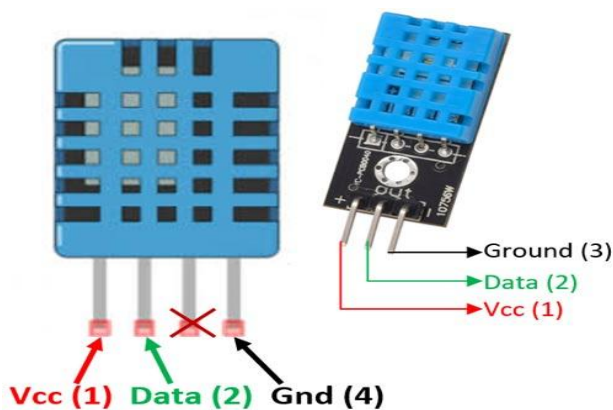


Fig 3.3 DHT11 (DHT11-DIGITALER-TEMPERATUR-UND-LUFTFEUCHTESENSOR, n.d.), 2018

**3.4 Liquid Crystal Display (LCD):** The LCD RoHS 16x2 is a liquid crystal display module that can display two lines of text, with a maximum of 16 characters per line. It is commonly used in electronics projects for visual displays and user interfaces. The "RoHS" designation indicates that the module complies with the Restriction of Hazardous Substances directive, making it environmentally safe. (LCD-016N002B-CFH-ET, n.d., 2013).



Fig 3.4 LCD RoHS (LCD-016N002B-CFH-ET, n.d., 2013)

**3.5 Serial Communication (8574T-I2C):** The 8574T-I2C is an I/O module that connects to microcontrollers via the I2C (Inter-Integrated Circuit) communication protocol. It provides extra digital input/output pins for microcontrollers like Arduino and Raspberry Pi, allowing for enhanced functionality in projects that need more GPIO (General Purpose Input/Output) pins. (Semiconductors, n.d., 2013).

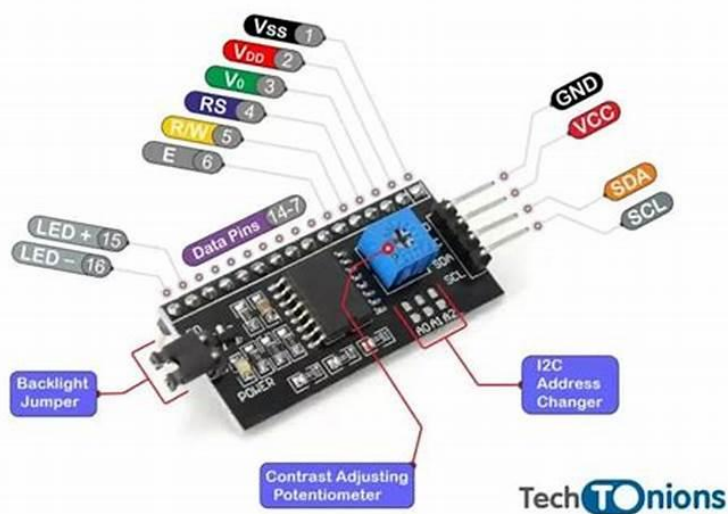


Fig 3.5: 8574T-I2C (Semiconductors, n.d., 2013)

**3.6 Buck Converter (LM2596S):** The LM2596S is a step-down (buck) voltage regulator IC designed to efficiently convert higher DC voltages to lower DC voltages. It is widely used in power supply designs where voltage reduction is needed with minimal energy loss, offering both high efficiency and stability. (LM2596 SIMPLE SWITCHER® Power Converter 150-KHz 3-A Step-Down Voltage Regulator, 2023)

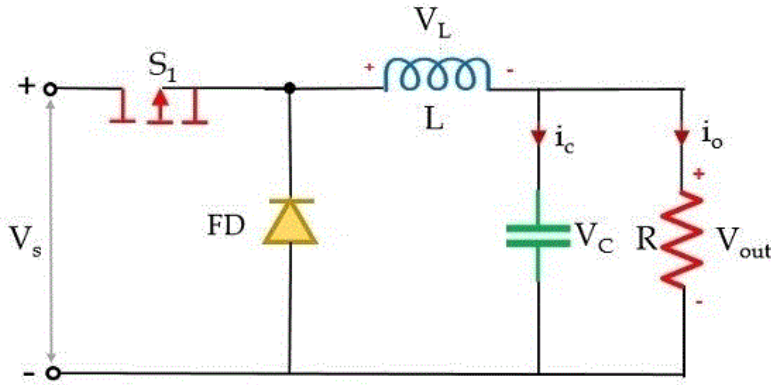


Fig 3.6: Buck Converter LM2596S (LM2596 SIMPLE SWITCHER ® Power Converter 150-KHz 3-A Step-Down Voltage Regulator, 2023)

**3.7 Relay (T90-12-C-6P):** The T90-12-C-6P is a high-power relay designed for controlling both DC and AC loads, typically used to switch heavy electrical equipment. Part of the T90 series, this relay is commonly used in automation, industrial control, and other applications that require high-current switching. (Grubb, 2011).



Fig 3.7: Relay (T90-12-C-6P) (Grubb, 2011)

**3.8 COMPRESSOR (BD35F):** The compressor serves as the "heart" of the refrigeration cycle, essential for circulating the refrigerant throughout the system. The BD35F is an energy-efficient, variable-speed DC compressor developed by Secop (formerly Danfoss), commonly used in both portable and stationary refrigeration systems. Noted for its compact size and low power consumption, the BD35F is especially ideal for battery-powered systems, including off-grid and solar-powered applications. (Danfoss A, n.d, 2016.).

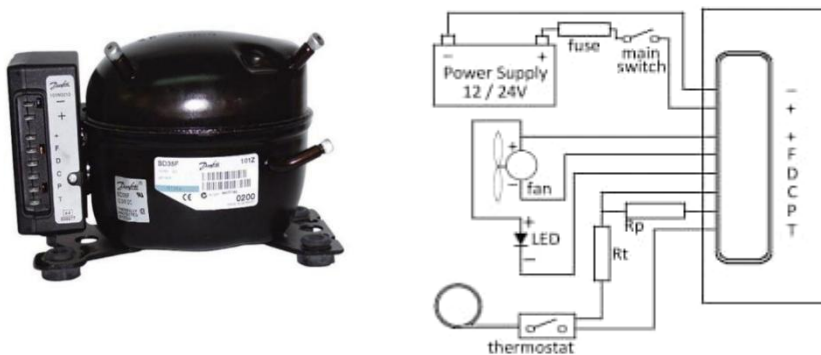


Fig 3.8: BD35F (Danfoss A, n.d, 2016.)

**3.9 Battery Management System (JH 996040-4S):** The JH 996040-4S BMS is designed for a 4S lithium-ion battery pack, where "4S" indicates the pack contains four cells connected in series, delivering a nominal voltage of 14.8V (3.7V per cell). The Battery Management System (BMS) is crucial for monitoring the battery's performance, ensuring its safety, and extending its lifespan. (Model: BMS-20A-3S-S & BMS-20A-3S-EFJ Ms:72M5366,72M5373, 2010).

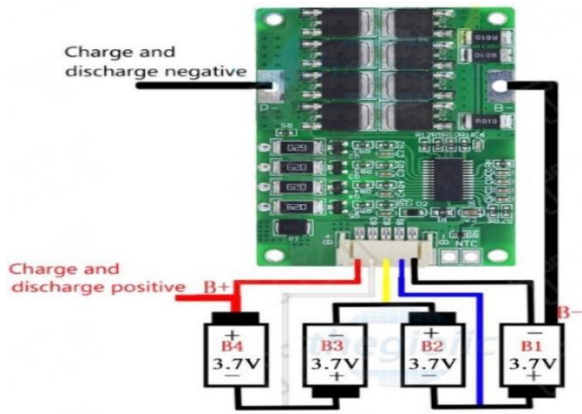


Fig 3.9: JH 996040-4S BMS (Model: BMS-20A-3S-S & BMS-20A-3S-EFJ Ms:72M5366,72M5373, 2010)

**3.10 Lithium Ion Battery (4S5P 14.8V/20A power bank):** A Lithium-ion (Li-ion) battery is a rechargeable power source commonly used in electronic devices, electric vehicles, and energy storage systems. Known for its high energy density, efficiency, long lifespan, portability, and lightweight design, Li-ion batteries are preferred for gadgets like smartphones, laptops, and cameras. However, they must be handled carefully and charged properly to ensure safety and extend their lifespan.

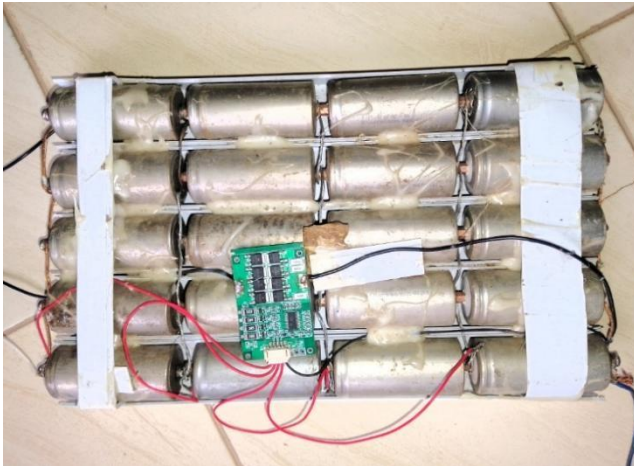


Fig 3.10: Lithium Ion Battery 4S5P

**3.11 Insulator Material: Polyurethane (PU):** Polyurethane (PU) is a versatile polymer material widely used across different industries due to its durability, flexibility, and outstanding insulating properties. It is produced through a chemical reaction between polyols and isocyanates, and can be found in various forms such as foams, elastomers, coatings, adhesives, and sealants (Ye & Zhu, 2017). In this case, the rigid form was used, with a thickness of 20mm.



Fig 3.11: Insulation Material

**3.12 Freezer Cabin: 3.4.3:** Polyurethane is a flexible and durable polymer widely used across different industries for its strength, flexibility, and superior insulating qualities. It is formed through a chemical reaction between polyols and isocyanates and is available in several forms, such as foams, elastomers, coatings, adhesives, and sealants. (*Stainless Steel: Tables of Technical Properties Materials and Applications Series, Volume 5, 2007*).



Fig 3.12: Stainless Steel

## SOFTWARE DESIGN

### 3.0 Designing of a Machine Learning Items Recognition using edge impulse

The methodology employed to develop a machine learning-based image recognition system. The process is divided into several stages, from setting up the environment to deploying the trained model on an ESP32-CAM. The primary tools used include the Arduino IDE, Edge Impulse platform, and the Eloquent Library.

#### 3.1 Setting up the Environment: To set the environment following steps was followed

- 1) Installing the Eloquent Library in Arduino IDE: Data collection is one of the examples from Eloquent Library, which was edited with the desired username and password, in order to collect images directly from ESP32-CAM at edge impulse platform.
- 2) Configure ESP32-CAM: The board was connected by following all the necessary protocols and upload the program.

#### 3.2 Image Data Collection: Different sample of images was capture from the camera mounted on ESP32-CAM, which was saved as a zip file.

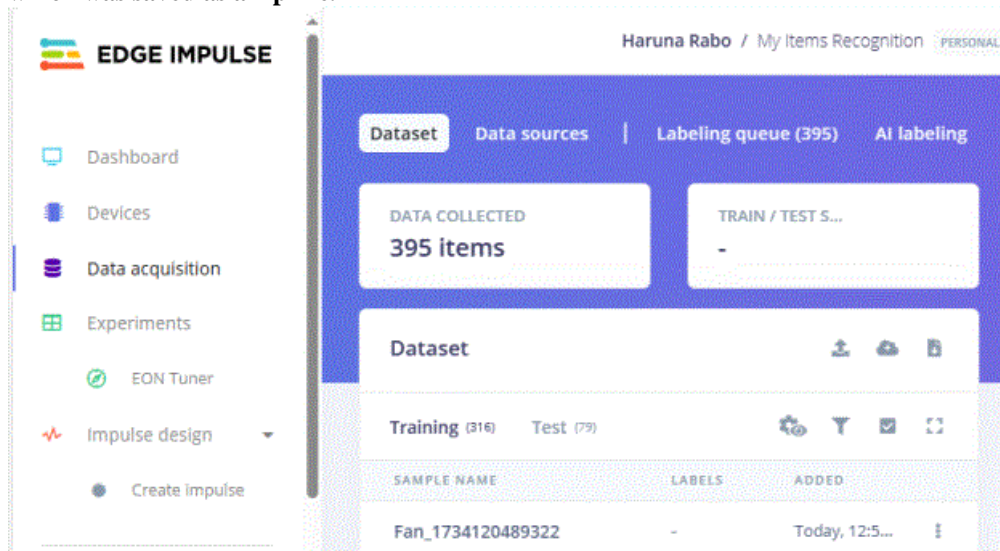


Fig 3.13: Screenshot of Data Collection

#### 3.3 Model Training using Edge Impulse:

- 1) Uploading Images Data: After capturing all set of images with camera, there is need to upload it to edge impulse, then followed by label at edge impulse platform.
- 2) Designing Neural Network: NN designing comprises of processing parameter like image size, grayscale or RGB as well as chooses learning block then save and deploy the impulse design.

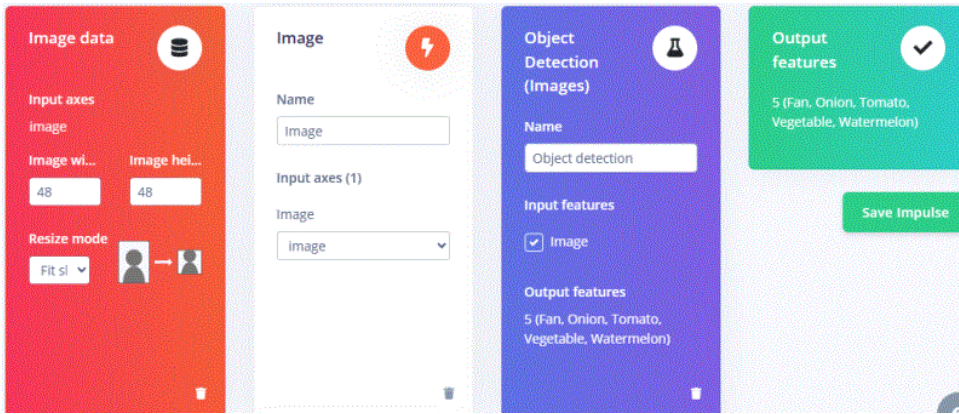


Fig 3.14: Screenshot Training Preparation

**3.4 Training the model:** Configure the training parameter like Epochs and learning rate, start the training process and monitor the accuracy and loss matrix, then validation the model performance using test set. Validation set performance is 98.1%.

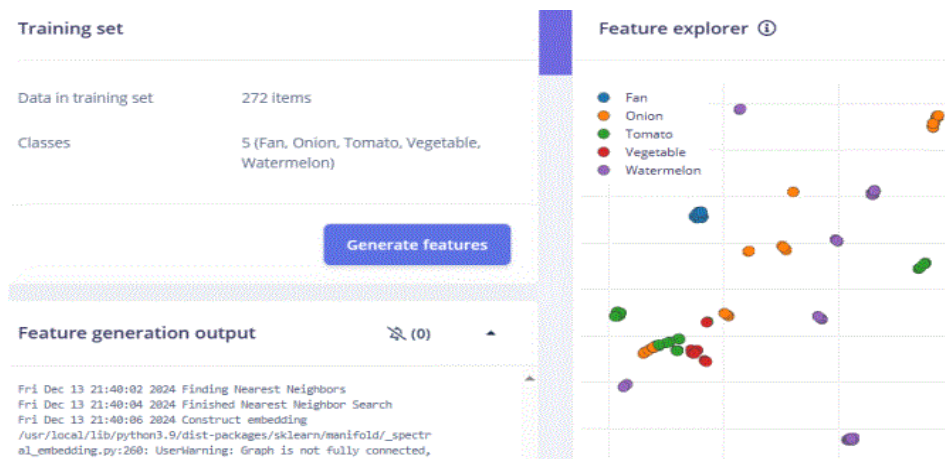


Fig 3.15: Screenshot of Training set

**3.5 Exporting the model:** Upon satisfied with the performance metrics, navigated to the **Deployment** tab and Arduino Library selected as the deployment format. Downloaded the generated library and added it to the Arduino IDE.

**Configure your deployment**

You can deploy your impulse to any device. This makes the model run without an internet connection, minimizes latency, and runs with minimal power consumption. [Read more.](#)

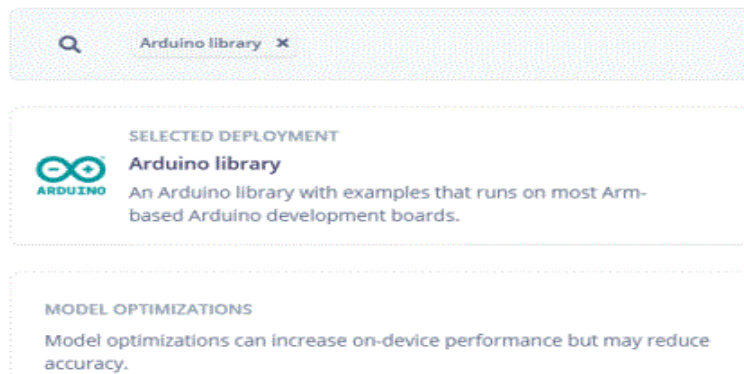


Fig 3.16: Screenshot of Deployment Selection

**3.6 Deploying the model to ESP32-CAM:** The model was uploaded to the board for running after following all the connection protocols.

**3.7 Testing and Validation:** ESP32-CAM power on and run the deployed code. Verified the system’s ability to recognize objects in real-time, extensive testing conducted under various conditions to ensure robustness, the recognition accuracy, response time, and reliability of the system was recorded.

Systematic approach to developing an image recognition system using machine learning. By leveraging tools such as the Arduino IDE, Eloquent Library, and Edge Impulse, the process is streamlined from data collection to deployment, resulted in a functional as shown in fig 3.17

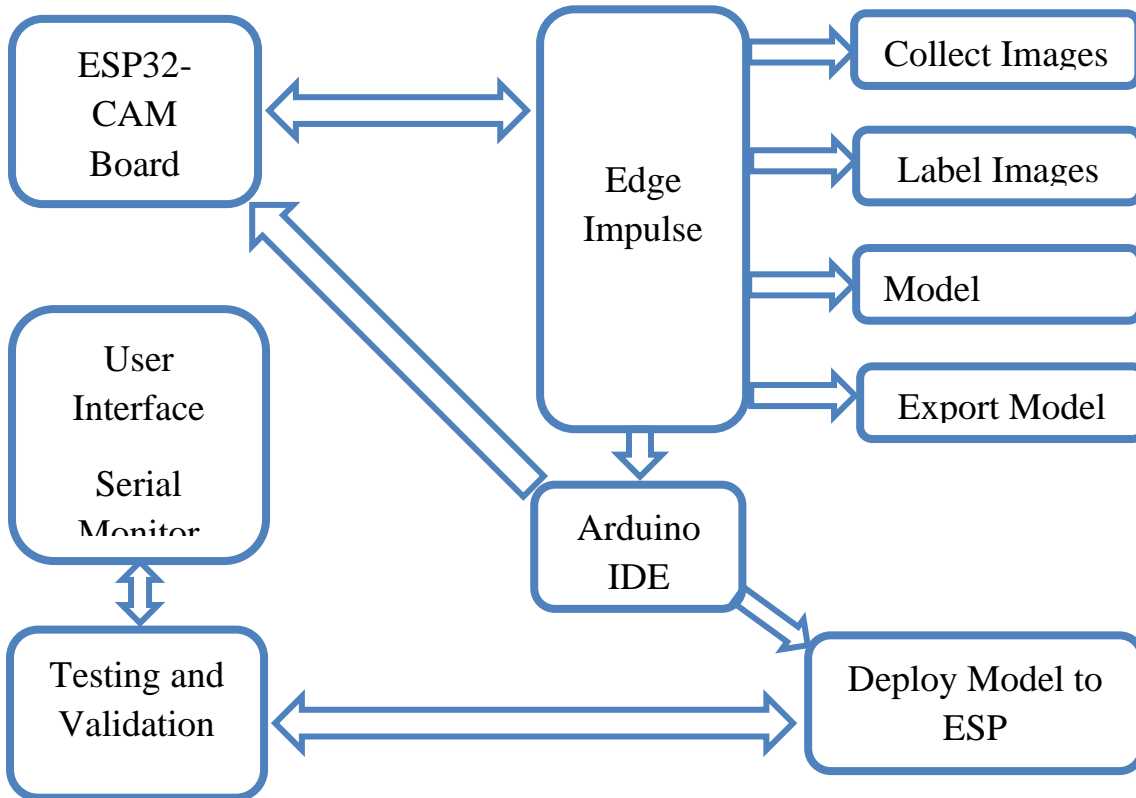


Figure 3.17: Image Recognition System Architecture

**IV. RESULTS OBTAINED**

The image recognition was started by 395 data collected which was label to 272 for training, comprises of 5 image classes of Onion, Tomatoes, Watermelon, Leaves and none food item Fan (it was used to shows the versatility of the freezer in such away that, it can be used in any inventory like pharmaceutical stores. The table 4.1 shows the accuracy of items recognition by the camera attached to ESP32 and displayed at Serial Monitor of Arduino IDE. The overall training results shows 98.1% accuracy, while testing result accuracy varies based on the positioning and quality of the items placed on the freezer as illustrated in table 4.4 below. Compared to 97.9% accuracy during training and dropped to 89% during testing as found by (Regina Pinaso et al., 2024).

Table 4.1: Images Recognition accuracy

Vegetable	Onion	Watermelon	Tomato	Fan
0.98	0.90	0.71	0.73	0.90
0.97	0.88	0.57	0.88	0.89
0.99	0.96	0.75	0.97	0.94

From the above table, it can be observed that during testing the accuracy varies based on the object positions. When no object placed, the controller displayed “Object Detection Bounding Boxes” that means it detect nothing, while when either of the trained items placed in the freezer it will get the accuracy of visualizing the object, as it was indicated below each items, the more the visual of the item to the ESP CAM, the more the accuracy.

The figures below, from fig 14 to fig 21 indicates the items in right position for ESP 32 CAM to read it, while fig 22 and fig 23 give the reading of ESP 32 CAM from Arduino IDE serial Monitor.

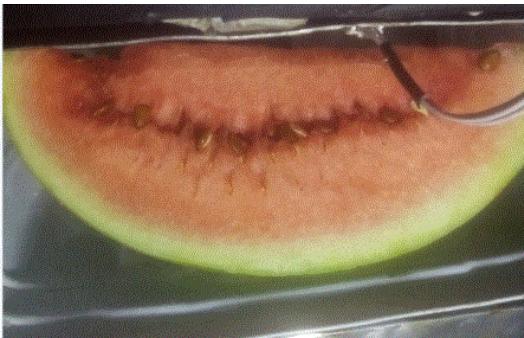


Fig 18: Watermelon during a test



Fig 19: Meat during a test



Fig 20: Fish during a test



Fig 21: Vegetable during a test

```
COM5
06:27:43.749 -> Vegetable (0.976562) [ x: 16, y: 16, width: 16, height: 16 ]
06:27:43.982 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:43.982 -> Object detection bounding boxes:
06:27:43.982 -> Vegetable (0.976562) [ x: 16, y: 16, width: 16, height: 16 ]
06:27:44.264 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:44.264 -> Object detection bounding boxes:
06:27:44.264 -> Vegetable (0.968750) [ x: 16, y: 16, width: 16, height: 16 ]
06:27:44.546 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:44.546 -> Object detection bounding boxes:
06:27:44.546 -> Vegetable (0.996094) [ x: 16, y: 16, width: 16, height: 16 ]
06:27:44.778 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:44.824 -> Object detection bounding boxes:
06:27:44.824 -> Vegetable (0.988281) [ x: 24, y: 16, width: 8, height: 16 ]
06:27:45.057 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:45.057 -> Object detection bounding boxes:
06:27:45.057 -> Vegetable (0.976562) [ x: 16, y: 16, width: 16, height: 16 ]
06:27:45.334 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
06:27:45.334 -> Object detection bounding boxes:
06:27:45.334 -> Vegetable (0.992188) [ x: 16, y: 16, width: 16, height: 16 ]
Autoscroll Show timestamp Newline 115200 baud Clear output
```

Fig 22: Arduino IDE Serial monitor result of vegetable during a test

```

03:11:31.111 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:31.111 -> Object detection bounding boxes:
03:11:31.111 -> Watermelon (0.726562) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:31.346 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:31.346 -> Object detection bounding boxes:
03:11:31.346 -> Watermelon (0.664062) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:31.626 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:31.626 -> Object detection bounding boxes:
03:11:31.626 -> Watermelon (0.558594) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:31.903 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:31.903 -> Object detection bounding boxes:
03:11:31.903 -> Watermelon (0.804688) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:32.139 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:32.139 -> Object detection bounding boxes:
03:11:32.185 -> Watermelon (0.765625) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:32.417 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):
03:11:32.417 -> Object detection bounding boxes:
03:11:32.417 -> Watermelon (0.730469) [ x: 24, y: 24, width: 8, height: 8 ]
03:11:32.697 -> Predictions (DSP: 2 ms., Classification: 132 ms., Anomaly: 0 ms.):

```

Fig 23: Arduino IDE Serial monitor result of vegetable during a test

## V. CONCLUSION

The total of 395 data collected which was label to 272 for training, comprises of 5 image classes of Onion, Tomatoes, Watermelon, Leaves and none food item Fan. Machine Learning for object recognition with the help of ESP32-CAM and Edge Impulse was used to build and deployed model of the Image recognition to Arduino codes. It was trained with the accuracy of 98.1% it was improved compared to previous work. It helps to monitored the items situation through the accuracy displayed in serial monitor of Arduino IDE. In addition, it gives accountability of object stored especially if freezer used for inventory with capacity of 3471BTU/h.

## REFERENCES

1. Basa, J. J. A., Cu, P. L. G., Malabag, N. N., Naag, L. A. V., Abacco, D. F. P., Siquihod, M. J. M., Madrigal, G. A., & Tolentino, L. K. S. (2019). Smart inventory management system for photovoltaic-powered freezer using wireless sensor network. *International Journal of Emerging Trends in Engineering Research*, 7(10). <https://doi.org/10.30534/ijeter/2019/057102019>
2. Bonaccorsi, M., Betti, S., Ratani, G., Esposito, D., Brischetto, A., Marseglia, M., Dario, P., & Cavallo, F. (2017). 'HighChest': An augmented freezer designed for smart food management and promotion of eco-efficient behaviour. *Sensors (Switzerland)*, 17(6). <https://doi.org/10.3390/s17061357>
3. *CNIOT 2020: conference proceeding: April 24-26, 2020, Sanya, China.* (2020). The Association for Computing Machinery.
4. Cortella, G., Agaro, P. D., & Saro, O. (2011). *Prediction of the energy consumption of a supermarket refrigeration system.* <https://www.researchgate.net/publication/299409288>
5. Danfoss A. (n.d.). *BD35F Direct Current Compressor R134a, 12-24V DC, 10-45V DC Solar & 100-240V AC 50/60Hz; BD35F Direct Current Compressor R134a, 12-24V DC, 10-45V DC Solar & 100-240V AC 50/60Hz.* [www.secop.com](http://www.secop.com)
6. *DHT22-DIGITALER-TEMPERATUR-UND-LUFTFEUCHTESENSOR.* (n.d.).
7. Dossat, R. J., Professor of Refrigeration, A., & York, N. (1961). *Wiley International Edition PRINCIPLES OF REFRIGERATION.*
8. *ESP32-CAM Development Board.* (n.d.).
9. Evans, J. A., Foster, A. M., & Brown, T. (2014). *TEMPERATURE CONTROL IN DOMESTIC REFRIGERATORS AND FREEZERS.*
10. Freon. (2018). *Product Information.*
11. Grubb, K. (2011). *General Purpose Relays Power Relays T90 Series, 30A PCB Relay.* [www.te.com](http://www.te.com)
12. Hymel, S., Banbury, C., Situnayake, D., Elium, A., Ward, C., Kelcey, M., Baaijens, M., Majchrzycki, M., Plunkett, J., Tischler, D., Grande, A., Moreau, L., Maslov, D., Beavis, A., Jongboom, J., & Reddi, V. J. (2022). *Edge Impulse: An MLOps Platform for Tiny Machine Learning.* <http://arxiv.org/abs/2212.03332>
13. <http://home.iitk.ac.in/~samkhanWebpage:home.iitk.ac.in/~samkhan/>
14. Khandekar, S., & Visvesvaraya. (2016b). *Vapor Absorption Refrigeration Systems.* <http://home.iitk.ac.in/~samkhanWebpage:home.iitk.ac.in/~samkhan/>
15. <https://doi.org/10.15680/IJIRSET.2024.1309092>
16. *LCD-016N002B-CFH-ET.* (n.d.). [www.vishay.com](http://www.vishay.com)
17. *LM2596 SIMPLE SWITCHER® Power Converter 150-kHz 3-A Step-Down Voltage Regulator.* (2023). [www.ti.com](http://www.ti.com)

18. *Model: BMS-20A-3S-S & BMS-20A-3S-EFJ ms:72M5366,72M5373.* (2010).
19. Mohammad, I., Shah Imran Mazumder, M., Saha, E. K., Razzaque, S. T., & Chowdhury, S. (2020, January 10). A deep learning approach to smart refrigerator system with the assistance of IOT. *ACM International Conference Proceeding Series*. <https://doi.org/10.1145/3377049.3377111>
20. Padmaja, B., Ch, V., Patro, E. K. R., & Shashirekha, B. (2021). *A Smart IoT System for Remote Refrigeration Monitoring*. <https://doi.org/10.21203/rs.3.rs-432649/v1>
21. *Part I-Fundamentals of Refrigeration Refrigeration Manual.* (1968).
22. Patel, K. K., Patel, S. M., & Scholar, P. G. (2016). Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. *International Journal of Engineering Science and Computing*. <https://doi.org/10.4010/2016.1482>
23. Patel, S., Salazar, C., Patel, K. K., Patel, S. M., & Scholar, P. G. (2016). Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. *International Journal of Engineering Science and Computing*. <https://doi.org/10.4010/2016.1482>
24. Paul, A., Baumhögger, E., Elsner, A., Moczarski, L., Reineke, M., Sonnenrein, G., Hueppe, C., Stamminger, R., Hoelscher, H., Wagner, H., Gries, U., Freiberger, A., Becker, W., & Vrabec, J. (2021). Determining the heat flow through the cabinet walls of household refrigerating appliances. *International Journal of Refrigeration*, 121, 235–242. <https://doi.org/10.1016/j.ijrefrig.2020.10.007>
25. Puigdueta, I., Aguilera, E., Cruz, J. L., Iglesias, A., & Sanz-Cobena, A. (2021). Urban agriculture may change food consumption towards low carbon diets. *Global Food Security*, 28. <https://doi.org/10.1016/j.gfs.2021.100507>
26. *Refrigeration And Air Conditioning - C P Arora.* (n.d.).
27. Regina Pinaso, G., Marcondes Figueiredo, L., Rosa Júnior, O., & da Silva Richetto, M. R. (2024). Edge Impulse Potential to Enhance Object Recognition Through Machine Learning. *Semina: Ciências Exatas e Tecnológicas*, 45, e49197. <https://doi.org/10.5433/1679-0375.2024.v45.49197>
28. *Stainless Steel: Tables of Technical Properties Materials and Applications Series, Volume 5.* (2007). [www.outokumpu.com](http://www.outokumpu.com)
29. Ye, Y., & Zhu, Q. (2017). *The development of polyurethane.*
30. Zainuddin, Nurdin, J., & Is, E. (2016). The Heat Exchanger Performance of Shell and Multi Tube Helical Coil as a Heater through the Utilization of a Diesel Machine's Exhaust Gas. *Aceh International Journal of Science and Technology*, 5(1), 21–29. <https://doi.org/10.13170/aijst.5.1.3842>

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