Meat Quality Grading and Contamination Identification to Avoid Foodborne Infection and Food Quality Control

By

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A Final Year Design Project (FYDP) submitted to the Department of Electrical and Electronic Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering

Electrical and Electronic Engineering
BRAC University
October 2024

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October 2024

Declaration

It is hereby declared that

1. The Final Year Design Project (FYDP) submitted is my/our own original work while completing degree at Brac University.
2. The Final Year Design Project (FYDP) does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The Final Year Design Project (FYDP) does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. I/We have acknowledged all main sources of help.

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Approval

The Final Year Design Project (FYDP) titled "**Meat Quality Grading and Contamination Identification to Avoid Foodborne Infection and Food Quality Control**" submitted by

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of Summer 2024 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Bachelor of Science in Electrical and Electronic Engineering on 19-Oct-2024

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Ethics Statement

This final year design project (FYDP) has been done with a great amount of research to get the relevant and proper information. During the research process, we maintained the highest ethical standards and ensured that we have given in-text citations and references properly to all the information that has been collected from relevant external sources. In addition, the similarity index of this paper has been kept under 15%, which followed the instructions of keeping the similarity index under 35%. To conclude, the in-text citations and references have been done properly by following the IEEE guidelines to maintain the ethical standards, which have been checked by the Turnitin website that showed the similarity index of the paper is 15%, which followed the requirements.

Abstract/ Executive Summary

Ensuring the safety and quality of meat production has a huge impact on preventing foodborne illness, which is also connected to the betterment of public health. Meat being highly decomposable is bound to be contaminated by such bacteria as E. coli, Salmonella and Listeria, which is responsible for serious health hazards. This paper mainly focuses on the development of a system with advanced technology that can provide an accurate meat quality detection. As a result, all this spoilage identification has been integrated by real time monitoring technologies like machine learning, sensors and microcontrollers. Besides, these technologies aim to detect spoilage indicators such as volatile organic compounds (VOCs), harmful bacteria and environmental factors. Furthermore, this can help for more identification, grading and contamination of meat processing. Ultimately, through detecting the spoilage of meat products, this project will not only help to ensure public health but will also have a great impact on the meat supply industry, society and the environment.

Key words: meat spoilage; spoilage identification; machine learning; gas sensors; image processing.

Dedication

To our respective parents, who have always been there and supportive towards us.

Acknowledgement

By the grace of Almighty, we got the ability to finish our final year design project with patience and consistent hard work.

Thanks to the respected faculty members of our ATC panel for their constant guidance towards us.

Special thanks to Dr. A.S. Nazmul Huda Sir and Raihana Shams Islam Antara Ma'am, who have been giving us constant guidance and insightful feedback from the beginning. Without their guidance, this project would be impossible for us to complete.

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Additionally, we would like to show our gratitude to Lasset lab and FYDP lab for giving us the opportunity to work there for the hardware part of this project and supporting us with relevant tools that they owned.

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1.1 Introduction

To prevent foodborne illnesses and ensure the safety of public health, spoilage detection of any food product is a must needed process to follow. As meat is a highly vulnerable food product to get spoiled due to the presence and growth of harmful bacterias like: E. coli, Salmonella etc. which would be responsible for serious health risk to the meat consumers [1]. While meat can start to get contaminated from any stage or multiple stages like: production, distribution or handling process, meat spoilage is not only harmful for the meat related businesses and environment but it also causes serious, even life-threatening foodborne diseases to the meat consumers. As it has been annually reported 600 million cases (approximately) of foodborne illnesses worldwide, a significant portion of those foodborne illnesses are connected with meat products [2]. Moreover, meat spoilage may go undetermined during the initial stages of spoilage due to the absence of certain visible or sensational factors like changes in texture, badly discoloration of the meat, gross odor from the meat etc [3]. On the other hand, to tackle the issue, this project made a system to detect the meat spoilage in the early stages with the help of a collaboration of technologies, including: machine learning, gas sensors and image processing. These innovative technologies not only have gained a huge popularity and attention in recent years but also they have the record to ensure the highest amount of effectiveness in their respective areas. As a result, the combination of these innovative approaches has a potential to offer the highest quality assessment in determining the conditions or the freshness of meat products. For example: the gas sensors will be able to detect the volatile organic compounds that get released by the spoiled meat, even at a very early stages of the spoiling process, whenever the meat gets tested [4]. Besides, the image processing techniques with the help of machine learning algorithms will be to detect any changes in texture from the surface of the tested meat through evaluating colors and other relevant characteristics [3]. Additionally, by the help of the training models and tested data, machine learning algorithms will most accurately determine the condition of the meat. Ultimately, with the collaboration of these innovative approaches, this will help both the meat consumers to ensure health safety and the meat industry to get economically benefited through detecting the meat spoilage in early stages.

1.1.1 Problem Statement

In the meat industry, meat quality grading and contamination identification is one of the essential aspects of food safety and quality control that is vastly required. Meat, being a highly degradable product, has a tendency to spoil rapidly due to factors such as temperature, humidity, and bacterial growth [5]. Besides, some major causes behind meat spoilage is that meat contains different types of carbohydrates, proteins which get contaminated in the presence of enzymatic activities[6]. Hence, in order to safeguard consumers absorbing spoiled meat, the identification of spoiled meat is imperative. The level of spoiled meat consumption can lead to various health issues such as foodborne illness, which can be highly severe that can lead to hospitalization and even fatality. Again, meat might also get contaminated during the butchering process which might result in spoilage later on [7]. Besides, most of the meat consumers will also agree that through the process of meat getting spoiled from fresh condition, the meat would become discolored, spread a bit off-odors, and the meat surface would become slimy[5]. However, in the primary stage of meat getting spoiled from fresh to half fresh condition, these factors are not humanly possible to determine. Therefore, promptly identifying meat spoilage is crucial to prevent the spread of harmful bacteria and fungi that contribute to deterioration. Additionally, meat spoilage is also a major concern for the food industry, especially the highly degradable items like beef, mutton and poultry items. As the complication of food loss and waste is severely threatening the food security at present time, which is also a serious threat to the environment and global economies. Ultimately, this will help the meat industry to analyze the meat condition at an early stage, which will be effective not only for their business but also the health and safety of the consumers will be ensured.

1.1.2 Background Study

Globally, the presence of meat presents a significant threat to food safety. Every year even in the developed countries like: United States, Australia, Germany, and India, 30% people of their population face foodborne illnesses [1]. It has been proved that unsafe food causes more than 200 types of foodborne illnesses from diarrhea to cancers, which causes 600 million cases of foodborne illnesses every year, from which 420,000 people died, among them 125,000 cases are children under the age of 5 [8]. The number is 9.4 million people in the United Kingdom who suffer from foodborne diseases yearly, while in the United States 1200 million diarrheal cases have been reported annually mostly for food related contaminations [1]. Even because of the foodborne illnesses, there has been reported 1.8 million cases of children deaths annually, in the developing countries [1]. Besides, every year diarrheal diseases have been the most common effect of food contamination which results in 550 million cases of sick people with 230,000 cases of deaths worldwide [8]. Approximately 30% people in the first world country suffer from foodborne diseases, while only in the United States of America 76 million cases of foodborne diseases get reported every year, from which 325,000 cases get hospitalized and 5,000 cases of deaths get reported every year [7]. This information declares a prime picture of the potential consequences resulting from the consumption of spoiled or improperly handled meat and poultry, as a major number of those foodborne illnesses would be caused by the spoilage of these types of products.

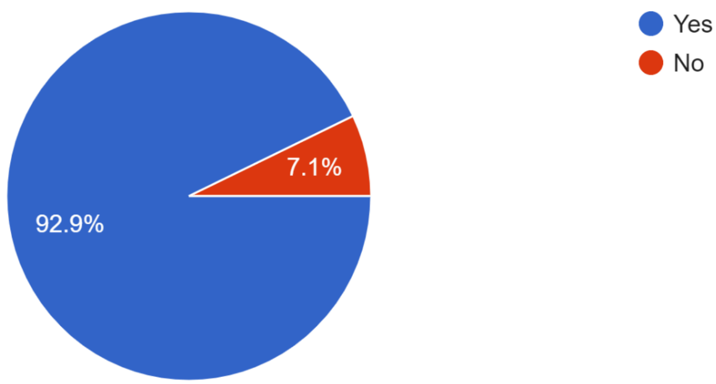
In 2011, due to E.coli contamination Germany experienced a significant outbreak, where over 852 people became ill, 32 died [1] . After that, in 2019, in Spain, a bacterial infection outbreak named Listeriosis occurred due to *Listeria monocytogenes* that was directly linked with contaminated cold meat that leads to more than 300 cases that are reported and 3 deaths to count [9]. There was also an outbreak of hand, foot and mouth disease in 2018, that encounter happened in Vietnam that generally correlated with contaminated meat that affected about more than 130,000 people with 17 deaths case reported, which was more serious in 2011-2012, when 200,000 people got affected and 200 cases of death had been reported [10] . The largest Listeriosis outbreak observed in South Africa in 2018 was globally known as the most terrified outbreak of that time, which occurred over 1,024 laboratory confirmed cases with 28.6% case fatality rate that were directly linked to contaminated processed meats [11] . In Brazil 13,163 foodborne outbreaks had been reported between the time frame 2000 to 2018 where 247,570 cases had been reported and 195 cases had been reported death[12]. In 2008, Chile reported about 91 cases of food poisoning, resulting in 5 cases of death associated with contaminated pork products. Here in Bangladesh, every year approximately 30 million people suffer from foodborne diseases and two-thirds of the food items get directly to the consumers without being supervised quality checking [13]. During another ground report in 87 slaughterhouses of Dhaka, Bangladesh it has been also found out that half of the slaughterhouses contaminate high quality meat, mixing it with lower quality one and 85% of slaughter houses found doing unhygienic practices without even caring about consumers' health and safety concerns [14] .

The occurrence of meat spoilage can yield economic drawbacks for products due to spoilage and subsequent decrease in the duration that the meat can be stored. In the process of detecting meat spoilage at an early stage, to prevent it the producers can easily take some essential steps for further spoilage and reduction of financial losses. Overall, identifying meat spoilage is crucial to ensuring food safety and quality. Also, there is a huge responsibility for protecting consumers and public health that can maximize economic benefits for the producers [3]. Food is one of the most basic needs for human life so according to that food safety is a matter of great urgency for every individual. It also has particular importance in the need of meat products. The evaluation of meat quality and the identification of contamination represent crucial procedures that guarantee the safety and excellence of the meat that we consume.

1.1.3 Survey Report

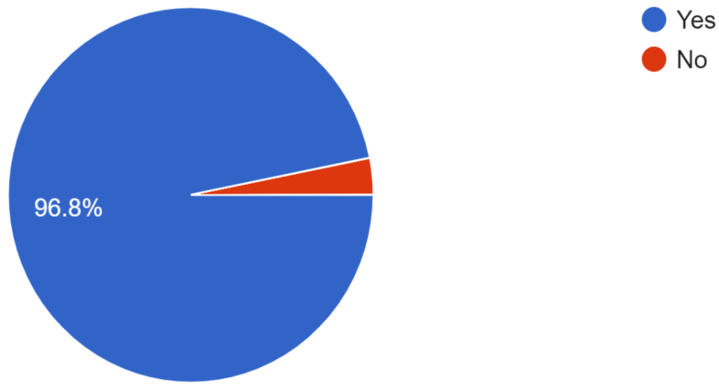
For making our problem statement more strong, we conducted a survey in which approximately 126 individuals provided responses. In addition to the aforementioned respondents, individuals from diverse professional backgrounds such as professors, students, housewives, academicians, engineers, developers, doctors, sales executives, and others also contribute to the response. Moreover, we also collaborate with the Center for Food Studies through a professor in the United States to gather valuable insights. Ultimately, the purpose of this survey was to investigate the reasons behind the implementation of meat quality grading and contamination identification in order to prevent foodborne infections and ensure food quality control.

Question 1: Is meat contamination a serious public health issue? What do you think?
126 responses



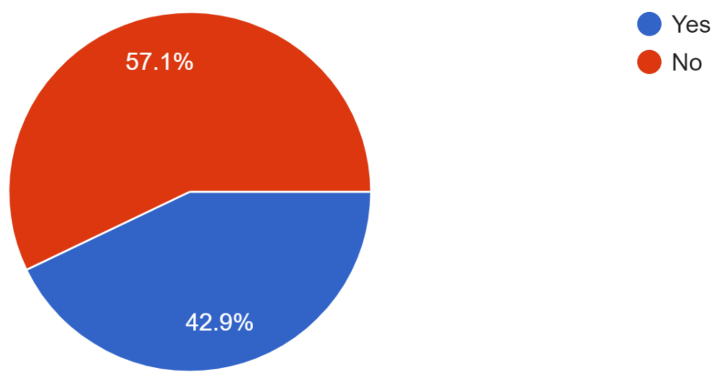
- ❖ In this diagram, a considerable portion of the population, specifically 92.9%, hold the belief that meat contamination is a matter of great significance in terms of public health.

Question 2: Can contaminated meat cause foodborne illness?
126 responses



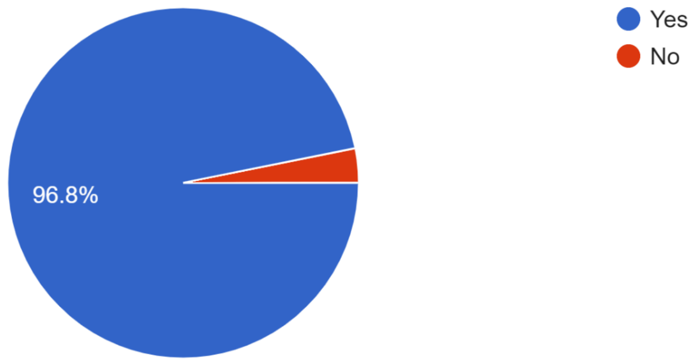
- In addition, it was found that 96.8% of individuals believed that the consumption of contaminated meat is the leading cause of foodborne sickness.

Question 3: If yes, has anyone in your family been affected by spoiled meat?
126 responses



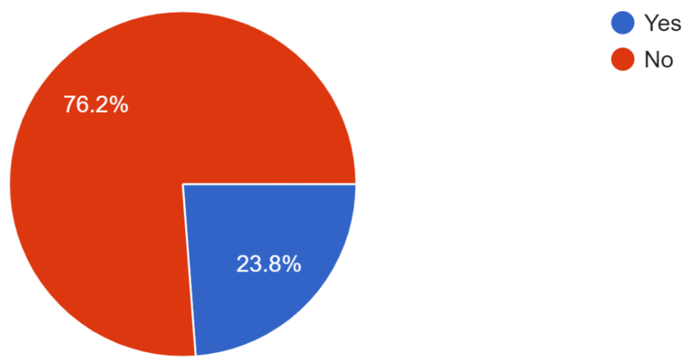
- This diagram provides us with crucial data pertaining to the fact that out of the total population, approximately 57% of individuals have at least one family member who is impacted by the consumption of spoiled meat.

Question 4: Are there any hidden contaminants that are not visible to the naked eye?
126 responses



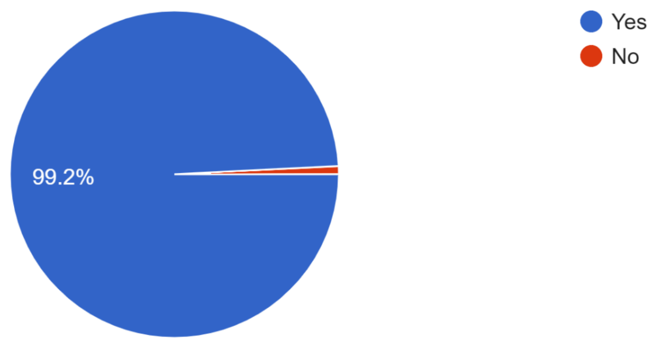
❖ Also, 96.8% of individuals believed that meat may contain concealed contaminants that are not visible. This poses a significant threat to human well-being.

Question 5: Do you get sold by/used before/best before/expiration date, when you buy the meat?
126 responses



❖ In this figure, a significant majority of individuals, accounting for 76.2%, tend to purchase meat without the presence of a date indicating its usability, such as a best before or expiration date. Moreover, within this proportion, the majority are of Bangladeshi origin. Conversely, a minority of 23.8% of individuals adhere to the practice of acquiring meat with a sell by, used before, best before, or expiration date in their daily routines. Notably, the predominant group within this subset is the American population.

Question 6: What do you think, should we work on Meat Spoilage Detection for Food Quality Control?
126 responses



❖ Here we notice, Among the 126 individuals, a substantial proportion of 99.2% opine that the implementation of meat Spoilage Detection for food Quality Control is of utmost importance for the well-being of human beings. Additionally, they strongly advocate for our involvement in this particular endeavor.

1.1.4 Literature Gap

Meat contamination is a very common issue worldwide yet there is not much focus on developing any system that can prevent this particular issue. In all other research based on this meat contamination and detection system has been thoroughly explained about the level of contamination that has occurred till date that caused foodborne illness and also death [3]. So it is undoubtedly a concerning topic to develop a system that can prevent this uncertainty of consumption of meat [5].

Through this our main focus is to determine the conditions of the meat, if it is spoiled or not. For this, machine learning algorithms, image processing and gas sensors have been used. Where the combination of these innovative approaches will be able to test a sample of meat in early stages. By monitoring with a real time monitoring system and the detection level using ML (Machine Learning), the accurate data of spoilage level can be beneficial for all the stakeholders all around the world to detect the quality of meat and its consumption.

However, there has been an increasing popularity with frozen meat over the recent years, and our research still has not worked with frozen meats. Besides the frozen meats products, in households and super shops, meat often gets stored in the freezer, which gets used after so many days, often months. So, those meat which get frozen for a long time will need the detection too, with research data of their biological spoilage process. So, our research needs to be worked with frozen meat to upgrade with the popular choices.

1.1.5 Relevance to Current and Future Industry

Currently there are not any industrial existence relevant to the meat quality control system in Bangladesh but some of the multinational authorities that are working with meat processing are JBS, Cargill etc. JBS is a Brazilian company that is working largely with meat processing [15]. This is the developing industry that can align with meat processing and contamination detection systemic verification. This is addressed that due to potential contamination of food any dietary risk can be introduced so it is important to focus on contamination detection and test protocols [16].

So, for future relevance industry in Bangladesh we can focus on some sector that can be helpful such as –

Restaurant: As in most of the slaughterhouses of meat's quality does not get maintained, from time to time it is becoming stricter in the restaurant industry to ensure the food quality and good quality of meat that need to be provided by restaurant food items [14] . So, any system with real time monitoring can be beneficial in different aspects for the consumption of meat.

Supermarket: Real time spoilage detection can be done when any of the stakeholders or consumers needed to collect meat and that will increase customer trust and safety as this retail industry highly depends on customers trust. And also food safety regulation will be followed in a good manner with supply chain transparency.

Food Safety Regulatory Body: Government and regulatory bodies can have advanced contamination detection systems that will be helpful for stricter compliance and this will influence industries across the food supply chain to introduce advanced technology[8].

Online Food Delivery: They can provide customer real time spoilage detection to ensure the meat that is delivered is fresh. Following this system consumer's demand for safety and fresh meat items will have transparency.

1.2 Objectives, Requirements, Specification and Constraints

1.2.1 Objectives

The fundamental objective of our project regarding meat quality grading and contamination identification is listed below:

- Developing an advanced detection technology.
- Securing public health.
- Economic resilience.

In this project, we have a chance to develop and implement a comprehensive system for improving meat quality grading and contamination identification, thereby promoting food safety and ensuring high-quality meat for consumers. On the other hand, in this project we are able to bridge the gap between existing systems for meat quality grading and contamination identification, creating a more comprehensive and robust approach to ensure food safety and deliver high-quality meat to consumers. Moreover, by this project we can strengthen the food industry's resilience by minimizing the financial impact of meat contamination incidents and preserving consumer trust in meat products.

1.2.2 Requirements

1.2.2.1 Functional Requirements

Sensitivity and Accuracy: Our system needs high sensitivity and accuracy in detecting meat spoilage, microbial contamination and grading meat quality. To prevent foodborne illness this can help with a small area in quality of contamination.

Real Time Monitoring: The system should provide real time monitoring of meat for the proper quality detection throughout the supply chain. Such as, from production to consumption and responding rapidly with any contamination and spoilage risk.

Detection of Various Types of Gas: The system needs to have a wide range of gas detection ability such as ammonia, hydrogen sulfide or volatile organic compounds (VOCs) is essential. This is the main source to identify the responsible gasses for spoilage and bacterial growth.so, the early detection can help with the safety of meat[4].

User Friendly Interface: The system should be easy to operate with a spontaneous interface that allows operators and also the food inspectors to navigate quickly and retrieve the prime information on meat quality and status.

Remote Monitoring: The way of monitoring meat quality remotely is a tough process for the large scale meat production facilities [17]. That will help to access real time data and also quality control from different locations that can ensure efficient management of meat safety.

Contamination Detection: To project potential contamination the system should have the given ability and it can work based on current meat handling practices or storage conditions, providing proactive measures to prevent future contamination.

1.2.2.2 Non-Functional Requirements:

Easy Maintenance and Modular Components: The design of the system should be easy going such as ease of maintenance that the modular components allows for quick replacement or upgrades, minimizing downtime and ensuring continuous monitoring of meat quality[18].

Energy Efficiency: For sustainability, we have to focus that energy efficient operation can be crucial distinctively in large scale meat processing plants [19]. To ensure low energy consumption without undermining the functionality of the system that can reduce the operational cause.

Low Cost: The system must be cost effective that can be easy to use by several engagers. That can provide affordable solutions for meat quality grading and contamination detection. We must focus on accuracy and reliability. This procedure can be more accessible for both large and small producers.

Reliable System: To ensure consistency and accuracy reliability is the most essential part. That can upgrade the meat quality grading with a trustworthy process. By open examination of frequent breakdown and errors by operating the system the food safety and quality can be maintained with standards.

Aligning with Stakeholders Requirement: The stakeholders are the main concentration to build up any system so, that must meet the expectations of stakeholders and need to fulfill the requirement of various sectors [13]. Such as, regulators, food safety authorities, producers and consumers. All the concerns of them must be addressed and should take necessary steps to fulfill.

1.2.3 Specifications

Table 1.1: Component Level Specifications

Description	Part	Specification
CO_2 Sensor	MH-Z14	Working voltage: 4.5 V ~ 5.5V DC Average current: < 85 mA Interface level: 3.3 V
Alcohol Sensor	TGS822	Heater Voltage : 5.0±0.2V (AC or DC) I = 132 mA (typ) Ps ≤ 15 mW; Ph = 660 mW (typ)
Temperature and Humidity Sensor	DHT22	Source Voltage 3.3V - 6V Typical: 3.3V Power Consumption: 7.5 mW Current: 1.5 mA (typ)
Bluetooth Module	HC-05	The specifications are as follows: Communication Interface: UART Supply Voltage: 3.3V Supply Current: maximum 40mA Power: 132 mW
LCD Screen	Grove - LCD RGB Backlight	
Power Supply		Current: DC 1.2A Power: 12W Input: AC 100-240V AC Output: DC 3-12 V
Battery (Backup Power)		Battery: ● Capacity: 1500-2200 mAh ● Output Voltage: 3.7V Charger: ● Input AC: 100-240V @47-63Hz ● Output DC: 3.7V @500mA ● Terminal Voltage:4.2V±1% [19]
Microcontroller	Raspberry pi 4	Clock Cycle: 1.4GHz SDRAM: 1GB LPDDR2 IEEE standard: 802.11.b/g/n/ac Wireless connectivity: ● 2.4GHz and 5GHz wireless LAN ● Bluetooth 4.2 ● BLE Connectivity:

		- Gigabit Ethernet over USB 2.0 (maximum 300 Mbps) 4 USB 2.0 ports - CSI camera port - DSI display port Terminals: 40-pin GPIO header Storage: Micro SD port Operational Voltage: 5V DC current: 2.5A Case dimensions: Varies depending on case, typically around 85 x 56 mm with 20-25 mm height
Charger	UL 60950-1	
LDO Voltage Regulator	LP2985	
LDO Voltage Regulator	STLQ50C33R	Mounting Style: SMD/SMTPackage Case: SOT-323-5 Output Voltage: 3.3 V Output Current: 50 mA Number of Outputs: 1 OutputPolarity: Positive Quiescent Current: 3 uA Output Type: Fixed Minimum Operating Temperature: - 40 C Maximum Operating Temperature: + 150 C Dropout Voltage: 400 mV
LDO Voltage Regulator	LDK320M50R	Mounting Style: SMD/SMTPackage Case: SOT-23-5 Output Voltage: 5 V Output Current: 200 mA Number of Outputs: 1 OutputPolarity: Positive Quiescent Current: 70 uA PSRR / Ripple Rejection - Typ: 48 dB Output Type: Fixed Minimum Operating Temperature: - 40 C Maximum Operating Temperature: + 125 C Dropout Voltage: 200 mV
L298N H-Bridge Dual Motor Driver	L298N H-Bridge Dual Motor Driver	Motor Supply Voltage (Maximum): 46V Motor Supply Current (Maximum): 2A

		Logic Voltage: 5V Driver Voltage: 5-35V Driver Current:2A Logical Current:0-36mA Maximum Power (W): 25W [23]

1.2.4 Technical & Non-technical Constraints

Regulatory Compliance: Food safety regulations must comply with the system. And need to follow the standards to maintain everything such as HACCP, FDA, or EU food safety laws to ensure that meat contamination is detected following all the legal requirements. To prevent foodborne illness meeting all the regulatory standards are important.

Stakeholder Demand: Firstly, the system should address the specific demands of all the stakeholders. Without ensuring the demand no one can have any solution. So it is needed to have the demand from producers, retailers and consumers who require precise grading and contamination detection that will help them to ensure the meat is safe and high in quality.

Equipment Compatibility: There must be an existing meat processing system in place so our system must work well with current control tools already in place. Without changing major infrastructures some important features can be set up that can upgrade the equipment. This can help transition smoothly and without unnecessary extra cost.

Product Variability: Variability in meat products must be accommodated by the system such as different texture , fat content and processing methods to provide accurate data of contamination and quality assessment.

Cultural Consideration: Cultural differences is a sensitive issue that must be handled with the system such as meat management, consumption and quality standards. To explain, there can be such rules for some cultures to have premium meat with a freshness threshold that the system must accommodate according to acceptance.

1.3 Applicable Compliance, Standards and Codes

Table 1.2: Applicable Standards and Codes

Standards	Definition	Application
ISO 22000	ISO 2200 transforms organizations 'food safety operation by reducing the risks of food and eliminating poor performance in this area. Such as enhanced health and safety, increased customer satisfaction, helping with regulation requirements (and meeting other standards or guidelines), and being more transparent up front-all of this feedback into our project [20].	Compliance
ISO 9001: 2015	ISO 9001 is primarily a quality management standard, it could be relevant for ensuring that the processes associated with spoilage detection and food quality control are well-defined and consistently implemented [21].	Certification
IEEE SA P2796.1	Standard for Data Requirements for Internet of Food (IoF) Systems. Volume I of the Codex Alimentarius: Defines a food contaminant: Any substance present in food as a result of the production, manufacture, processing, preparation, treatment, packing, packaging, transport or holding of such food or as a result of environmental contamination [22].	IoT
SQF 2000	The Safe Quality Food Program (SQF) is a food safety and quality management certification system. SQF 2000 is applied for food manufacturers and distributors [23].	Certification

ISO 4833.2: 2013	Defines a technique for horizontally counting microorganisms capable of developing colonies on a solid medium by aerobic incubation intended for human consumption and environmental samples in food [24].	To sense the microbiological existence
ISO 13720:2010	Defines the counting of presumed Pseudomonas spp. in meat and meat products [25].	To confirm meat hygiene
ISO 2917 :1999	Specifies the reference method for measuring the pH level of all kinds of meat. Applicable for homogenized and non-destructive measurement on meat [26].	pH measurement
GS1	Standards for Traceability: GS1 standards focus on supply chain traceability and can be crucial for tracking and tracing meat products from farm to table. Compliance with GS1 standards helps enhance transparency and accountability [27].	Standardization
ASTM D7329	Specification for Food Preparation and Food Handling (Food Service) Gloves including food testing. The project may reference ASTM standards for testing methods related to meat quality and safety [28].	Body protection
IEEE 2700-2017	Common framework code concerning sensor performance specifications, units, conditions and limits [29].	Sensor performance

IEEE 1298-1992	Software quality management system to be designed, developed and maintained [30].	Software

National and Regional Food Safety Regulations: It is also necessary to conform strictly to national and regional food safety standards. It would also have to meet the particular standards laid down by those agencies charged with overseeing this type of work in a given nation or area.

Ethical Guidelines and Industry Best Practices: The project should also be in conformity with ethical principles and current norms in the food safety, spoilage detection, and quality control industries. This might entail following rules dictated by an ethical standards authority or a trade association.

Data Protection and Privacy Standards: If the project involves the collection and processing of data, compliance with data protection and privacy standards, such as GDPR (General Data Protection Regulation), may be necessary.

To conclude, if the project entails collecting and processing data, then any applicable international data protection and privacy regulations must be followed.

1.4 Systematic Overview/Summary of the Proposed Project

This project presents an innovative approach to detection systems in the food industry. And, meat spoilage and contamination is one of the major problems nowadays due to the large food supply chain. So our proposed system is firstly using a sensor to detect the gas from bacteria and also have a Bluetooth module. Also to have the proper picture of meat spoilage level LCD screen also will be used. There are both AC and DC power supplies that input AC 100-240 V and output DC 3-12 V. The microcontroller system used is Raspberry pi 4 along with LDO Voltage regulator. And for the motor supply L298N H-Bridge Dual Motor Driver has been used.

This project result demonstrates the effectiveness of proper detection for meat spoilage that is done by using ML and other sufficient methods to assure the consumers about the meat consumption and meat processing assurance. This can be an exquisite solution for the food supply chain.

1.5 Conclusion

It is never possible for there to be no meat consumption by humans in the near future so it can be a sufficient system to detect meat quality. There are different kinds of meat processing methods but nothing can provide accuracy of the quality level. So, this technology can help with this uncertainty of meat processing. Many considerable latest devices and technology have been used to get the more reliable result from the system. Our focus on decreasing foodborne illness by detection can be beneficial worldwide if the execution can be perfect. So, we are hoping to develop a reliable system that can help with all the acceptance of meat processing and contamination detection systems.

Chapter 2: Project Design Approach

2.1 Introduction

The sensor array-based approach is a widely utilized method for designing electronic noses (e-noses), mimicking the human olfactory system's ability to detect and differentiate between a variety of odors. In this approach, a diverse array of gas sensors, each sensitive to different chemical compounds, is employed to detect the presence of volatile organic compounds (VOCs) and other gasses. Each sensor in the array responds differently to a specific odor or gas, producing a distinct pattern of responses. By analyzing these patterns, the system can recognize and classify different odors or chemical substances.

The key concept behind this approach is that individual sensors may not provide sufficient information to uniquely identify complex odors, but when combined into an array, the collective response creates a "fingerprint" that can be analyzed for pattern recognition. These fingerprints are processed using advanced data analysis techniques, such as machine learning algorithms, which can classify the sensor responses and match them to known odor profiles.

Another approach is the machine learning-based approach to electronic nose (e-nose) design that represents a modern and innovative method that harnesses the power of artificial intelligence (AI) to enhance odor detection and classification. Unlike traditional systems that rely heavily on large sensor arrays, this approach utilizes fewer but more precise sensors and leverages machine learning algorithms to interpret complex odor patterns. By training these algorithms on large datasets of known odors and gas mixtures, the system learns to identify and differentiate various chemical compounds, even when dealing with subtle or overlapping signals.

In this approach, machine learning models such as neural networks, support vector machines (SVM), and deep learning techniques are used to process the sensor outputs. These algorithms can detect correlations between sensor responses and specific odors, enabling the system to "learn" from experience and improve its performance over time. The ability of these models to generalize beyond the data they were trained on allows them to accurately detect new or unanticipated odor profiles, making the system more adaptive and versatile.

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2.2 Identify Multiple Design Approaches

2.2.1 Design Approach 1: Sensor Array-Based Approach

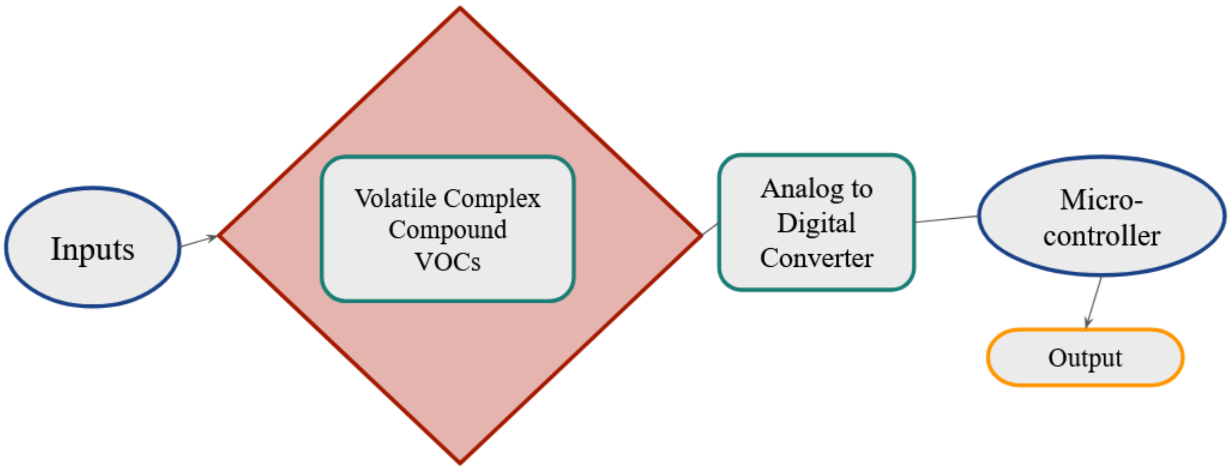

Fig 2.1: Block Diagram of Sensor Based Approach

Metal Oxide Semiconductor (MOS) sensors are widely used in electronic nose (e-nose) systems to detect various gases and volatile organic compounds (VOCs). These sensors operate based on changes in their electrical resistance when exposed to specific gases. MOS sensors typically consist of a metal oxide material, such as tin oxide (SnO_2), zinc oxide (ZnO), or titanium dioxide (TiO_2), deposited on a sensing layer. When target gases interact with the metal oxide surface, a chemical reaction occurs, leading to a change in the sensor's conductivity or resistance.

2.2.2 Design Approach 2: Machine Learning-Based Virtual Sensor Approach

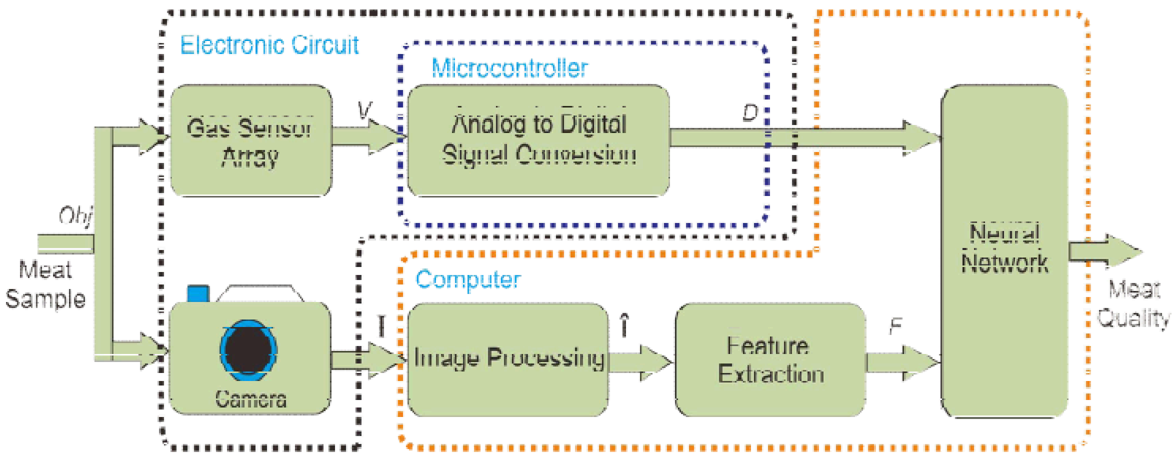

Fig 2.2: Block Diagram of Machine Learning Based Approach

This represents a system for assessing meat quality using a combination of a gas sensor array and image processing. The gas sensor array detects chemical properties of the meat, with the signals being converted from analog to digital by the microcontroller. Simultaneously, a camera captures visual data, which undergoes image processing. Both data streams—sensor signals and image features—are used for feature extraction. These features are then input into a neural network, which processes the combined information to evaluate and determine the quality of the meat.

2.3 Describe Multiple Design Approach

2.3.1 Design Approach 1: Sensor Array-Based Approach

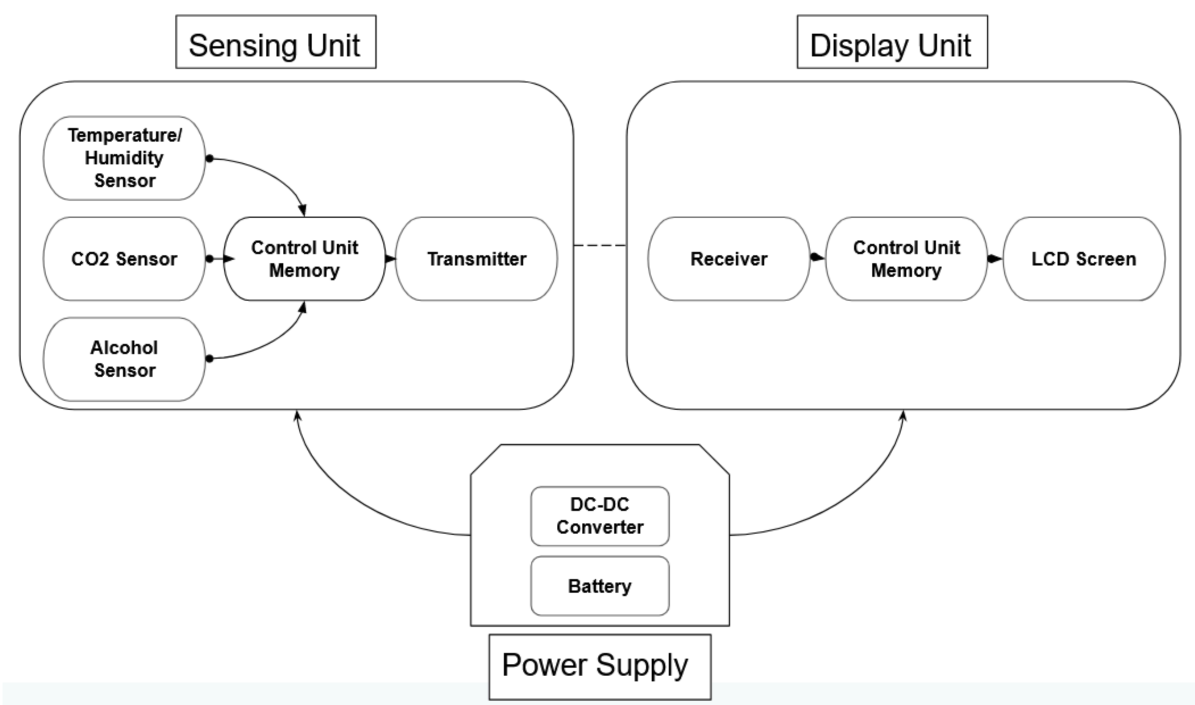

Fig 2.3: Block Diagram of Sensor Based Approach with Hardware Selection

Our design is divided into two main sections. The power supply system consists of a 12V battery that powers all the circuitry, and a DC-DC converter that provides the appropriate voltage levels to each component. The sensor unit includes an array of sensors for CO_2, alcohol, and organic solvents, along with a temperature and humidity sensor. These sensors work together to deliver more accurate readings by detecting specific chemicals under varying temperature and humidity conditions.

The sensor unit sends its data to a microcontroller, which processes the information and transmits a signal via Bluetooth to a receiver. The receiving unit contains a Bluetooth receiver module and another microcontroller, which interprets the received data and displays the results on an LCD screen in front of the test subject. If contamination is detected in food, the screen displays a warning message. The operator can acknowledge the warning by pressing a push button, which clears some of the data.

Additionally, if the refrigerator's internal unit detects a drop in battery voltage, it will send a notification to the LCD screen, alerting both the driver and passenger that the battery needs to be replaced.

2.3.2 Design Approach 2: Machine Learning-Based Virtual Sensor Approach

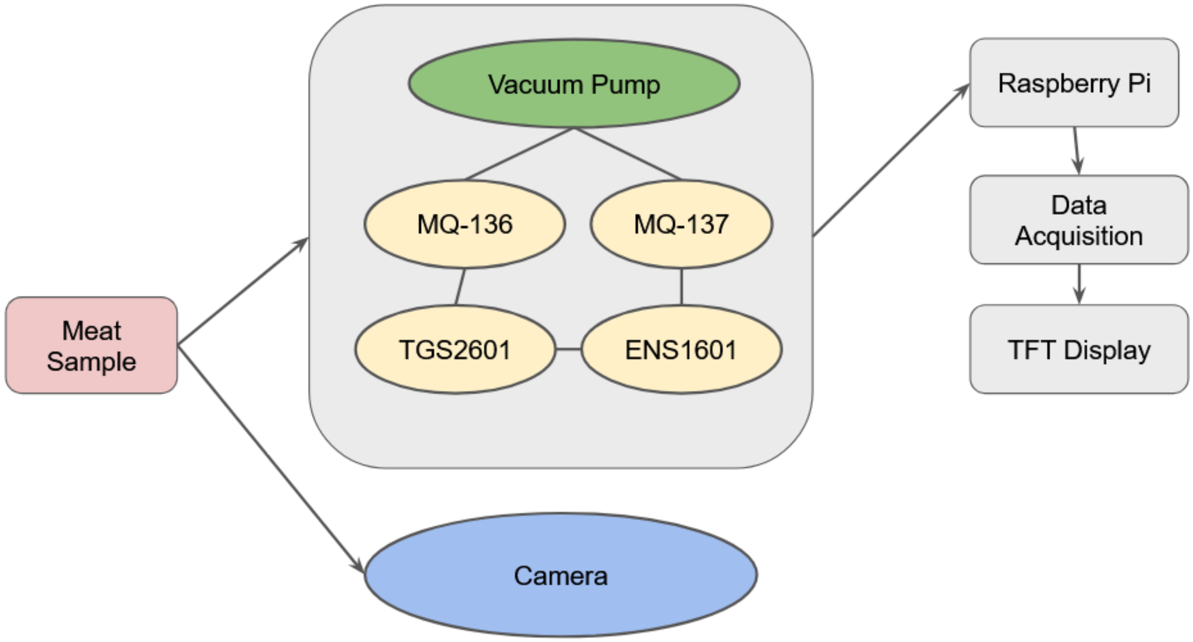

Fig 2.4: Block Diagram of Machine Learning Based Approach with Hardware Selection

The electronic nose consists of two main components: the sensor probe, which houses sensors within the sensor chamber, and the main electronic unit connected to a computer. Various types of metal oxide sensors are used in the design. The device is powered by an ESP32 microcontroller, responsible for managing communication between the sensors and the computer. Sensor resistances are measured through a multiplexer sequentially, with a brief delay of a few milliseconds between readings, allowing the sensors' conditions to be considered nearly simultaneous. The sensor readings are repeated in cycles every 0.75 seconds.The electronic circuit of the nose allows for modulation of the sensors' heater voltage, which, in turn, adjusts their operating temperature. These adjustments can be made during each sensor reading cycle, with voltages ranging from 0 to 7 V, in steps of 30 mV. All sensors in the device receive the same voltage modulation, simplifying the construction and reducing costs. However, this does not guarantee that all sensors maintain the same internal temperature, as this depends on their resistance and the heat generated by their heaters.The main unit connects to the sensors via wires, links to the computer through a USB cable, and uses a 12 V DC power supply. This supplied voltage is divided into two sub-circuits: one stabilized at 5 V, which powers most electronic components and sensor readings, and another adjustable sub-circuit that powers the sensors' heaters.

2.4 Analysis of Multiple Design Approach

Table 2.1: Multiple Design Approach

Category	Design Approach 1	Design Approach 2
Approach	Detects gasses or scents using a present set of sensors that are dependent on variations in electrical characteristics such as voltage, resistance	Processes sensor data using Complex technique, frequently combining several sensors for feature extraction and categorization.
Data Processing	Straightforward interpretation of data, frequently based on thresholds.	Interprets complicated sensor data using advanced machine learning or pattern recognition techniques.
Error Handling	Increased vulnerability to noise and sensor drift, which might result in false positives.	More adept at managing interference, drift and noise through data acquisition and learning algorithms.
Scalability	Less scalable;increasing the number of sensors adds complexity without appreciably raising accuracy.	Extremely scalable; by including more sensors, the model's accuracy and versatility are enhanced by new features.
Training and Adaptability	It has a set configuration and doesn't require any training.	To enhance performance and adaptation to novel smells and environments, training on datasets is necessary.
Flexibility	Restricted adaptability; sensor sensitivity to certain gases is the only factor influencing performance.	High adaptability; without requiring hardware modifications, machine learning algorithms can adjust to novel gasses, smells and patterns.
Accuracy	For wide detection, moderate accuracy frequently depends on sensor cross-sensitivity.	High accuracy as a result of neural networks learning from sensor data and pattern recognition.
Expenses	29,900 tk	39,600 tk

2.5 Conclusion

Sensor-based arrays and machine learning-based systems are the two types of electronic nose systems that may be compared. While both have advantages and disadvantages, machine learning-based systems perform better in more complicated scenarios. Sensor-based array systems are rather easy to use and reasonably priced. Based on variations in their electrical characteristics, they employ unique sensors to identify particular gases or substances. For simple gas detection jobs like tracking air quality or finding gas leaks, these devices' quick reactions are helpful. Their effectiveness is constrained in more demanding situations, though. Due to the possibility of their sensors reacting to many substances, they frequently have trouble telling apart identical gases. Additionally, because sensors can drift over time and experience a decline in performance, they need to be calibrated on a regular basis to preserve accuracy. However, systems based on machine learning are more potent and adaptable. They examine the sensor data using a combination of sensors and advanced algorithms. This enables them to perform more difficult jobs, such as distinguishing between different gas combinations or picking up on minute aroma variations. Machine learning models are capable of being trained to identify various patterns in the data, allowing them to get better over time and adjust to diverse situations. False readings are less likely with these systems because they are more adept at handling noise and sensor drift. Machine learning-based systems offer better accuracy and longer-term dependability, but they are initially more expensive and complicated to set up. Advanced applications where complex scents or chemical patterns need to be recognized, such as food quality monitoring, breath analysis-based disease diagnosis, or sophisticated air quality monitoring, are a perfect fit for them.

In summary, a sensor-based array may be adequate for straightforward, inexpensive applications that need for quick gas detection. However, machine learning-based systems are ultimately significantly more effective and efficient for applications that demand greater precision, flexibility, and the capacity to manage complex odor combinations.

Chapter 3: Use of Modern Engineering and IT Tools [CO9]

3.1 Introduction

Our project is based on the data collection process from the different gas sensors values and webcam for taking photos for analysis. In order to figure out the best optimal design, we used different types of tools. In the case of simulation, proteus, blender, labview had been used for analysis. Those tools help us to get the data directly and help us to compare between two different approaches.

3.2 Select Appropriate Engineering and IT Tools

3.2.1 Fusion 360

Fusion 360 is a potent open-source 3D modeling program that lets designers make realistic and complex 3D models, such as electronic noses—devices that imitate human smell by utilizing a variety of chemical sensors to detect and analyze scents. When designing an electronic nose with Blender, the first step is conceptualization. The designer looks into important parts like the housing, processing unit, and sensor array and makes preliminary sketches to see how these parts will be put together and work as a unit. Fusion 360's versatile modeling tools allow designers to create the outer casing of an electronic nose using basic shapes like cubes and cylinders, refined with advanced techniques like subdivision surface modeling for smooth, ergonomic designs. Texturing enhances realism surfaces can be done such as matte plastic for the housing and metallic finishes for sensors. Its rendering capabilities produce high quality images and animations offering a professional design. Additionally, animation features can demonstrate the 3D printing with electronic nose detection process. Overall, Blender provides a blend of artistic creativity and technical precision for designing a detailed 3D mode of electronic nose.

3.2.2 Proteus

Proteus is a very well known and versatile software platform ideal for simulating the hardware of electric circuit design. It allows users to model any electric design before physical prototyping to verify functionality. The electronic nose here means the design all uses sensors that can detect chemicals and gas due to bacteria . tries to detect humans and analyze different odors. The process of using proteus is being started by creating a schematic design where we can use integrated components such as metal oxide semiconductor (MOS) sensors, microcontroller, power supplies and output displays. Proteus mainly enables the simulation of sensor interaction with chemicals with microcontroller signal processing. The problems in a design can be easily found out using this softwaretech as the wrong connection of wiring. Also supports programming languages like C and Arduino. That allows users to code directly and use that for any system with the help of simulation. The overall effective electronic nose design can occur by using sensor calibration circuit design and overall functionality. We can use this for environmental monitoring, ensuring food safety and others.

3.2.3 Google Colab

Google Colab is a powerful cloud based platform that facilitates the development and training model using machine learning (ML). It helps deal with electronic noses such as utilizing chemical sensors to detect and analyze. Google colab is a build model which helps to do an interpretation of data from electronic noses using Python libraries. For example the libraries are TensorFlow, Keras etc.there are step by step ways to work with google colab. Firstly, we need to do the data collection and after that result in a dataset of the target table after that input different attributes (such as sensor reading). Secondly, they can include normalization and splitting into training , validation, and test sets. After data preparation, users can design any neural network using architectures like CNNs or RNNs that help with classification. Multiple users can work in a project simultaneously at a time and helps to capture more output in a short time. It enhances the development and accuracy for real time monitoring odor or gas detection.

3.2.4 Altium

Altium is one of the most powerful design tools for PCB. It is very important to create printed circuit boards (PCBs) that can also integrate gas sensors in the electric nose that are designed to capture and analyze. People can use Altium to create complex schematics that incorporate gas sensors along with microcontroller , signals, and communication interface. The intuitive workflow of this software is very much user friendly and the interface enables efficient component arrangement and routing. That can ensure potential mechanical use and optimize a great accurate gas sensor. It allows to model a circuit and reduces errors before fabrication with various conditions. It also has collaboration features that allows multiple users to work on a project simultaneously. The software also simplifies the access to manufacturing outputs , ensuring compliance with industry standards and enhancing the reliability of electronic nose systems in applications like food quality control .

3.2.5 LabVIEW

LabVIEW (Laboratory Virtual Instrument Engineering Workbench) is a powerful graphical programming environment that simplifies sensor-based arrays' simulation. Engineers and researchers can develop and test odor detection algorithms by creating complex simulation models allowing real-time monitoring and processing of sensor data. LabVIEW supports various gas sensor types, including polymers and metal oxide sensors, ensuring easy integration. Its user-friendly interface facilitates the creation of virtual instruments to visualize control and data flow , helping to model sensor behavior in different conditions. The platform also offers advanced data analysis capabilities , enabling statistics analysis and machine learning to enhance detection accuracy and reliability. Additionally, labviews simulation features allow for virtual testing of sensor arrays, optimizing setups and improving detection performance without the need for physical prototypes ultimately advancing applications like food quality assessment safety detection and environmental monitoring.

3.3 Use of Modern Engineering and IT Tools

3.3.1 Proteus

3.3.1.1 Raspberry Pi 3

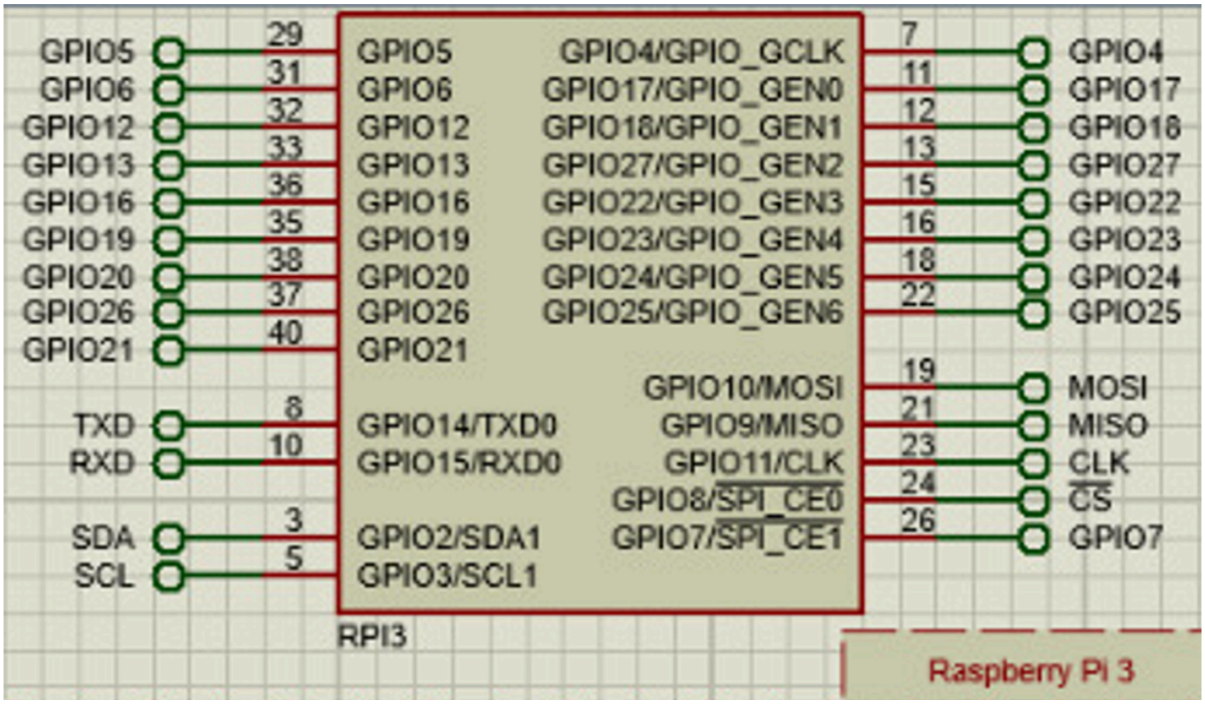

Fig 3.1: Block diagram of Raspberry pi 3 in proteus

One of the key reasons for using Raspberry pi 3 in simulation for an electronics nose project is its extensive GPIO pin layout, which allows connectivity with various types of sensors including gas or chemical sensors. These sensors are crucial in electronic nose systems as they detects specific odors by covering the chemical composition of the air into electrical signals. The raspberry pi 3 provides a sufficient number of GPIO pins to facilitate this connection, enabling real-time data acquisition from different sensors instantly.

Moreover to its hardware abilities, the processing power of the raspberry pi 3 is another significant advantage for machine learning applications. With its quad-core CPU and sufficient RAM, the raspberry pi can efficiently run basic machine learning algorithms. This processing power allows for real time analysis and classification of sensor data which is essential for distinguishing between different smells in an electronic nose system. This ability to handle machine learning models at the edge level, makes the raspberry pi 3 a robust platform for standalone systems like electronic noses. The raspberry pi 3 also supports communication protocols such as I2C and SPi, which are frequently used by sensors to transmit data to the processing unit. We have chosen the raspberry pi because of its connectivity capabilities, low power consumption and machine learning capabilities.

3.3.1.2 BH1750 Light Intensity Sensor

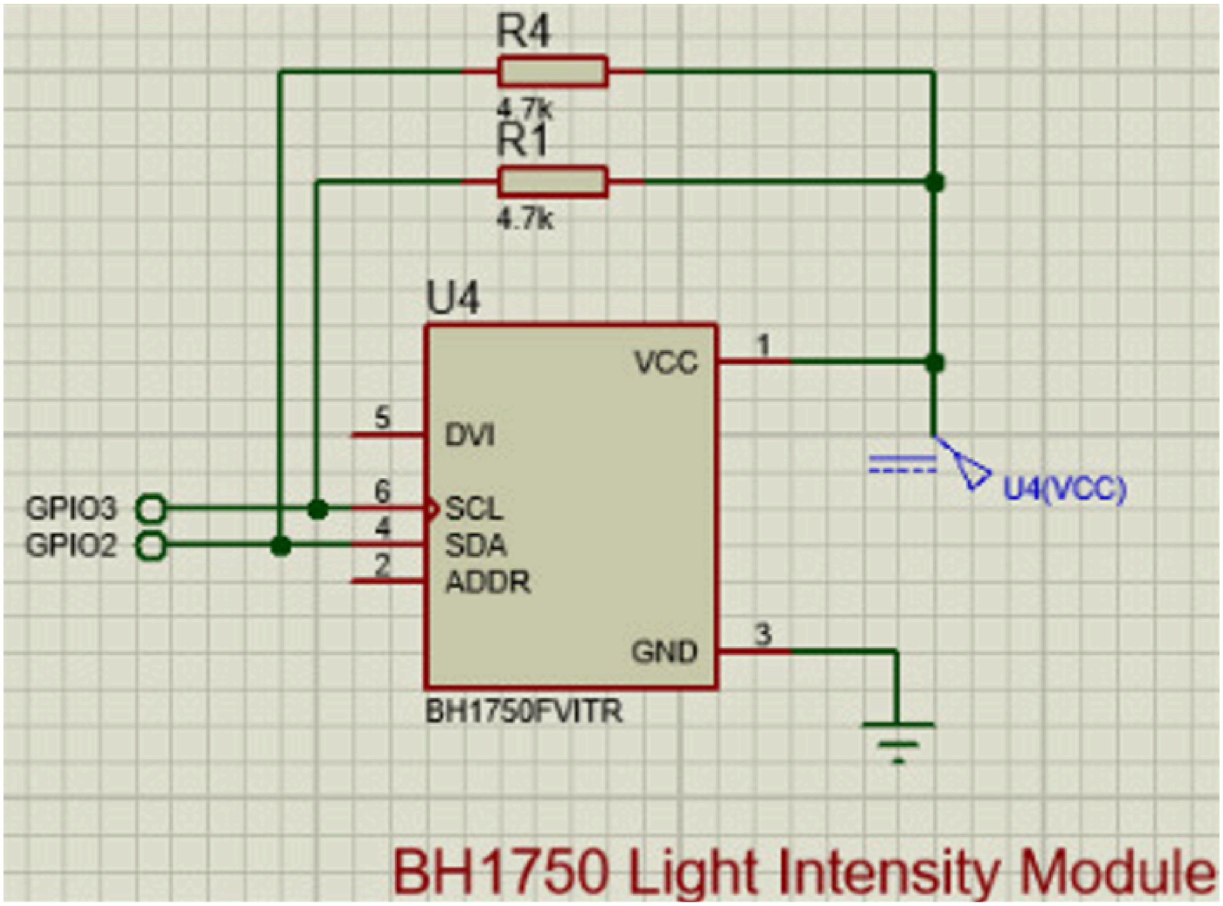

Fig 3.2: Block Diagram of BH1750 Light Intensity Module in Proteus

The BH1750 Light Intensity module is used in proteus simulation for machine learning based electronic nose systems initially to measure ambient light intensity, which can affect the performance of odor sensors and overall system accuracy. In an electronic nose system, light intensity measurements provide crucial environment context that can help adjust or calibrate sensor readings, especially if the system is being deployed in various lighting conditions. For example, many gases and chemical sensors are sensitive to changes in temperatures and light. Most importantly, the BH1750 is used in a machine learning based system where the collected light data can be integrated as a feature in the machine learning model. The BH1750 is simple to integrate into simulations, like proteus and real world systems because of its straightforward I2C interface. It requires minimal wiring and provides highly accurate light readings without the need for complex calibration. The sensor's small size, low power consumption and high accuracy also align well with the design principles of portable and low-power electronic nose devices.

3.3.1.2 ENS160 Volatile Compound Gas Module

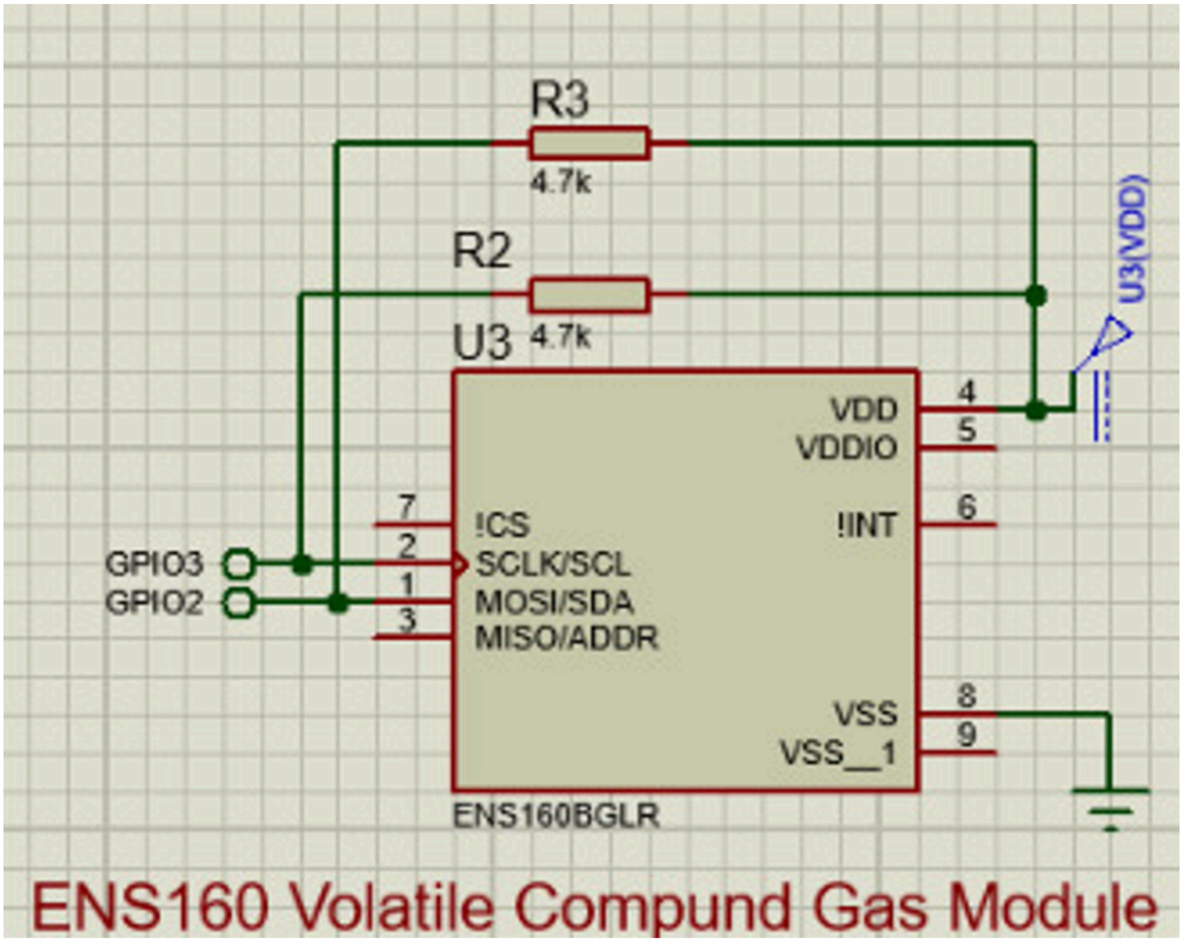

Fig 3.3: Block Diagram of ENS160 Volatile Compound Gas Module in Proteus

The ENS160 Volatile Compound Gas Module is used in proteus simulation for electronic nose systems due to its advanced capabilities in detecting and measuring a wide range of VOCs, which are crucial for odor recognition. Electronic nose systems are designed to mimic the human sense of smell, identifying and analyzing different chemicals in the air. The ENS160 sensor excels in detecting VOCs such as ethanol, acetone, toluene and other organic compounds. By implementing the ENS160, the system can feed this real-time VOC data into a machine learning algorithm, enabling accurate odor classification and identification. Its digital output via I2C or SPI simplifies integration, making it an appropriate fit for the systems that require easy communication between sensors and processors. The ENS160 also features built-in algorithms for indoor air quality evaluation, allowing it to process some of the sensor data internally. This reduces the computational load on micro-controller while delivering key food quality information that can be associated into machine learning models for better food quality context. Its low power consumption and compact design further make it suitable for portable, battery-powered devices.

3.3.1.3 MQ-137 Gas Sensor

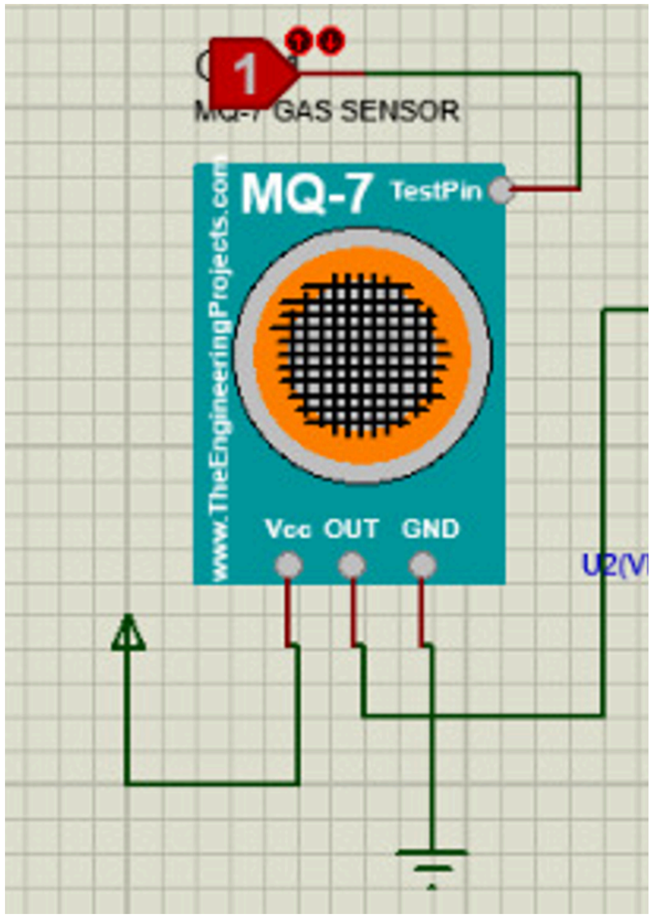

Fig 3.4: Block Diagram of MQ-137 Gas Sensors in Proteus

The MQ-137 gas sensor is used in proteus simulation for machine learning based electronic nose systems due to its capability to detect ammonia gas, which is crucial for odor analysis and food quality monitoring. The MQ-137 is specifically designed to detect ammonia within a range of 5 ppm to 500 ppm, making it suitable for detecting food exhales gas, ensuring food safety and identifying odors containing ammonia. The MQ-137 is easy to integrate due to its analog output which can be processed by a microcontroller or single board computer. In the machine learning based electronic nose system, the data from the MQ-137 can be used as a key feature in the model to classify different odors or identify hazardous conditions. By feeding ammonia concentration level into machine learning algorithms, the system can help in recognizing specific odor patterns or warning about dangerous levels of ammonia in the environment. This is particularly useful when combined with other gas sensors to create a more comprehensive odor profile.

3.3.1.4 MQ-136 Gas Sensor

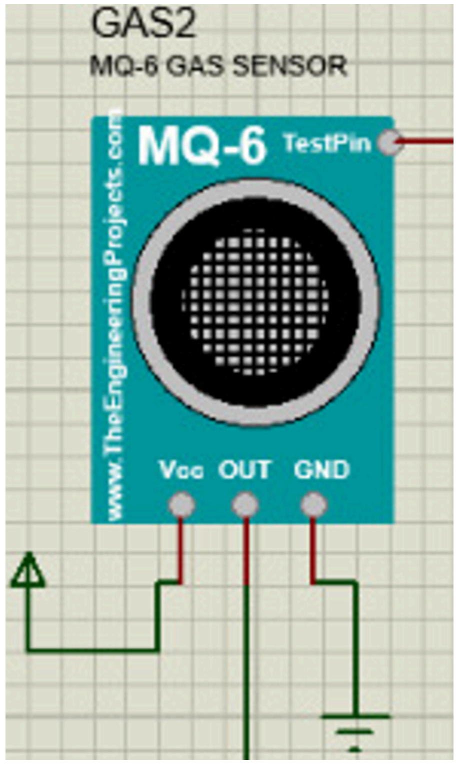

Fig 3.5: Block Diagram of MQ-136 Gas Sensors in Proteus

The MQ-136 gas sensor is used in proteus simulation for detecting hydrogen sulfide, a highly toxic and odorous gas often present in food industrial and environmental applications. Hydrogen sulfide has a distinct, rotten meat like smell and is commonly found in sewage systems and chemical industries. The MQ-136 sensor is specifically designed to detect H2S in low concentrations, making it an essential tool for food monitoring. This sensor is chosen for its high sensitivity to hydrogen sulfide, allowing it to detect even trace amounts of the gas(in the range of 1 ppm to 200 ppm). This makes the MQ-136 ideal for safety critical environments where early detection of H2S is important to prevent food contamination or operational risks. Its ability to detect H2S allows the electronic nose system to identify specific odor signatures associated with food vacuum environments where hydrogen sulfide is a key component such as food waste plants or industrial. In proteus simulation, the MQ-136 allows the users to model how the system responds to varying concentrations of hydrogen sulfide, enabling them to optimize sensor readings for more accurate machine learning predictions. Its affordability, ease of integration and reliability on detecting toxic gases make it a practical choice for real world electronic nose systems.

3.3.1.5 MCP3208 Analog to Digital Converter

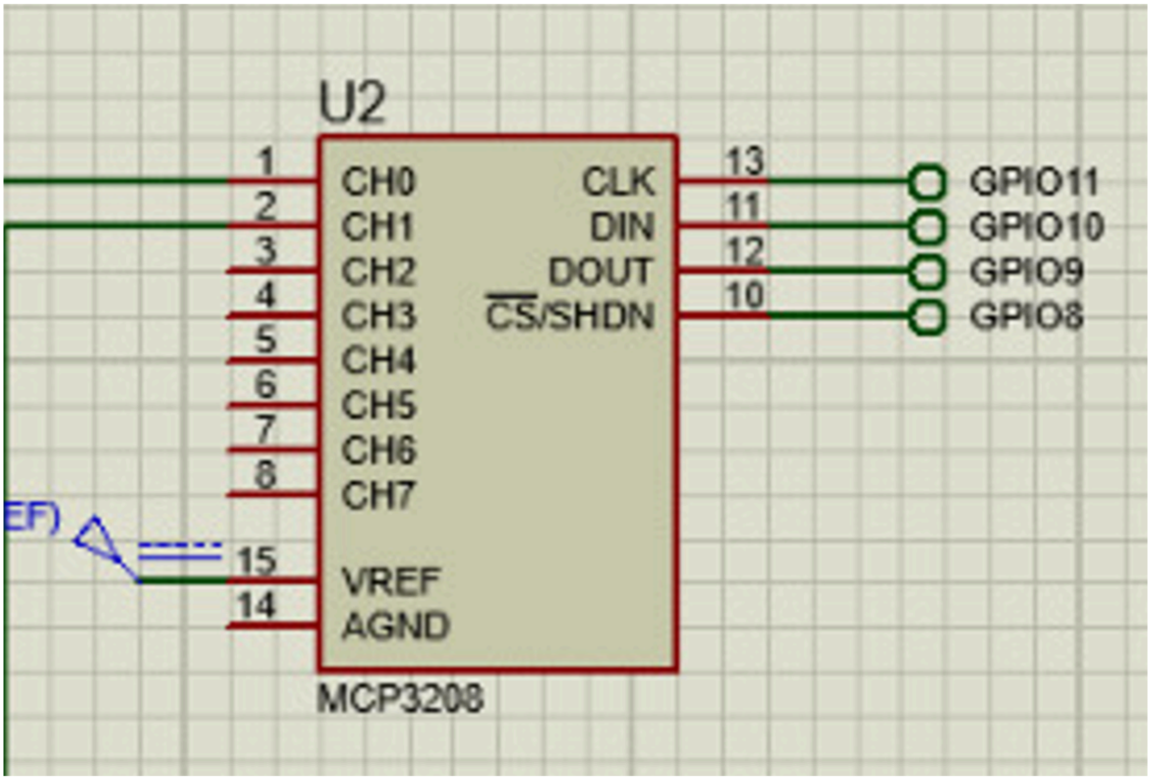

Fig 3.6: Block Diagram of MCP3208 Analog to Digital Converter in Proteus

The MCP3208 Analog to digital Converter is integral to electronic nose systems due to its high resolution capabilities, offering 12-bit precision essential for detecting subtle variations in food gases concentrations and odors. With eight input channels, the MCP3208 allows for simultaneous interfacing with multiple gas sensors, such as the MQ series, which can detect a range of volatile organic compounds(VOCs). This multi-channel functionality enhances the system's ability to analyze complex odor profiles. Additionally, the ADC supports both single-ended and different inputs, improving noise immunity and ensuring stable readings even in electrically noisy environments. Its SPI interface facilitates high-speed data transfer, crucial for real time processing in machine learning applications where prompt responses are necessary. The low power consumption of the MCP3208 makes it suitable for portable electronic noses. Allowing them to operate efficiently over extended periods. With a wide operating voltage range, the MCP3208 can easily integrate with various microcontrollers, further enhancing its versatility in different use cases. The sensors used in electronic noses play a pivotal; role in detecting and quantifying odors, which is vital for food quality control, environment monitoring and safety systems. By processing the high-resolution data from multiple sensors through the MCP3208, machine learning algorithms can be trained to classify different odors accurately. This integration allows for real time analysis and visualization of sensor data, facilitating the development and testing of machine learning models before implementation in physical hardware, ultimately improving the efficacy of odor systems.

3.3.1.6 Potentiostat

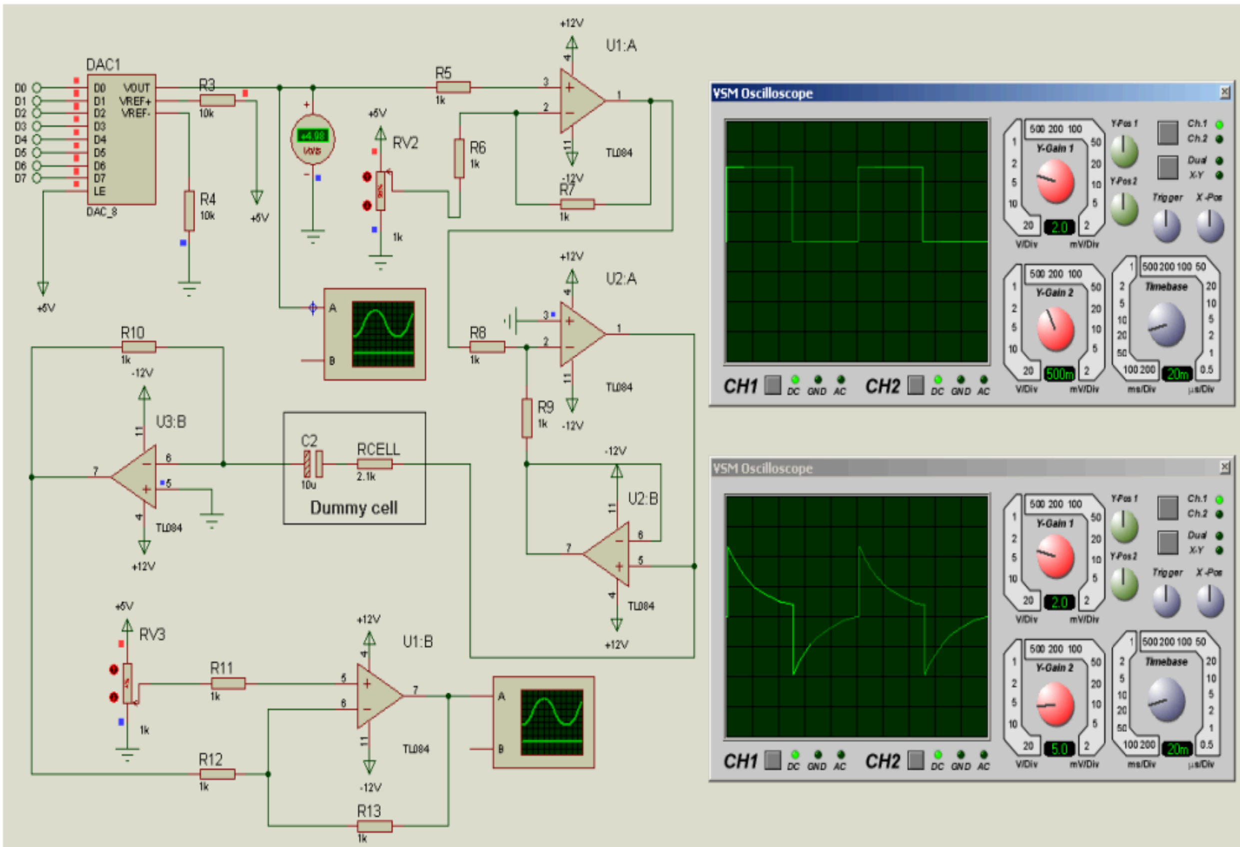

Fig 3.7: Potentiostat in Proteus

A potentiostat is important for making an electronic nose system. In the simulation, potentiostat, we have used for measuring the gas array sensors for calculating the voltages. It actually controls the voltage applied to electromechanical sensors and measures the resulting current, which is directly related to the concentration of gases or volatile compounds. In electronic nose systems, accurate detection of these compounds is crucial for differentiating between odors, and the potentiostat ensures precise control of electrochemical reactions at the sensor electrodes. This enables real-time, high fidelity data acquisition, which is necessary for training machine learning models to recognize and classify odors effectively. Without the potentiostat, the system would lack the sensitivity and accuracy needed for reliable gas detection and odor analysis. For the purpose of our project, we use it for identifying the level of different gas sensors.

3.3.1.7 LabVIEW

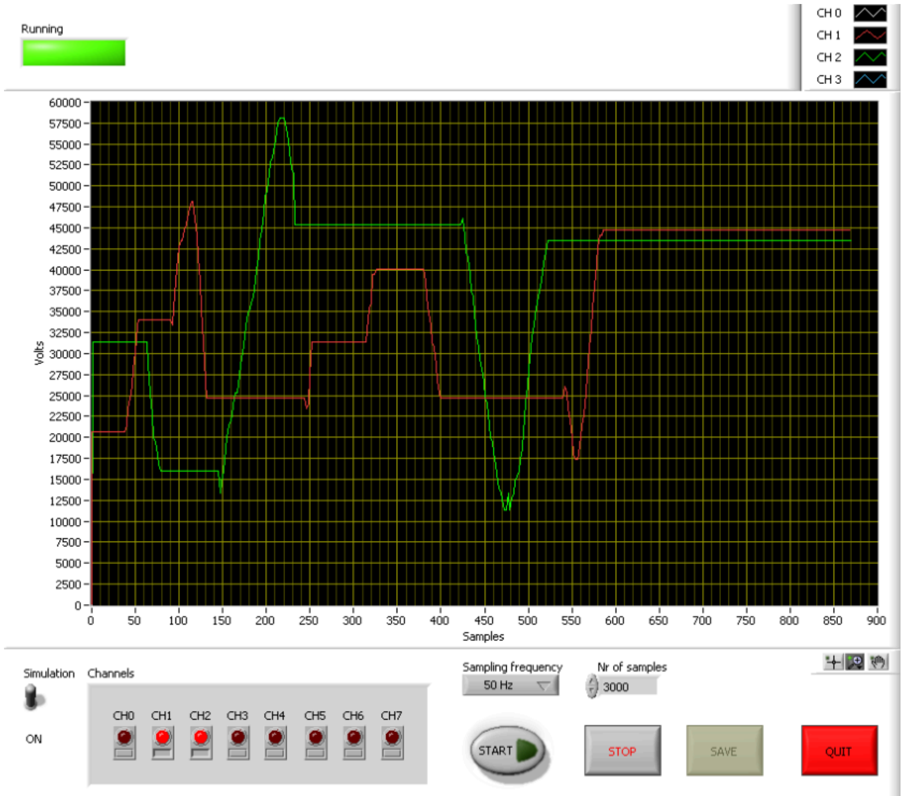

Fig 3.8: Front Panel of Electronic Nose

LabVIEW is used in Proteus simulation for detecting the gases values. We have used these tools for a powerful graphical interface for data acquisition, visualization and real-time processing of sensor data. In an electronic nose system, multiple sensors generate complex signals from detecting volatile compounds and Lab VIEW helps manage this data flow sufficiently. It allows for integration of machine learning algorithms, enabling real time analysis and classification of odors based on sensor inputs. The intuitive interface simplifies the process of programming and controlling the sensors, making it easier to simulate the behavior of the electronic nose system. By using LabVIEW, we can make comparisons among different gas sensors. For the purpose of our project, we use it for identifying the level of different gas sensors.

3.4 Conclusion

To detect the contaminations, simulation and analysis needs to be designed. This design will also involve the electronic nose system to detect the volatile organic compounds. Again a combination of modern engineering and IT techniques like proteus, Lab views, MCP3208, analog to digital converter has been used for their accessibility. Besides, protest has been essential for precise circuit design and simulation. Again, LabVIEW helped to collect real time data to make the classifications of gases that came out from the meat. On the other hand, the MCP3208 enables high resolution data collection from the gas sensors to make the system more accurate. By the combination of these technologies, it would help the system to process the data more efficiently and quickly and detect the odor more accurately. Hence, the use of these contemporary tools the system would be more effective, which will help to create sophisticated solutions for the project's technology

Chapter 4: Optimization of Multiple Designs and Finding the Optimal Solution [CO7]

4.1 Introduction

There are many approaches we have figured out in order to accomplish our project. After getting from the literature review, we have picked up two different approaches. Here, one is a sensor based array and another one is a machine learning based design approach. By implementing various types of gas sensors which actually detect different level gas ppm. Even those sensors' sensitivity and reliability are different as well as errors level are different. Sensor based array is capable of detecting the gas smells. After the process, the threshold parameters for specific gas will be calculated by the microcontroller. Using pattern recognition and signal processing the intense response of the sensors will be categorized on the basis of threshold parameters. But there are some limitations in this approach like we can not put more sensors based on the quantity of the meat. In some cases the pattern recognition results are very inefficient and unreliable.

Machine learning based design approach is the optimum for our project. Previous design approaches did not always give us good results. On the other hand, machine learning effectively calculates data analysis via complex algorithms. As we have collected more than 4000 data on our own, the result was actually categorized in good manner. Machine learning based system increases the accuracy and quick detection ability which will help the real world practical implementation. This system is used by vector machines and neural networks to minimize noise and at the same time amplify scalability for large data collection. With the algorithm, the data acquisition is more precise and reliable to get the results whether meat is contaminated or not. Therefore, machine learning with sensor implementation is better than any other approaches for its simple circuit, reliable output and addition of more complex components.[31].

4.2 Optimization of multiple design approach

4.2.1 Circuit Design of Approach 1: Sensor arrays' Based Design Approach

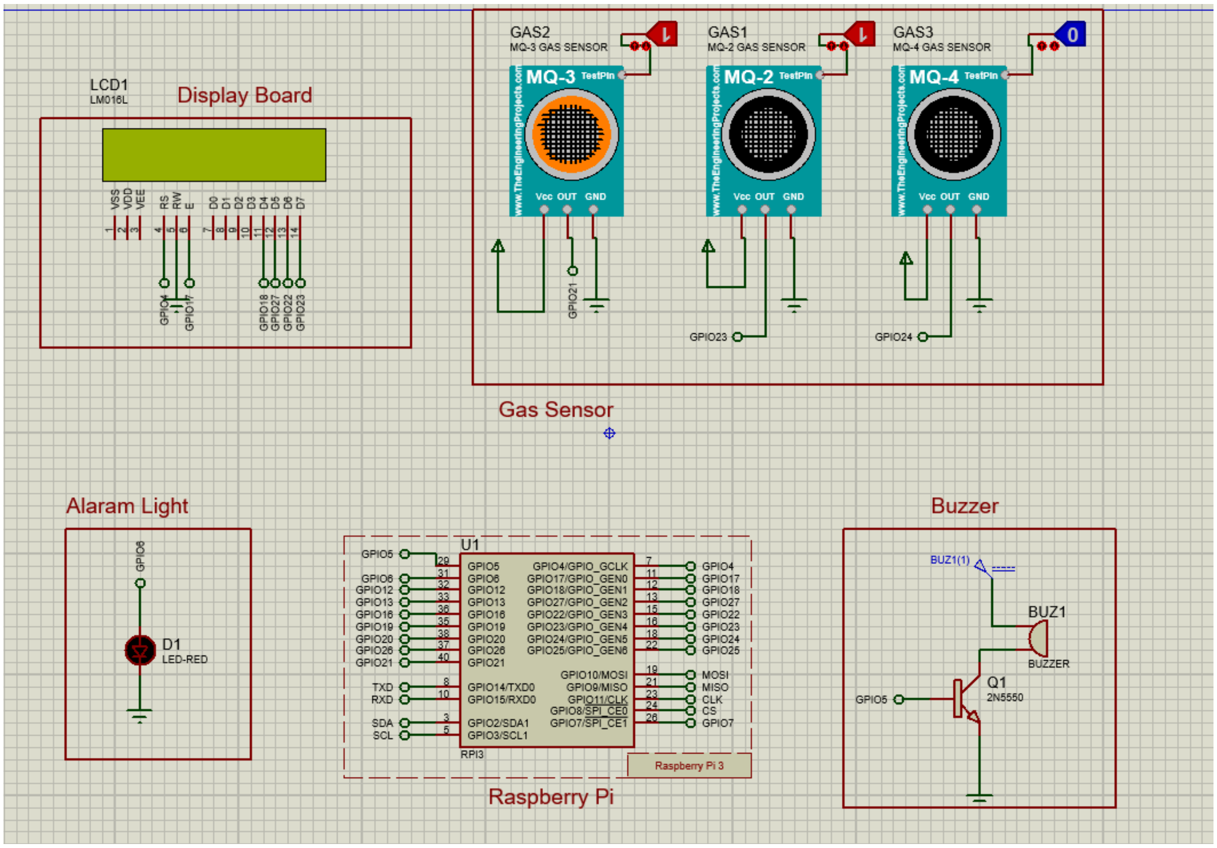

Fig 4.1: Circuit Design of Sensor Based Arrays's Approach

Using a sensor array, this electronic nose circuit can identify particular gases and offers real time feedback through an LCD, Buzzer and alarm light. A through explanation of the circuit's operation is provided below:

- **Raspberry pi 3:** This functions as the system's main processing unit. Through its GPIO pins, it receives the voltage signals from each sensor. The raspberry pi uses the input signals to control the display board, buzzer and alarm light as well as to carry out the necessary computations such as translation analog voltage to gas concentration.

- **Gas Sensors:** These sensors identify particular gases and produce an analog output voltage that ambient gas concentration. The raspberry pi's many GPIO are linked to each sensor.

- **Display:** The Raspberry Pi is linked to the LCD(LM016L), which shows the current gas concentration readings. The LCD displays the relevant data such as the gas concentration in parts per million as the sensors pick up various gas levels.

- **Alarm Light:** The Straightforward LED is attached to the Raspberry Pi's GPIO. It works as a visual warning by turning on when any of the gas has been detected above a predetermined threshold.

- **Buzzer:** A transistor Q1-2N5550 which works as a switch, is attached to the buzzer. The raspberry pi activates the transistor by sending a signal to the base via GPIO pin when it detects hazardous gas concentrations. This produces an audible alarm by cutting the circuit and turning on the buzzer.

The gas sensors in this circuit continuously check the surrounding air for particular gases. Each sensor's resistance varies in response to the concentration of the gas generating a voltage signal corresponding to the gas levels. The raspberry pi's associated GPIO pins receive these analog signals. Although it is not displayed in this configuration, an analog to digital converter would normally be needed to transform the signals into digital form because the Raspberry Pi only has digital input ports. These signals are processed by the raspberry pi and converted into gas concentrations. The raspberry pi is programmed to sound and display warnings when the gas rises above a certain level. When the threshold is reached, the LEd attached to GPIO6 illuminates and a transistor switch activates the buzzer, producing an instantaneous audio warning. Moreover, users may continuously check the meat for any changes in gas levels because the real time gas detection is displayed on the LCD.

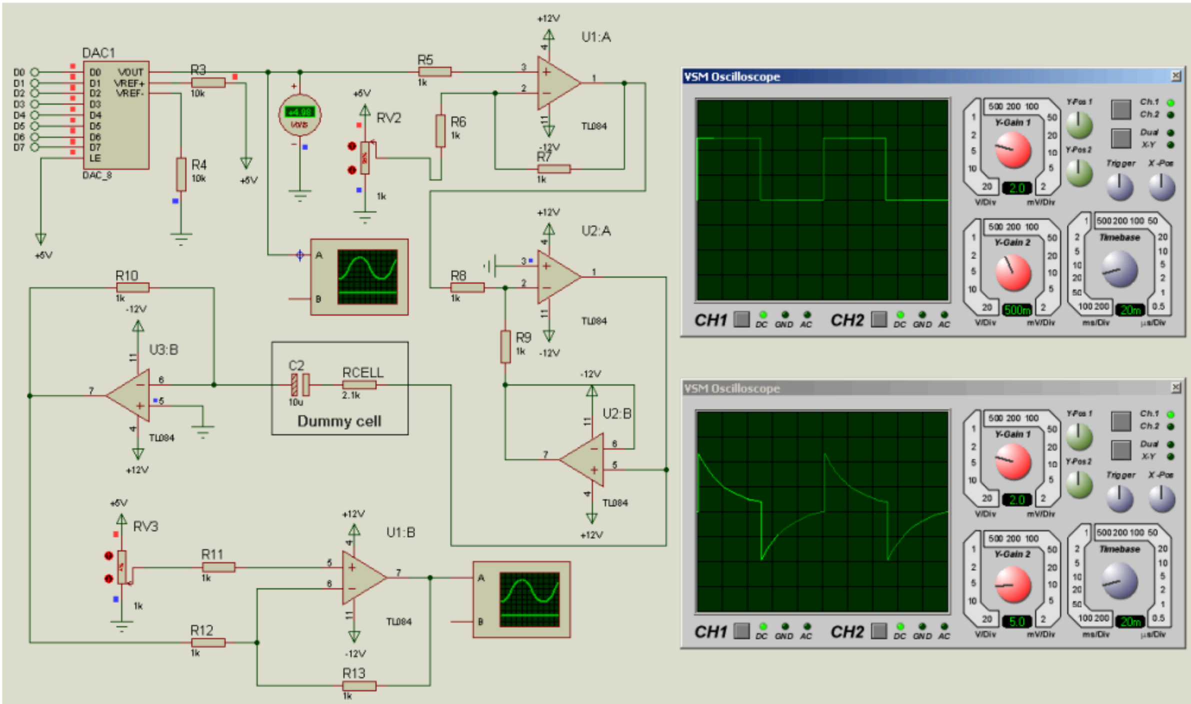

Fig 4.2: Simulation of the Potentiostat in Proteus

Proteus can also replicate the potentiostat. A 10 Hz square wave with an amplitude of 5V is input. The potentiostat's input is displayed on the top oscilloscope, while its output is displayed on the lower. Every horizontal line in both oscilloscopes counts two volts. The electrodes are linked in series with 2.1K resistor and 10uF capacitor to a dummy cell. The results from thus false cell are identical to those from the actual cell. A DAC with a voltage output has been utilized in this instance rather than one with a current output. Therefore, an additional operational amplifier is not required in this case to transform current to voltage. The reduction in size at the output in this particular case is not particularly appealing. Peak to peak voltage is approximately 10V, according to the oscilloscope for the potentiostat's output. The output of potentiostat will fall between 0V to 5V if R10 at the I/E converter is changed from 1k to 500k.

4.2.2 Circuit Design of Approach 2: Machine Learning Based Design Approach

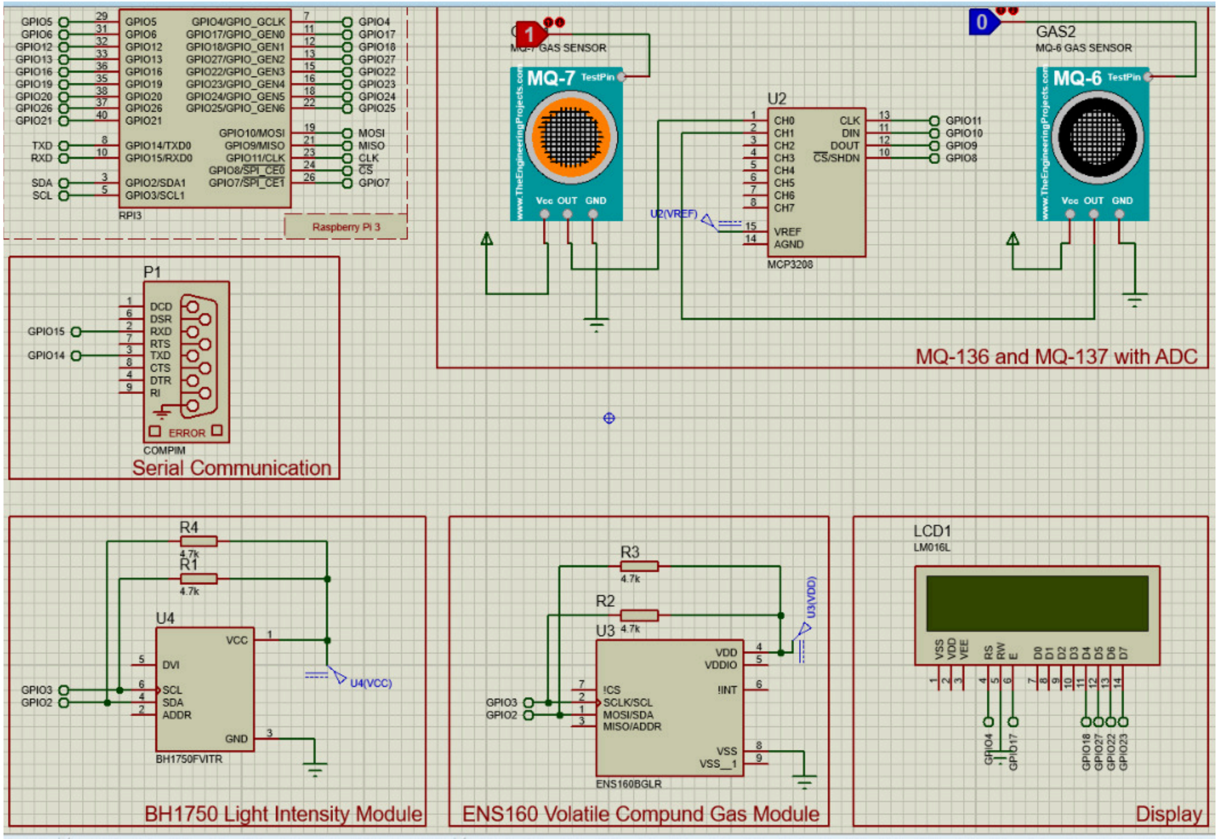

Fig 4.3: Circuit Design of Machine Learning Based Approach

The Circuit in this approach is a component of an electronic nose system, which uses a variety of sensors to identify gasses and air quality and sends data for additional processing. When combined with ML, this type of system can be used to categorize gasses or scents according to patterns found in sensor data. The elements and their functions are broken down as follows:

- **MQ-136, MQ-137:** Gases based on sulfur and ammonia are detected by MQ-136 and MQ-137. The analog output produced by these sensors is dependent on the concentration of gas that must be transformed into digital form for processing.

- **ADC:** The analog signals from the MQ series gas sensors are read by the MCP3208, an 8-channel ADC, which then transforms them into digital data that a computer or microcontroller can process. By transforming the signals from the sensors into readable digital values, the ADC enables the sensor to communicate with digital devices like a microcontroller or Raspberry Pi.

- **Light Intensity Module (BH1750):** This module uses a digital light sensor to detect the intensity of the light. It could be incorporated into the systems to help account for ambient variables, as light intensity may influence sensor data in specific environments.

- **Volatile Organic Compound (VOC) sensor (ENS160):** This module is capable of detecting a class of gases known as volatile organic compounds (VOCs). It can digitally interface with a microcontroller via an I2C interface and gives data on the gas quality index.

- **TFT Display:** This helps us to see the real time data got from the sensors.

- **Raspberry Pi 4:** This is the system's main processing unit. Data is gathered by the Raspberry Pi from the ENS160 VOC sensor, the BH1750 light sensor and the ADC. Raspberry pi can show the results on the TFT display after the data is sent over the GPIO pins. Through the communication interface, the Pi manages serial connectivity as well, potentially for data transfer to machine learning models.

The BH1750 light sensor in this electronic nose system tracks light levels, which affect gas readings, while gas sensors such as the MQ series and ENS160 detect gases. The ADC digitizes these sensors' analog output signals so they can be processed further. ADC and I2C interfaces are used by the Raspberry Pi to collect the digital data, which is then preprocessed by lowering noise, leveling the data, and occasionally combing the readings. This data is then used to extract important properties like light intercity and gas concentration. The machine learning model used the processed data to classify various gases according to patterns it has learnt. The model can operate locally on Raspberry Pi via serial communication device.

4.3 Identify Optimal Design Solution

We have consider some parameters,

1. True Positive value
2. True Negative Value
3. False Positive Value
4. False Negative Value

We have run both systems 20 times for each design approach in order to identify the gas detection data.

For, **sensor based design** approach, four important value we get,
It correctly identify gas 13 out of 15, therefore, True positive value, TP= 15
It incorrectly identify gas 5 cases where no gas in present, False Positive Value, FP= 5
It correctly detects that there is no gas 2 times out of 5. True Negative Value TN =2
It fails to detect the gas 3 times out of 20, False Negative Value, FN = 3.

Then we get the values for **machine learning based** electronic nose system,
It correctly identify gas 16 times out of 18, Therefore, True positive value, TP= 16
It incorrectly identify gas 2 cases where no gas in present, False Positive Value, FP= 2
It correctly detects that there is no gas 1 times out of 2. True Negative Value, TN =1
It fails to detect the gas 1 times out of 20, False Negative Value, FN = 1

Table 4.1: Four Parameter Value for Both Design Approach

Design Approach	True positive value, TP	False Positive Value, FP	True Negative Value, TN	False Negative Value, FN = 2
Sensor arrays based	15	5	2	3
Machine Learning based	16	2	1	1

Now calculating the accuracy factor for both cases,

- Sensor Based Arrays accuracy,

$$\frac{True\ positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} = \frac{15 + 2}{15 + 2 + 5 + 3} = 0.68 = 68\%$$

- Machine learning based accuracy,

$$\frac{True\ positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} = \frac{16 + 1}{16 + 1 + 2 + 1} = 0.85 = 85\%$$

Table 4.2: Accuracy Value for Both Design Approach

Approach	Sensor Based Arrays	Machine Learning Based
Accuracy	68%	85%

The performance efficiency differences between a machine learning based system and a sensor based array system are highlighted. From the data, we can observe that the Ml based system has more memory, accuracy and precision, which improves its ability to identify and categorize gases accurately while reducing false positives and false negatives. On the other hand, the sensor is basically slower, requires more memory and utilizes more processing power. The sensor based array is less precise and more likely to misclassify. The sensor based system works well when minimal resource usage is crucial whereas the machine learning based system is better suited for complex environments needing high detection accuracy.

4.4 Performance Evaluation of Developed Solution

4.4.1 Output Performance for Design Approach 1

Fig 4.4: Front Side of LabVIEW Detecting System

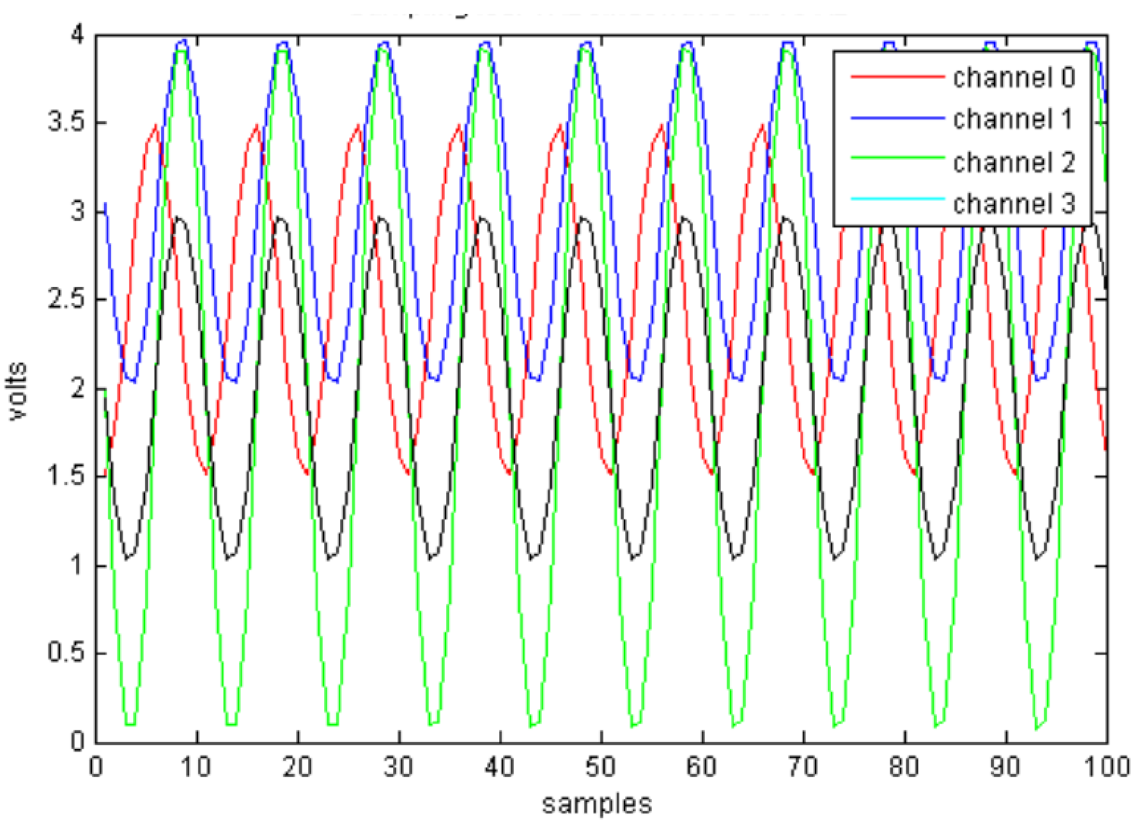

Fig 4.5: Electronic Nose Measurement System Test 1 for Sensor Based Design

A measurement using the electronic nose measurement system is displayed in this result. At a frequency level of 10Hz, four channels are simultaneously sampled. Every sinus wave has a frequency of 1Hz and varies in phase and amplitude.

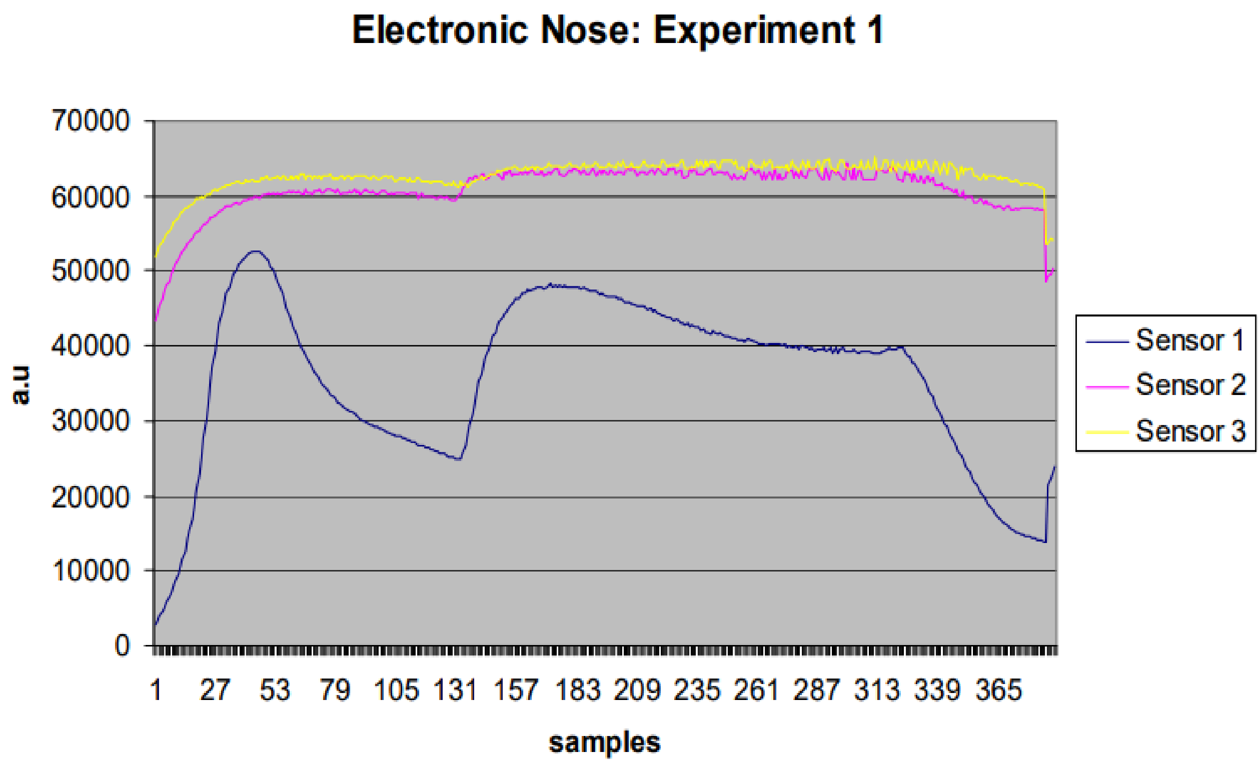

Fig 4.6: Electronic Nose Experiment 1, 100% Queirolo Sensor 1: MQ-2, Sensor 2: MQ-3, Sensor 3: MQ-4

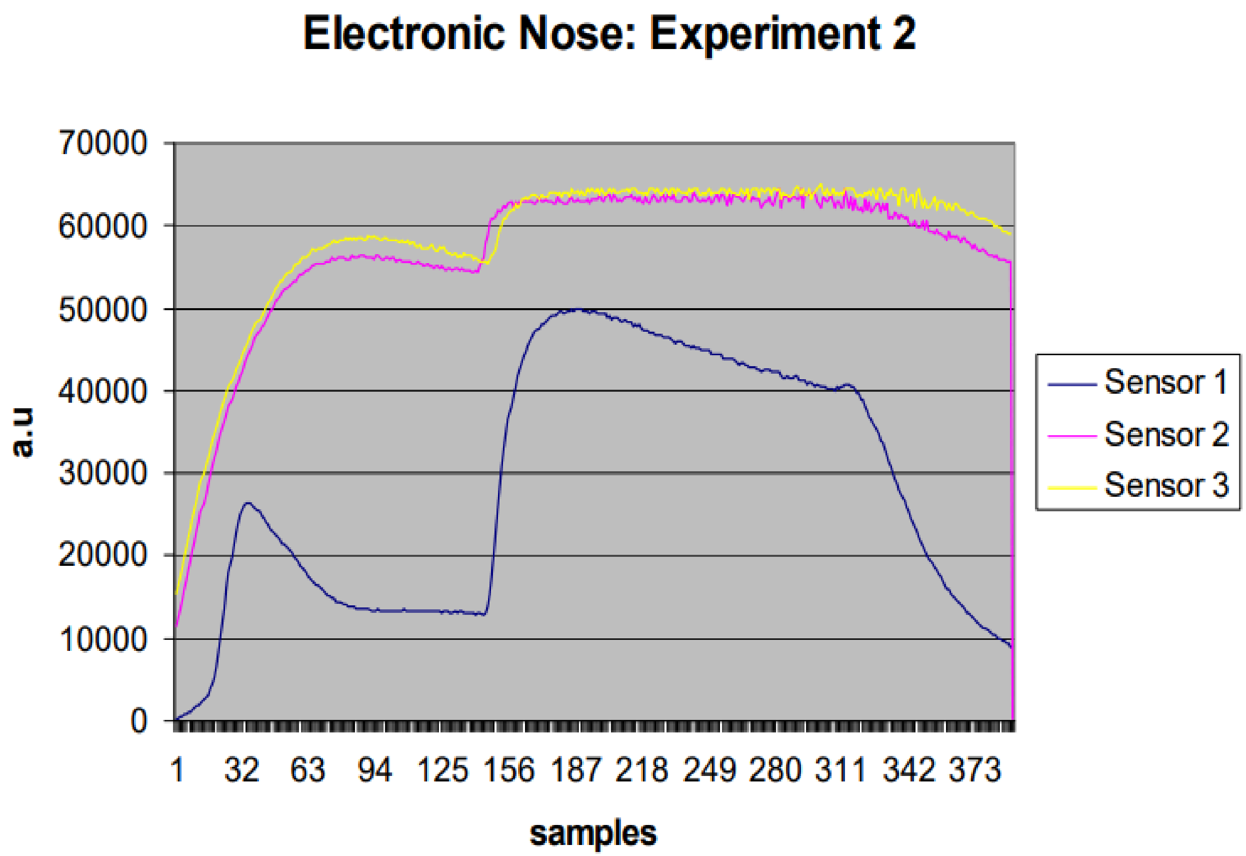

Fig 4.7: Electronic Nose Experiment 2, 75% Queirolo 25% Caballero Carmelo

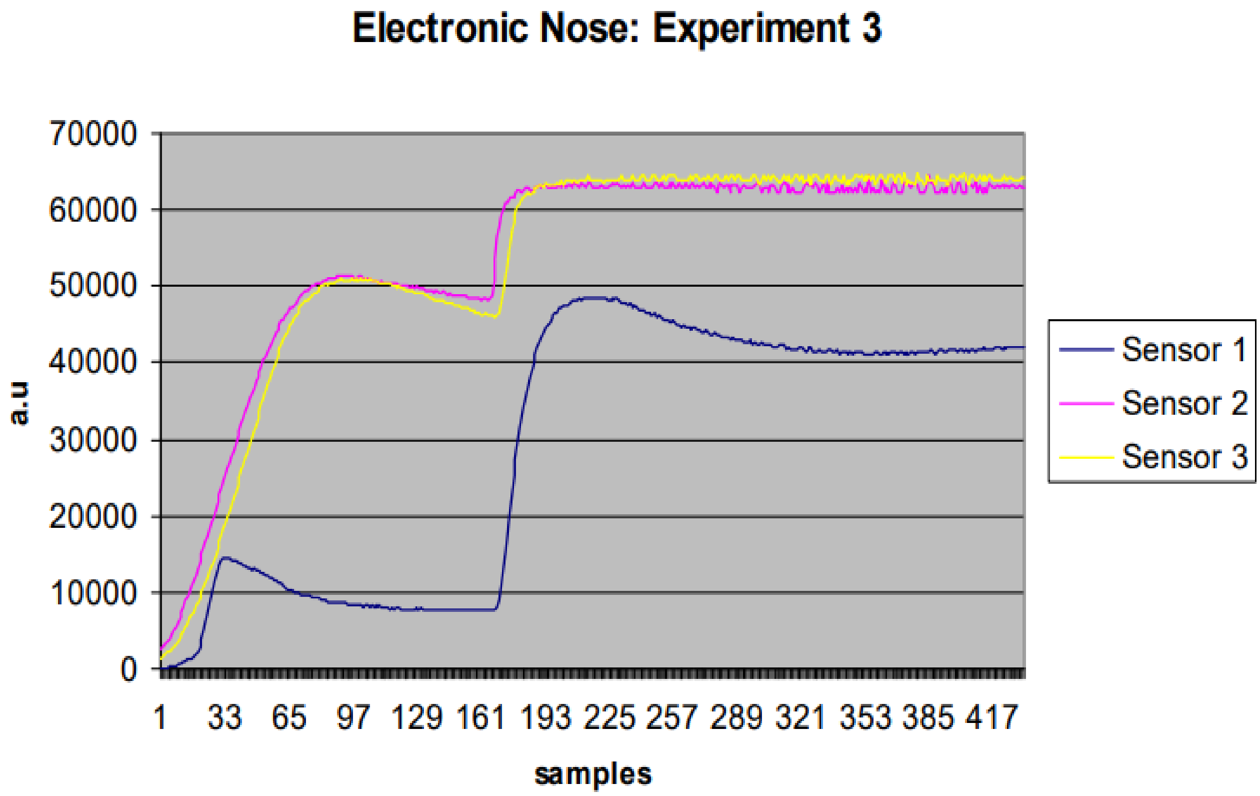

Fig 4.8: Electronic Nose Experiment 3, 50% Queirolo 50% Caballero Carmelo

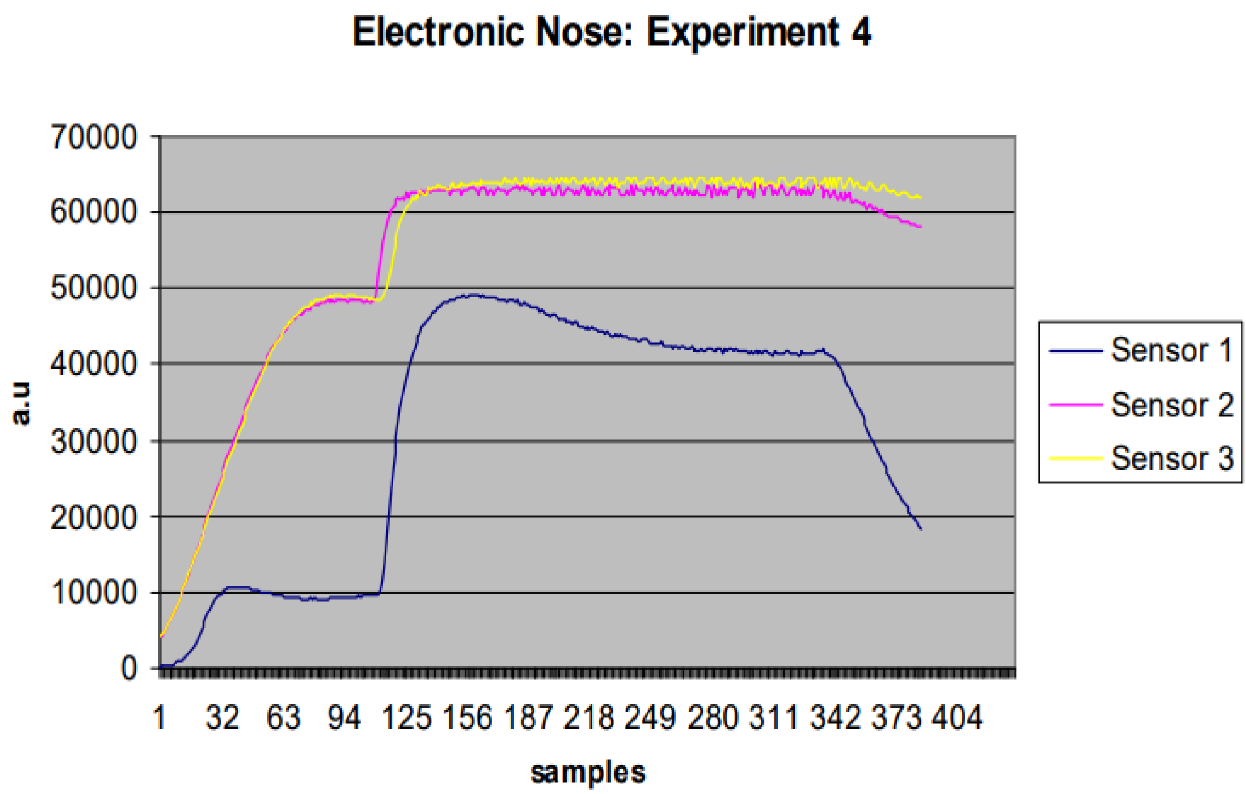

Fig 4.9: Electronic Nose Experiment 4, 100% Caballero Carmelo

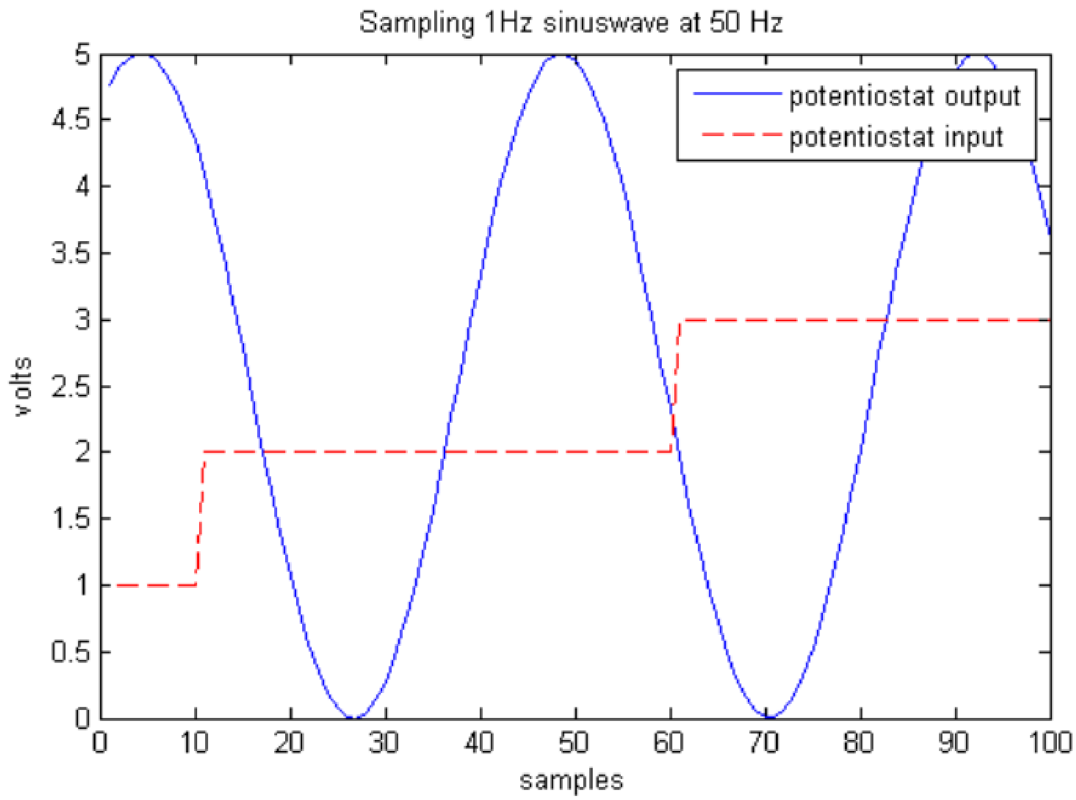

Fig 4.10: Potentiostat Measurement Test

This finding uses a dummy cell and a simulated potentiostat. A measurement using the electronic nose measurement equipment is displayed. The red dashed presents the potentiostat's input which is a square wave that is updated to 50 Hz. It repeats itself with 10 samples at 0V and another 10 samples at 5V. At 50 Hz, a sample of the potentiostat's output is taken. A 2.1k resistor and a 10uF capacitor connected in series served as a dummy cell to mimic an actual electrochemical cell.

4.4.2 Output Performance for Design Approach 2

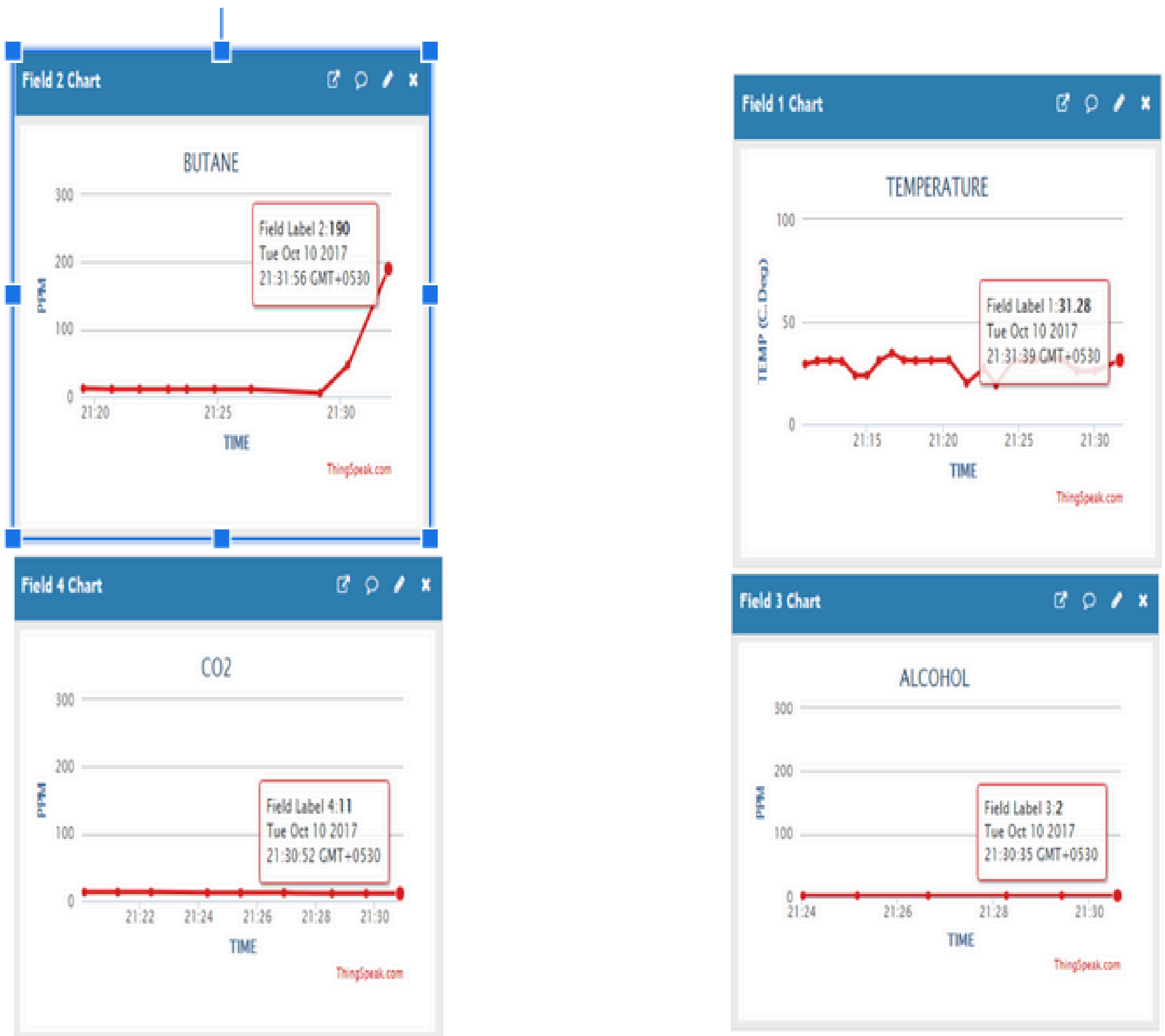

Fig 4.11: Different Gas Detection Using Design Approach 2

4.4.3 Parameters Comparison

We get the values from table 4.1,

Now calculating the **precision factor** for both cases,

- Sensor Based Arrays accuracy,

$$\frac{True\ positive}{True\ Positive + False\ Positive} = \frac{15}{15+5} = 0.75 = 75\%$$

- Machine learning based accuracy,

$$\frac{True\ positive}{True\ Positive + False\ Positive} = \frac{16}{16+2} = 0.8889 = 88.89\%$$

Now calculating the **recall factor** for both cases,

- Sensor Based Arrays recall,

$$\frac{True\ positive}{True\ Positive + False\ Negative} = \frac{15}{15+3} = 0.8333 = 83.33\%$$

- Machine learning based recall,

$$\frac{True\ positive}{True\ Positive + False\ Negative} = \frac{16}{16+1} = 0.9412 = 94.12\%$$

Now calculating the **speed factor** for both cases,

- Sensor Based Arrays speed,

$$\frac{1}{Detection\ time} = \frac{1}{10} = 0.1 \text{ operations/speed}$$

- Machine learning based speed,

$$\frac{1}{Detection\ time} = \frac{1}{15} = 0.0625 \text{ operations/speed}$$

Now calculating the **energy efficiency** for both cases,

- Sensor Based Arrays energy efficiency,

$$\frac{Output}{Input} = \frac{2.8}{3} = 0.93 = 93\%$$

- Machine learning based energy efficiency,

$$\frac{Output}{input} = \frac{7.6}{8} = 0.95 = 95\%$$

Table 4.3: Final Comparison for Both Design Approach

Approach	Precision factor	Recall factor	Speed factor	Energy efficiency
Sensor Based Arrays	75%	83.33%	0.1	93%
Machine Learning Based	88.89%	94.12%	0.0625	95%

4.5 Conclusion

When it comes to accuracy, recall, precision and energy efficiency, Ml-based electronic nose systems perform better than conventional sensor based systems. Machine learning models can lower the incidence of false positives and false negatives since they are very good at identifying intricate patterns in sensor data. When there are several gasses or smells present and accurate classification is essential, this is a big benefit. The Ml system's capacity to learn from big datasets enables it to evolve and get better over time, making it even more effective in precisely identifying and categorizing.

However, when it comes to speed and resource utilization, they are generally better. They are typically speedier in detecting gases because they use simple processing that requires less memory and compute. Their straightforward design enables quicker reaction times, which is crucial in situations requiring instant gas detection. Moreover, demanding machine learning methods, sensor-based systems are usually less costly to construct and use less electricity.

In the end, the Ml-based system is the most effective choice as our main target is high accuracy and precision in gas detection and classification especially in complex or changeable situations. It is perfect for crucial activities like meat contamination detection in industry.

Chapter 5: Completion of Final Design and Validation [CO8]

5.1 Introduction

The application of image processing techniques in determining the freshness of meat has emerged as a promising solution in food safety and quality control. The process begins with the systematic collection of meat samples, which are then analyzed using high-resolution cameras to capture detailed images. These images serve as the foundation for further analysis, where machine learning (ML) models come into play. By leveraging advanced algorithms, the models extract critical features from the images, such as color, texture, and other visual indicators of freshness. Ultimately, the analysis yields a clear output, classifying the meat as either fresh or spoiled. This innovative approach not only enhances the accuracy of meat quality assessment but also aids in reducing food waste and ensuring consumer safety. As the demand for reliable quality assurance methods grows, the integration of image processing and machine learning holds significant potential for the meat industry.

5.2 Completion of Final Design

5.2.1 3D design

The vacuum chamber is a very well planned unit intended for accurate testing and experimental purposes. It has a height of 1 foot and is made up of two sections, one cubical and one cylindrical, which serve the purpose of enhancing the functionality of the unit, as well as providing protection to delicate components or circuits.

The upper section spans the last 4 inches of the chamber and 9 is intended for the essential circuitry and other electronics that are necessary for operation. This part is cut off from the lower part in order to shield the electronic items such as the microcontroller, sensors and wires, etc. from the vacuum. Because the circuitry portions 4 of the system have been separated, there can be no adverse conditions such as pressure difference on the system components or moisture absorbing wires.

The bottom section of the compartment which has a height of 8 inches serves the purpose of accommodating the sample under test. Here, a vacuum is generated and is called the main working area. This zone is made of strong and pressure tight A-grade materials which make this zone maintain low pressure during testing to imitate conditions of use, for example, in food storage, contamination testing, etc. The interior of the compartment is large enough to facilitate different types of samples but small enough to make it easy to remove air when a vacuum is being established.

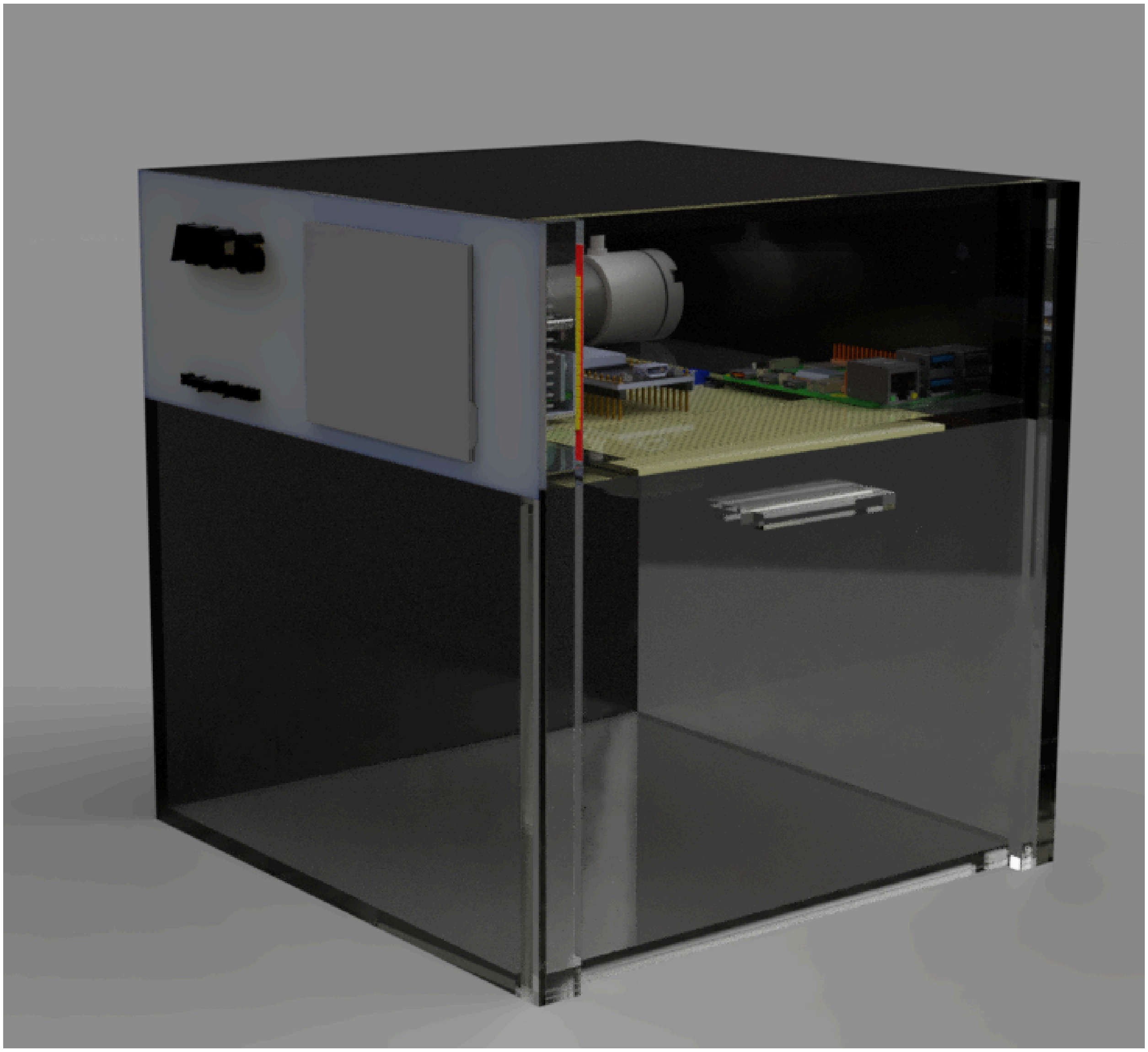

Fig 5.1: 3D Design of the Model (View Point 1)

Fig 5.2: 3D Design of the Model (View Point 2)

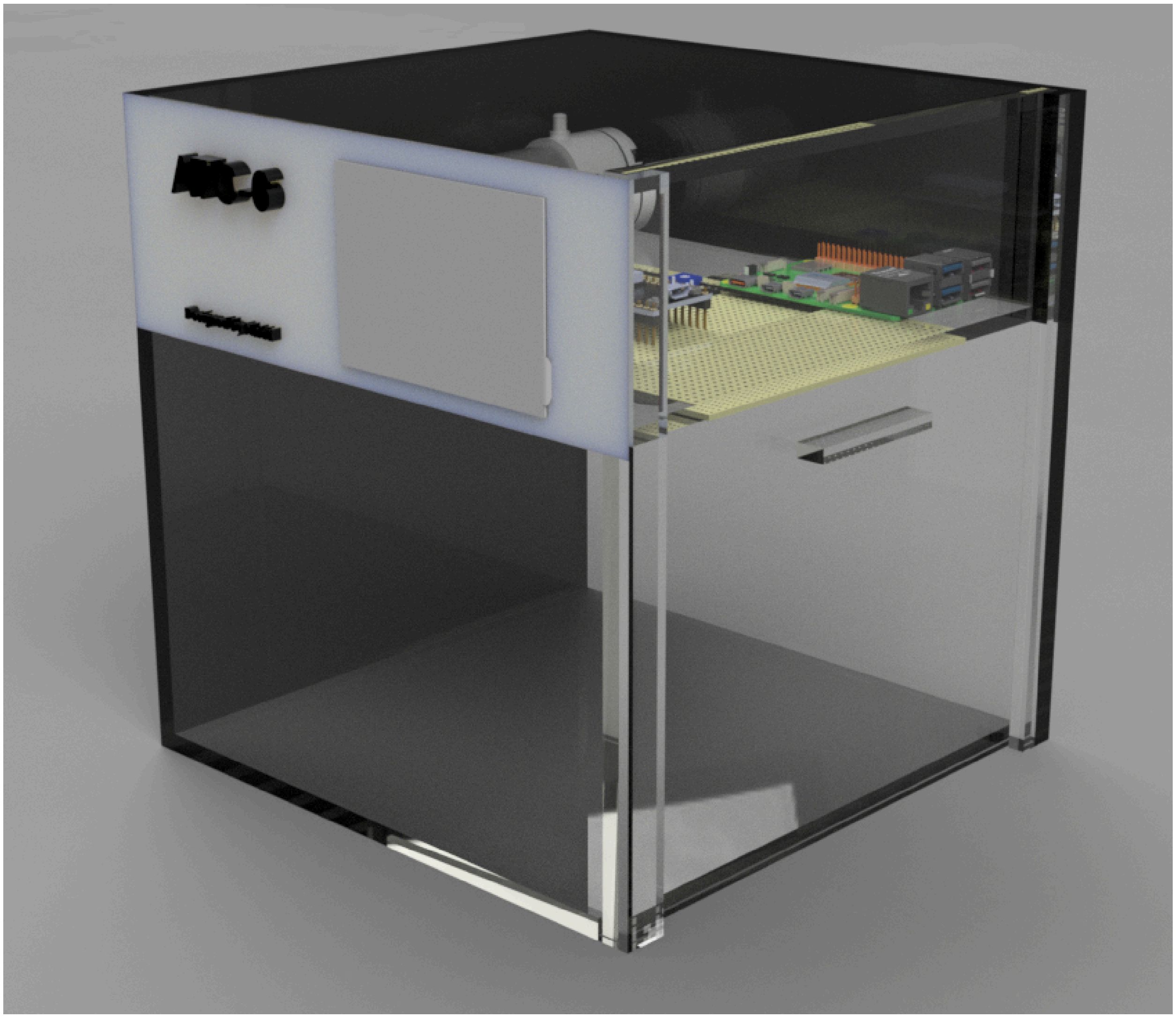

Fig 5.3: 3D Design of the Model (View Point 3)

The chamber is designed with machined interface gaskets and sealing between chambers or access points to eliminate the possibility of any leaks which would prevent the vacuum pump from working effectively to lower the pressures in the sample chamber. It is also worth noting that your chamber has been designed in a way that does not obstruct the sample and the circuitry, thus making it simple to carry out maintenance, adjustments and addition or removal of the samples. The vacuum chamber is a well-designed feature that creates controlled and isolated settings for measurement and testing, which serves to ensure the electrical, as well as mechanical components, function effectively as well as remain safe in the course of the procedure.

5.2.2 Hardware Implementation

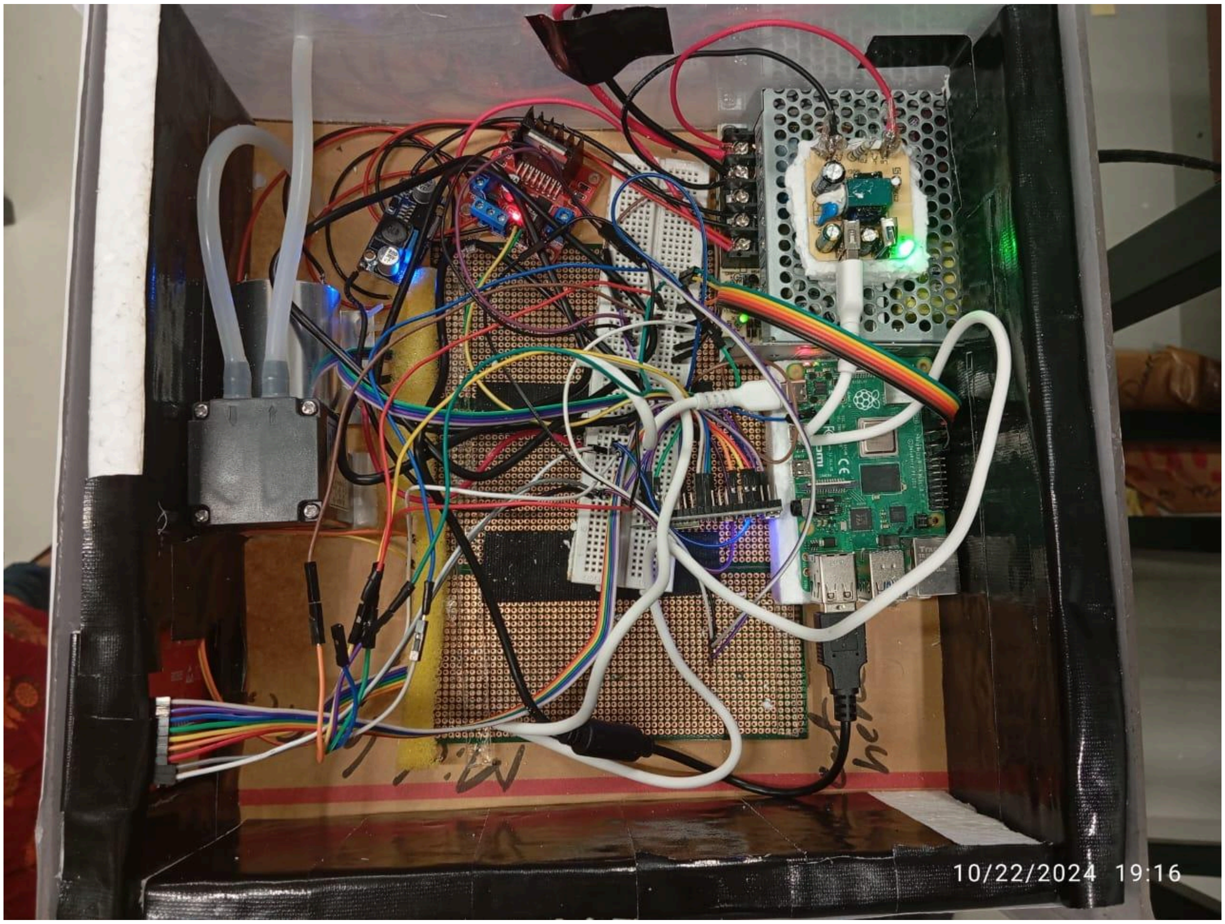

Fig 5.4: Hardware Circuit of the Machine

Fig 5.5: Image of the Vacuum Chamber and Full Machine

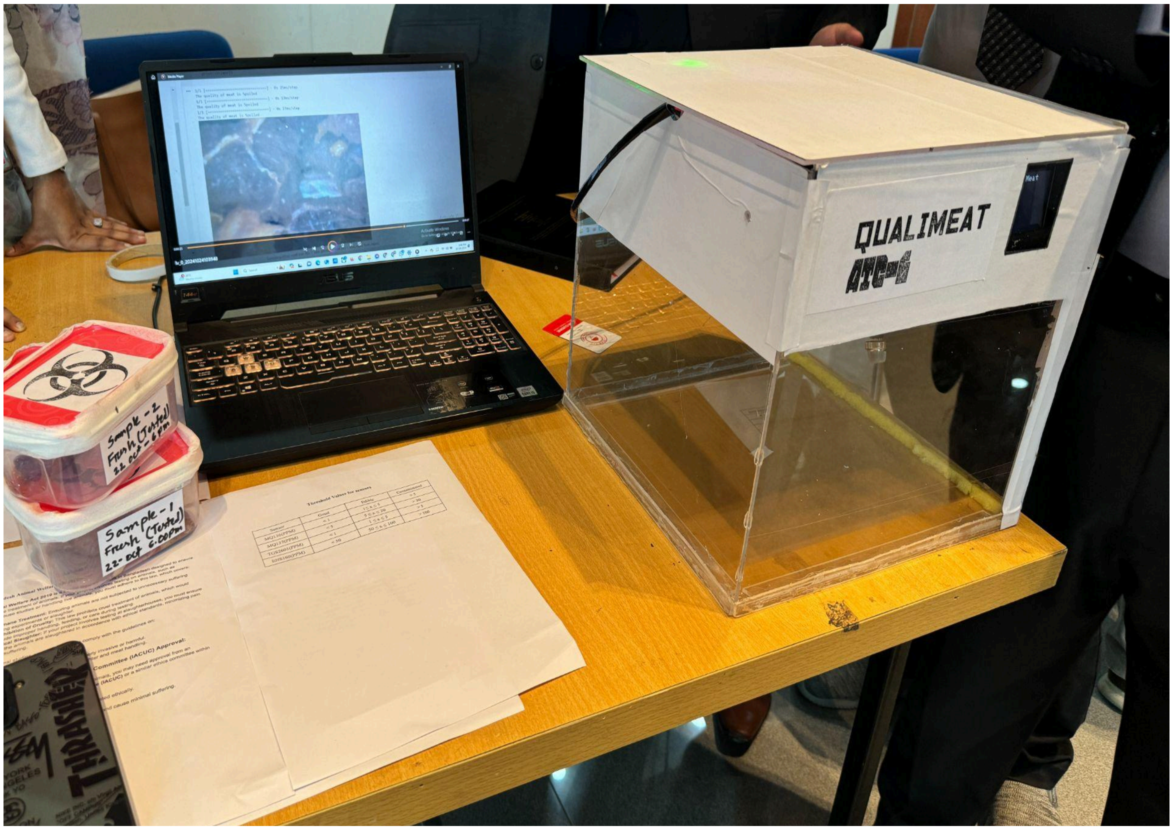

Fig 5.6: Complete Machine with Test Units

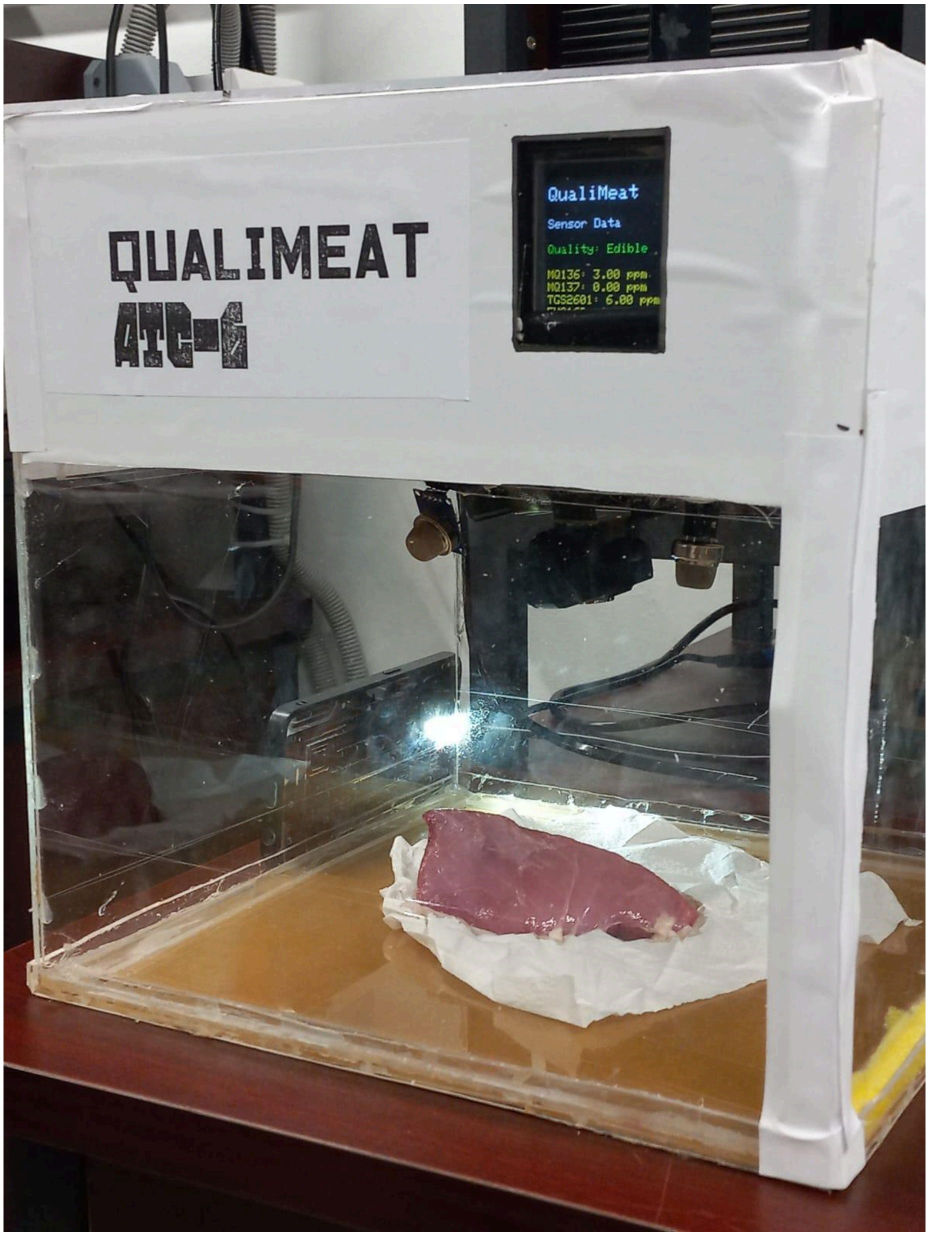

Fig. 5.7: Image of Sample Being Tested Using Our Machine

Assembling within a vacuum chamber, this apparatus allows the use of four sensors and a camera to do meat quality assessment in real time. A vacuum pump is alternatively used to keep ambient temperature constant in an oven while data is processed through Raspberry Pi and FireBeetle 32E. The feedback from the display screen is instantaneous and a mobile app facilitates monitoring the process. With the assistance of the power supply, all parts cooperate well for precise sensor readings and meaningful analysis.

5.2.3 Machine Learning Algorithm

In the final design part we have successfully completed using the image processing technique to identify the meat quality. This unique process of detection explores the modern algorithms to visualize the quality of meat, maintain the exact quality or processing. By squaring machine learning algorithms and high resolution imaging systems, its quality differentiates a variety of meat grading. First we should collect meat samples. Later on using the camera we capture the image. Using ML models features will be extracted. Then, it shows the output, like the meat is Fresh or spoiled.

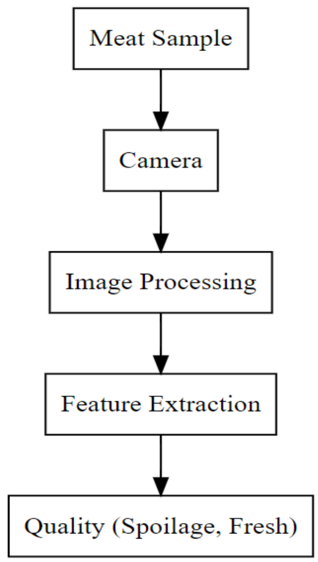

Fig 5.8: Use of Machine Learning (Image Processing)

5.2.3 Data Set

The datasets we used for our ML algorithms are kaggle datasets [13]. On the other hand, we attached 200 samples in our manual hand. Altogether our total data set ration is 1117 is for fresh and 990 is for spoilage meat.

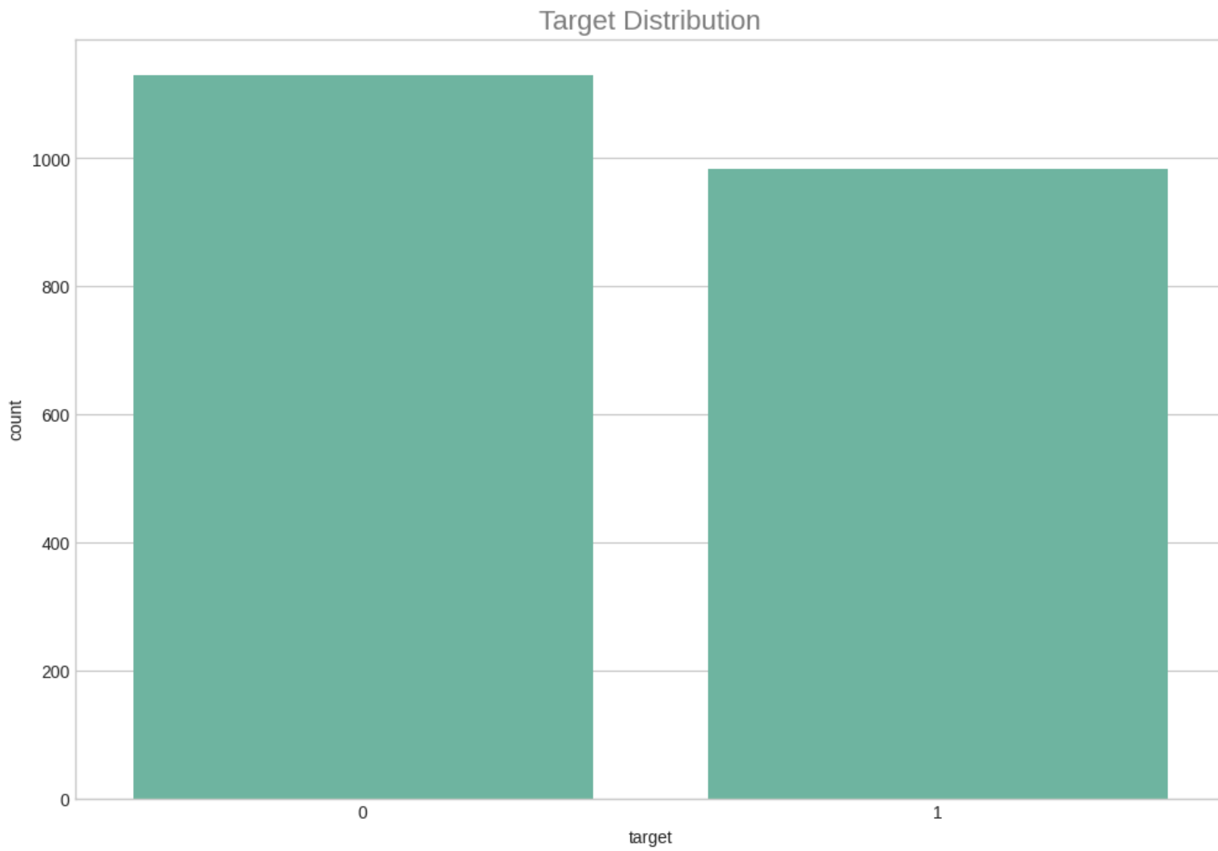

Fig 5.9: Our Targeted Distribution (0) Represented Fresh and (1) Represented Spoiled

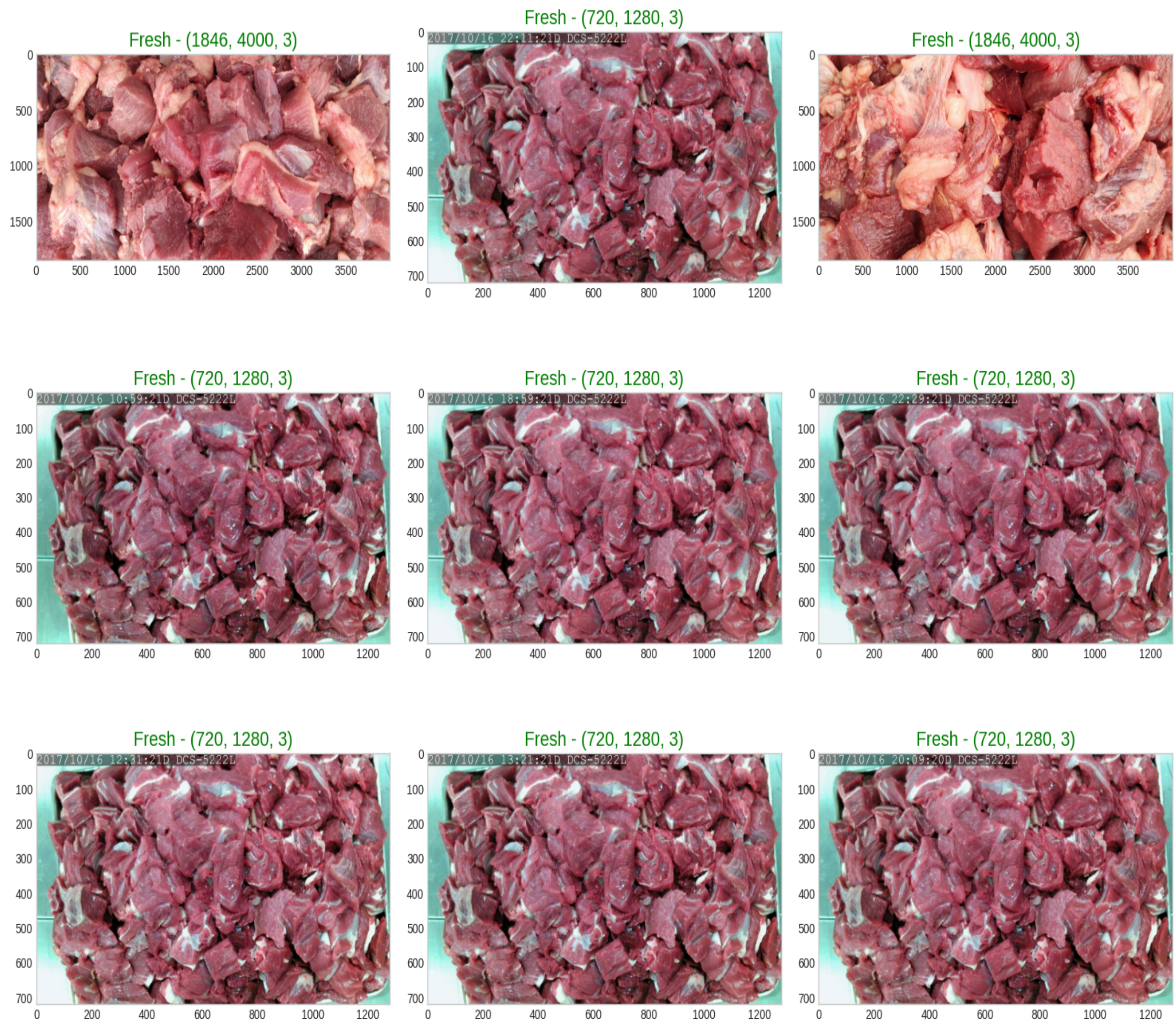

Fig 5.10: Fresh Meat Sample

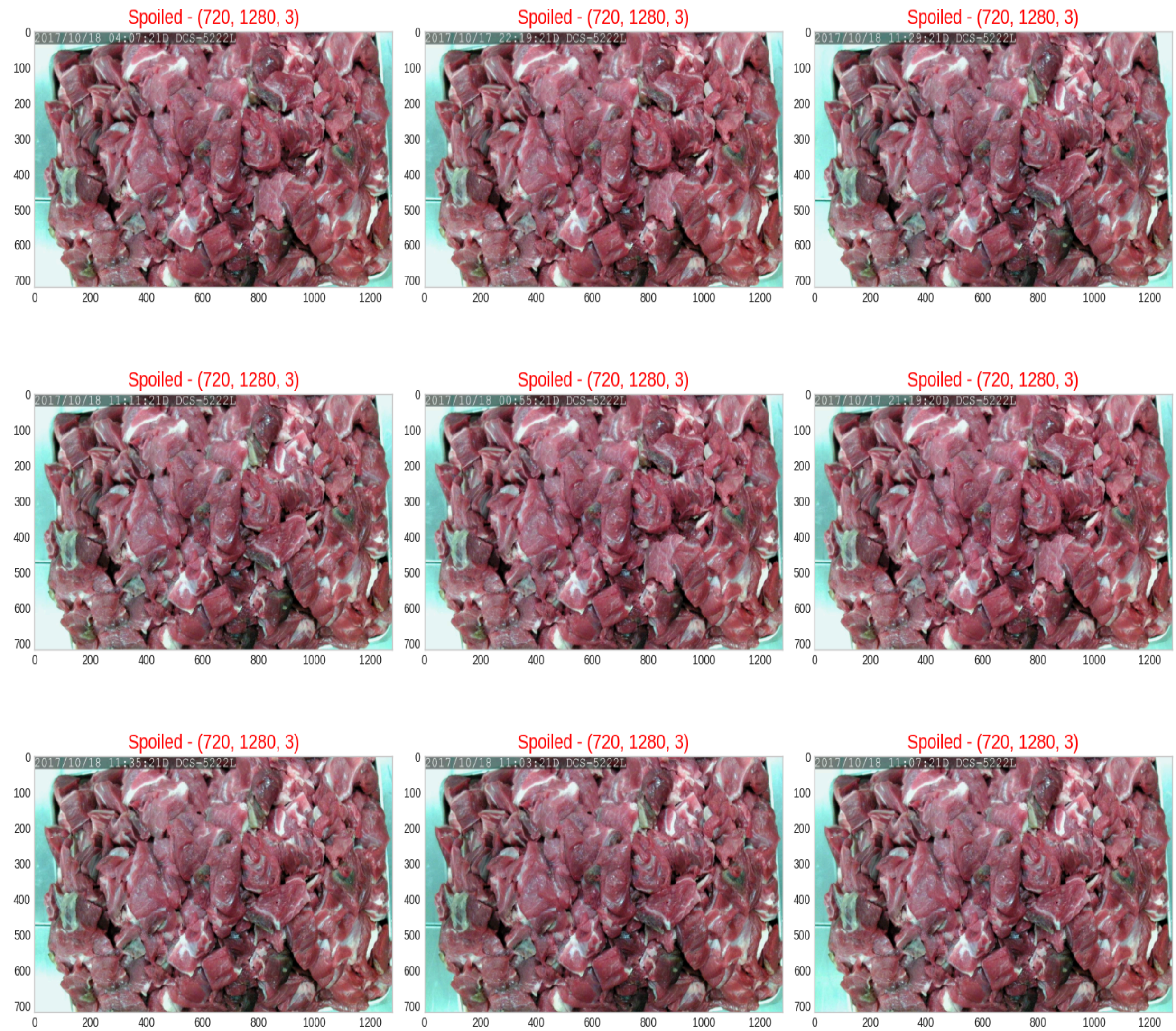

Fig 5.11: Spoiled Meat Sample

Fig 5.12: Train Dataset Images Without Augmentation

Finally, we are done with our samples. Then we applied a Supervised Machine learning technique that helps us to work on these data sets. Also, Our model name is pre-trained Densnet 121 and align with ANN. After that we trained our model, 2107 images belonging to 2 classes. Using 1897 images for training. Using 210 images for validation.

5.2.4 Model Architecture

DenseNet121 is a convolutional neural network architecture characterized by dense connections between layers, which enhances feature propagation and reduces vanishing gradients. Comprising 121 layers, it includes convolutional layers, pooling, dropout, and fully connected layers. This design improves efficiency and performance on various image classification tasks, facilitating deeper learning.

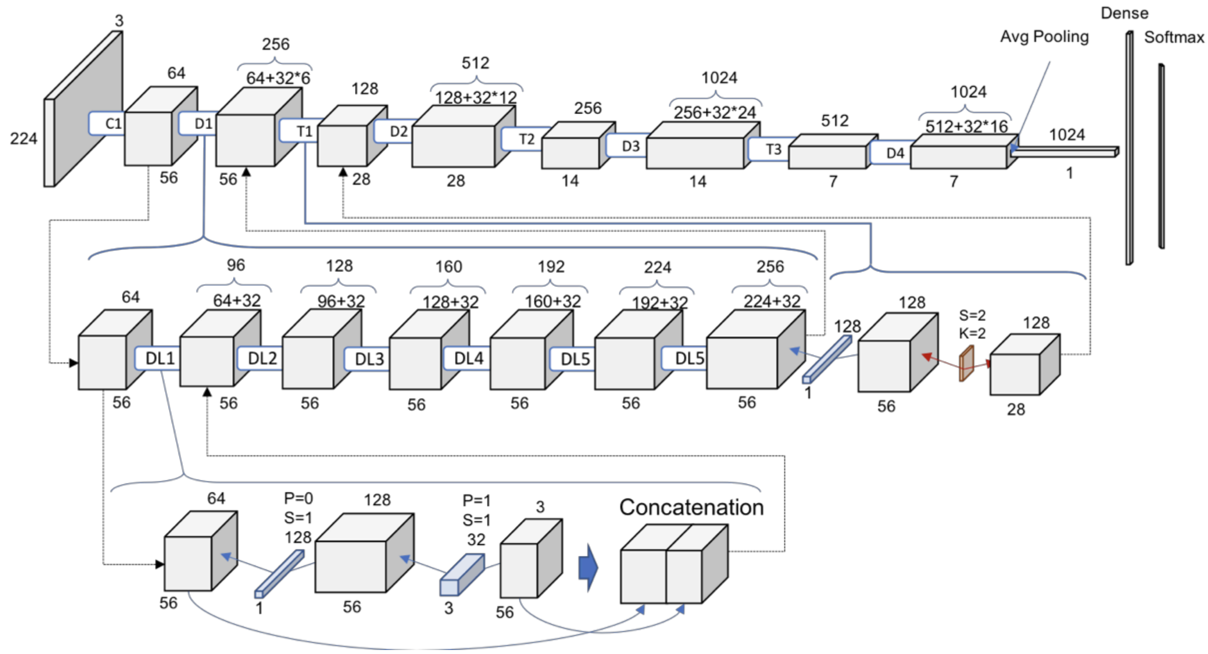

Fig 5.13: Architecture of DenseNet121 model.

5.3 Evaluate the Solution to Meet the Desired Need

This model is built on the DenseNet121 architecture and incorporates several layers to facilitate image classification tasks, particularly suited for distinguishing between categories such as fresh and spoiled meat. The model begins with DenseNet121, a convolutional neural network (CNN) that outputs feature maps of shape (None, 94, 94, 32), effectively capturing intricate visual patterns from the input images. According to this, a layer of global average pooling decreases the dimension of the axis. Moreover, the shoe's result is called the flattened vector and its size is 1024.

On the other hand, it has subsequent layers that result with the connection of (Dense Layer) associated with the layers of Dropout to remove the overfitting condition. Specifically in our model it has 1 Dense layer associated with 128 units, respectively followed by further 64 units. Our final output has 2 units of Danse layer. Following the respected (Fresh and Spoiled) two layers for classification algorithm. The model is sequential and details of model is given below:

```
Layer (type)                Output Shape              Param #
=================================================================
conv2d (Conv2D)             (None, 94, 94, 32)        896

max_pooling2d (MaxPooling2  (None, 47, 47, 32)        0
D)

conv2d_1 (Conv2D)           (None, 45, 45, 64)        18496

max_pooling2d_1 (MaxPoolin  (None, 22, 22, 64)        0
g2D)

conv2d_2 (Conv2D)           (None, 20, 20, 128)       73856

max_pooling2d_2 (MaxPoolin  (None, 10, 10, 128)       0
g2D)

flatten (Flatten)           (None, 12800)             0

dense (Dense)               (None, 128)               1638528

dropout (Dropout)           (None, 128)               0

dense_1 (Dense)             (None, 64)                8256

dropout_1 (Dropout)         (None, 64)                0

dense_2 (Dense)             (None, 1)                 65
```

Fig. 5.14 : Model Summary Densenet 121

Our model has a significant portion of total 1740097 parameters, where 1740097 are used for training, and it takes up approximately 29.03 MB memory. Additionally, the model contains 0 parameters of non-trainable. Our structure is a far efficient learning while managing a sustainable model for the real life application.

Additionally, in every model loss function and model accuracy plays a vital role to measure the performance of a model. Accuracy defines the overall percentage of prediction that our model is correct or not. Similarly, Loss function shows the difference between actual and predicted levels. A good performing model gives high accuracy value and must give the less low value, resulting in the most effective and good performance at the time of training periods. Monitoring these metrics throughout the training process helps optimize the model and ensure reliable predictions in real-world applications.

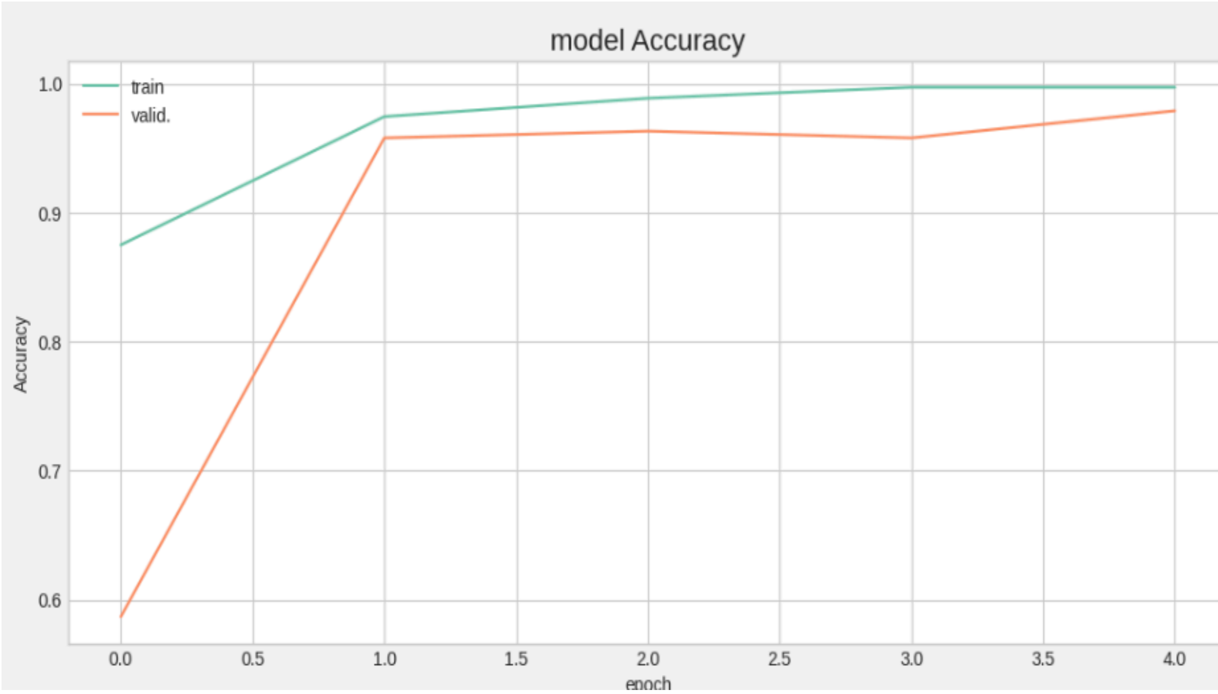

Fig. 5.15: Model Accuracy of Our Esteemed Model

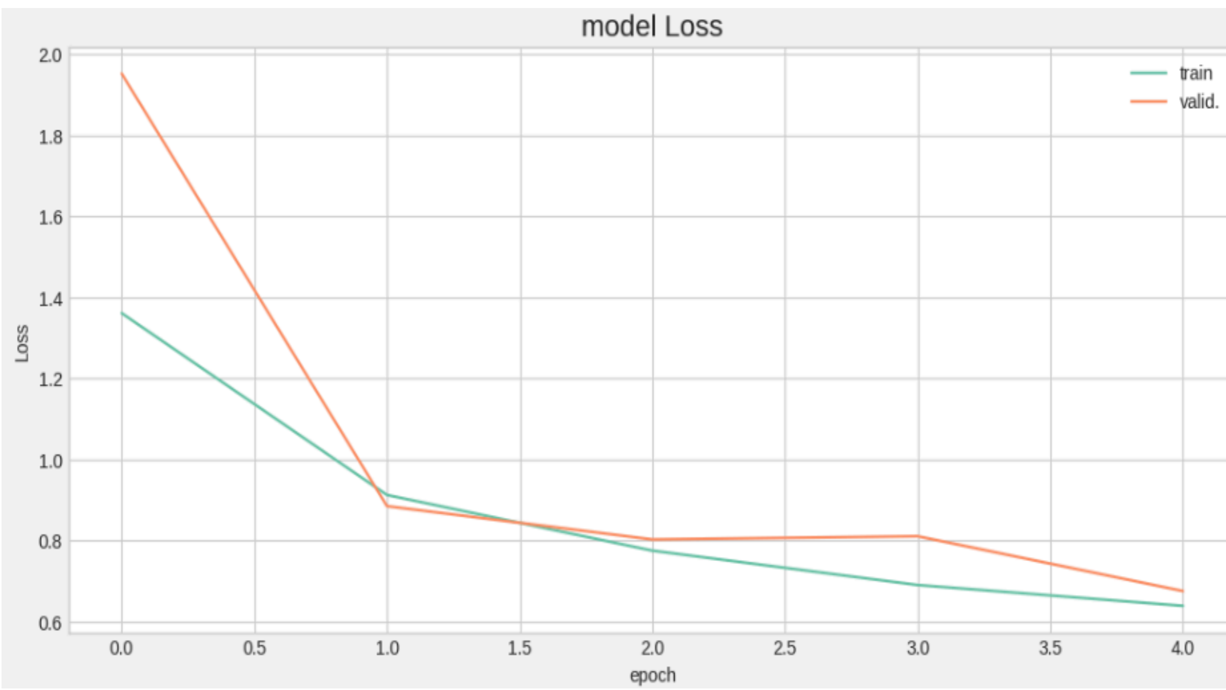

Fig 5.16: Loss Function of Our Esteemed Model

```
Evaluate Model....
24/24 [==============================] - 65s 3s/step - loss: 0.2789 - accuracy: 0.9921
{'loss': 0.2789297103881836, 'accuracy': 0.99210524559021}
```

After the evaluation of our model. The total accuracy of our model is 99%. On the other hand tha loss function is 0.27, which is very low and negligible for our model predictions. So, finally because of our good accuracy which is pretty dependable and believable in our meat contamination identification system.

5.4 Conclusion

In conclusion, the application of image processing techniques for assessing meat quality offers a promising approach to enhance food safety and reduce waste. The process begins with the careful collection of meat samples, followed by capturing high-quality images using a camera. For Example,

We just take a fresh image and spoiled meat from our home to find out if our model is working or not.

Fig 5.17: Fresh Meat Image as a Sample for Detection

After passing through the algorithm our prediction shows that,

```
1/1 [==============================] - 0s 82ms/step
The quality of meat is Fresh
```

So, the figure represents that Our ML Image processing Image technique works the actual way in our to find out the fresh and spoiled meat detection.

Fig 5.18: Spoiled Meat Image as a Sample for Detection

After passing through the algorithm our prediction shows that,

```
1/1 [==============================] - 0s 136ms/step
The quality of meat is Spoiled
```

So, it’s proved that by employing machine learning models, specific features of the meat are analyzed to determine its freshness. The outputs of this analysis provide clear indications of whether the meat is fresh or spoiled, enabling consumers and retailers to make informed decisions. This innovative method not only streamlines quality assessment but also has the potential to improve overall efficiency in food supply chains. As technology continues to advance, the integration of image processing and machine learning in food safety practices could significantly contribute to public health food safety.

Chapter 6: Impact Analysis and Project Sustainability [CO3, CO4]

6.1 Introduction

As our project mainly aims to ensure the public health and safety issues by providing the spoilage detection of the meat that the consumers will buy from the super shops, our project has a great impact on preventing foodborne diseases and also on the society. Not only for our project, impact analysis is a critical component of any project to assess the project's sustainability throughout the implementation of the project.

For our project, it can be also said that it would be a very sustainable project once it's successfully implemented by evaluating the potential impact of our project on various stakeholders, including consumers, producers and other individuals. Besides, our project also addresses sustainability in terms of environmental, economic and social aspects. Our goal is not only to ensure immediate benefits through the project, but also we have the plan to ensure long lasting viability through the project after it's successfully implemented, by contributing to ensuring food safety and continuation of the meat supply chain.

6.2 Assess the Impact of the Solution

Throughout the implementation of our meat spoilage detection system, we are expecting to have a long lasting impact on multiple areas,which can be categorized as follows:

6.2.1 Impact on Public Health and Well-Being

The most significant impact of our project will be the detection of the spoilage of meat products to avoid foodborne illnesses. These early detection of contaminants will help to prevent meat related health safety issues and ultimately it will help to reduce public health risks [32]. By maintaining food safety throughout the process, consumers will trust the sellers about the condition of the meat while buying it[33].

6.2.2 Impact on Consumer Satisfaction

As our project offers to accurately determine the conditions of the meat through the system, it will ensure that higher-quality meat products will be reached to the consumers. As a result, if it is successfully implemented, it will boost the trust among the consumers and meat suppliers will also try their best to maintain their highest standards to provide the best quality of meat [33]. If the transparency of the grading process can be maintained properly, it will allow the consumers to see the accurate conditions of the meat and thus it will improve the overall satisfaction of the consumers with the meat quality.

6.2.3 Economic Impact on Meat Supply Business

Once the project is successfully implemented, it will not only help the consumers but also have a great economic impact on the meat supply business. The overall standards of meat supply will increase as the condition of any spoiled meat will be detected throughout our system. The people who wish to sell spoiled meat will not be able to do so, as they also will need to maintain the highest standard of supplying fresh meat[34]. However, once the consumers will be comfortable with the standards of this detection system on the super shops, medium and small scale businesses from the cities and villages may struggle to follow that highest standard.

6.2.4 Impact on Enforcing Food Safety Standards

After successfully running our project it will also help the regulatory bodies to enforce the available meat safety standards with more effectiveness. The system will also have an impact on the monitoring and enforcement process, which will help the respective authority to ensure that only the fresh, safe and high standard maintained meat reaches the market and to the consumers[35]. Additionally, the project can also help with the data collection for the authoritative body to provide more valuable insights for meat spoilage related illness.

6.2.5 Environmental Impact

Our project can play a vital role to reduce food waste by identifying the spoiled meat earlier before the consumers buy it. As a result of this, it will help to minimize the disposal of spoiled meat products in the environment. As the spoiled meat discharges toxic gasses in the environment [19]. So, when the meat spoilage gets detected early, it will help to minimize those toxic gas releases in the environment.

6.2.6 Social Impact

With the detection of meat spoilage our project will also increase the accountability and ethical practices among the meat supply industry, to ensure that they are supplying fresh meats and this will ensure a significant good impact in the society as the meat supply businesses have to be honest with the consumers and consumers will regain their trust towards the suppliers, if the project can be implemented successfully [14]. Besides, it will help safeguard public health and the system will also contribute to our societal well-being in the long-term.

6.3 Evaluate the Sustainability

With the multiple positive impacts of our project, the sustainability of this project includes areas like: environmental, economic and social dimensions which are vital for long-term growth of the project.

6.3.1 Environmental Sustainability

One of the major factors of our project sustainability will be reducing the negative environmental impact of spoilage meat production, supply and waste. The system will also help to minimize the wastage from spoilage or contamination of the meat products by determining those early which will be helpful to lower the environmental footprint of the meat industry by decreasing waste and encouraging more responsible practices in production, handling, and processing[19].

6.3.2 Economical Sustainability

Our project would be also economically sustainable, when it will provide cost-effective solutions that can be adopted by the meat businesses of all sizes, from large-scale meat suppliers in the cities or supermarkets to small farms or shops. Though the initial making of the project might get economically harder to afford for the small meat related businesses but with more investment in technologies in near future we will be able to overcome those concerns and make them sustainable for the long run. Besides, the use of our gas sensors and machine learning models will serve long-term benefits, such as improving product quality, reducing foodborne illnesses, and increasing consumer trust. Again, economic sustainability will be achieved by providing adequate training and resources to the medium and small scale businesses for running the system, which will help them to adopt the system without suffering any financial strain.

6.3.3 Social Sustainability

Social sustainability will focus on fairness and equity within the continuous supply of the fresh meat. The grading and contamination identification system will be gradually accessible to all producers, including small-scale and rural farmers, to prevent monopolization by large corporations. Additionally, by ensuring fair trade practices and promoting ethical treatments, the system will promote social responsibility within the meat industry. The project will also ensure that the benefits of improved food safety reach all levels of society.

6.3.4. Technological Sustainability

For long term sustainability, it is needed to use the technology that is upgraded and new to adopt not the previously used technology till this date for meat spoilage. The new responsible contaminants also need to be involved to identify the song behind spoilage of meat. The system can gradually be able to adopt all this advancement from time to time.

6.3.5. Cultural Sustainability

In our country, most of the regions have to consume meat for different purposes. And here, most of the supply and consumption are deeply connected with cultural practice. So, the system will be needed to work with flexibility that can cooperate with cultural variations , according to the ethical standards of food safety and public health consideration. The collaboration with the cultural values of the system can have a greater acceptance across different communities.

6.4 Conclusion

Our project is building up on the concept of a meat spoilage and contamination identification system that has the potential to substantially impact the public health , consumers' trust and the meat industry of processing meat in a whole system. However, early detection can reduce the possibility of foodborne illness and the safety of the food industry can be increased. Besides, our project also, adresse environmental , economical, social and technological challenges to be sustainable which ensures that it can be maintained and scaled. By promoting ethical practices and fostering collaboration between producers, regulators, and consumers, the system can create long-term benefits. Its sustainability will also increase with its ability of adapting future needs, while remaining cost-effective and accessible to all stakeholders in the meat supply chain. As a result, the project will contribute to a healthier, safer and more equitable food system for all in the long run.

Chapter 7: Engineering Project Management [CO11, CO14]

7.1 Introduction

Engineering management is a very important and crucial aspect of any technological pursuit specially when it comes to industry like food safety and quality control where the exact execution and coordination are must for ensuring the public health and business success . In the term of meat spoilage detection, as this is an engineering project it needs so many technologies which must be advanced. Such as, sensors, machine learning and real time monitoring systems that can always help to early identification of the meat. This chapter outlines the application of engineering project management in developing a meat spoilage detection system. It highlights the importance of setting clear objectives , structured workflow and continuous progress evaluation to ensure timely and high quality outcomes. Key steps discussed include project definition, planning and success evaluation based on performance.

7.2 Define , Plan and Manage Engineering Projects

The first step in managing a meat spoilage detection project is to clearly define the scope and objectives focusing on creating a real time monitoring system using gas sensors, machine learning and image processing to detect spoilage indicators like VOCs and bacterial activity. Aligning technical and business requirements with industry public health and sustainability goals is crucial. Project planning involves outlining tasks, timelines and resource allocation, With collaboration between engineering , data scientists, microbiologists, and food safety experts. Teams address sensor development , machine learning and risk mitigation for potential challenges like technological or regulatory issues. Effective management ensures team members understand their roles particularly during prototype testing and emphasizes continuous communication. Progress must be tracked closely with project adjustments made as needed to stay on schedule and budget often aided by project management software.

Table 7.1: FYDP (P) Students and ATC Details

	Final Year Design Project (P) Fall 2023		
Student Details	**Name & ID**	**Email Address**	**Phone**
Member 1	Md. Fardaus Hasan Faruk 20321024	md.fardaus.hasan.faruk@g.bracu.ac.bd	
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Member 3	Md. Rakibul Islam 20321030	md.rakibul.islam9 @g.bracu.ac.bd	
Member 4	Sakib Sadi 20321052	sakib.sadi@g.brac u.ac.bd	
Member 5	Tasnuva Meherin Srabonti 20121067	tasnuva.meherin.sr abonti@g.bracu.ac. bd	
ATC Details:			
ATC 1			
Chair	Dr. A.S. Nazmul Huda	nazmul.huda@brac u.ac.bd	
Member 1	Raihana Shams Islam Antara	raihanashams.antar a@bracu.ac.bd	
Member 2	Nahid Hossain Taz	nahid.hossain@bra cu.ac.bd	

Table 7.2: FYDP (P) Fall 2023 Summary of Team Log Book/ Journal

Date/Time/Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
5-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. General discussion 2. Proposing few topic 3. Proposing new ideas	Task 1: All Task 2: Rakib, Shihab Task 3: Faruk	N/A as it was an Introductory meeting. Task 1: completed. Task 2: partially Completed. Task 3: Completed.
12-10-2023	1. Faruk	1. Gather	Task 1: All	Task:1 Partially

(Weekly ATC Consultation)	2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	information about food contamination 2.Learn the working mechanism of Electronics nose system 3. Find the major defects in yarn production 4. Finalizing topic	Task 2: Tasnuva, Shihab Task 3: Faruk Task 4: Rakib, Sadi	Completed Task 2: Not Completed Task3: Partially Completed Task4: Completed
19-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Learn the working mechanism of Electronics nose 2.Gather information about	Task1: Faruk, Nahid, Rakib Task2: Tasnuva, Sadi	Task1: Completed Task2: Completed
26-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Modification of system specification	Task1:Faruk, Rakib, Shihab, Sadi, Tasnuva	Task1: Partially Completed
26-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Final modification of design approach 2. Consultation regarding international codes 3. Final discussion regarding functional and nonfunctional requirement	Task1: Faruk, Nahid Task 2: Sadi, Tasnuva Task 3: Rakib	Task1: Completed Task2: Completed Task3: Completed
16-11-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. specific details about design approach 2.Effective method selection 3.Problem solving about grading and contamination detection	Task1:Faruk, Rakib Task2: All Task3: Nahid, Sadi, Tasnuva	Task 1: Completed Task 2: Partially Completed Task 3: Partially Completed
23-11-2023 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi	Design approach modification	Task: All	Task1: Completed

	5. Tasnuva			
7-12-2023 (Additional Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	Task 1: Survey form Task 2: Discuss with real problem of customer	Task 1: Tasnuva Task 2: Nahid, Rakib, Faruk, Sadi	Task 1: Completed Task 2: Completed
8-12-2023 (Additional Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Finalizing the project proposal 2. Specification and Functional & Non Functional requirements modification.	Task 1: Tasnuva, Faruk Task 2: Nahid, Rakib, Sadi	Task 1: Completed Task 2: Completed

Table 7.3: FYDP (D) Students and ATC Details

	Final Year Design Project (D) Spring 2024		
Student Details	**Name & ID**	**Email Address**	**Phone**
Member 1	Md. Fardaus Hasan Faruk 20321024	md.fardaus.hasan.faruk@g.bracu.ac.bd	
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Member 3	Md. Rakibul Islam 20321030	md.rakibul.islam9@g.bracu.ac.bd	
Member 4	Sakib Sadi 20321052	sakib.sadi@g.bracu.ac.bd	
Member 5	Tasnuva Meherin Srabonti 20121067	tasnuva.meherin.srabonti@g.bracu.ac.bd	
ATC Details:			

ATC 1			
Chair	Dr. A.S. Nazmul Huda	nazmul.huda@bracu.ac.bd	
Member 1	Raihana Shams Islam Antara	raihanashams.antara@bracu.ac.bd	

Table 7.4: FYDP (D) Spring 2024 Summary of Team Log Book/ Journal

Date/Time/Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
5-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. General discussion with our ATC panel members.	Task 1: All	N/A as it was an Introductory meeting.
12-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Select tools and software for software simulation	Task 1: All	Task:1 Partially completed
19-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Finalize tools for software simulation. 2. Software implementation first designing approach. 3.Using Proteus, altium, fusion 360.	Task1: All Task2: Faruk, Nahid, Rakib Task3: Tasnuva, Sadi	Task1: Completed Task2: Partially Completed Task3: Partially Completed
26-03-2024 (Weekly ATC	1. Faruk 2. Shihab	1.Software implementation	Task1:Faruk, Rakib, Shihab,	Task1: Partially Completed

Consultation)	3. Rakib 4. Sadi 5. Tasnuva	first designing approach 2. Using Proteus, altium, fusion 360. 3. Making slides for progress presentation.	Sadi, Tasnuva	Task 2: Partially Completed Task 3: Completed
26-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	4. Progress Presentation	Task1: Faruk, Nahid Task 2: Sadi, Tasnuva Task 3: Rakib	Task1: Completed
16-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Fixing the software error from the ATC'S feedback 2. Implement our third design approach using a machine learning algorithm.	Task1:Faruk, Rakib Task2: All Task3: Nahid, Sadi, Tasnuva	Task 1: Completed Task 2: Partially complete
23-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Implement our third design approach using a machine learning algorithm. 2. Implement another machine learning algorithm to justify the software accuracy.	Task 1: Rakib, sadi Task 2: Rakib, Faruk	Task 1: Completed Task 2: Completed
1-05-2024 (Additional Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Finding best design solutions are explored to find the optimal solution	Task 1: All	Task 1: Completed
5-05-2024 (Weekly ATC	1. Faruk 2. Shihab	1. Making the slides for the final	Task 1: All Task 2: All	Task 1: Completed Task 2: Completed

Consultation)	3. Rakib 4. Sadi 5. Tasnuva	presentation. 2. Final presentation.		

Table 7.5: FYDP (C) Students and ATC Details

	Final Year Design Project (C) Summer 2024		
Student Details	**Name & ID**	**Email Address**	**Phone**
Member 1	Md. Fardaus Hasan Faruk 20321024	md.fardaus.hasan.faruk@g.bracu.ac.bd	
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Member 4	Sakib Sadi 20321052	sakib.sadi@g.bracu.ac.bd	
Member 5	Tasnuva Meherin Srabonti 20121067	tasnuva.meherin.srabonti@g.bracu.ac.bd	
ATC Details:			
ATC 1			
Chair	Dr. A.S. Nazmul Huda	nazmul.huda@bracu.ac.bd	
Member 1	Raihana Shams Islam Antara	raihanashams.antara@bracu.ac.bd	
Member 2	Sharif Mohd Shams	sharif.mohd@bracu.ac.bd	

Table 7.6: FYDP (C) Summer 2024 Summary of Team Log Book/ Journal

Date/Time/Place	**Attendee**	**Summary of Meeting Minutes**	**Responsible**	**Comment by ATC**
22-07-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. FYDP-C, First session attending.	Task 1: All Task 2: Rakib, Shihab Task 3: Faruk	N/A as it was an Introductory meeting.
29-07-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Order the components for our proposed model 2. Complete the payment for the components.	Task 1: Faruk Tasnuva,Shihab Task 2: Rakib Sadi	Task:1 Partially Completed Task 2: Completed
19-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Received and collect all the components	Task1: All	Task1: Completed
09-09-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Starting of implementation of pcb designing, 2. Order the pcb for hardware.	Task1: Shihab, Sadi, Tasnuva Task2: Faruk, rakib	Task1: Partially Completed Task 2: Completed
23-09-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1.Using the components making the final project. 2. Integrating ML in hardware.	Task1: Faruk Tasnuva,Shihab Task2: Rakib, Sadi	Task1: Partially Completed Task2: Partially Completed

07-10-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1.Using the components making the final project. 2. Integrating ML in hardware.	Task1: Faruk Tasnuva,Shihab Task2: Rakib, Sadi	Task 1: Partially Completed Task1: Partially Completed
14-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1.Using the components making the final project. 2. Integrating ML in hardware.	Task 1: All Task 2: All	Task1: Completed
14-10-2024 (Additional Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Complete the report writing and final improvements for report writing 2. Finalized the design report	Task 1: Tasnuva Task 2: Nahid, Rakib, Faruk, Sadi	Task 1: Completed Task 2: Completed
22-10-2024 (Weekly ATC Consultation)	1. Faruk 2. Shihab 3. Rakib 4. Sadi 5. Tasnuva	1. Report summary and design report improvements for report writing 2. Finalized the design report 3. Making posters for presentations.	Task 1: Tasnuva, Faruk Task 2: Nahid, Rakib, Sadi Task3: All	Task 1: Completed Task 2: Completed Task 3: Completed

7.3 Evaluate Project Progress

Evaluating an engineering project's progress requires setting measurable indicators, such as sensor accuracy, machine learning model efficiency and hardware software integration. Regular milestone reviews help identify deviations and make necessary adjustments.Success is measured by technical and operational outcomes. Technically, tests should verify accurate detection of spoilage indicators across various meat types and conditions and the machine learning models must reliably predict spoilage. Operationally, the system’s scalability and cost effectiveness should be assessed including real world tests in settings like meat processing plants and cost analyses for industry adoption. Feedback from stakeholders ensures the project aligns with industry and societal goals and final assessments should highlight strengths and areas for improvement.

7.4 Conclusion

Effective project management is essential for developing complex systems like meat spoilage detection. By defining clear objectives, creating a detailed plan and regularly evaluating progress managers ensure the project meets its technical , operational and business goals. In meat silage detection the focus extends beyond creating a reliable system to addressing public health, economic and environmental issues related to food safety and waste. With proper management this technology can help prevent foodborne illness, improve meat quality and reduce food waste and environmental impact.

Chapter 8: Economical Analysis [CO12]

8.1 Introduction

Nobody wants to spend his potent resources on something that appears to be doomed from the start, especially with time, resources and funds on the line. In order for any innovation process to be successful in the current market, it has not only to resolve an issue but also to generate profits. Our sensor-based system for detecting food contamination is no exception. However, in order to attract potential investors, interested parties, and future customers, this project should, indeed, bring cash and practical benefits.The core of our design is proving that such values as decrease of food loss, increase of food safety, and warning users of critical updates of the battery system is more valuable than the costing of its parts. While the primary costs of sensors, microcontrollers and wireless communication peripherals may look very high, the benefits over time and even socially justifies this system.Because of all that, evaluating the cost structure, estimating returns and market for our project, we can unravel how our project is not only just about an ingenious product but also about a sound business opportunity. Proving that there are positive returns for investing in this concept is an indispensable step in converting this idea into an actual, functional one with possible return on investment.

8.2 Economic Analysis

Other than technology, the competitiveness of a new technology also depends on its costs. In the context of our edible food detection sensor based system, the main difficulty is related to hardware implementation expenses and its total cost due to savings in overtime costs. Even though the system integrates dedicated sensors for CO2, alcohol, and organic solvents, temperature, and humidity, and more, these units including microcontrollers and Bluetooth modules have a big initial capital investment.

It can be achieved by combining systems of this kind and modifying them for use in a greater number of installations, which avoids substantial monetary expenses. Keywords: food warehouse, food safety principles, system implementation. The importance of this system becomes more visible when it is larger in scope and usage such as in food preservation systems in the food supply chain, food transport units, or industrial freezers. In these settings where food safety and food spoilage are of paramount consideration, the system's capability of minimizing food wastage, increasing safety, and sending out warning signals in real time can result in enormous operational savings. From this observation, when the system is implemented on a larger scale, it will also be possible to offer higher savings in prevention of food spoilage as well as prolonging the lifespan of the products which will lower the payback of the first cost. Nevertheless, the high initial investment of the system especially its sensors and wireless communication devices is a hindrance to the prospective investors. Even though there are huge benefits in the future, the need to come up with strategies that will cut the costs of persuading the first consumers is imperative. To tackle this, people should focus on the chances this system has in terms of enhancing food quality control, waste management alongside consumers' safety all of which will lead to cost savings in the long run.

8.2.1 Cost Benefit Analysis

In order to fulfill the need for a feasibility study, a cost-benefit analysis has been performed for the real time application of the sensor based food contamination detection system proposed in this work and also for the hardware prototype built. It can be inferred from within that this analysis gives insight into the economic issues that affect the designs which are the costs of building the system and the operational costs.

Table 8.1: Cost Analysis

Description	Part	Specification	Cost(BDT)
CO2 Sensor	MH-Z14	Working voltage: 4.5 V ~ 5.5V DC Average current: < 85 mA Interface level: 3.3 V	4200
Alcohol Sensor	TGS822	Heater Voltage : 5.0±0.2V (AC or DC) I = 132 mA (typ) Ps ≤ 15 mW; Ph = 660 mW (typ)	1500
Temperature and Humidity Sensor	DHT22	Source Voltage 3.3V - 6V Typical: 3.3V Power Consumption: 7.5 mW Current: 1.5 mA (typ)	950
Bluetooth Module	HC-05	The specifications are as follows: Communication Interface: UART Supply Voltage: 3.3V Supply Current: maximum 40mA Power: 132 mW	2100

LCD Screen	Grove - LCD RGB Backlight		1100
Battery	Ni-MH 10.8V 1600mAh		4500
Charger	UL 60950-1		1900
LDO Voltage Regulator	LP2985		580
LDO Voltage Regulator	STLQ50C33R		700
LDO Voltage Regulator	LDK320M50R		850
Microcontroller	Raspberry pi 4		16000
PCB			5000
		Total	48,380

Table 8.2: Approximate Lifetime and Cost for Replacement

Equipment	***Approx. Lifespan***	***Unit price (BDT)***
Vacuum chamber	Lifetime	
Raspberry Pi 4	Expected Lifetime	16000
Power unit	7-8 years	450
Sensors	10-12 years	7500
Vacuum pump	20000 Hours	700
Battery	3-4 years	1500
Camera	7-10 years	2500
Safety seals	6-7 years	300

The cost analysis addresses essential elements including CO2, alcohol, and organic solvent detection sensors, microcontrollers, Bluetooth communication modules and an LCD display These components account for one of the larger portions of the project cost which is about 60,000 BDT. Even so, these expenditures are expected to be compensated over time due to advantages that include savings on reducing food spoilage, safety concerns, and limiting contamination through early detection.The prototype has been tweaked with few imported items to control costs without affecting the performance of the system. It is to be noted that this design approach keeps the system inexpensive but reliable and effective for practical applications. Overall the economic evaluation shows that all aspects of the system are affordable and it would provide the necessary returns in terms of preventing losses associated with food contamination and also improving efficiency in production.

8.4 Evaluate Economic and Financial Aspects

The estimated expenditure for our project is in the range of 50,000 BDT, therefore resources such as design shall be judiciously utilized if at all we are to remain within this amount. Such availability of parts within the vicinity facilitated the economical utilization of the budget. Even with that very low budget, we made sure that the parts we will be using such as sensors, microcontrollers and the like will be the best quality and long lasting. This means that their replacement will not be done often thus maintenance will be cheap with time. As such, we have done this project without economic loss by embracing the use of locally available components and efficient allocation of resources. This approach does not only ensure that we are able to work on the defined budget, but also eliminates excessive operational expenditures for the systems in the future. Such provision and optimization discipline will enable us to incur savings both with regard to the project initiation phase and the operation and the system as such making its application in the food safety industry efficient from an economical perspective.

8.4.1 Return on Investment

The ROI analysis performed here is concerned with short, as well as the long-term financial benefits of applying the sensor-based food contamination detection systems such as for food safety monitoring in food and storage areas like warehouses and transportation vehicles. The verification of food quality and safety, and reduction of food waste make it possible to obtain measurable savings in operating costs.

The system's **initial investment** is 48,380 BDT, covering essential hardware components:

- CO2, alcohol, and temperature/humidity sensors: 6,650 BDT
- Microcontroller (Raspberry Pi 4): 16,000 BDT
- Bluetooth module: 2,100 BDT
- LCD screen and battery: 5,600 BDT
- Vacuum chamber, camera, and power unit: 8,650 BDT
- Miscellaneous components (chargers, voltage regulators, PCB): 9,380 BDT

8.4.2 Long-Term Operational Benefits and Savings

In a business context, the advantages of the system primarily arise out of its potential to identify contaminations on time, stopping food around the places from spoiling or going to waste. This can be related to cost savings on:

a. Amount of Food Wasted Due to Spoilage

Industry Background: In the food business, 10-15 percent of total inventory can be lost because of spoilage.

Projected Savings: With the system in place, it is projected that food wastage such as the 10 percent in spoilage, could be reduced to around 10,000 BDT per year.

b. Improvement of Health and Safety

Economic Relevance: The risk of problems caused by contamination decreases with proper supervision regarding the food, thus avoiding possible accounts for health related issues. Small losses resulting from contamination can range between 5,000 and 10,000 BDT on the upper hand.

Projected Savings: This could result in an annual cost of around 5,000 BDT, assuming the system only prevented one incident a year.

c. Replacement and Maintenance Costs are Minimal

Component Durability: In order to decrease the chances of replacements, sensible system designs incorporate reliable sensors and components.

Annual Maintenance Savings: This figure could be up to 2,000 BDT on account of durability owing to maintenance savings per annum.

8.4.3 Projected Total Savings (1 Year, 5 Years, 10 Years)

$$ROI = \frac{(Total\ savings - Initial\ Investments)}{Initial\ Investments} \times 100\%$$

1-Year ROI

- **Annual Savings Breakdown (Considering for 1 Machine)**
    - Reduced spoilage: 10,000 BDT
    - Health and safety: 5,000 BDT
    - Maintenance and durability: 1,000 BDT
    - Total Savings (1 Year): 16,000 BDT

ROI Calculation for 1/5/10 year:

$$ROI\ (1\ year) = \frac{16000 - 48380}{48380} \times 100\% = -66.92\%$$

Following the initial year, the return on investment stands at -66.92% because the system is still in the process of recouping its initial outlay. Nonetheless, predicted total gains gradually increase return on investment.

5-Year ROI:

Total Savings (5 years) = $16000 \times 5 = 80000\ BDT$

ROI (5 Years) = $\frac{80000 - 48380}{48380} \times 100\% = 65.4\%$

10-Year ROI:

Total Savings (10 years) = $16000 \times 10 = 160000\ BDT$

ROI (10 Years) = $\frac{160000 - 48380}{48380} \times 100\% = 230.8\%$

The benefits of this system can be dramatically improved if applied on a more widespread basis. In industrial applications, such as storage, food distribution, and warehousing, the savings in operational costs could be several times higher since the system cuts down on spoilage and the probabilities of contamination on a larger scale. Such scale up might enhance the investor attractiveness and food industry stakeholders making it easier to apply the system wider and leverage more economic benefits.

8.5 Conclusion

This project aims to design a sensor-based system that is able to ensure food safety by monitoring food for contamination in real time. In regard to the economic analysis we have tried to analyze geographical aspects of the introduction of this system in Bangladesh as well as addressing the possibilities of finances. As with any project, the economic and financial prospects are important especially in the case of a densely populated country like Bangladesh. It follows that for us to win over participants and arouse the interest of consumers, it is of vital importance that the system should be economical.

The less expensive our solution is, the more it will be accepted by the food suppliers and retailers and businesses involved in food quality control. Our analysis also showed that however, the upfront expenditure on quality sensors and other hardware tends to be high for our forecasted market growth, the long-term gains for instance prevention of food wastage and better health justify this investment. There are greater returns for the system when it is deployed in bigger scale foods operations such as industrial storage and distribution of foods, which can otherwise provide general health promotion through proper nutrition.

Chapter 9: Ethics and Professional Responsibilities

9.1 Introduction

As our project is related to food safety and also public health is a big concern, we have to be very careful about maintaining ethics and professional responsibilities throughout the project, which will play a very important role in the success of this project in the future. As our aim is to develop the system for meat quality grading and contamination identification to prevent foodborne illnesses and ensure food quality control, it will be a great responsibility to maintain all the highest standards of ethics. Besides, ethical issues which will arise in our project and the professional responsibilities which will need to be maintained by us, will also be observed by all the stakeholders, including researchers, food industry professionals and others in near future. Throughout maintaining the ethical and professional responsibilities, our goals will be ensuring all the public health, our consumers protection and also not to harm the meat supply chain.

9.2 Identify Ethical Issues and Professional Responsibility

In our project there will be numerous ethical issues arising which will question our standards for food quality control and contamination detection, specifically while grading the meat. Some of the ethical issues and professional responsibility that might possibly be:

9.2.1 Maintaining Accuracy of Contamination Detection to Ensure Consumers Health

Our first and foremost ethical responsibility will be protecting our consumers health from contaminated meat products. So if we fail to grade the meat accurately or fail to detect the contaminations accurately, it would lead to serious health issues among the consumers, including foodborne illnesses, which will be harmful for the public health and not be fulfilling the goals of the project, which is ensuring public health.

9.2.2. Maintaining Transparency to Ensure Public Trust

An important ethical consideration will be ensuring transparency through the contamination detection and grading process. Any kind of manipulation in the detection system or in the grading systems, may cause serious trust issues among the consumers which would also lead to cancellation of our project. Besides, the international and national standards have to be followed strictly and safety protocols need to be updated to align with regulations by ethical conduct of food safety practices.

9.2.3 Ensure to Follow Environmental Responsibility

Our ethical and professional responsibilities also include accepting the environmental risks and ensuring how to manage or tackle them. As meat production has a great environmental impact, our systems have to promote sustainable practices which will reduce food waste and environmental impact and maintain the consumers health safety. Besides, we can also implement measures to reduce food waste with sustainable packaging practice in industry by engaging with recycling initiatives and waste reduction programs, while the distribution process can be more minimized to ensure sustainability.

9.2.4 Equally Supporting the Large Scale and Small Business to Minimize Economic Loss

One of our professional and ethical responsibilities will ensure that we will support the meat supply chain business from small scale to large scale. Though our primary target is to implement our projects in the super shops in the cities where they will be able to afford it. However, in the near future we have to make sure that the project will be also affordable to the medium scale and large scale meat businesses in cities and villages too, otherwise it will be only effective to the large businesses and consumers living in the cities, which will make it unfair for the medium and small scale business and people living in the villages. So, in near future we also need to collaborate with meat producers of all levels so that it can be effective for the consumers with our contamination and spoilage detection during production and distribution, which will enhance the quality control, efficiency by minimizing economic losses.

9.2.5. Ensuring Data Integrity

As our project involves sensors and machine language based detection, we will also have the responsibility to safeguard the data integrity as manipulation or misinterpretation of data that are related to meat's quality grading or contamination detection, would lead to ethical violations. Besides, all the data which will be collected from other sources to train the machine learning model will need to be appropriately credited to tackle any kind of plagiarism in our project. Again when we will supply the detailed and easily accessible data of the spoilage detection, we will also need to maintain transparency on labeling it for the consumers.

9.2.6. Ensuring Animal Welfare Throughout the Process

As our project mainly aims to ensure the quality of the meat, we will also have to be careful about any kind of practices that may lead to unethical treatment of the cattles. For ensuring this we can also collaborate with some animal welfare organizations who will help us to ensure the maintain the meat supply ethically.

9.2.7. Safety Consideration while Implementing the Project

Safety issues like chemical exposure, electrical hazards, gas leakage, human made errors, equipment maintenance error may also arise while implementing and running the system.

9.3 Apply Ethical Issues and Professional Responsibility

As our projects have multiple ethical issues and professional responsibilities to consider, we will also need to apply those principles and maintain the professional responsibilities through the process of spoilage detection. So some steps like this can be followed:

9.3.1. Implementing the Highest Level of Standards for Food Safety to Ensure Public Health

The food safety guidelines have to be established strictly for the project to ensure the highest level of health standards, while spoilage detection. For the process, we need to follow the food safety codes and develop the model by training the model with the threshold of when the meat is fresh, when the meat starts to spoil and when the meat is half spoiled and when the meat is totally spoiled. These thresholds need to be clarified while training the machine learning model to ensure the accuracy of spoilage detection. Besides, the national and international food safety codes and standards have to be maintained and followed regularly to ensure the ethical and professional responsibilities to the consumers.

9.3.2. Ensuring Data Transparency

While checking and after checking the meat through the designed process, the system have to provide all the relevant data that suggest whether the meat is fresh, or half fresh, or in a process of spoilage or totally spoiled to ensure the system is giving accurate data to the consumers so that then can be fully aware of what they will be buying and get the full functionality of our desired system. Ultimately, by following the process it will be helpful to keep the consumers trust on our project and they will be able to know the conditions of the meat they are buying. Besides all the other stakeholders will also know about the conditions of the meat, which will help them to ensure the best quality of the meat and also from economical aspects.

9.3.3. Ensure the Training of the Operators to Avoid Safety Issues

In the beginning of implementing our project, this may become a bit complex and unknown system for the operators to run, who will use the system for spoilage detection in the super shops. Those individuals who are involved in operating the process must be professionally trained and also have to follow the ethical guidelines. Besides, this will also make sure that the operators are well aware of their responsibilities toward consumer health safety and the consequences of their negligence. So the process of accountability must be there to handle any ethical violations and manipulation to the transparency of the project.

9.3.4. Making Sure that Medium Scale and Lower Scale Businesses also Get the Effectiveness

Though at first, our initial plan is to set up our project in only the super shops of the city area, soon we will have to design the detection system in a way that eventually will help the medium and small scale meat supply business and village peoples as well. As a result, soon after the implementation of our project in the city areas, we need to take our time and design the system in a more affordable, effective and less complex way, so that all kinds of people can get the effective side of our project and run the system without any hassle. We can also check for regular transparent supply chain practice to trace the meat supply with the help of our system that properly labels the accurate information such as the condition of the meat.

9.3.5. Ensuring the Technical Responsibilities

For our project as we are using machine learning methods to train the model with appropriate datasets for spoilage identification, the development and deployment of these models will need to be accurate and fair. They have to be examined to avoid any kind of biases or inaccuracies which could harm the detection and ultimately it hamper the consumers health or producers business.

9.3.6. Ensuring Continuous Monitoring

Continuous monitoring of the system will have to be maintained to tackle the safety issues like chemical exposure, electrical hazards, gas leakage, human made errors, equipment maintenance error etc. while implementing and running the system. Besides ethical practices will also be required constant monitoring to ensure that any kind of violations will not happen. Again updates of our systems will need to be maintained to fulfill industry standards and evolving expectations of the consumers. Lastly, a frequent review of our detection system will be needed, along with research into new methods for detecting contamination to commit all the professional responsibility.

9.4 Conclusion

As our project is directly connected to public health and safety ethics and professional responsibility will be integral to the success of the system designed to detect the meat spoilage and identify contamination. Protecting consumer health, ensuring fair trade practices, and promoting transparency and accountability in the food supply chain are essential for maintaining public trust and safeguarding food safety. By maintaining the highest ethical standards and professional responsibilities, the project will not only prevent foodborne infections but also contribute to a more equitable and sustainable meat industry. This approach will ensure that both consumers and producers benefit from a fair and reliable system that prioritizes health, safety, and ethical integrity.

Chapter 10: Conclusion and Future Work

10.1 Project Summary/Conclusion:

Our project's main aim is to develop a system that can detect meat spoilage and ensure the meat supply with fresh and healthy meat for the consumers to get rid of foodborne illness. As we know, a huge amount of meat is contaminated due to bacteria and gas that causes illness and also in some locations it causes death. So, it is the principal objective to determine a reliable method for the detection.

We go for two different design approaches in which design approach 2 is more relevant and sustainable. In approach 1, we can see the power supply will be 12 V in a DC-Dc converter that contains a sensor array with CO_2 and several organic sensors. Microcontrollers have been used also to send signals of temperature and humidity. The LCD chamber also works here. In approach 2, this is a more reliable method that has been used with a vacuum pump with sensor and ML detection procedure. So that can give more accurate data for spoilage.

For this project, we mainly designed a prototype that can give accuracy with contamination and spoilage of meat that can reduce foodborne illness. With advanced technology this system can be widespread to help humanity.

10.2 Future Work:

Frozen Meat: The system will need to be worked with meat that is kept under frozen condition too. As a result, further research needed to be done on frozen meat.

Categorizing Different Meat: we can develop a feature that can categorize different meat such as white meat and red meat. Also, if the vendor is giving our desired meat such as chicken or buffalo but not any restricted meat etc.

Supermarket and Retail Chains: Can be used in supermarkets to continuously monitor meat quality in real time while on display.

Restaurant and Food Supply Industry: By using real time monitoring restaurants can prevent the use of spoiled or contaminated meat and ensure food quality.

Butcher Shop and Local Meat Vendors: Any butcher shop and vendors can use this system to grade meat and identify potential contamination before sale that can provide small business access with product safety.

Meat Import & Export Inspection: In the inspection for meat import and export it will be so much beneficial to check premium meat that can reduce contamination rate internationally and help with meat trade risk for quality following standards.

Personal Use Only: In this project we mostly focused on the food supply chain industry and stakeholders but we can also go for personalized use at home for the near future.

This is how we can improve our project of meat detection in various ways such as in the development of the system in future and also the uses of the product in different fields. This can be more useful in this way of future work with more capabilities.

Chapter 11: Identification of Complex Engineering Problems and Activities

11.1. Identification of Attributes of Complex Engineering Problems (EP)

	Attributes	**Put tick (√) as appropriate**
P1	Depth of knowledge required	√
P2	Range of conflicting requirements	
P3	Depth of analysis required	√
P4	Familiarity of issues	√
P5	Extent of applicable codes	√
P6	Extent of stakeholder involvement and needs	√
P7	Interdependence	

11.2: Reasoning of How the Project Address Selected Attribute (EP)

11.2.1 P1 Depth of Knowledge Required

For this project a deep understanding is compulsory about food science for the requirements of meat spoilage detection. Also, we have to use some algorithms also to detect the level of meat quality so understanding of machine learning (ML) and also about sensor technology. The spoilage of meat occurs due to changes of microbial or chemical level so the knowledge of these topics are also very important to understand and to apply this knowledge the involvement of complex biochemical , machine learning analysis and sensor design is essential.

11.2.2. P3 Depth of Analysis Required

The project incorporates subtle interpretations to differentiate between various spoilage stages that can detect gasses using sensors that are needed according to the gas and also pH changes. The analysis is required to ensure the level of spoilage detection is accurate and helps to get rid of false positives or missed spoilage cases.

11.2.3. P4 Familiarity of Issues

This two term food spoilage and foodborne illness is commonly known within food science and public health. Despite that, integrating all these essential terms with technological solutions like sensors may entail areas that demand creativity.

11.2.4. P6 Extent of Stakeholder Involvement and Needs

There are various stakeholders in the food industry that can be involved with meat spoilage detection directly such as consumers , food safety authorities and manufacturers. There is also a societal impact on food quality and avoiding foodborne illness that needs to be involved significantly, making stakeholder engagement essential for the project's success.

11.3. Attributes of Complex Engineering Activities (EA)

	Attributes	**Put tick (√) as appropriate**
A1	Range of resource	√
A2	Level of interaction	√
A3	Innovation	√
A4	Consequences for society and the environment	√
A5	Familiarity	√

11.4 Reasoning of How the Project Address Selected Attribute (EA)

11.4.1. A1 Range of Resources

To complete this project we need so much information from various resources that includes advanced sensor technology, laboratory equipment and computational tools to analyze the data we get from sensors.

11.4.2. A2 Level of Interaction

A high level interaction is needed between multiple domains such as microbiology , sensor technology and public health that can give an effective solution to this project. Collaboration with the food industry can help.

11.4.3. A3 Innovation

Detecting meat spoilage in real time can be highly innovative work with the help of technology. The food safety technology would have been pushed by this project with integrated sensors or AI based detection systems in the food supply chain.

11.4.4. A4 Consequences for Society and the Environment

There are different aspects of benefits and societal benefits is one of them. This can be achieved by preventing foodborne illness through early detection of spoilage meat that can improve public health. Also, there would be environmental impact such as reducing meat spoilage can minimize the unnecessary waste of meat processing and improve food sustainability.

11.4.5. A5 Familiarity

It is noticeable that our project food spoilage and consumption detection can go under the food safety and microbiology field. The use of technology and advanced sensors within previously mentioned concepts can be innovative in this field. That can also provide new challenges. The project might introduce emerging technologies such as sensors from IoT or AI algorithms which are very less known in the field of food quality control process in the food industry. The blending of food science with leading edge technology can make it an interaction of an evolving field.

This project is an excellent example of addressing both complex engineering problems and activities by requiring deep technical knowledge, stakeholder engagement, and innovation while having a wide societal impact.

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Appendix

Logbook

FYDP (P) Fall 2023 Summary of Team Log Book/ Journal

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FYDP (P) Fall 2023 Summary of Team Log Book/ Journal

Date/Time/Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
5-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. General discussion 2. Proposing few topic 3. Proposing new ideas	Task 1: All Task 2: Rakib, Shihab Task 3: Faruk	N/A as it was an introductory meeting. Task 1: completed. Task 2: partially Completed. Task 3: Completed.
12-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Gather information about food contamination 2.Learn the working mechanism of Electronics nose system 3. Find the major defects in yarn production 4. Finalizing topic	Task 1: All Task 2: Tasnuva, Shihab Task 3: Faruk Task 4: Rakib, Sadi	Task:1 Partially Completed Task 2: Not Completed Task3: Partially Completed Task4: Completed
19-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Learn the working mechanism of Electronics nose 2.Gather information about	Task1: Faruk, Nahid, Rakib Task2: Tasnuva, Sadi	Task1: Completed Task2: Completed
26-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Modification of system specification	Task1:Faruk, Rakib, Shihab, Sadi, Tasnuva	Task1: Partially Completed
26-10-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Final modification of design approach 2. Consultation regarding international codes	Task1: Faruk, Nahid Task 2: Sadi, Tasnuva Task 3: Rakib	Task1: Completed Task2: Completed Task3: Completed

		3. Final discussion regarding functional and nonfunctional requirement		
16-11-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. specific details about design approach 2.Effective method selection 3.Problem solving about grading and contamination detection	Task1:Faruk, Rakib Task2: All Task3: Nahid, Sadi, Tasnuva	Task 1: Completed Task 2: Partially Completed Task 3: Partially Completed
23-11-2023 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	Design approach modification	Task: All	Task1: Completed
7-12-2023 (Additional Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	Task 1: Survey form Task 2: Discuss with real problem of customer	Task 1: Tasnuva Task 2: Nahid, Rakib, Faruk, Sadi	Task 1: Completed Task 2: Completed
8-12-2023 (Additional Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Finalizing the project proposal 2. Specification and Functional & Non Functional requirements modification.	Task 1: Tasnuva, Faruk Task 2: Nahid, Rakib, Sadi	Task 1: Completed Task 2: Completed

FYDP (D) Spring 2024 Summary of Team Log Book/ Journal

	Final Year Design Project (D) Spring 2024		
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FYDP (D) Spring 2024 Summary of Team Log Book/ Journal

Date/Time/Place	**Attendee**	**Summary of Meeting Minutes**	**Responsible**	**Comment by ATC**
5-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. General discussion with our ATC panel members.	Task 1: All	N/A as it was an Introductory meeting.
12-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Select tools and software for software simulation	Task 1: All	Task:1 Partially completed
19-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Finalize tools for software simulation. 2. Software implementation first designing approach. 3.Using Proteus, altium, fusion 360.	Task1: All Task2: Faruk, Nahid, Rakib Task3: Tasnuva, Sadi	Task1: Completed Task2: Partially Completed Task3: Partially Completed
26-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1.Software implementation first designing approach 2. Using Proteus, altium, fusion 360. 3. Making slides for progress presentation.	Task1:Faruk, Rakib, Shihab, Sadi, Tasnuva	Task1: Partially Completed Task 2: Partially Completed Task 3: Completed
26-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	4. Progress Presentation	Task1: Faruk, Nahid Task 2: Sadi, Tasnuva Task 3: Rakib	Task1: Completed

16-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Fixing the software error from the ATC'S feedback 2. Implement our third design approach using a machine learning algorithm.	Task1:Faruk, Rakib Task2: All Task3: Nahid, Sadi, Tasnuva	Task 1: Completed Task 2: Partially complete
23-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Implement our third design approach using a machine learning algorithm. 2. Implement another machine learning algorithm to justify the software accuracy.	Task 1: Rakib, sadi Task 2: Rakib, Faruk	Task 1: Completed Task 2: Completed
1-05-2024 (Additional Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Finding best design solutions are explored to find the optimal solution	Task 1: All	Task 1: Completed
5-05-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Making the slides for the final presentation. 2. Final presentation.	Task 1: All Task 2: All	Task 1: Completed Task 2: Completed

FYDP (C) Summer 2024 Summary of Team Log Book/ Journal

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FYDP (C) Summer 2024 Summary of Team Log Book/ Journal

Date/Time/Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
22-07-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. FYDP-C, First session attending.	Task 1: All Task 2: Rakib, Shihab Task 3: Faruk	N/A as it was an Introductory meeting.
29-07-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Order the components for our proposed model 2. Complete the payment for the components.	Task 1: Faruk Tasnuva,Shihab Task 2: Rakib Sadi	Task:1 Partially Completed Task 2: Completed
19-03-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Received and collect all the components	Task1: All	Task1: Completed
09-09-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Starting of implementation of pcb designing, 2. Order the pcb for hardware.	Task1: Shihab, Sadi, Tasnuva Task2: Faruk, rakib	Task1: Partially Completed Task 2: Completed
23-09-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1.Using the components making the final project. 2. Integrating ML in hardware.	Task1: Faruk Tasnuva,Shihab Task2: Rakib, Sadi	Task1: Partially Completed Task2: Partially Completed
07-10-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1.Using the components making the final project. 2. Integrating ML in hardware.	Task1: Faruk Tasnuva,Shihab Task2: Rakib, Sadi	Task 1: Partially Completed Task1: Partially Completed
14-04-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab	1.Using the components making the final project.	Task 1: All Task 2: All	Task1: Completed

	4. Sadi 5. Tasnuva	2. Integrating ML in hardware.		
14-10-2024 (Additional Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Complete the report writing and final improvements for report writing 2. Finalized the design report	Task 1: Tasnuva Task 2: Nahid, Rakib, Faruk, Sadi	Task 1: Completed Task 2: Completed
22-10-2024 (Weekly ATC Consultation)	1. Faruk 2. Rakib 3. Shihab 4. Sadi 5. Tasnuva	1. Report summary and design report improvements for report writing 2. Finalized the design report 3. Making poster for presentations.	Task 1: Tasnuva, Faruk Task 2: Nahid, Rakib, Sadi Task3: All	Task 1: Completed Task 2: Completed Task 3: Completed

Code Used in ML

```
from google.colab import drive
drive.mount('/content/drive')
!pip install -q tensorflow==2.15
%matplotlib inline

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

pd.set_option('display.max_columns', None)
pd.set_option('display.max_colwidth', None)

from glob import glob
import gc

import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display

import cv2

from tqdm import tqdm, tqdm_notebook
tqdm.pandas()

from sklearn.model_selection import train_test_split

plt.rcParams["figure.figsize"] = (12, 8)
plt.rcParams['axes.titlesize'] = 16
plt.style.use('seaborn-whitegrid')
sns.set_palette('Set2')

import tensorflow as tf

import os
# print(os.listdir('../input/'))

import warnings
warnings.simplefilter('ignore')

from time import time, strftime, gmtime
```

```
start = time()
import datetime
print(str(datetime.datetime.now()))
base_dir = '/content/drive/MyDrive/project/FYDP-C'
os.listdir(base_dir)
batch_size = 32
img_height = 96
img_width = 96
train_val_ds = tf.keras.utils.image_dataset_from_directory(
  base_dir,
  validation_split=0.1,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

test_ds = tf.keras.utils.image_dataset_from_directory(
  base_dir,
  validation_split=0.1,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

train_val_size = len(train_val_ds)
train_size = int(0.75 * train_val_size)

train_ds = train_val_ds.take(train_size)
val_ds = train_val_ds.skip(train_size)
normalization_layer = tf.keras.layers.Rescaling(1./255)

train_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
val_ds = val_ds.map(lambda x, y: (normalization_layer(x), y))
test_ds = test_ds.map(lambda x, y: (normalization_layer(x), y))
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
test_ds = test_ds.cache().prefetch(buffer_size=AUTOTUNE)
import tensorflow as tf
```

```
from tensorflow.keras import layers, models

def create_model():
    model = models.Sequential([

        layers.Conv2D(32, (3, 3), activation='relu', input_shape=(96, 96, 3)),
        layers.MaxPooling2D((2, 2)),
        # layers.BatchNormalization(),

        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        # layers.BatchNormalization(),

        layers.Conv2D(128, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        # layers.BatchNormalization(),

        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(64, activation='relu'),
        layers.Dropout(0.3),
        layers.Dense(1, activation='sigmoid')
    ])

    model.compile(
        optimizer='adam',
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model

model = create_model()

model.summary()
EPOCH = 10

history = model.fit(
    train_ds,
```

```
    validation_data=val_ds,
    epochs=EPOCH,
    verbose=1
)
import tensorflow as tf
import numpy as np
from sklearn.metrics import accuracy_score, classification_report

# Get predictions and true labels from the test dataset
y_true = []
y_pred = []


for images, labels in test_ds:
    batch_predictions = model.predict(images, verbose=0)
    batch_predictions = (batch_predictions > 0.5).astype(int)

    y_true.extend(labels.numpy())
    y_pred.extend(batch_predictions.flatten())

accuracy = accuracy_score(y_true, y_pred)
print(f"Test Accuracy: {accuracy*100:.2f}%")

print("\nClassification Report:")
print(classification_report(y_true, y_pred))

tf_evaluation = model.evaluate(test_ds, verbose=1)
print(f"\nTensorFlow built-in evaluation:")
print(f"Test Loss: {tf_evaluation[0]:.4f}")
print(f"Test Accuracy: {tf_evaluation[1]*100:.2f}%")

misclassified_indices = np.where(np.array(y_true) != np.array(y_pred))[0]
print(f"\nNumber of misclassified samples: {len(misclassified_indices)}")
def display_images(paths, rows, cols, cat = None):
    fig, ax = plt.subplots(rows, cols, figsize = (16, 12))
    ax = ax.flatten()
    if cat == 'Fresh':
        c = 'green'
    else:
        c = 'red'
```

```
    for i, path in enumerate(image_paths):
        img = cv2.imread(path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        ax[i].set_title(f"{cat} - {img.shape}", color = c)
        ax[i].imshow(img)
        ax[i].grid(False)
    plt.tight_layout()
    plt.show()
image_paths = np.random.choice(fresh, 9)
display_images(image_paths, 3, 3, 'Fresh')
image_paths = np.random.choice(spoiled, 9)
display_images(image_paths, 3, 3, 'Spoiled')
df = pd.DataFrame(columns = ['image', 'target'])
df['image'] = fresh + spoiled
df['target'] = df['image'].apply(lambda x: 0 if 'Fresh' in x else 1)
df = df.sample(frac = 1).reset_index(drop = True)
labels = ['Fresh', 'Spoiled']
df.head()
plt.title('Target Distribution', color = 'grey')
sns.countplot(data = df, x = 'target');
def decode_image(filename, label = None, image_size = (dim, dim)):
    bits = tf.io.read_file(filename)
    image = tf.image.decode_jpeg(bits, channels = 3)
    image = tf.cast(image, tf.float32)
    image /= 255.0
    image = tf.image.resize(image, image_size)

    if label is None:
        return image
    else:
        return image, tf.one_hot(label, depth = len(labels))

def data_augment(image, label = None):
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_flip_up_down(image)
    image = tf.image.random_brightness(image, 0.2)
    image = tf.image.random_contrast(image, lower = 0.3, upper = 0.9)

    if label is None:
        return image
```

```
    else:
        return image, label
train_dataset = (
    tf.data.Dataset
    .from_tensor_slices((train_df['image'], train_df['target']))
    .map(decode_image, num_parallel_calls = AUTO)
    #.map(data_augment, num_parallel_calls = AUTO)
    .repeat()
    .shuffle(512)
    .batch(BATCH_SIZE)
    .prefetch(AUTO)
)

valid_dataset = (
    tf.data.Dataset
    .from_tensor_slices((valid_df['image'], valid_df['target']))
    .map(decode_image, num_parallel_calls = AUTO)
    .batch(BATCH_SIZE)
    .cache()
    .prefetch(AUTO)
)

test_dataset = (
    tf.data.Dataset
    .from_tensor_slices((test_df['image'], test_df['target']))
    .map(decode_image, num_parallel_calls = AUTO)
    .batch(BATCH_SIZE)
    .cache()
    .prefetch(AUTO)
)

def plot_dataset(dataset, row, col):
    for (img, lbls) in dataset.take(1):
        for i in range(row * col):
            ax = plt.subplot(row, col, i + 1)
            plt.imshow(img[i].numpy())
            if labels[np.argmax(lbls[i].numpy())] == 'Fresh':
                c = 'green'
            else:
                c = 'red'
```

```
            plt.title(labels[np.argmax(lbls[i].numpy())], color = c)
            plt.axis('off')
            plt.grid(False)
        plt.show()
from IPython.display import display, Javascript
from google.colab.output import eval_js
from base64 import b64decode

def take_photo(filename='photo.jpg', quality=0.8):
  js = Javascript('''
    async function takePhoto(quality) {
      const div = document.createElement('div');
      const capture = document.createElement('button');
      capture.textContent = 'Capture';
      div.appendChild(capture);

      const video = document.createElement('video');
      video.style.display = 'block';
      const stream = await navigator.mediaDevices.getUserMedia({video: true});

      document.body.appendChild(div);
      div.appendChild(video);
      video.srcObject = stream;
      await video.play();

      google.colab.output.setIframeHeight(document.documentElement.scrollHeight, true);

      await new Promise((resolve) => capture.onclick = resolve);

      const canvas = document.createElement('canvas');
      canvas.width = video.videoWidth;
      canvas.height = video.videoHeight;
      canvas.getContext('2d').drawImage(video, 0, 0);
      stream.getVideoTracks()[0].stop();
      div.remove();
      return canvas.toDataURL('image/jpeg', quality);
    }
    ''')
  display(js)
  data = eval_js('takePhoto({})'.format(quality))
```

```
  binary = b64decode(data.split(',')[1])
  with open(filename, 'wb') as f:
    f.write(binary)
  return filename
from IPython.display import Image
try:
  filename = take_photo()
  print('Saved to {}'.format(filename))

  display(Image(filename))
except Exception as err:
  print(str(err))
import tensorflow as tf

image_raw = tf.io.read_file(filename)

image_tensor = tf.image.decode_jpeg(image_raw, channels=3)

resized_image = tf.image.resize(image_tensor, [96, 96])
final_image = tf.expand_dims(resized_image, 0)

print(final_image.shape)
y_pred_cam = np.argmax(model.predict(final_image))

fresh_quality_cam = "Fresh" if y_pred_cam == 0 else "Spoiled"

print(f"The quality of meat is {fresh_quality_cam}")
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
 display_training_curves(
     history.history['loss'],
     history.history['val_loss'],
     'Loss', 211)

display_training_curves(
     history.history['accuracy'],
     history.history['val_accuracy'],
     'Accuracy', 212)
fresh_decoded =
decode_image("/content/drive/MyDrive/project/outt/image-1620127109_-768x513.jpg")
```

```
fresh_aug = data_augment(fresh_decoded)
fresh_array = tf.expand_dims(fresh_aug, 0)

fresh_pred = model.predict(fresh_array)
fresh_pred = np.argmax(fresh_pred)

fresh_quality = "Fresh" if fresh_pred == 0 else "Spoiled"

print(f"The quality of the meat is {fresh_quality}")
```