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A Design of IoT-based Monitoring System for Intelligent Meat Quality in Vyas Municipality, Nepal

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Abstract

The integration of Internet of Things (IoT) technologies and machine learning (ML) has introduced transformative solutions in food quality monitoring, particularly in developing nations like Nepal. This research presents an IoT-based smart monitoring system designed to assess meat quality through environmental and gas-sensing techniques. Methane and ammonia gases primary indicators of meat spoilage were measured using gas sensors, alongside temperature and humidity sensors. Laboratory experiments were conducted to validate sensor reliability by producing controlled gases and comparing outputs with standard indicators. The validated system was deployed across meat shops in Vyas Municipality for six months, monitoring buff, mutton, chicken, and fish. Findings indicated that methane and ammonia levels began to increase after 3 hours at room temperature and peaked significantly between 48 to 60 hours. Fish exhibited the fastest spoilage rate, with high gas levels detected within 5 hours of exposure. Machine learning models including random forest, decision tree, and logistic regression were trained on the collected dataset. The random forest model achieved the highest accuracy and was used for predicting meat freshness. Analysis revealed that 95% of fish samples were sold in spoiled condition, while 60% of buff meat and 10% of mutton were found deteriorated. In contrast, chicken meat was sold 100% fresh.This study, conducted with support from the Vyas Municipality Office, Nepal Food Institute Tanahun, and the Meat Traders Association, highlights the alarming state of meat quality in local markets. It also addresses the absence of standardized methods for evaluating meat freshness in Nepal, where consumers largely rely on sensory judgment. The proposed system offers a scalable, cost-effective, and data-driven approach for real-time meat quality monitoring. By leveraging IoT and ML technologies, this research contributes a practical solution to improve food safety and public health awareness, particularly in resource-constrained settings. It also provides a replicable framework for similar applications in other developing countries facing parallel challenges in food quality assurance.

Keywords: *Internet of Thing, Machine Learning, Meat Quality, Random Forest, Rotton*

1. Introduction

The contemporary food industry operates as a complex network that connects farmers, wholesalers, retailers, and consumers in a joint effort to meet global food demands. However, maintaining food quality and safety within this intricate system remains a constantly evolving challenge. Food quality is not just a matter of profitability; it is also a critical issue for public health and safety. In this context, the incorporation of advanced technologies has led to significant changes. This research explores the realm of an Internet of Things (IoT)-based Food Quality Monitoring System, representing a technological advancement aimed at ensuring the integrity of the food supply chain(Siddharth Mudgal et al., 2024).

The need for food technology arises from several key factors that contribute to improvement of food production, preservation, safety, and quality. Food technology helps develop methods to prevent contamination from pathogens, toxins, and chemicals, ensuring food is safe for consumption. Developing technologies for better storage conditions ensures food security by reducing spoilage, specially in regions with inadequate infrastructure. Advances in food technology can help create climate-resilient crops, mitigating the effects of climate change on food production. In our research on IoT-based monitoring for met quality, food technology could be crucial in integrating smart system to ensure the safety, quality, and traceability of food products, meeting both consumer demand and regulatory standards.

The Internet of Things (IoT) refers to the concept of connecting everyday objects and devices to the internet, enabling them to send and receive data. These objects, often referred to as smart devices, are equipped with sensors, software, and connectivity features that allow them to interact with each other and with users, making systems more efficient, intelligent, and responsive. Sensors are deployed to monitor meat quality, air quality, water quality, and pollution levels, providing data that helps address environmental issues. It help us Automation and real-time monitoring reduce human error and improve the efficiency of operations. In the context of our research on an IoT-based monitoring system for meat quality, the IoT concept is applied by connecting sensors the monitor gas emissions like ammonia and methane to a system that can predict meat quality using real-time data. This system would ensure meat safety and quality by providing immediate feedback or alerts about the meat's condition.

Machine Learning is a branch of artificial intelligence that enables computers and systems to learn from data and improve their performance over time without being explicitly programmed. Machine Learning algorithms use statistical techniques to identify patterns in data, make prediction, and automatically improve through experience. Machine learning uses algorithms to process data and make predictions or decisions. Different algorithms are suitable for different types of problems. Training is the process where an algorithm is fed with data and learns from it by adjusting its parameters to minimize errors. For example, in our research, we could train a model using data from gas sensors to predict whether the meat is of fresh or non-fresh quality. In our case, the model could predict the freshness or spoilage of meat based on the real-time gas sensor data. Once a model is trained, its performance is evaluated using matrices like accuracy, precision, recall, and F1 score, depending on the task. In our research, we could evaluate how well our model predicts meat quality by comparing its prediction to actual quality assessments. In our IoT-based research for monitoring meat quality, machine learning could analyze real-time data from sensors and make predictive model to determine the freshness or spoilage of meat. This would help optimize quality control in the food industry.

In Vyas Municipality, Nepal, maintaining the quality and safety of meat products is a significant challenge due to inadequate monitoring systems, poor handling practices, and inconsistent storage conditions. Traditional methods of assessing meat quality rely on manual inspection, which is not only time-consuming but also prone to human error. These outdated techniques often fail to detect early signs of spoilage, leading to the sale of unsafe or low-quality meat to consumers. This poses health risks, undermines consumer trust, and results in economic losses for vendors. The lack of real-time monitoring system exacerbates this issue. Factors such as improper temperature control, high humidity, and the accumulation harmful gases like ammonia and methane during storage and transportation contribute to the degradation of meat quality. In a context where meat is a vital component of the local diet, ensuring freshness and safety critical. The problem, therefore, lies in the need to develop and implement and advanced automated, and scalable solution that ensures real-time, accurate meat quality monitoring, particularly for municipalities like Vyas, where existing infrastructure technology are insufficient for modern food safety demand.

To address this, the problem focuses on designing an IoT-based monitoring system that can continuously and intelligently track meat quality by detecting environmental parameters, such as gas emissions ammonia, methane, temperature, and humidity levels. By leveraging IoT sensors and machine learning algorithms, this system will provide real-time data, predict meat spoilage, and alert stakeholders when quality thresholds and breached. This technology can ensure higher standards of met safety and quality, reduce waste, and improve public health outcomes in Vyas Municipality, Nepal.

In this research, several hypotheses were considered, and the most suitable one was selected to formulate the research question. There are two main research question: First, is the dataset generated from IoT-based devices appropriate for analysis using machine learnings algorithms? Second, what will be the actual condition of the meat in the selected research area?

This research aims to have a significant impact both now and in the future. It is intended to serve as a foundation for supporting more advanced research moving forward. The study has two key objectives. The first is to use IoT technology to create a dataset that tracks different types of meat over time, with a focus on ammonia and methane gas levels as the primary indicators. The second objective is to gather real time ammonia and methane gas samples from meat directly in the shop to predict the actual condition and shelf life of the meat.

The proposed research on designing an IoT-based monitoring system for intelligent meat quality in Vyas Municipality, Nepal, Holds significant value across various domains. By providing real-time monitoring of environmental condition such as gas emissions ammonia, and methane, the system will enhance food safety by ensuring that meat products meet quality standards. This can reduce the risks of foodborne illnesses caused by consumption of spoiled or contaminated meat, safeguarding public health. This system will help meat vendors, suppliers, and distributors minimize spoilage by identifying the onset of meat degradation early. This reduces waste and prevents financial losses due to the disposal of low-quality products. The system can also lower costs associated with the need for frequent manual inspections. Implementing an IoT-based solution marks an important step toward modernizing the meat supply chain in Vyas Municipality. The research will promote the use of smart technology in food production and distribution, which could be adapted for other agricultural and food safety applications, benefiting the broader industry. With real-time data and predictive insights, vendors can make informed decisions regarding storage conditions, transportation logistics, and inventory management. Similarly, consumers will benefit from safer, high-quality met products, which will build trust in local food markets. This research will lay the groundwork for future advancements in IoT, machine learning, and food safety technologies. The findings can inspire further studies in other areas of food production and agriculture, promoting innovation in smart monitoring system.

This research is not only vital for ensuring the quality of meat in Vyas Municipality but also has broader implications for improving food safety, supporting local economics, and technological advancement in Nepal's agriculture and food sectors.

The scope of the research has been narrowed to ensure simplicity, reliability, and effectiveness. Key elements considered include the timing of sample collection, selection of devices suited to the purpose, the sample area, and the data analysis algorithm. A dataset has been constructed by collecting up to 167 hours of reports on humidity, temperature, ammonia gas, and methane gas levels. Ammonia and methane gases are the primary indicators used to assess meat quality. The study only utilizes sensors for humidity, temperature, methane gas, and ammonia gas, with the Random Forest Algorithm being the sole machine learning method employed. Data was gathered directly from meat shops between January 20, 2024 AD, and July 20, 2024 AD. The study focuses exclusively on mutton, beef, chicken, and fish, with 12 meat shops selected (3 shops per type of meat). Both fresh and non-fresh meat were examined and the spoilage time of fresh meat was predicted in hour using machine learning. For the study area, Vyas Municipality wards 2 and 3 have been selected by random sampling method.

These limitations need to be considered when designing and implementing the IoT-based system, as they could affect its feasibility, scalability, and long-term success in ensuring meat quality and safety in Vyas Municipality.

Research must be through and dependable. To achieve this, understanding how other researchers have approached the topic is essential. This study presents several examples of related research as outlined below.

The sale of various types of meat in markets, rather than the meat that is actually needed, is on the rise. This paper suggests a method for assessing the freshness of raw meat through gas sensors that detect the levels of genetic amines produced by the meat. Additionally, it proposes using Near Infrared spectroscopy technology to identify the type of meat. These two approaches are combined and implemented using the Internet of Things (IoT) and Machine Learning(J, n.d.).

Annual methane emissions from nine cattle farms in Denmark were assessed using the tracer gas dispersion method. Among these farms, seven were dairy farms and two were beef cattle operations, representing common Danish breeds, housing systems, and manure management practices. To account for seasonal variations, emissions were measured bi-monthly over a full year. Methane emissions ranged from 0.7 to 28 kg h^{-1}, with normalized emission factors varying from 14 to 54 g LU^{-1} h^{-1} for dairy cattle and 11 to 24 g LU^{-1} h^{-1} for beef cattle(Vechi et al., 2022).

The experimental findings indicated that onion slices dried under vacuum, by maintaining very low moisture levels and minimizing injuries that can lead to oxidative degradation, can be preserved for a longer duration compared to traditional drying methods. The risk of product contamination is reduced since the entire process occurs within a sealed chamber. Future research will involve collecting additional experimental data to enhance system performance, and the detection system currently in development will be tested on refrigerated vacuum-packed foods. This system will be miniaturized to assist elderly and disabled individuals by alerting them if the food begins to spoil. Additionally, integrating the monitoring system with a smartphone will further streamline the process of tracking the condition of stored food(Popa et al., 2019).

The Earth's atmosphere is made up of nitrogen, oxygen, trace gases, and various other gas mixtures. Trace gases, which exist in small quantities, include carbon monoxide, methane, carbon dioxide, hydrogen, argon, and neon, among others. Recently, the concentration of these trace gases has risen, negatively impacting human health, making it crucial to monitor them. In recent decades, the use of sensors has expanded across various technological fields. This paper presents an IoT framework for a food monitoring system designed to safeguard food quality based on environmental conditions using a range of low-cost sensors. The proposed system monitors temperature, humidity, and gases emitted from food, as these factors influence the nutritional value of food items. The analyzed data will be displayed on an LCD, and notifications will be sent to an Android phone or any internet-enabled device through an application(Rounak et al., 2022).

Ensuring food safety and hygiene is crucial to minimizing food waste. It's important to monitor food quality and protect it from deterioration caused by environmental factors such as temperature, humidity, and darkness. Thus, implementing quality monitoring devices in food storage facilities is beneficial. These devices track the environmental conditions that contribute to food decay, allowing for interventions like refrigeration and vacuum storage to be employed. The system uses an Arduino board connected to various sensors, including the DHT-11 for measuring temperature and humidity, the MQ3 for detecting alcohol content, and an LDR for assessing light exposure. This IoT device transmits the collected sensor data to an online platform. The Arduino is equipped with an ESP8266 Wi-Fi modem to establish an internet connection via a Wi-Fi router. Additionally, sensor data is displayed on a character LCD connected to the Arduino UNO. The logging and monitoring of sensor data are managed through the Freeboard.io IoT platform. With the capabilities of the Internet of Things, monitoring the environmental factors impacting food storage can be done from any location, at any time, and using any device. Multiple devices can be set up in a given area for enhanced monitoring and quality control. The Arduino Sketch running on the device carries out various project functions, including reading sensor data, converting it to strings, displaying it on the character LCD, and sending it to the IoT platform. This Sketch is created, compiled, and uploaded using the Arduino IDE(Kaviya, 2020a).

The Smart Food Quality and Safety Monitoring System outlined in this project illustrates the potential of utilizing advanced technologies to safeguard the integrity of the food supply chain. By incorporating an ESP32 microcontroller, DHT sensors, gas sensors, ESP32 CAM, Blynk IoT, and a Telegram bot, the system offers real-time monitoring, analysis, and decision-making support for stakeholders in the food industry. This allows for proactive measures to be implemented to maintain food quality and safety, thus decreasing the risks of foodborne illnesses, product recalls, and financial losses. The system enhances transparency, traceability, and adherence to regulatory standards. Furthermore, it fosters sustainable practices by reducing food waste and optimizing resource use. The project underscores the significance of leveraging IoT, machine learning, and data analytics to tackle complex issues within the food industry. Future improvements, such as adding more sensors, incorporating predictive analytics, and integrating blockchain technology, could further enhance food quality and safety protocols(- et al., 2023).

In recent years, there has been increasing concern over food waste, prompting extensive research aimed at mitigating its far-reaching effects. This issue poses a significant risk to the long-term sustainability of food supply chains, demand trends, and production methods. Given the critical importance of nutrition, maintaining food quality and safety remains a top priority. To tackle this challenge, an innovative food deterioration monitoring system has been developed. This system employs sensors and actuators to track gas emissions, humidity, and temperature in fruits and vegetables. It utilizes the Node MCU microcontroller along with sensors such as the MQ2/MQ4 methane sensor and the DHT11 humidity/temperature sensor. The system enables real-time assessments for various food items, including rice, bread, samosas, and dal. It is supported by a comprehensive dataset that includes a wide range of food items, locations, temperatures, and humidity levels, serving as a foundation for predictive and analytical activities. The analytical process involves several critical steps. Data preprocessing techniques are applied to improve dataset quality by addressing issues such as missing values and outliers. The Recursive Feature Elimination (RFE) method enhances predictive performance by iteratively selecting important features and reducing the risk of overfitting. The M-SMOTE technique addresses class imbalances by generating synthetic samples to ensure balanced model training for underrepresented classes. The Random Forest algorithm aggregates decision trees to provide reliable predictive insights. These analyses enable the system to identify spoilage, offer decision-making support, and predict remaining shelf life, leading to more efficient resource allocation. The results of the proposed system demonstrate an impressive accuracy of 94.76%, highlighting its practical applicability(Nemade et al., 2024).

The increasing focus on food quality and safety necessitates the development of sensitive and reliable research methods and technologies for preserving freshness and ensuring food quality. This review outlines the current status of chemical and biological sensors used for food monitoring and smart packaging. It discusses various sensing techniques and their analytical capabilities for measuring freshness indicators, allergens, pathogens, adulterants, and toxic substances, along with examples of their applications. Integrating these sensors into smart packaging could enhance food status monitoring, reduce waste, extend shelf life, and improve overall food quality. However, many sensors are still in the development phase and require significant work before they can be implemented in real-world applications. Challenges such as sensitivity, sustainability, robustness, and the safety of sensing materials—due to potential contact or migration into food—must be addressed. The review also covers the current state of development for these technologies, along with a discussion of the challenges and opportunities for future research(Kaviya, 2020b).

Food safety and hygiene are critical concerns for minimizing food waste. Monitoring food quality is essential to protect it from spoilage and decay caused by environmental factors like temperature, humidity, and darkness. Therefore, employing high-quality monitoring systems in grocery stores is advantageous. These advanced monitoring devices track environmental conditions that contribute to food degradation. Subsequently, these conditions can be managed through methods such as refrigeration and vacuum storage. This article outlines the construction of a food quality monitor that can assess environmental factors, including temperature, humidity, alcohol content, and light exposure. The device is built using the increasingly popular Arduino NANO prototyping board. It is connected to various sensors, such as the DHT-11 for measuring temperature and humidity, and the MQ3 for detecting methane levels. This setup forms an IoT device capable of transmitting data to an IoT platform. The Arduino is paired with an ESP8266 Wi-Fi module to connect to the internet through a Wi-Fi router. The sensor data will be displayed on a temperature LCD connected to the Arduino NANO. The embedded IoT platform is used for data logging and monitoring(Lakshmi & Babu, 2022).

A Food Monitoring System that utilizes Bluetooth Low Energy (BLE) and the Internet of Things (IoT) offers numerous advantages across various commercial sectors, including agriculture, biomedicine, cosmetics, environmental monitoring, food production, military applications, pharmaceuticals, regulatory compliance, and diverse scientific research areas. This system incorporates a gas sensor to detect gases released from food, a temperature sensor to monitor the temperature of the storage environment, and a humidity sensor to assess moisture levels. The data gathered from test samples is transmitted to an application via Bluetooth, utilizing either BLE or IoT, depending on the server's range. The system also employs a GSM/GPRS public wireless network for remote data transfer. By integrating IoT technology with GSM/GPRS wireless networks and the Internet, the overall cost of the system is significantly reduced while enhancing tracking capabilities and overall performance. Improvements in quality control, enabled by this food monitoring system based on BLE and IoT, have led to enhancements in product attributes, consistency, and uniformity throughout various stages of industrial manufacturing processes. This paper reviews some of the key and innovative applications that have greatly benefited humanity(Venkatesh et al., 2017).

Freshness can be assessed through various factors, including the presence of microorganisms, bacteria, and gases. This paper focuses on monitoring the temperature, humidity, and gases emitted by meat. We examined the factors influencing meat freshness and chose to utilize a gas sensor as the primary detection method, with temperature and humidity sensors serving as auxiliary tools to determine the food poisoning index. The proposed system includes an RFID tag, temperature sensor, humidity sensor, gas sensor, reader, and server. By comparing the temperature, humidity, and gas concentration in the meat storage environment, we can establish the correlation between meat freshness and sensor signals. This monitoring system categorizes meat freshness into four distinct grades: High, Medium, Low, and Spoilage. To validate the effectiveness of the proposed system, we conducted experiments using pork, and with the smart RFID tag, we successfully assessed the freshness of the meat(Eom et al., 2014).

The literature review aimed at enhancing the effectiveness of the research revealed that prior studies were not particularly impactful. While various sensors were used to assess food quality, no substantial research had been carried out. Despite Nepal's unique geography and environment, no studies have focused on this region. Additionally, no research was found that involved testing meat quality directly in meat shops, this gap highlighted the need for this study. It stands out as a unique approach, with the hope of offering new insights, information, and guidance distinct from previous research.

2. Materials and Methods

This research differs from other approaches due to the various risks, challenges, and issues associated with assessing met quality. A dataset has been created specifically for this study, and using IoT technology, the data collected from sensors has been analyzed to predict the real condition of the meat through machine learning techniques. The key components of the research methodology are outlined as follows.

2.1 Conceptual Framework

Several factors influence meat quality, with the most critical being environmental temperature, Humidity, ammonia, and methane gases. Hence, this research also examines the temperature, humidity, ammonia, and methane gases dat. To detect meat spoilage, gas sensors have been detected. These sensors convert the data into digital format and display the results. The collected data is stored in a database, and a machine learning algorithm is then used to predict the condition of the meat based on the collected data.

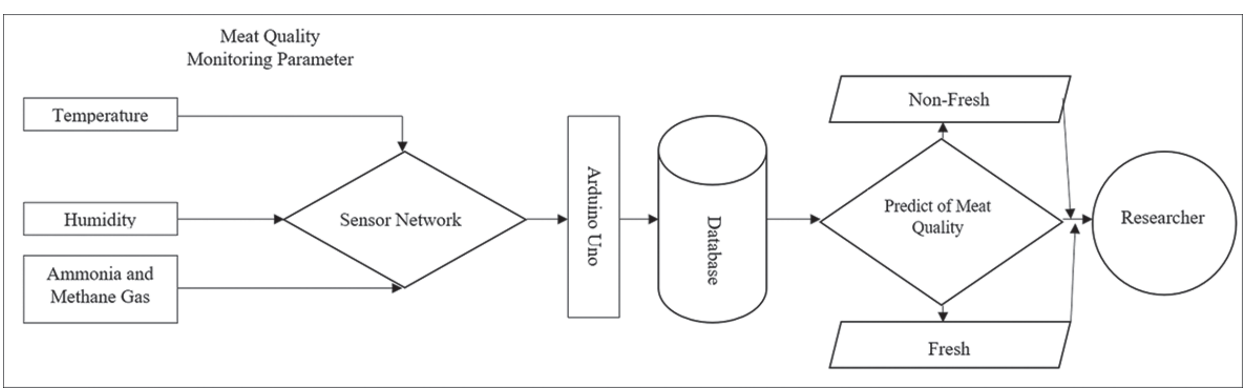

Figure 1: Conceptual Framework

2.2 Algorithm

In this research, Random Forest Algorithm has been used for the selection of meat quality detection. This algorithm is chosen because of its higher accuracy than other algorithms. In a comparative study, Logistic Regression, Decision Tree can give higher accuracy than Random Forest, so this algorithm is used.

Random Forest is widely used for tasks like classification, regression, and feature importance analysis due to its robustness and performance. Random Forest works by creating an ensemble of decision trees, each trained on different subsets of data and features, and combining their predictions to improve accuracy and reduce overfitting. It achieves this through bagging or bootstrap aggregation and random feature selection, making it a highly effective and robust model for both classification and regression tasks.

2.1.1 Random Forest Algorithm

The working principle of Random Forest Algorithm cleared by algorithm step.

Step 1: Start

Step 2: Input Data (Collect the dataset for training.)

Step 3: Select Random Samples

Step 4: Build Decision Trees

Step 5: Classification

Step 6: Averaging for Regression (Calculate the average of predictions from all trees)

Step 7: Display prediction

Step 8: End (Complete the process)

The Random Forest algorithm is an ensemble learning method, typically for classification and regression, which operates by constructing multiple decision trees. For predicting meat quality based on ammonia and methane levels, the algorithm would use these gas concentration readings as features to classify or predict quality levels.

Equation of Random Forest for Meat Quality Prediction

Each tree in the random forest model $T_i(x)$ predicts an outcome based on the input features (here, ammonia and methane levels, denoted as x). Final prediction y is calculated by averaging the outputs of all N decision tree in the forest.

$$y = \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

Where, y = predicted quality level of meat, N = total number of trees, and $T_i(x)$= prediction from I-th tree based on ammonia and methane levels. If meat quality is categorized ("Fresh, and Non-Fresh"), the Random Forest model would use classification instead. In that case, the final predicted class y is determined by majority voting across all trees:

$$y = \text{mode}\ \{T_i(x) \mid i = 1, 2, 3, \ldots, N\}$$

In this way, the Random Forest algorithm integrates ammonia and methane data through ensemble learning to produce robust quality predictions.

Requirement

Operating system: Windows 11, Arduino IDE 2.0 and Arduino Libraries for various sensors

Programming Language: Python and C++ for Arduino IDE

Hardware: Processor: Intel core TM i5, RAM: 8 GB and Hard Disk: 500 GB

Requirement of IoT: Humidity and Temperature Sensor (DTH 11), Methane Gas Sensor and, Ammonia Gas Sensor

Validation

IoT vs. Manual

A group discussion was conducted for the validation of all the sensor devices used in the research. In the seminar conducted in the presence of the relevant stakeholders, a comparative study was conducted with the report of sensors based on IoT and the report given by analog machine using traditional methods. The same sample was used in this test.

IoT-based sensors were compared with traditional manual methods in this research. Humidity and temperature data were analyzed using technology at the Agriculture Knowledge Center office in Tanahun. When tested with the Agricultural Knowledge Center's current method, it took around 40 minutes to obtain humidity results, while the temperature test took about 5 minutes. However, with IoT technology, both humidity and temperature result were obtained simultaneously within 5 seconds. According to the technicians at Agriculture Knowledge center, manual humidity testing is prone to errors and various factors affect its accuracy. They noted that IoT technology could significantly reduce errors, improve accuracy, and provide instant results from any location. Though the manual method produced temperature results faster, the IoT approach demonstrated much greater efficiency overall. Based on the report compiled with the help of group discussion, a comparative study of monitoring system based on traditional method and monitoring system based on IoT has been done as follows.

Table 1: [Manual vs. IoT based sensor]

Exp.	Monitoring	Manual based	IoT based (Average)
1	Humidity	87%	92%
2	Temperature	26^{0}C	26^{0}C

Methane Gas Sensor

The accuracy of the methane gas sensor's readings needed to be confirmed, but validating the results proved challenging. Up to 70% methane gas is produced from cow dung. Based on this, the validation of the methane gas sensor has been done. To test the sensor, dung gas was used. When the dung gas valve was opened, the sensor readings began to rise. As the valve was opened further, the methane sensor's output continued to increase. This behavior suggests that the sensor is functioning correctly(Arifan et al., 2021)-(Baitha & Kaushal, 2019).

Ammonia Gas Sensor

To confirm the presence of ammonia gas through a physical test, expose a piece of damp red litmus paper to the gas. Ammonia, being a basic gas, will turn the red litmus paper blue. Additionally, ammonia gas has a strong, sharp odor that can help identify its presence. Simultaneously, the same sample will be tested using the methane gas sensor. If both the litmus paper and gas sensor readings show an increase, it can be assumed that the sensor is functioning properly. The results from our ammonia gas sensor were aligned with those of the wet red litmus paper, phenolphthalein and Eber test, thereby validating the accuracy of the ammonia gas sensor. Since ammonia gas is alkaline, it turns wet red litmus paper into blue and colourless phenolphthalein into pink during pH test. The meat quality parameters included meat texture, tenderness, odour and spoilage. Spoilage was tested by the Eber test. The Eber test is one of the methods used to determine the spoilage of meat and its derivatives and is shown by the production of NH_3 gas due to the biochemical activity of detrimental micro-organisms(Sukrama et al., 2020). This is confirmed by the formation of white cloud when small piece of the sample meat was introduced over the mixture of HCl, ethanol and ether in 1:3:1 ratio. These experiments confirm that the ammonia sensor is working correctly.

Random Forest vs. Decision Tree vs. Logistic Regression.

Accuracy is a commonly used metric to evaluate the overall performance of a classification model in meat quality predict using machine learning. It measures the proportion of correctly classified samples out of the total number of samples.

$$\text{Accuracy} = \frac{No.of\ images\ correctly\ classified}{Total\ no.of\ images}$$

Table 2: [Logistic Regression vs. Decision Tree vs. Random Forest]

Logistic Regression	Decision Tree	Random Forest
95%	96%	98%

Based on the given results, it appears that the Logistic Regression, Decision Tree, and Random Forest algorithms have performed quite well, achieving high accuracy rate of 95%, 96%, and 98%, respectively. The Logistic Regression algorithm, on the other hand, has achieved a lower accuracy rate of 95%. It's worth nothing that accuracy alone may not be the only metric to consider when evaluating the performance of a model. Other metrics such as precision, recall, and F1 score can provide additional insights into the model's performance. It may be helpful to conduct additional testing and evaluation of these models before making a final decision.

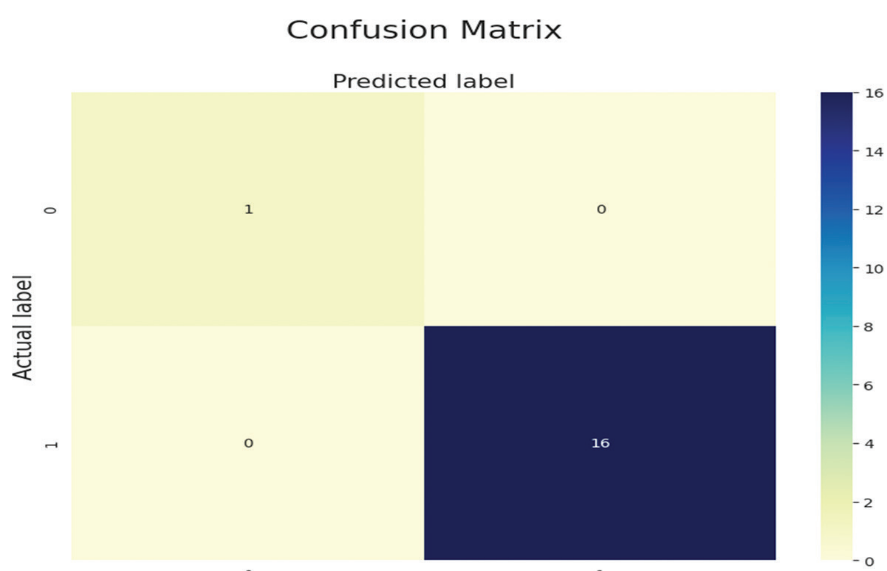

Figure 2: [Confusion Matrix of Random Forest]

Data Set

Once the validation process is completed, the dataset is prepared. Various types of meat are tested individually using an IoT device. During testing, humidity, temperature, methane, and ammonia levels are recorded for fresh meat within first hour and then every two hours. Data collection continues for up to 168 hours (one week) to build the dataset. The data is logged at intervals of approximately 10 minutes and recorded this average value. Machine learning is then used to predict the condition of the directly gathered data based on this dataset.

Data

This research utilized only primary data, gathering two types of data, one for building the dataset and the other for conducting the study. Samples of fresh mutton, beef, chicken, and fish were collected for the dataset, and these were kept at room temperature for 167 hours. Ammonia and methane gas levels were measured every 2 hours. The data collected over this period were compiled into a CSV file and used in a machine learning model. Over the course of six months, samples were directly obtained from mutton, beef, chicken, and fish shops. Samples were taken from 12 different shops, with 3 shops for each meat type, collected weekly. These samples were then thoroughly analyzed.

Area and Population

For this study, wards 2 and 3 of Vyas Municipality were chosen as sample area using a random sampling method. Prior to the research, a group discussion was organized with the participation of 12 meat shop owners, the head of the food department, the president of the meat business association, the mayor of Vyas Municipality, and the ward presidents of the selected wards. The discussion focused on the quality of meat and the issues associated with consuming spoiled meat. In total, 17 individuals took part in this study.

3. Results and Discussion

In the result analysis, two key tasks were performed. First, the sensor readings from IoT sensors were analyzed by generating a time-based dataset. Then using this dataset, the condition of various types of meat was examined, and a comparative analysis was conducted.

3.1 Dataset Analysis

In this research, various precautions were taken in the dataset to minimize errors in the results. For instance, since methane and ammonia are light gases, the sample were placed in sealed bags, and the gas levels were measured for about 5 minutes to ensure accurate results. Throughout the study, humidity levels remained relatively stable. However, the research also accounted for the impact of temperature changes as higher temperatures can increase bacteria and fungal activity in meat. During the research period, room temperatures ranged from 17^{0}C to 30^{0}C. The base of the study was on ammonia and methane gas levels. The dataset revealed that meat samples remained fresh for up to 7 hours and became non-fresh after 9 hours. Fresh meat had ammonia levels between 402 ppm and 630 ppm and methane levels between 192 ppm and 300 ppm. In contrast, non-fresh meat had ammonia levels exceeding 630 ppm and methane levels above 300 ppm. These findings helped determine the freshness of the collected meat samples.

In this research, datasets were created for various types of meat, including mutton, chicken, beef, and fish. These datasets track the decay timeline of the meats. It was observed that the meat starts to rotten after 9 hours, with the level of spoilage progressively increasing, reaching a severely decayed state by 81 hours. If the meat is stored for more than a week, it becomes completely spoiled, losing even its odor. This dataset enables easy prediction of the spoilage timeline in meat shops using machine learning. Ammonia concentration trend start at 402 ppm at 1 hour. Gradually increase over time, reaching a peak of 2545 ppm at 89 hours. After this point, ammonia concentration slowly declines, with slight flections, ending at 1811 ppm at 167 hours. Similarly, Methane concentration trend start at 192 ppm at 1 hour. Reses consistently until it reaches its peak at 863 ppm at 129 hours. After 129 hours, methane levels remain high but fluctuate slightly, ending at 780 ppm at 167 hours. The datasets developed through this research are presented as follows.

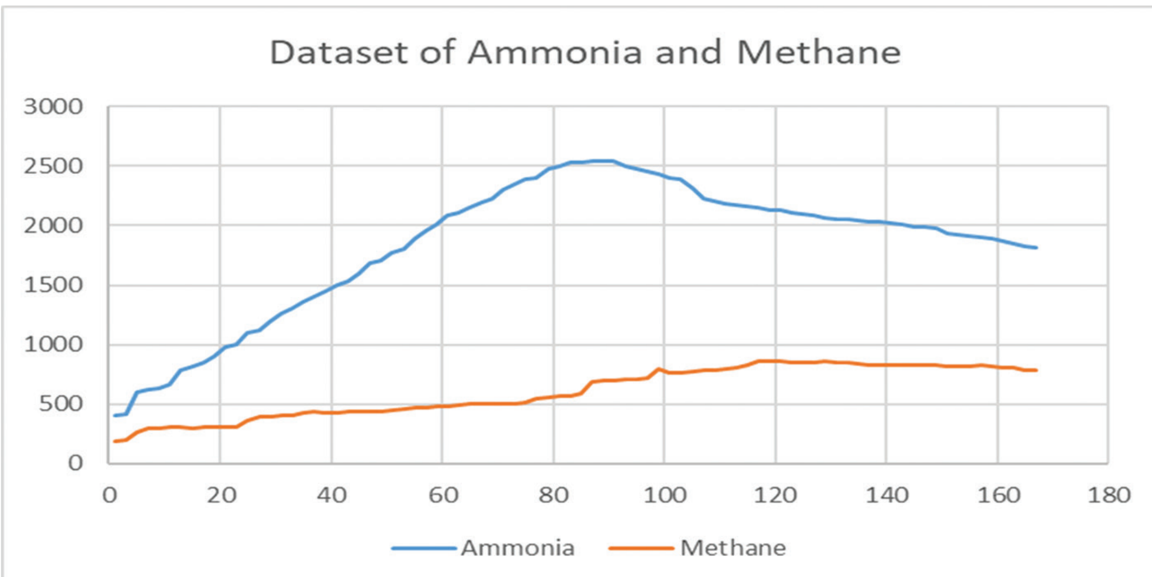

Figure 3: [Dataset of Ammonia and Methane]

Ammonia shows a steady increase until about 98 hours, then beings to decline slightly, while methane rises more consistently until 129 hours. After peaking, both gases maintain relatively high concentrations but do not continue to increase.

3.2 Meat Item Analysis

In this research, four types of meat were chosen and analyzed over a period of six months. Samples from each meat type were collected weekly. Using machine learning, the sample were classified into fresh and non-fresh categories based on the data from the collected samples.

3.2.1 Mutton Analysis

Must of the dates show only fresh mutton, with few occurrences of non-fresh samples. This may indicate consistent preservation or quality control. February 3, 2024 and April 6, 2024 have the highest number of non-fresh sample. February 10, 2024, February 17, 2024, and May 25, 2024 also have a mix of fresh and non-fresh mutton, with 1 non-fresh sample. The data shows a pattern where a majority of samples are fresh, but periodic occurrence of non-fresh samples could indicate storage or supply chain issues on specific dates.

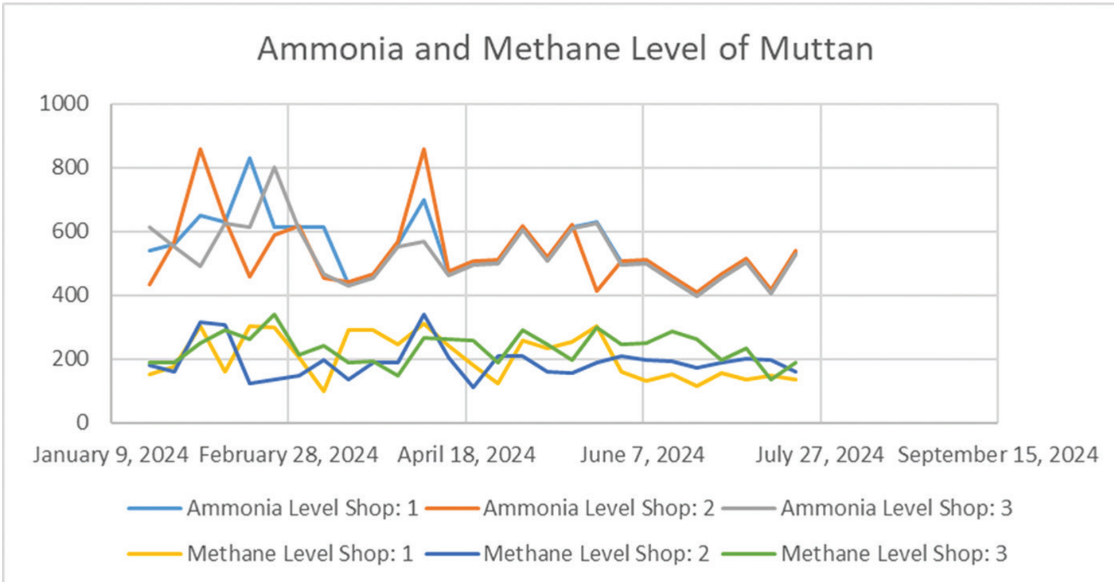

Figure 4: [Ammonia and Methane level of Mutton]

Finally, 90.12% and 11.11% of Mutton fresh and non-fresh respectively.

3.2.2 Beef Meat Analysis

On certain dates (March 16, 2024, March 23, 2024, March 30, 2024 and June 1, 2024), there are three fresh samples. Other dates, can't found fresh sample. On certain dates, such as March 2, 2024, April 13, 2024 and April 20, 2024, all samples are non-fresh. The lowest non-fresh count is observed on date like January 27, 2024, March 16, 2024, and March 23, 2024 with 0 non-fresh samples.

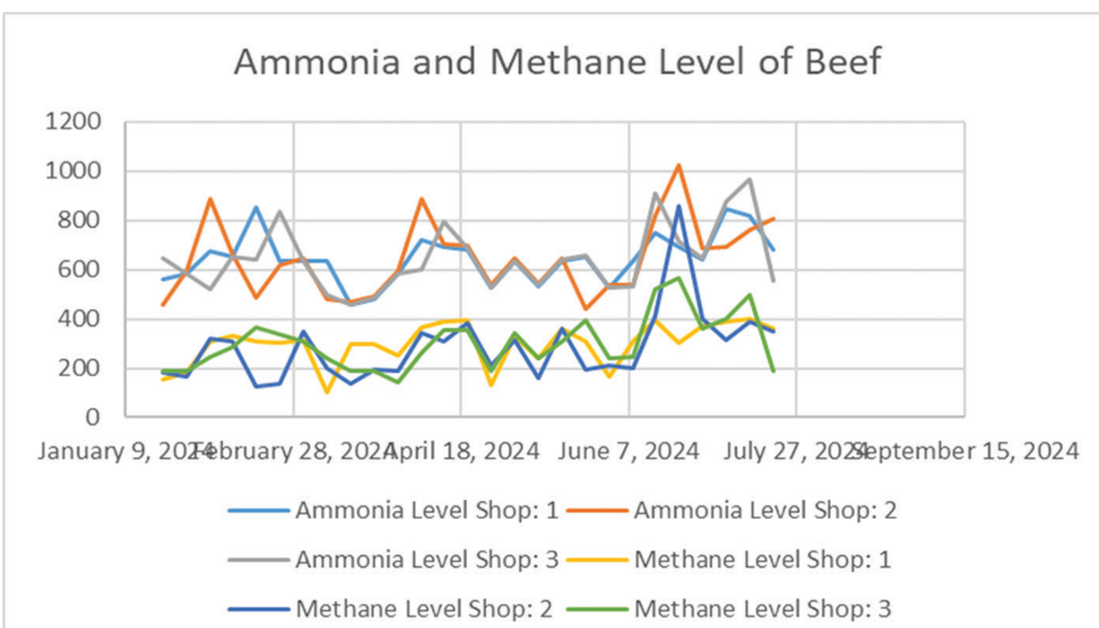

Figure 5: [Ammonia and Methane Level of Beef]

Finally, 32% and 60.49% of Beef are fresh and non-fresh.

3.2.3 Chicken Meat Analysis

This data shows perfect consistency in the freshness of the chicken samples. There are no non-fresh samples recorded at any point during this period. This level of consistency could indicate excellent quality control, presentation techniques, and handling in the supply chain for chicken. The data shows a 100% fresh rate for chicken, with no issues related to non-fresh samples. This could be an indicator of stable environmental condition or a highly efficient management system in place during this period.

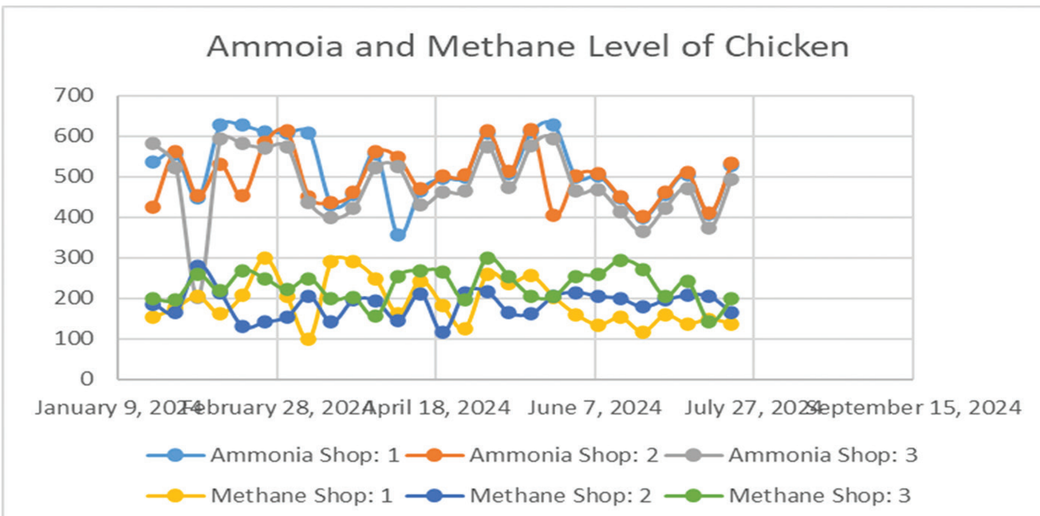

Figure 6: [Ammonia and Methane Level of Chicken]

Finally, 100% and 0% chicken are fresh and non-fresh.

3.2.4 Fish meat analysis

The number of fresh samples is extremely low, ranging 0 and 1 out of 3 shops per days. Only five dates have fresh samples. January 20, 2024, February 3, 2024, May 25, 2024 and July 20,2 2024 1 fresh and 2 non-fresh fish. Non-fresh sample dominate the data, with a consistent all shop non-fresh samples on the majority of the dates. Out of 27 table data points, 22 dates recorded all non- fresh fish. Fresh fish samples are quite rete, appearing only five times, and even then, always accompanied by two non-fresh samples. The high proportion of non-fresh samples could indicate poor storage, handling, or transportation conditions for fish. The consistent lake of fresh fish suggests ongoing issues with maintaining freshness over time. The few instances where fresh fish is recorded could be anomalies or cases where the supply chain performed better for the day. The fish data shows a prevalent issue of non-fresh samples, with the vast majority of the data showing non-fresh, and fresh samples being a rate exception. This points to significant challenges in maintaining the quality and freshness of fish during the study period.

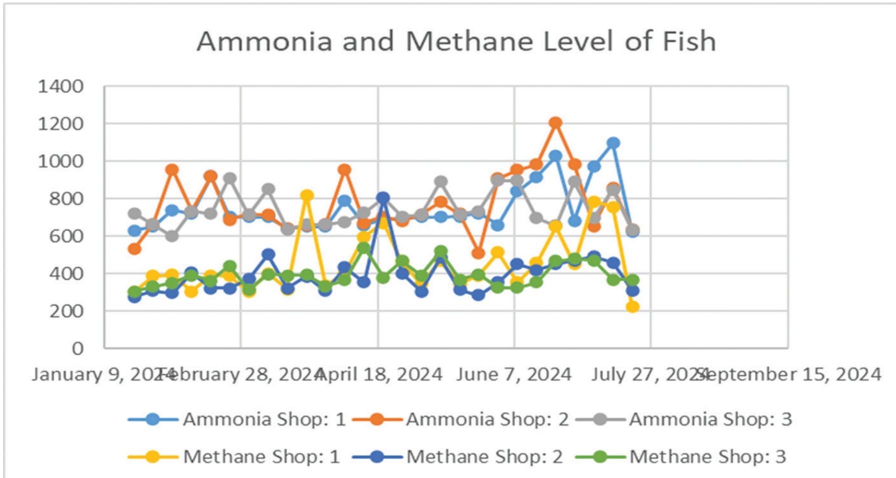

Figure 7: [Ammonia and Methane Level of Fish]

Finally, 4.94% and 95.06% of fish are fresh and non-fresh.

3.2.5 Comparative Analysis of Meat Item

The table displays an analysis of fresh and non-fresh meat items. Mutton: 73 samples are fresh (90.12%), while 9 samples are non-fresh (11.11%). Similarly, Chicken: all 81 samples are fresh (100%), with no non-fresh samples. Similarly, Beef: 32 samples are fresh (39.51%), and 49 samples are non-fresh (60.49%). Similarly, fish: only 4 samples are fresh (4.94%), while 77 samples are non-fresh (95.06%). In total (324), fresh samples 190 and non-fresh 135. This data given an overview of the freshness of data meat items, showing that chicken has the highest freshness rate, while fish has the highest percentage of non-fresh items. The details are given table.

Table 3: [Meat Condition Analysis]

SN	Meat Item	Fresh		Non-Fresh	
		Number	Percentage	Number	Percentage
1	Mutton	73	90.12	9	11.11
2	Chicken	81	100	0	0
3	Beef	32	39.51	49	60.49
4	Fish	4	4.94	77	95.06
Total		**190**		**135**	

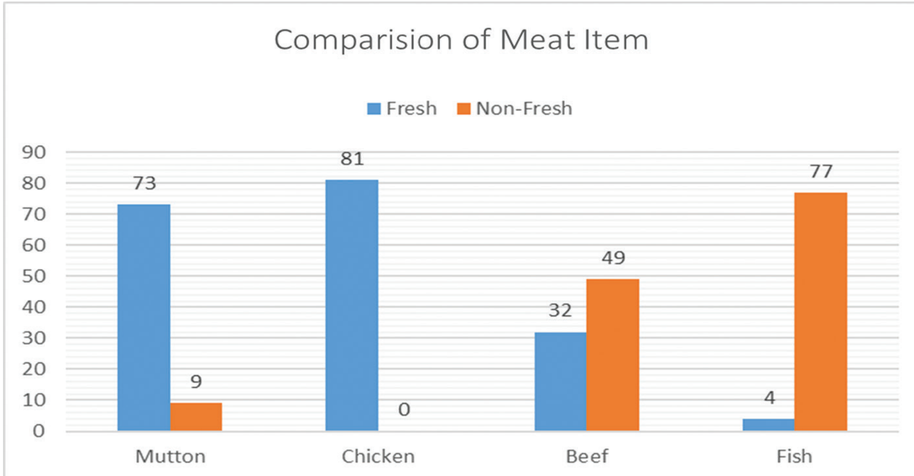

Figure 8: [Condition of Meat]

Time Prediction of Sample Meat

In this research, machine learning algorithms were employed to predict the self-life of meat. The observation period for mutton extended between 20 to 25 hours. Likewise, beef was sold in significant amounts during two-time frames: between 10 to 15 hours and again from 40 to 45 hours. Chicken was sold entirely fresh. As for fish, it was noted that it was sold in large quantities between 15 to 20 hours and again from 40 to 45 hours. A detailed summary of these finding is provided in the table below.

Table 4: [Predicted of self-life of meat Condition]

Time (Hour)	Mutton		Beef		Chicken		Fish		Total Sample	
	No	%	No	%	No	%	No	%	No	%
1--5 hr	70	86.42	12	14.81	81	100	3	3.70	166	51.23
5--10 hr	3	3.70	20	24.69			1	1.23	24	7.41
10--15 hr	4	4.94	26	32.10			18	22.22	48	14.81
15--20 hr	3	3.70	4	4.94			23	28.40	30	9.26
20--25 hr	1	1.23	6	7.41			19	23.46	26	8.02
25--30 hr			8	9.88			6	7.41	14	4.32
30--35 hr			3	3.70			2	2.47	5	1.54
35--40 hr			1	1.23			4	4.94	5	1.54
40--45 hr			1	1.23			5	6.17	6	1.85
Total	**81**		**81**		**81**		**81**		**324**	

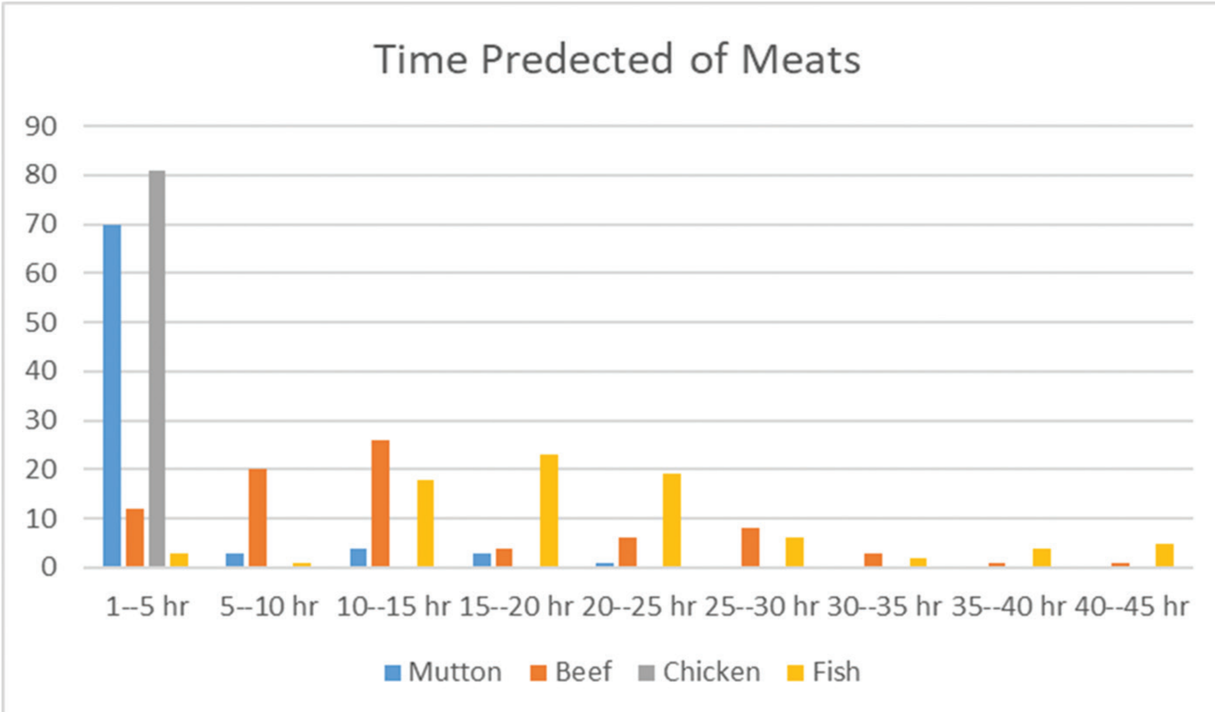

Figure 9: [Predicted of self-life of meat Condition]

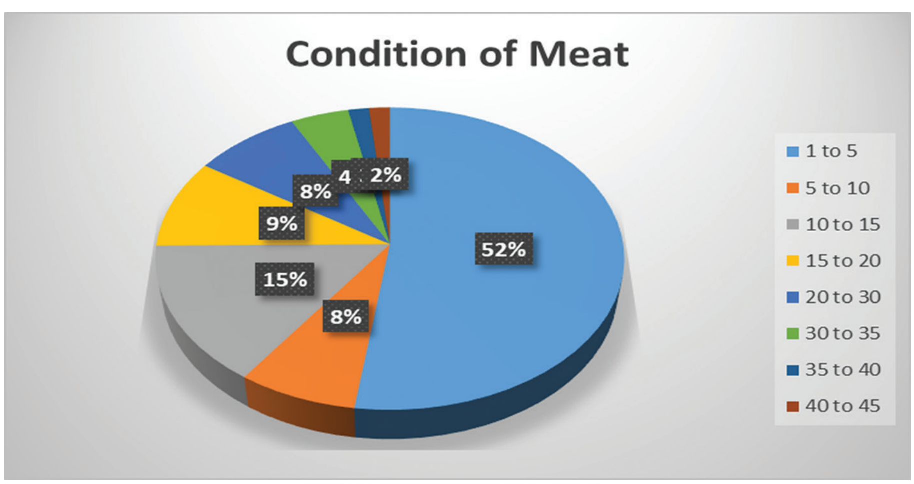

Figure 10: [Predicted of self-life of meat condition by pie-chart]

Discussion

This research systematically identified the condition of various types of meat based on data gathered by IoT sensors. The IoT sensors, though challenging to validate, were successfully compared against manual methods for verification. Additionally, the study successfully generated datasets using these sensors, with the primary goal of predicting meat quality through machine learning. The dataset, combined with the machine learning algorithm, accurately predicted the actual condition of the meat. Over six months of research across 12 meat shops, it was observed that when fresh meat is left at room temperature, ammonia and methane levels rise steadily, indicating that spoilage occurs after 9 hours.

From the six-month study, it was found that 11% of the mutton, 32% of the beef, all the chicken, and 96% of the fish samples were spoiled. Shopkeepers and consumers were often unable to detect normal levels of spoilage. In this context, the proposed method can be highly beneficial in preventing health risks. The traditional food quality testing methods currently used by food authorities take up to 24 hours to identify spoilage, making this new IoT-based approach a valuable tool for timely detection.

4. Conclusions

Meat consumption is on the rise in Nepal, with a variety of animal meats being consumed. As a key source of protein, meat is prone to rapid bacterial infection, and consuming spoiled meat can lead to serious health issues. Often, the spoilage is not immediately noticeable, highlighting the need for a more intelligent detection method. In many under developing countries, traditional methods are still used to test food quality. This research explores the use of smart technology to address these challenges. The primary goal of the research is to create a dataset based on the levels of methane and ammonia gases emitted as meat deteriorates. By analyzing this dataset, the actual condition of meat in sample meat shops can be identified. While the validation of IoT sensors proved complex, they were successfully verified by comparison with manual methods. The research also succeeded in building datasets using IoT sensors, with the aim of predicting meat quality through machine learning. The dataset and machine learning algorithm were able to accurately predict the condition of the meat. After six months of research conducted in 12 meat shops, it was found that when fresh meat is left at room temperature, ammonia and methane levels rise, with spoilage occurring after 9 hours. The study revealed that 11% of mutton, 32% of beef, all the chicken, and 96% of fish samples were spoiled. Both shopkeepers and consumers were often unable to detect early spoilage. This method could prove beneficial in preventing health risks by offering a more efficient solution. Currently, the food department uses traditional methods that can take up to 24 hours to identify spoiled meat. This new approach could be an essential tool for timely detection. If the government supports and implements this technology, it could greatly benefit public health by preventing the consumption of spoiled meat. Widespread use of such technology in meat shops would reduce the health risks associated with spoiled meat. Furthermore, this research provides a foundation for future studies to build on and advance the development of this smart monitoring system.

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