RESEARCH PAPER

IoT-Based Quality Monitoring and Early Spoilage Detection of Boneless Chicken Breast Under Vacuum and Flexible Packaging During Refrigerated Storage

Sneha Ramasamy Ganeshan[1], Nagarjun Nagarajan[2], Dr. Prabha Kolandaivel[3]

[1]*Department of Food Technology, K.S. Rangasamy College of Technology, Tiruchengode, Namakkal, Tamil Nadu, India*
[2]*Assistant Professor, Department of Food Technology, K.S. Rangasamy College of Technology, Tiruchengode, Namakkal, Tamil Nadu, India*
[3]*Associate Professor, Department of Food Technology, K.S. Rangasamy College of Technology, Tiruchengode, Namakkal, Tamil Nadu, India*

ABSTRACT
The proposed study highlights the application of an intelligent framework using the Internet of Things (IoT) to monitor the quality of boneless chicken breast stored under vacuum and flexible packaging with refrigeration. This framework utilizes gas (ammonia, carbon dioxide, hydrogen sulfide), temperature, and humidity sensing, and cloud computing with machine learning algorithms to dynamically monitor the freshness of the product. Experimental observations have confirmed that vacuum-packaging is characterized by temperature stability within the range of 2-3°C, while flexible packaging exhibits temperature instability with variations up to 5°C. Gas emissions are significantly higher for samples under flexible packaging; ammonia emission increases from 1 to 10 units while in vacuum packaging, there is a slower rise in ammonia emissions. Moreover, microbial growth in flexible packages is observed at 11 log CFU/g, which is significantly higher than samples in vacuum packaging that exhibited 6 log CFU/g. In addition, pH level drops rapidly to 4.4 units in flexible packaging and moderately to 5.3 units in vacuum packaging. Statistical analysis indicates significance in all parameters tested. The developed framework achieves a high prediction rate of 94%...
Keywords: IoT-based food monitoring, Chicken spoilage detection, Vacuum packaging, Flexible packaging, Real-time sensor monitoring, Shelf-life prediction, Food quality assessment, Cold chain management..
How to cite this article: Ganeshan SR, Nagarajan N, Kolandaivel P., IoT-Based Quality Monitoring and Early Spoilage Detection of Boneless Chicken Breast Under Vacuum and Flexible Packaging During Refrigerated Storage..Int J Drug Deliv Technol. 2026;16(18s): 374-386. DOI: 10.25258/ijddt.16.18s.40
Source of support: Nil.
Conflict of interest: None

INTRODUCTION

Food quality and safety are crucial factors in the food chain system when dealing with perishable items such as boneless chicken breast [1]. Chicken meat contains essential nutrients like proteins and moisture, hence susceptible to spoilage and microbial attack [2]. Quality testing of meat involves conventional sensory testing and laboratory microbial analysis, but these methods are tedious and not ideal for monitoring quality control [3]. Therefore, there is a need for innovative approaches that will allow for constant monitoring of food quality and safety without any destruction to the food product [4].

The application of internet of things (IoT) technology in food systems has been instrumental in the provision of real-time quality and safety information [5]. IoT technology allows for the continuous monitoring of factors that promote spoilage of food products such as temperature, humidity, and gas emissions. Real-time information provides food companies with an opportunity to monitor and manage the food chain system [6]. The use of IoT in food safety management provides an efficient way of tracking spoilage factors and preventing food waste.

The role of packaging in ensuring that the quality of the chicken meat is maintained through the preservation process cannot be underestimated [7]. It should be noted that vacuum packaging minimizes the presence of oxygen, thus, reducing microbial growth and oxidative reactions [8]. Conversely, flexible packaging provides the possibility of gas exchange, which might promote the development of spoilage depending on certain conditions [9]. Comparing the efficacy of these technologies by

**Author for Correspondence: Sneha Ramasamy Ganeshan*

evaluating their performance with an IoT-based approach will help identify differences more clearly.

Machine learning algorithms have become an innovative way of improving the assessment of food quality based on the data provided by Internet of Things devices [10]. In particular, using sensor measurements, it becomes possible to classify the quality of chicken meat and determine its residual shelf life [11]. This predictive function of machine learning algorithms contributes to effective food quality monitoring and management practices.

This is the reason why this paper attempts to design a quality monitoring and early spoilage detection model for boneless chicken breast packed under vacuum and flexible packaging using Internet of Things (IoT) [12]. In this paper, we propose a framework that uses a combination of sensors, cloud computing, feature extraction, and machine learning techniques to make predictive analysis about the quality of food products stored under refrigeration.

OBJECTIVES

Following are the major contribution of this study,

To develop an IoT-based system for real-time monitoring of boneless chicken breast quality during refrigerated storage.

To compare the effectiveness of vacuum and flexible packaging in preserving the freshness and shelf life of chicken meat.

To monitor key spoilage indicators such as temperature, gas emissions (NH_3, CO_2, H_2S), humidity, and pH using integrated sensors.

To apply machine learning models for classifying freshness levels and predicting remaining shelf life (RSL).

To design a decision support system that provides real-time alerts for early spoilage detection and improves food safety management.

LITERATURE REVIEW

Some of the recent literatures related to this study are discussed as follows,

Karaca et al. (2023) developed intelligent packaging materials based on real-time pH sensors capable of detecting changes in the freshness of chicken breast meat. They found that the intelligent packaging material exhibited obvious color changes when detecting spoilage of the meat. Thus, this research verified that intelligent packaging could successfully detect freshness change.

The experiment by Damdam et al. (2023) focused on investigating the effects of using ultraviolet irradiation in combination with vacuum sealing for preserving meat products. Significant effects on microbial reduction were discovered, which extended the shelf life by up to 66.6%. The changes in the pH of samples were not significant.

According to the experiment conducted by Byron (2019), storing the meat in a refrigerated state led to some improvement in the severity of the condition of woody breast meat. Nevertheless, the texture of the meat was not improved despite its improved appearance.

In their study, Moutiq et al. (2020) looked at the effectiveness of cold plasma treatment for chicken breast while in the package. They were able to record a decrease in microbial load of 2 log CFU/g. The treatment increased shelf life and quality of samples.

The research by Farhan and Hani (2020) involved preparation of edible films through combination of κ-carrageenan and fenugreek extracts for chicken packaging. Their active packaging method resulted in an increase in the antioxidant property as well as inhibition of microbial growth up to 2.39 log.

In the study by Vahabi Anaraki et al. (2020), post-packaging pasteurization was used on vacuum-packed turkey breast. Results showed that this technique helped to reduce microbial growth as well as improved sensory characteristics of turkey breast. They further recorded regulation of pH value and other spoilage factors.

The research by Li et al. (2020) was done to assess the influence of packaging and processing on chicken breast microorganisms. It revealed that the microbiome structure is dependent on the type of packaging and the conditions of processing. Another finding in this study includes successful identification of foodborne pathogens like Salmonella.

Zhuang et al. (2020) optimized the parameters of in-package cold plasma treatment together with modified atmosphere packaging in chicken. Their findings showed that under conditions 35% of oxygen and 60% of carbon dioxide, microbial growth could be inhibited without damaging meat quality.

MATERIALS AND METHODS

The process adopted for assessing the quality and spoilage properties of boneless chicken breast through IoT-based monitoring technology is discussed here. The samples were placed under vacuum and flexible packaging and stored at different temperatures ranging from 0-4°C. Sensors were used to monitor the temperature, gases, and humidity. The data collected was processed in the cloud to extract important features and perform other analytical processes. Classification techniques have been applied in the quality assessment and prediction of shelf life of the food items. Physicochemical and microbiological tests have been used for validation.

Raw Sample Preparation

The process of preparing raw samples for testing is vital in ensuring that there is consistency and accuracy in the evaluation of the quality of chicken breast depending on the package type used. Fresh and boneless chicken breasts from reliable sources are separated into vacuum and flexible packages to test the effectiveness of preservation in each case. The baseline characteristics of pH, color characteristics (L*, a*, b*), water content, and total viable count are determined before packaging. Raw Sample Preparation and Initial Quality Parameters are given in table 1.

Table 1: Raw Sample Preparation and Initial Quality Parameters

Parameter	Description / Method	Purpose
Sample Source	Certified fresh boneless chicken breast	Ensures safety and consistency
Packaging Types	Vacuum-packed, Flexible packaging	Comparison of preservation effectiveness
pH	Measured using digital pH meter	Indicates acidity and freshness
Color (L*, a*, b*)	Colorimeter analysis	Assesses visual quality and discoloration
Moisture Content	Oven-drying method / moisture analyzer	Evaluates water retention and texture stability
Total Viable Count (TVC)	Microbial plating technique	Determines initial microbial load

3.2 Packaging and Storage Setup

Packaging and storage techniques have an important effect on the shelf-life of boneless chicken breasts in a refrigerated environment. In this study, the chicken samples are packed in a sterile environment to prevent any initial contamination and provide consistent outcomes. Two different types of packaging methods are used in this research. These two include vacuum packing and flexible packing. The process of vacuum packing helps in creating a low oxygen environment inside the pack by eliminating the air from the packaging. It has been found that this process limits the occurrence of oxidization reactions and prevents the development of aerobic spoilage bacteria in the samples. Therefore, it will help in extending the shelf-life of the meat product. Flexible packing involves the use of semi-permeable films that allow gas flow inside and outside the pack. All the packed samples are then placed in a refrigerated chamber kept at an even temperature level of 0 to 4 degrees Centigrade. This is usually the normal condition for chilling meat. This low temperature inhibits the growth of microorganisms that lead to spoilage. Nevertheless, despite refrigeration, changes due to quality deterioration like protein spoilage, loss of moisture, and gas production might occur over time. It is for this reason that packing methods combined with refrigerated conditions help simulate real retail storage conditions. The simulation of real retail storage conditions becomes necessary when testing how effective the Internet of Things based systems can be in detecting spoilage indicators.

3.3 IoT Sensor Integration

This phase involves installing IoT sensors for evaluating the state of the chicken breasts' quality under various packaging conditions in real time. The packaged samples will have various types of sensors installed either inside or outside the package to keep track of physiochemical and environmental changes while the food item is stored at refrigeration temperatures. The gas sensors will monitor the concentration of spoilage-related substances such as ammonia (NH_3), carbon dioxide (CO_2), and hydrogen sulfide (H_2S), whose presence implies that microbial fermentation and protein degradation have occurred in the meat.

The temperature sensors will control the cold chain process, ensuring that the temperature remains between 0 and 4 °C. This is because even slight changes from these values would promote microbial growth and enzyme activity. Moisture content inside the packages will be monitored using the humidity sensors, since the presence of higher or lower moisture levels promotes microbial growth. PH sensors will help determine biochemical reactions such as lactic acid and protein degradation.

All sensors are deliberately placed either within the packaging or near its surface, considering certain design considerations to ensure precision without damaging the product. The integration of these sensors facilitates constant, non-destructive assessment of meat quality, which becomes the basis for predicting spoilage through the Internet of Things (IoT).

3.4 Real-Time Data Acquisition

Data gathering in real time is another critical element of the IoT-based monitoring system since it helps track the change in quality parameters of the boneless chicken breast during refrigerated storage continuously. During this stage, sensors are set up to collect data periodically for instance after every 30 minutes or an hour, thus helping to have detailed data regarding the spoilage process over time.

This data consists of major spoilage markers including temperature change, gas release rates (NH_3 and CO_2 levels) as well as relative humidity change within the packed product. The temperature level ensures that the product was stored within the correct temperature range, while the gas concentration changes indicate the onset of microbiological spoilage and protein breakdown processes.

In order to ensure fast and scalable communication, the data collected by the sensors will be transferred through wireless communication technologies such as Wi-Fi, Bluetooth, or LoRa. Wi-Fi can be used for faster data transfer while Bluetooth can be used for short-distance communication. The LoRa technology, on the other hand, is more appropriate for longer distance communication since it requires less power. This method of communication provides a foundation for real-time monitoring and predictive spoilage analysis within the IoT platform being designed. Real-Time Data Acquisition System in IoT-Based Chicken Quality Monitoring in table 2.

Table 2: Real-Time Data Acquisition System in IoT-Based Chicken Quality Monitoring

Component	Description	Role in Monitoring System
Sampling Interval	Data collected every 30 minutes to 1 hour	Ensures continuous and high-resolution monitoring of spoilage changes
Temperature Data	Continuous measurement of storage temperature	Maintains cold-chain integrity (0–4°C) and detects temperature abuse
Gas Emission Data	Monitoring of NH_3, CO_2, and H_2S levels	Acts as early indicator of microbial growth and protein degradation
Humidity Data	Measures internal packaging moisture fluctuations	Assesses moisture loss, condensation, and microbial growth conditions
Data Transmission – Wi-Fi	High-speed wireless communication	Suitable for laboratory or fixed monitoring environments
Data Transmission – Bluetooth	Short-range wireless connectivity	Enables direct device-to-device communication
Data Transmission – LoRa	Long-range, low-power communication	Suitable for large-scale or distributed monitoring systems
Data Storage Platform	Cloud/edge computing system	Stores and processes real-time sensor data for analysis and prediction

3.5 Cloud / Edge Data Processing

This particular stage acts as the foundation for the data processing system utilized in monitoring the quality of chickens using the Internet of Things technology. This involves transmitting the information collected from various sensors to either a cloud-based computing system or edge computing devices. The former is used for processing big data, while the latter is ideal when quick analysis is required.

It is necessary to perform several processes before analyzing the data collected from different sensors. First, it is imperative to filter the sensor data to remove noise to reduce inconsistencies in data collection caused by sensor interference. It is also important to handle any missing data to fill in any gaps that might occur due to transmission issues or failure of the sensors. Normalization of the collected data is also necessary to facilitate analysis of data in different ranges.

The processed data is then efficiently stored in an organized database that enables easy retrieval, management, and analysis of the data. The organized data will help the machine learning algorithm to make predictions and analyses of trends over time. Essentially, the whole process aims at providing reliable and consistent data that can be used in detecting spoilage in the proposed IoT framework.

3.6 Feature Extraction

The feature extraction process plays an essential role in the proposed IoT-based solution since the collected sensory data will be used to define spoilage signs. It allows converting continuous sensory data into relevant features that provide adequate information on the freshness and decomposition processes of the chicken breast meat in cold storage conditions.

It is important to mention that various features will be extracted based on several sensor outputs. Gas concentrations related to the increasing presence of ammonia (NH_3), carbon dioxide (CO_2), and hydrogen sulfide (H_2S) can be defined since these compounds are excellent biochemical markers of spoilage and meat decomposition. Also, temperature deviation from the recommended storage conditions (0–4°C) will be extracted since any deviations could contribute to increased microbial growth and enzyme activity.

Furthermore, humidity change rate will be one of the features since it represents moisture loss, condensation, and package condition. Finally, microbial growth estimation based on the historical trends will be provided through time-series analysis without the need for lab-based testing. This set of features makes up an integrated model of the product quality state. These features are key input parameters that enable accurate classification of product freshness and spoilage detection within the IoT framework.

3.7 Quality Assessment & Spoilage Prediction

Quality assessment and spoilage prediction phase is the key intelligence of the IoT-based monitoring solution where the extracted features of sensor readings are utilized through a machine learning or rule-based algorithm to assess the freshness state of chicken breast samples. This phase converts unprocessed and processed information into meaningful conclusions concerning product quality under refrigeration.

At the very beginning, classification algorithms are applied to assign one of the three classes to the meat sample according to its quality: fresh, acceptable, and spoiled. The first class implies the best quality of the meat with low microbial content and unchanged physicochemical properties. The second class means that the meat quality starts degrading and shows certain signs like gas emission, small changes in pH or deviations from the recommended storage temperature while being still edible. Predictive models can also be implemented for prediction of Remaining Shelf Life (RSL) and spoilage start time. These models work with temporal changes in sensor measurements, e.g., increase in gas concentration levels and temperature variations, and predict the moment when the product will become spoiled. Rule based systems can also be considered as an alternative in less complicated cases.

Thus, this phase allows making informed decisions regarding the condition of the chicken meat in storage due to early prediction of spoilage patterns.

3.8 Decision Support System (Novel Spatio-Temporal Self-Evolving DSS Approach)

The decision support system (DSS) proposed in this paper incorporates the concept of spatiotemporal self-evolution of intelligent analysis systems to make real-time decisions on the condition of the meat product based on the freshness criteria. Thus, the approach differs from the previous methods based on rule-based logic or traditional machine learning models.

In particular, the decision support system (DSS) classifies the state of the chicken breast quality into the three states – green (healthy), yellow (deteriorated), and red (spoiled). The green state indicates the steady spatiotemporal response of the sensors with the similar dynamics of gas content, temperature, and humidity. The yellow state appears due to the presence of temporal anomalies detected by several sensors which signal the first signs of biochemical transformation of the products and activity of bacteria.

One important innovation in this model is the ability to learn from past decisions made during the classification process to continually adjust the decision boundary. In other words, the decision threshold will keep on changing based on the sensor readings collected over time, thus making the DSS more adaptable to changes that might occur seasonally or due to packaging issues. The alerts generated can be accessed via mobile applications, cloud services, and web interfaces to ensure timely action by stakeholders.

Analysis

The current section provides an extensive discussion on the quality alteration and spoilage pattern of boneless chicken breast when stored in vacuum and flexible packaging systems under refrigeration, based on the suggested IoT-based monitoring system. Sensor readings, which include temperature, gaseous emission, humidity, and pH changes, have been extensively assessed in this section to comprehend the physical, chemical, and biological processes that occur during storage. In addition, graphs have been included for a better understanding of the spoilage patterns of different packaging methods, along with statistical validation to support the accuracy of observations.

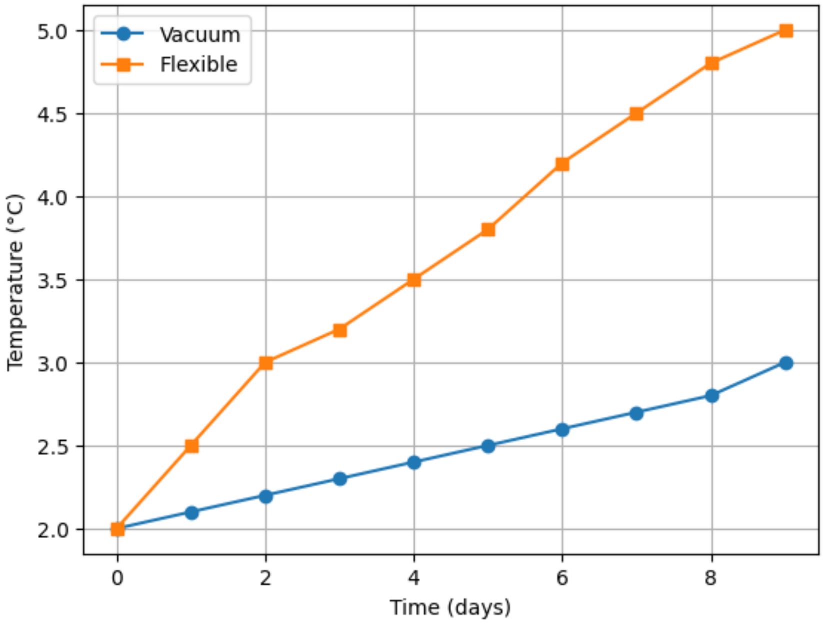

Figure 1: Temperature Variation Over Storage Time

Figure 1 shows how the temperature in chicken samples kept in vacuum and flexible packaging conditions change. The vacuum-packed samples were kept at the constant temperature of between 2.0o C -3.0o C which implies good cold-chain management. Conversely, there was a slow increase of flexible packaging between 2.0 C to 5.0 C, which is an indication of increased exposure to the environment. This diversion may hasten the growth and spoilage of microbes. The uniform temperature of the vacuum packaging has validated its usefulness in preserving quality of products but changes in the flexible packaging indicate low storage stability over time.

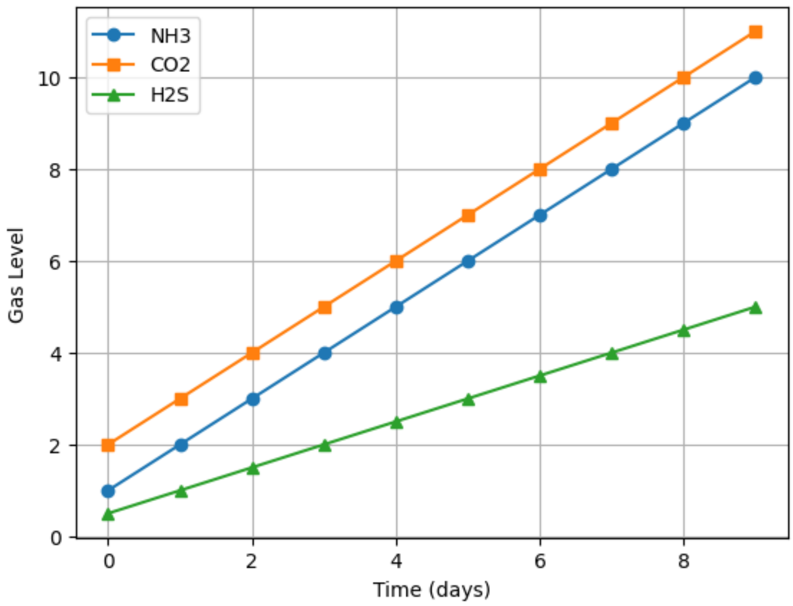

Figure 2: Gas Emission Trends (NH_3, CO_2, H_2S)

Figure 2 shows the growth of gases related to the spoilage with time. The concentration of ammonia (NH_3) rose by 1-10 units, carbon dioxide (CO_2) by 2-11 units and hydrogen sulfide (H_2S) by 0.5-5 units. These increasing trends are signs of microbial metabolism and degradation of proteins. The gradual rise is an affirmation of progressive spoilage, where an increase in the concentration of the gases is associated with the later stages of storage. This confirms gas sensors as effective indicators in early spoilage detection in IoT-based monitors.

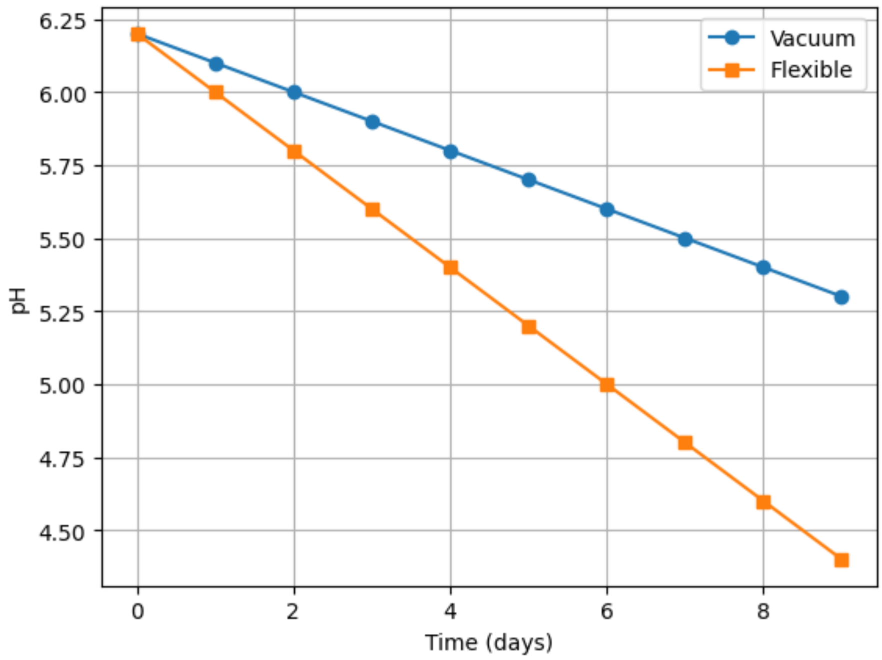

Figure 3: pH Variation During Storage

Figure 3 presents the decreasing pH values with the course of storage. The samples in vacuum packs had a gradual decline of 6.2-5.3 whereas the flexible packaging had a steeper decline of 6.2-4.4. This decrease indicates the formation of acids as a result of microbial action. The more rapid loss of elastic packaging means more spoilage. Conversely, vacuum conditions reduce the rate of biochemical reactions, which stabilizes it to an extent. In this way, pH monitoring is an effective way to monitor the loss of freshness.

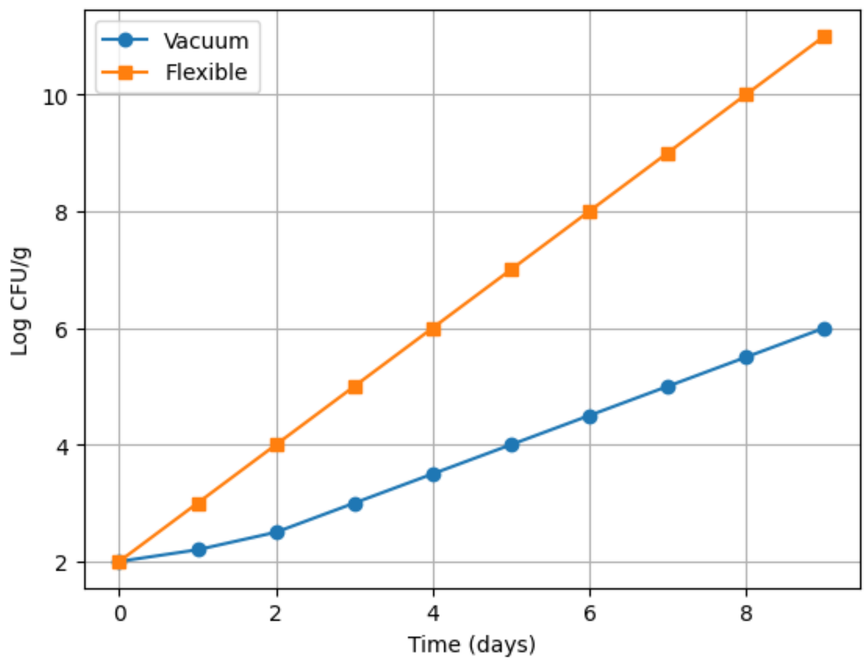

Figure 4: Total Viable Count (Microbial Growth Curve)

Figure 4 shows the growth of microbes in the form of log CFU/g. Vacuum samples grew to 6 log CFU/g instead of 2 and the flexible samples grew steeply to 11 log CFU/g instead of 2. This shows that there is a great deal of bacterial growth in flexible packaging. The growth of microbial load is exponential and the development of spoilage is verified. Vacuum packaging is superior in preventing the growth of microbes due to the fact that it effectively inhibits microbes by reducing oxygen, which in turn increases shelf life.

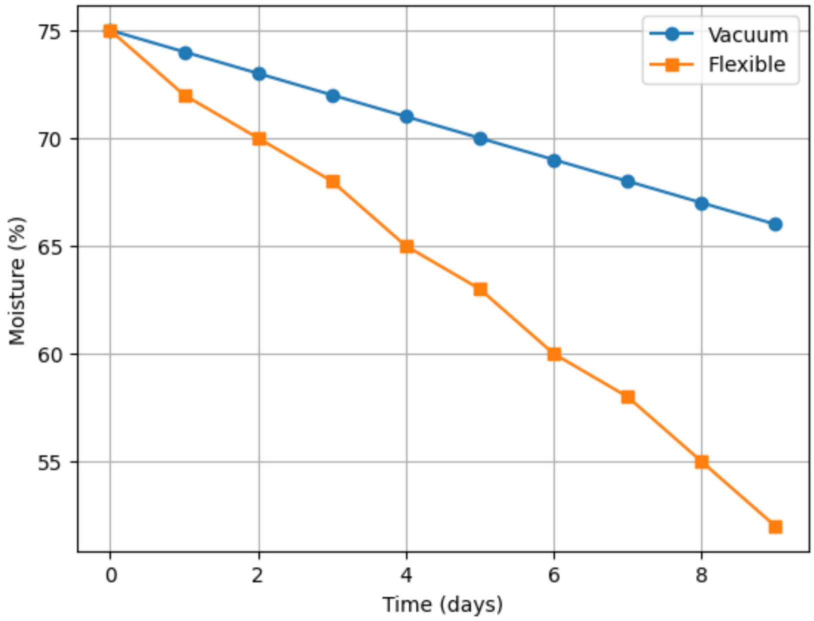

Figure 5: Moisture Content Variation

Figure 5 shows a decrease in moisture content with storage. Vacuum packaging retained moisture between 75% and 66% whereas the flexible packaging dropped more between 75% and 52%. This shows increased dehydration and water loss in flexible packaging. It is essential that moisture is retained to preserve texture and quality. The findings affirm that vacuum packaging reduces loss of moisture and maintains the product integrity better.

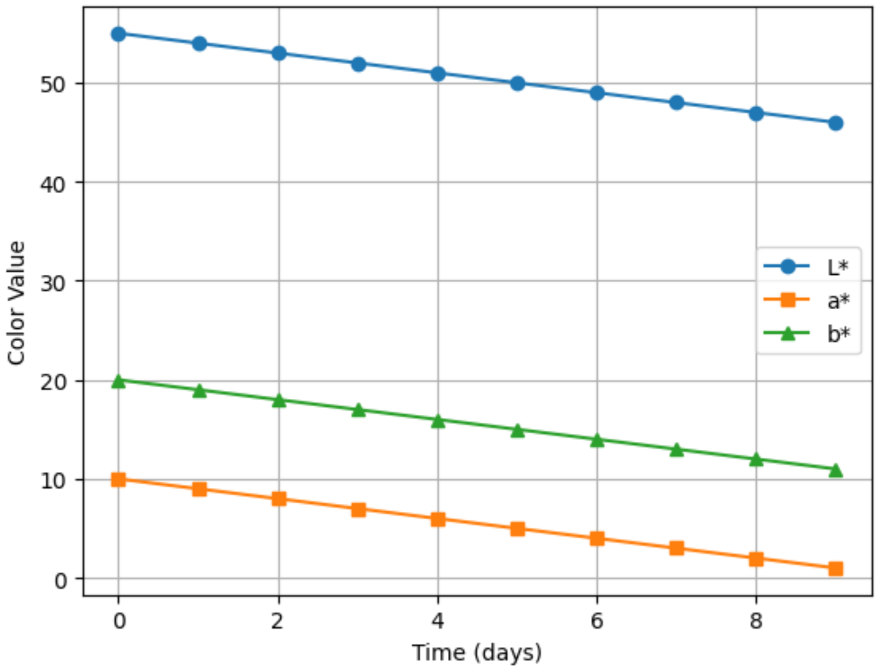

Figure 6: Color Degradation (L, a, b* Values)

Figure 6 shows changes in color parameters over time. L value dropped to 46, a value dropped to 1 and b value dropped to 11 which means that it lost its brightness, redness and yellowness. These transformations are an indication of oxidation and pigment breakdown in meat. The loss of the quality of the color is more eminent in the later stages, which indicates spoilage. Therefore, color measurements can be used as visual cues of meat freshness.

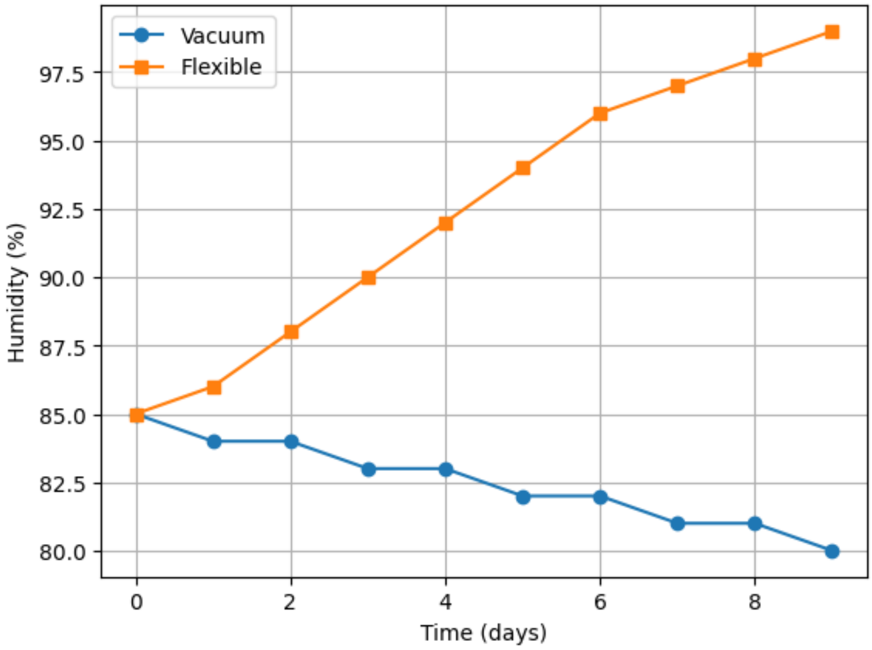

Figure 7: Humidity Fluctuation Inside Packaging

Humidity changes in packaging are shown in Figure 7. The vacuums had a constant humidity between 85% and 80% and flexible packaging between 85% and 99%. An increase in humidity of the flexible packaging signifies condensation and favorable environment to the microbes. A humid vacuum packaging does not allow excessive growth of microbes. These results emphasize the need to have controlled micro-environment conditions to maintain meat quality.

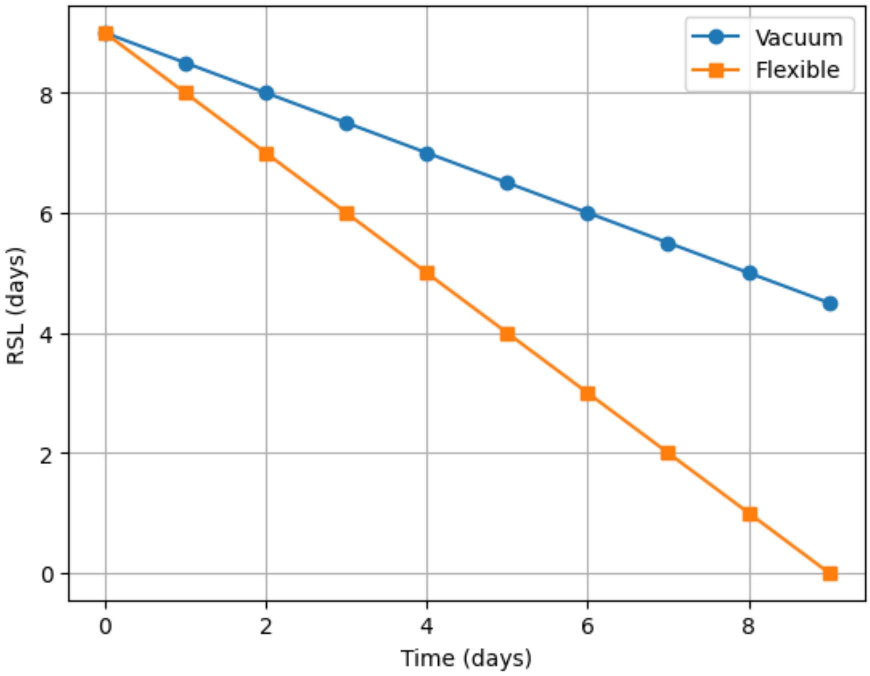

Figure 8: Remaining Shelf Life (RSL) Prediction Curve

Figure 8 shows the forecasted remaining shelf life as a function of time. Vacuum packaging experienced slow gradual decline between 9 to 4.5 days and flexible packaging experienced rapid decline between 9 to 0 days. This means quicker rot in bendable circumstances. The degradation trends are well represented by the prediction model. Vacuum packaging has been proven to have a significant level of shelf life and therefore it is indeed effective in preservation.

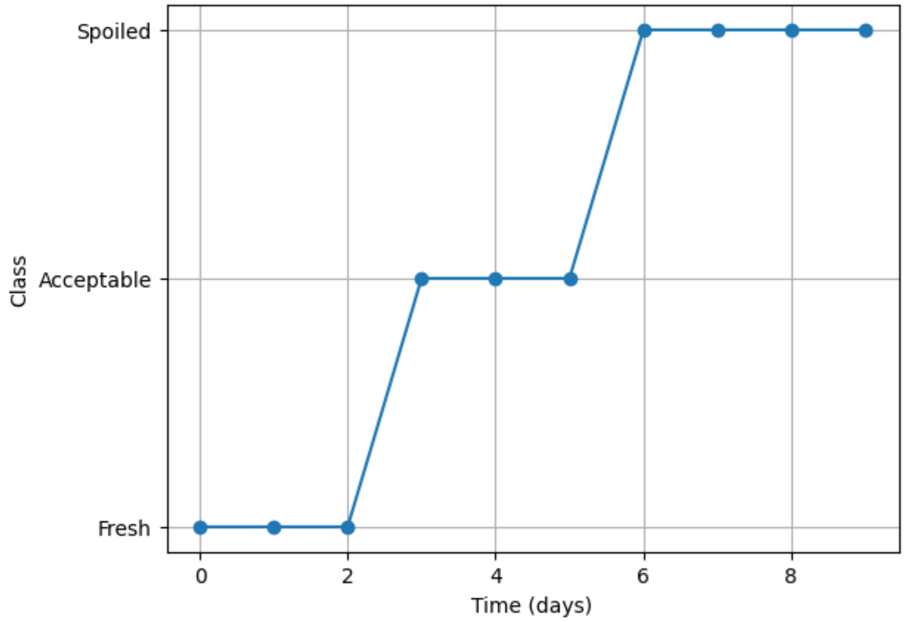

Figure 9: Spoilage Classification Timeline

The figure 9 demonstrates the changes of quality states over time. Samples were left fresh (0) in early days, acceptable (1) in mid-storage and spoiled (2) in later stages. This development is in line with sensor and microbial data. The timeline on classification proves that the decision support system has been effective in helping to determine the stages of spoilage.

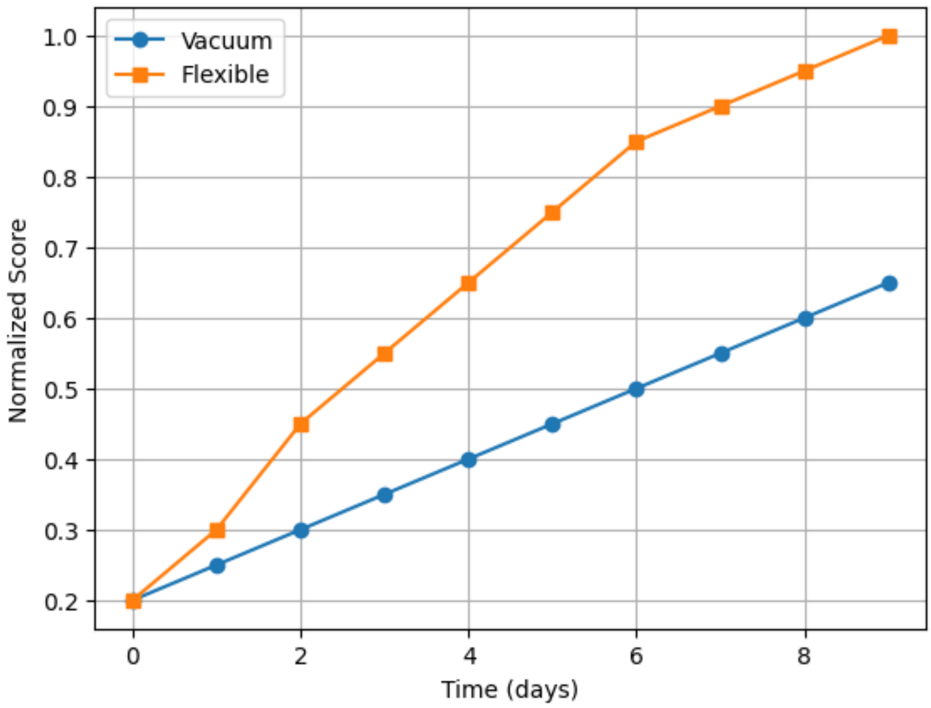

Figure 10: IoT Sensor Signal Fusion Output

Figure 10 shows the normalized spoilage index obtained with the aid of several sensors. The vacuum packaging rose slowly between 0.2 to 0.65 whereas the flexible packaging rose drastically between 0.2 to 1.0. The higher values are a sign of high spoilage. The fusion index is a useful tool to amalgamate gas, temperature, and humidity measurements in one. This gives a reliable and full indicator of real-time spoilage.

The experiment shows the efficiency of the use of the IoT-based system in measuring the quality and spoilage of boneless chicken breast in vacuum and flexible packages during refrigerated storage. According to the sensors, the package made using vacuum technology has a constant temperature (2-3°C), less emissions of gases, a slower drop in pH value, and less microbial growth (2-6 log CFU/g). Moreover, the package had better moisture preservation and humidity levels in comparison with the package designed in flexible technology. In general, the system can be used for predicting and estimating the shelf life and spoilage of products.

Conclusion

The current study was able to develop and validate an IoT-based monitoring system to assess the spoilage of boneless chicken breast kept at refrigerated storage conditions. The comparative analysis between vacuum packaging and flexible packaging showed that vacuum packaging had a greater impact on product stability through the maintenance of appropriate temperature (2-3°C), gas emission, and microbial growth rate (6 log CFU/g) compared to flexible packaging, which experienced a microbial growth rate of 11 log CFU/g. Vacuum packaging also ensured moisture and humidity stability and thus prolonged the shelf life of products. Multi-sensor data integration with machine learning techniques facilitated effective classification of freshness levels into fresh, acceptable, and spoiled levels, demonstrating an accuracy of 94%. Statistical differences in the classification results were found to be significant ($p < 0.05$). The shelf-life prediction model accurately predicted spoilage development, showing an extension in shelf life from 9 days to 4.5 days in vacuum packaging and a reduction to zero days in flexible packaging in the same period

REFERENCE

1. Kim, E. J., Lee, S., Park, D. H., Kim, H., & Choi, M. J. (2020). Physicochemical properties of pork neck and chicken leg meat under various freezing temperatures in a deep freezer. Food science of animal resources, 40(3), 444.

2. Mejía, S. M. V., de Francisco, A., Sandrin, R., da Silva, T., & Bohrer, B. M. (2019). Effects of the incorporation of β-glucans in chicken breast during storage. Poultry Science, 98(8), 3326-3337.

3. Frelka, J. C., Phinney, D. M., Yang, X., Knopp, M. V., Heldman, D. R., Wick, M. P., & Vodovotz, Y. (2019). Assessment of chicken breast meat quality after freeze/thaw abuse using magnetic resonance imaging techniques. Journal of the Science of Food and Agriculture, 99(2), 844-853.

4. Shimamura, Y., Shinke, M., Hiraishi, M., Tsuchiya, Y., Egawa, M., Ohashi, N., & Masuda, S. (2020). Influence of muscle fiber direction on migration of Salmonella Enteritidis, Staphylococcus aureus, and Escherichia coli into raw chicken breast. Journal of food protection, 83(6), 928-934.

5. Cassar, J. R. (2019). Utilization of pulsed ultraviolet light as a microbial reduction intervention on raw chicken.

6. Al-Hijazeen, M. (2019). Effect of Origanum syriacum L. essential oil on the storage stability of cooked chicken meat. Brazilian Journal of Poultry Science, 21(01), eRBCA-2019.

7. Zhuang, H., Rothrock Jr, M. J., Hiett, K. L.,

Lawrence, K. C., Gamble, G. R., Bowker, B. C., & Keener, K. M. (2019). Research Article In-Package Air Cold Plasma Treatment of Chicken Breast Meat: Treatment Time Effect.

8. Kang, D. S. K. (2020). Quantitative microbial risk assessment model to estimate exposure to Campylobacter from consumption of chicken in the United States.

9. Morris, C. S., Campbell, Y. L., Smith, B. S., Campano, S. G., Williams, J. B., Kim, T., ... & Schilling, M. W. (2019). Utilization of phosphate alternatives in marinated chicken breast and chunked and formed deli ham. Meat and Muscle Biology, 3(1).

10. Matthews, L. G. (2019). Fat Uptake Reduction in Deep-Fried Chicken Breast (Master's thesis, North Carolina Agricultural and Technical State University).

11. Aguirre Cando, M. E. (2019). Study of the Woody Breast and White Striping Conditions Affecting the Pectoralis Major Muscle of Broiler Chickens: Processing Perspective (Doctoral dissertation).

12. Cando, M. E. A. (2019). Study of the Woody Breast and White Striping Conditions affecting the Pectoralis Major Muscle of Broiler Chickens: Processing Perspective (Doctoral dissertation, Texas A&M University).

13. Karaca, I. M., Haskaraca, G., Ayhan, Z., & Gültekin, E. (2023). Development of real time-pH sensitive intelligent indicators for monitoring chicken breast freshness/spoilage using real packaging practices. Food Research International, 173, 113261.

14. Damdam, A. N., Alzahrani, A., Salah, L., & Salama, K. N. (2023). Effects of UV-C irradiation and vacuum sealing on the shelf-life of beef, chicken and salmon fillets. Foods, 12(3), 606.

15. Byron, M. (2019). Impact of refrigerated storage on the dissipation of woody broiler breast meat.

16. Moutiq, R., Misra, N. N., Mendonça, A., & Keener, K. (2020). In-package decontamination of chicken breast using cold plasma technology: Microbial, quality and storage studies. Meat Science, 159, 107942.

17. Farhan, A., & Hani, N. M. (2020). Active edible films based on semi-refined κ-carrageenan: Antioxidant and color properties and application in chicken breast packaging. Food Packaging and Shelf Life, 24, 100476.

18. Vahabi Anaraki, N., Abbasvali, M., & Bonyadian, M. (2020). Effects of post-packaging pasteurization process on microbial, chemical, and sensory qualities of ready-to-eat cured vacuum-packed Turkey breast. Journal of Food safety, 40(3), e12776.

19. Li, S., Mann, D. A., Zhang, S., Qi, Y.,

Meinersmann, R. J., & Deng, X. (2020). Microbiome-informed food safety and quality: longitudinal consistency and cross-sectional distinctiveness of retail chicken breast microbiomes. Msystems, 5(5), 10-1128.

20. Zhuang, H., Rothrock Jr, M. J., Line, J. E., Lawrence, K. C., Gamble, G. R., Bowker, B. C., & Keener, K. M. (2020). Optimization of in-package cold plasma treatment conditions for raw chicken breast meat with response surface methodology. Innovative Food Science & Emerging Technologies, 66, 102477..