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SMART IOT-BASED SHELF-LIFE MONITORING AND SPOILAGE PREDICTION SYSTEM FOR PERISHABLE PRODUCE

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Abstract

Ensuring the quality and freshness of fruits and vegetables during the transportation process after harvesting is an ever-present challenge in the food industry. The environmental conditions, including temperature, humidity, and gas concentration (CO2, O2, and Ethylene), play an important role in the shelf life of the fruits and vegetables. The traditional cold chain monitoring system generally monitors the temperature and does not provide predictive capabilities or real-time notifications. Hence, the system responds to the issues that have already occurred, rather than preventing them from happening in the first place. The proposed project in this paper focuses on the implementation of an intelligent system for shelf-life monitoring and prediction. The system monitors the environmental conditions, including temperature, humidity, gas, and light, using a multi-sensor device. The data collected from the sensors is processed using a rule engine, which calculates the loss in shelf life on the basis of the current values. The system also sends notifications in the form of an SMS or mobile application in the event of potential spoilage.

Keywords: Smart IoT system, perishable fruits and vegetables, temperature, gas concentration (CO_2, O_2, ethylene), real-time alerts, multi-sensor device, quality and freshness control, SMS and mobile alerts.

1. INTRODUCTION

1.1. Significance of Smart IoT in Shelf-Life Monitoring and Spoilage Prediction

Perishable products, such as fruits, vegetables, and dairy products, are highly sensitive to various environmental factors, including temperature, humidity, light, and gas concentration, all of which directly affect their freshness and shelf life [1][2]. Conventional methods, such as manual inspection and static labeling, are not reliable, as they do not provide real-time visibility into storage conditions, resulting in early deterioration, wastage, and financial loss [3][4]. Smart IoT technology has been recognized as a promising approach to address this issue, as it facilitates continuous sensing, wireless data transmission, and smart analysis for continuous quality monitoring [5][6]. By employing IoT technology, cloud computing, and prediction techniques, it is possible to analyze data, predict shelf life, and raise early alerts regarding potential spoilage [7][9]. Overall, smart IoT-based monitoring helps to improve efficiency, food safety, and sustainable food management [10].

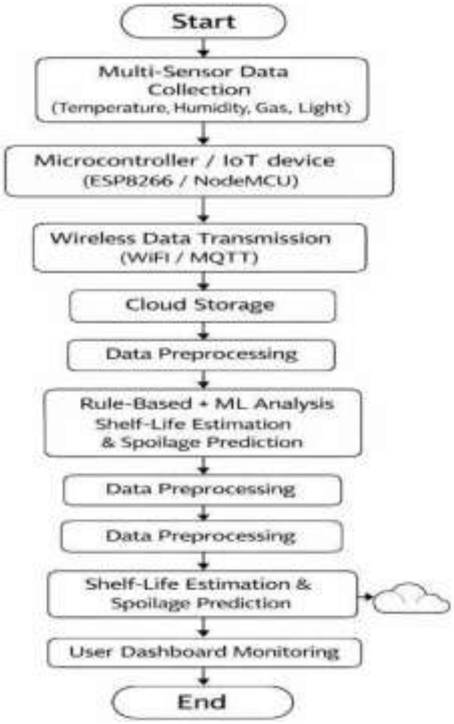


Fig.1 Workflow of Smart IoT-Based Shelf- Life Monitoring and Spoilage Prediction System.

Fig describes the complete workflow of the proposed Smart IoT-Based Shelf-Life Monitoring and Spoilage Prediction System for perishable fruits and vegetables. Recent advances in Smart IoT architecture have demonstrated the efficiency of the proposed system in maintaining the quality of perishable items using the effective integration of monitoring and predictive intelligence [1][2]. As shown in Fig. 1, the system's workflow starts by monitoring the environmental parameters in real-time using IoT sensors, where parameters such as temperature, humidity, gas concentration, and light intensity are monitored continuously [3][4]. The collected data is wirelessly transmitted to a central gateway or a microcontroller, which does preliminary preprocessing and sends the data to the cloud analytics platform using communication protocols such as MQTT or Wi- Fi [5][6]. In the cloud computing platform, machine learning algorithms are employed to analyze the sensor data and determine the spoilage probability and shelf life of the produce [7][8]. These models are also able to identify the early symptoms of deterioration by identifying changes from the ideal environmental conditions[9]. The system, therefore, sends predictive notifications upon identifying the potential spoilage risk factors, which are sent to the relevant parties using SMS or email notifications [10][11].

This process creates a closed-loop monitoring system, which promotes real-time decision-making, transparency, and automation in the entire value chain [12]. The proposed system, therefore, enhances the sustainability and efficiency of food quality assurance using IoT technology, cloud computing, and predictive modeling [13].

1.2. Limitations of Existing System

The currently used shelf-life monitoring systems have helped in efficient management of food storage through the use of sensors and IoT technologies. However, these systems have many limitations. The most common limitations of these systems include the fact that most of them can only monitor basic factors, which include temperature and humidity. However, they cannot monitor other important factors that contribute to food spoilage, which include ethylene, CO2, O2 imbalance, and light. These factors are very important in the evaluation of food freshness. Moreover, most of these systems cannot analyze the combined non-linear interactions of environmental factors, which makes them inaccurate in shelf-life estimation. The commonly used alert mechanisms in these systems include static threshold mechanisms, which cannot adapt to different types of food and real- world conditions.

Machine learning-based spoilage prediction models also have issues with poor reliability in practical applications, considering that most models were trained on small-scale laboratory datasets and may not be able to handle sensor noises, handling conditions, and cold chain environment changes [4][7]. The practical applicability of these models may be further limited by issues such as sensor calibration, gas sensor costs, power consumption, and network connectivity during transportation [3][6]. Moreover, most of these systems do not have real-time cloud analytics, instant alert notifications, or user-friendly interfaces, thereby affecting the usability of the system for farmers, distributors, or cold storage users [1][5]. This, in turn, creates a pressing need to design an affordable, scalable, and intelligent monitoring system that offers accurate spoilage detection through the fusion of multi-sensor data, cloud computing, and predictive analytics in real-time [9][10]. The second limitation of these systems is their inability to learn continuously. Machine learning algorithms are employed to train the model for estimating the shelf life of produce. However, the spoilage behavior of produce changes over time due to factors such as seasons, storage duration, packaging, and type of produce. In the absence of continuous learning, the accuracy of the model decreases significantly over time [7][8]. The third limitation of these systems is that they have not been validated at a larger scale. The majority of these systems are at the research prototype stage.

1.3. Research contributions

Several recent studies on smart packaging solutions for fresh produce have focused on improving shelf-life estimation, spoilage detection, and food quality monitoring using sensing and intelligent technologies. Multi- sensor-based packaging systems have been proposed to monitor environmental and biochemical parameters such as temperature, humidity, gas (ethylene or spoilage gases), and light exposure, all of which directly influence the freshness of fruits and vegetables. Some approaches employ IoT platforms and cloud- based systems to enable real-time monitoring across storage and transportation stages, while others utilize machine learning models to classify freshness levels and
predict spoilage probability. These advancements have significantly contributed to improved post- harvest management and cold- chain monitoring.

However, most of the existing smart packaging systems depend on static threshold-based decision-making strategies, which restrict their adaptability to varying environmental conditions and complex spoilage patterns. The methods may not be able to handle the non-linear relationships between various factors influencing the degradation process, which may lead to inaccurate predictions [10][11]. In addition, there are various intelligent models that have been developed based on small-scale or controlled conditions, which may not be applicable in practical conditions due to various uncertainties and sensor noises [12][13].

Recently, new research has been conducted to introduce machine learning-based approaches to improve the accuracy of freshness prediction and spoilage detection. The machine learning algorithms used include Random Forest, regression, classification, etc. These algorithms can learn from the past sensor readings and can detect the spoilage of food over time. Although these algorithms can improve the accuracy of freshness prediction, most of the existing solutions lack the facility of integrating with real-time alert systems, cloud visualization, etc.

1.4. Motivation of the Proposed Framework

The perishable food items are very sensitive to changes in temperature, humidity, and gas composition. This has a major impact on the deterioration of the food items [4][6]. The traditional method of monitoring the food items does not allow the changes to be monitored in real-time [7][9]. This has a major impact on the ineffectiveness of the monitoring process. In order to avoid the difficulties that have been faced while monitoring the food items, the proposed Smart IoT system uses the multi-sensor monitoring method [10][13].

The primary objective of the current study is to develop an intelligent and real-time smart packaging system that enhances the shelf-life monitoring and early spoilage detection of perishable food items. The gap between the conventional packaging systems and the intelligent packaging systems is filled with the proposed method, which uses the concept of multi- sensor monitoring, cloud-based analysis, machine learning-based predictions, and real-time notifications. The novelty and contribution of the current study are the reduction of food loss, enhancement of food safety, and sustainability in the food chain.

2. LITERATURE SURVEY

Maintaining the freshness and quality of perishable food items is now a critical issue in the field of agriculture and food systems. With the growing concerns over food safety, post-harvest losses, and the efficiency of the cold chain, researchers are now moving from traditional methods of monitoring food quality to intelligent methods using Internet of Things (IoT) and Artificial Intelligence (AI) technologies. The latest studies show the potential of using the concept of IoT with the help of machine learning and real-time processing to improve the efficiency of food quality monitoring systems.

Several studies have focused on IoT-based monitoring and control systems for food storage environments. Mohammed et al. [1]

developed a smart IoT control framework for remote cold- storage management, which successfully improved environmental regulation and energy efficiency but lacked predictive intelligence for spoilage estimation. Similarly, Visconti et al. [2] proposed a sensor-based traceability platform for monitoring agricultural conditions across storage and transportation stages, improving transparency but offering no intelligent shelf-life prediction. Bai et al. [3] reviewed advanced cold- chain technologies such as IoT, blockchain, and digital twins, identifying challenges including high implementation costs and system complexity, which limit large-scale deployment.

The integration of intelligent sensing and machine learning has shown strong potential for accurate spoilage detection. Feng et al. [4] introduced an IoT-enabled electronic nose system using deep learning models, achieving high accuracy in detecting fish spoilage. Peres et al. [5] presented the concept of Food Quality Management 4.0, emphasizing the role of automation and AI in future food systems, though their work remains conceptual. Perez- Solano and Ruiz-Canales [6] demonstrated the efficiency of lightweight communication protocols such as MQTT for real- time IoT monitoring systems. Aghababaei et al.
[7] and Shehzad [8] further confirmed that AI- based prediction models outperform traditional threshold-based monitoring by accurately identifying degradation patterns. Dakhia et al. [9] discussed scalability, interoperability, and security challenges in AI-IoT food systems, highlighting the need for flexible architectures. Balogun et al. [10] emphasized the importance of designing low-cost, energy-efficient monitoringsystems suitable for real-world and rural environments.

Although existing studies demonstrate the effectiveness of IoT and AI technologies in food monitoring, many systems still suffer from limitations such as lack of real-time alert integration, high implementation costs, limited scalability, and insufficient practical deployment. These gaps highlight the need for an affordable, intelligent, and real-time framework that combines multi-sensor monitoring, cloud analytics, machine learning-based prediction, and automated alert mechanisms, which the proposed system aims to address.

3. PROPOSED METHODOLOGY

The proposed system monitors and predicts the shelf life of perishable produce using a smart IoT and cloud- based framework. Multi-sensors continuously record temperature, humidity, gas levels, and light intensity during storage and transport. The data is sent to a cloud platform via Wi-Fi or MQTT. There, it is analyzed with rule- based and predictive models to estimate freshness and spoilage probability. When abnormal conditions are detected, the system sends instant alerts through SMS, email, or dashboard notifications. This approach ensures real-time monitoring, effective prediction, and timely intervention to reduce food waste and maintain product quality.

Fig. 2 shows the workflow of the Smart IoT- Based Shelf-Life Monitoring and Spoilage Prediction System. It outlines the steps of collecting sensor data, sending it to the cloud, preprocessing it, and analyzing it with rule-based and ML models. This is followed by generating real-time alerts and taking quality actions to reduce food waste and keep items fresh.

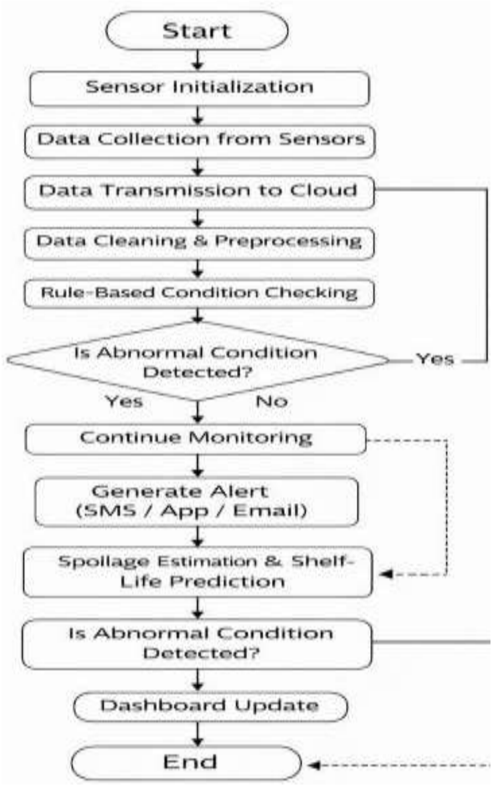


Fig.2 Flowchart of Methodology

3.1. Data Collection & Transmission

The system starts when storing or transporting perishable produce. Several IoT sensors constantly track important factors like temperature, humidity, gas concentration, and light intensity, all of which directly impact freshness and shelf life. A microcontroller unit, such as an ESP32 or Raspberry Pi, collects the sensor data and sends it in real time to the cloud using simple communication methods like Wi-Fi or MQTT. This setup guarantees dependable, fast data transfer. It allows for ongoing environmental monitoring and serves as the basis for predicting spoilage and assessing quality.

3.2. Cloud Data Storage & Preprocessing

The data collected by the sensors is stored in a cloud-based time-series database system for effective management of the data. In the preprocessing stage, the data is validated and cleaned to remove any inconsistencies, ensuring that there are no gaps, duplicates, or noise in the data due to faulty sensors or connectivity issues. The data is made more manageable by ensuring consistency, which helps in tracking changes in the levels of temperature, humidity, gas, and light. This managed data is essential in ensuring the accuracy of spoilage predictions in the next stage of the process.

3.3. Analysis: Rule-Based & Machine Learning Models

The preprocessed data set is then analyzed using a hybrid approach that incorporates both rule-based logic and machine learning (ML) techniques. The rule- based logic sends immediate alerts when the environmental parameters cross the threshold limits:

$$\text{If } (T > T\_max) \lor (H > H\_max) \lor (G > G\_max) \lor (L > L\_max) \Rightarrow \text{Alert} \qquad (1)$$

where T, H, G, and L represent temperature, humidity, gas level, and light level, respectively.

To increase the accuracy of the predictions made by the model, the Random Forest and Linear Regression ML techniques are used to compute the spoilage probability and shelf life based on the continuous sensor readings. This approach increases the accuracy of the predictions made by the model. The integration of the two techniques reduces the false alarm rates and increases the accuracy of the predictions made by the model. This approach also allows the model to learn from the data provided by the sensors in the system.

3.4. Shelf-Life Estimation & Spoilage Probability

Based on the data, the system estimates how long perishable produce will last by looking at how real- time sensor readings differ from ideal storage conditions. Machine learning models use regression to predict a Spoilage Probability Score (SPS). This score shows how likely a product is to degrade over time. The estimation looks at the total time the product is exposed to bad conditions, like high temperature or humidity, and updates the freshness index accordingly. This real-time assessment helps spot early signs of spoilage before any visible damage appears. By combining ongoing monitoring with predictive analysis, the system aids in making smart decisions for inventory rotation, reducing waste, and managing product quality better.

3.5. Alert Generation

After examining this data, if it identifies some unusual readings that are beyond the safety limits, it will automatically trigger a real-time alert. Such alerts will be sent if there are situations where the temperature, humidity, gas, or light levels exceed their limit. The system will be able to achieve this through the cloud and will be able to inform the user or manager through SMS, email, or IoT dashboard notifications. This will enable instant notification about poor storage conditions. It will be easy for the user to take corrective action, such as changing the temperature or humidity, to prevent food from spoiling and to keep it fresh.

3.6. Action & Intervention

In this phase, as soon as a system alert is generated, immediate actions are taken to avoid further loss of quality. The actions may be taken by the warehouse manager or transport operator, for example, by modifying the refrigeration system, humidity levels, or moving the produce to better storage areas. In this phase, there is a continuous feedback mechanism, and as soon as a problem is identified, actions are taken to resolve them. Thus, this phase helps to avoid any loss of quality and maintains the efficiency of the cold chain system. The automated response mechanism helps to avoid any delays in decision-making on the part of humans.

4. RESULTS

This section describes the experimental evaluation of the Smart IoT-Based Shelf-Life Monitoring and Spoilage Prediction System. The team implemented and tested the system in a real- time environment using IoT sensors connected to a cloud-based monitoring and alert platform. The evaluation focused on how accurately the sensors collected data, how effectively the alerts were generated, and how the system responded to unusual environmental conditions. The setup continuously monitored important environmental factors like temperature, humidity, gas concentration, and light intensity through a real- time dashboard. The sensor readings were sent to the cloud using wireless communication, showing that the data transmission was reliable. The dashboard displayed live data clearly, allowing users to easily see changes in environmental conditions during storage and monitoring.

During the experiments, the team intentionally created abnormal conditions, such as higher temperatures, the presence of spoilage gas, and exposure to light, to test how the system behaved. The results showed that the system could detect these abnormal conditions in real time. When the monitored values went above the preset safe limits, the system sent instant alerts via messaging notifications. This demonstrated that the alert system effectively supports early action and prevents further quality loss. The experimental observations also suggested that the system helps users make timely decisions. They can take actions like changing storage conditions, reducing light exposure, or improving ventilation. This proactive monitoring plays a big role in reducing food spoilage and extending the shelf life of perishable items. Overall, the results confirm that the proposed system is reliable, responsive, and suitable for real-world use. By combining multi-sensor monitoring, cloud processing, and real-time alerts, system provides a strong solution for better food quality management.

Fig 3. Smart IoT-Based Shelf-Life Monitoring and Spoilage Prediction System.

Figure 3 shows the hardware implementation of the suggested Smart IoT-based monitoring system. In this figure, a microcontroller, temperature sensor, humidity sensor, gas sensor, and light sensor are integrated to monitor the environmental changes. These changes are then displayed in real time on an LCD and sent for analysis to detect spoilage indicators. From this figure, it is confirmed that the suggested system is suitable for real-time monitoring of perishable food items, as it allows early detection of changes in the environment, which affect the freshness of food items.

4.1. Monitoring and Spoilage Prediction of Lemon

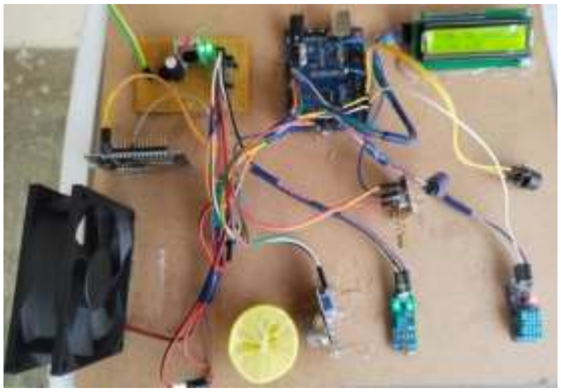
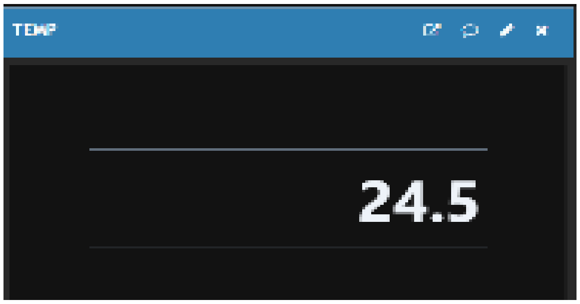


Fig 4. Spoilage prediction of lemon

The experimental prototype for the Smart IoT- based shelf-life monitoring system is shown in Fig. 4. The prototype has a microcontroller that, along with temperature, gas, humidity, and light sensors, monitors the storage conditions of lemons in real time. The system displays the readings on an LCD and also sends them to the cloud for analysis. The system successfully monitors changes in the environment, indicating early signs of spoilage. This demonstrates how real-time monitoring can be employed to extend the shelf life of food.



TEMP

24.5

Fig 5. Temperature monitoring for lemon

The real-time temperature of the lemon sample, as measured by the IoT sensor, is shown in Fig. 5. The system was able to measure a constant temperature of 24.5 °C during the experiment. The result verifies a successful environmental monitoring process through the inclusion of a temperature sensor. The constant monitoring of the temperature helps to identify conditions that may spoilage.

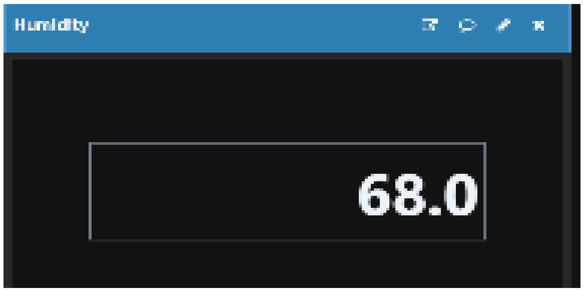


Fig 6. Humidity monitoring for lemon

Fig. 6 shows the humidity level of the lemon sample as detected by the system. The sensor detected the relative humidity of the lemon as 68%, indicating that the storage environment was moderately moist. It should be noted that proper humidity control is important in order to avoid excessive moisture, which may cause the growth of microorganisms.

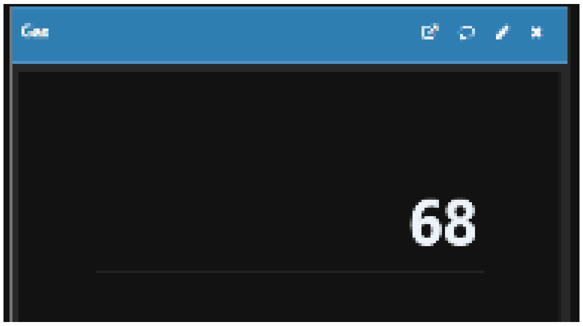


Fig 7. Gas monitoring for lemon

Fig. 7 shows the gas sensor reading obtained from the lemon sample. The value obtained from the sensor, 68, implies the presence of gases that are emitted during the respiration and spoilage process in fruits. The gas concentration helps in the identification of the biochemical changes that are taking place in the degradation process.

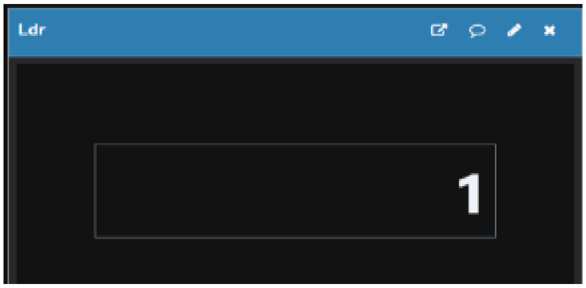


Fig 8. LDR monitoring for lemon

Fig. 8 shows the light intensity picked up by the LDR sensor. The value obtained from the sensor, 1, represents minimal light exposure during storage. The light conditions are also controlled because excessive light may cause chemical reactions, which in turn affects the shelf life of the produce.

4.2. Monitoring & Spoilage Prediction of Green Chilli

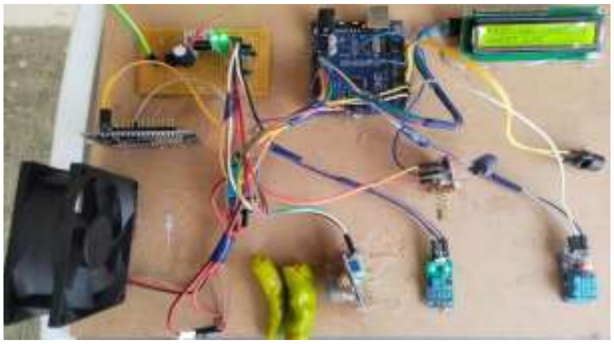


Fig 9. Spoilage prediction of Chilli

The experimental setup for monitoring the shelf life of the green chilli is shown in Fig. 9. The system incorporates various sensors to monitor temperature, humidity, gas concentration, and illumination around the green chilli sample. The readings from the sensors are displayed in real- time on the LCD screen and also transmitted to the cloud platform. The proposed system has been successfully able to monitor the changes in the environment that affect the freshness of the green chilli.

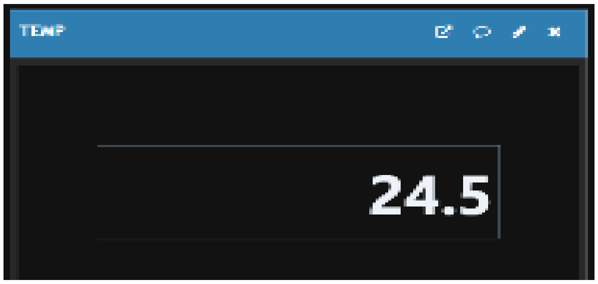


Fig 10. Temperature monitoring for Chilli

The real-time temperature of the chilli sample, as recorded by the system, is shown in Fig. 10. The recorded temperature remains stable, which confirms the proper functioning of the environmental sensor. The tracking of the temperature at all times helps in the prevention of spoilage and quality loss of the chilli sample.

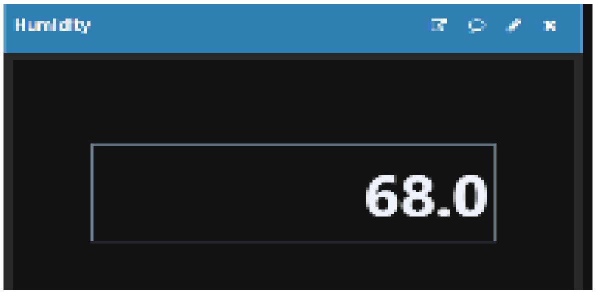


Fig 11. Humidity monitoring for Chilli

The humidity level around the chilli sample is shown in Fig. 11. The sensor has detected a controlled humidity condition, which is essential for maintaining the freshness of the vegetables. The balanced humidity condition helps in reducing dehydration and the growth of microorganisms in the vegetables. The maintenance of a consistent humidity condition is essential for the longer shelf life of the vegetables during storage. This proves the efficiency of the environment monitoring system in maintaining the quality of the vegetables.

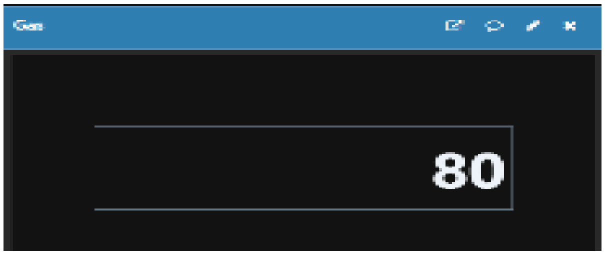
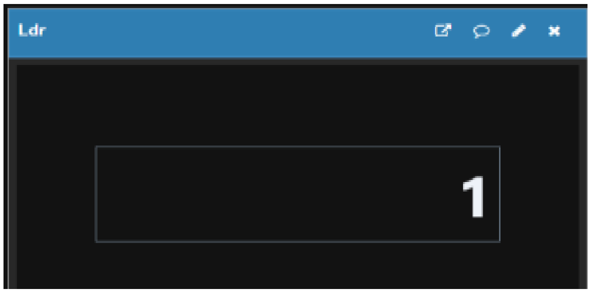


Fig 12. Gas monitoring for Chilli

Figure 12 shows the gas sensor reading of the chilli sample. The reading shows 80, which indicates the presence of an active gas emission. The emission is associated with the respiration and initial biochemical changes that take place. The monitoring of the gas concentration will aid in the identification of the changes in the freshness level and the possible deterioration. The tracking of the gas will aid in the early identification of the deterioration pattern. The reading shows the significance of the gas sensor in monitoring the shelf life of the product. The reading also shows the accuracy of the sensor system in monitoring the quality of the food.



Ldr

1

Fig13. LDR monitoring for Chilli

The LDR sensor confirms that the chilli sample is stored under controlled low-light conditions. Maintaining minimal light exposure helps prevent chemical degradation and moisture loss, thereby preserving freshness and extending shelf life.

4.3. Monitoring and Spoilage Prediction of Beans

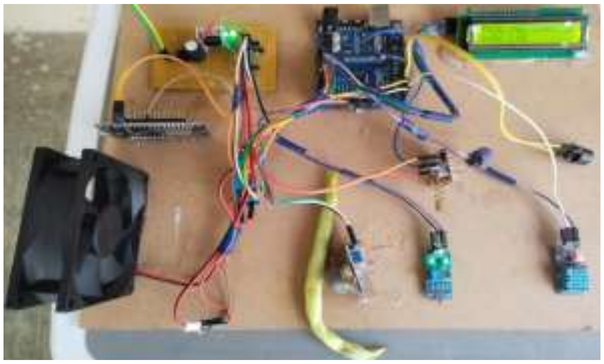
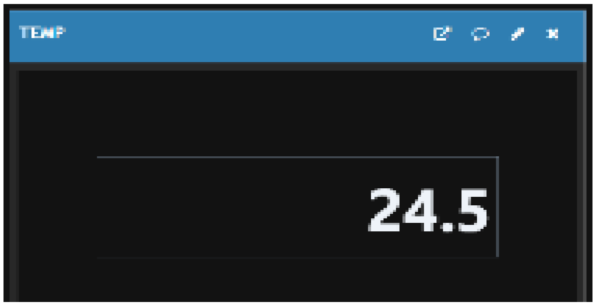


Fig 14. Spoilage prediction of beans

The monitoring system for the bean sample, as illustrated in Fig. 14, shows the introduction of partial spoilage. The sensors are able to detect the changes in the environmental conditions and the emission of gases, which are all related to the spoilage. The readings show the early signs of spoilage, proving the effectiveness of the IoT system in detecting the loss of freshness in the vegetable samples.

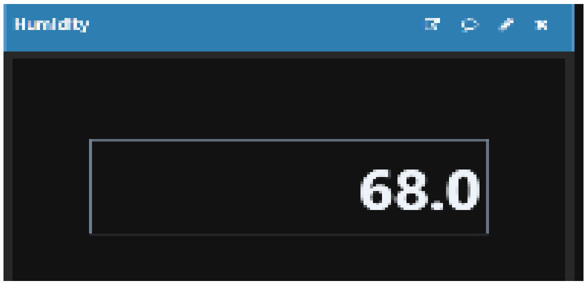


TEMP

24.5

Fig 15. Temperature monitoring for beans

The recorded temperature near the bean sample implies that it was stored while the conditions were being monitored. However, the presence of spoilage indicators implies that the conditions had already deteriorated, despite the stable temperature. Monitoring the conditions ensures that the deterioration process is recognized at an early stage.

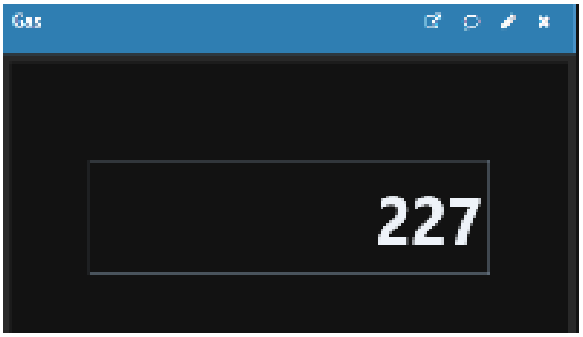


Humidity

68.0

Fig 16. Humidity monitoring for beans

The humidity level near the bean sample also remained within the range; meanwhile, the spoilage was visible. Too much moisture inside the product and the respiration can also lead to the spoilage of the product, even with the same level of humidity. This shows that the internal biochemical activities are major contributors to the spoilage of the product. The above observation shows that it is not possible to rely on a single parameter to assess the freshness of the product.

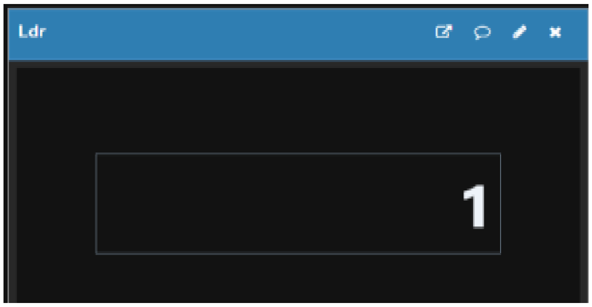


Gas

227

Fig 17. Gas monitoring for beans

The gas sensor detected a high reading of 227, which is a significant figure for the bean sample. It shows high levels of gases, indicating high gaseous emissions resulting from spoilage. High readings are usually detected when there is a high rate of microbial activities and organic matter degradation. The high rate of gas concentration detected by the sensor indicates that the beans have reached a deteriorated stage. This shows the sensitivity of the system in detecting high levels of spoilage in real time.



Ldr

1

Fig18. LDR monitoring for beans

It was noted that the LDR sensor had recorded low light exposure near the bean sample during storage. Despite the controlled light conditions, spoilage occurred, and this confirms that spoilage was mainly influenced by internal processes. This confirms the importance of controlling light conditions while considering the application of other environmental conditions in spoilage prediction. The results confirm the importance of multi-sensor data in spoilage prediction.

4.4. Alert Detection

ALERT! Abnormal High Temperature detected:

Fig 19. Abnormal High Temperature Detection

The above figure indicates the alert message “ALERT! Abnormal High Temperature detected” on the mobile device. This confirms that the system sends an instant notification to the user once the temperature increases beyond the set limit. The instant alert system enables users to respond appropriately in good time, preventing further spoilage. The instant alert system also increases the reliability of the system in food quality loss prevention. The feature clearly shows the effectiveness of the automated decision- making system in the smart shelf-life management system.


ALERT! Decompose Gas detected

Fig 20. Decompose Gas Detection

The above image represents the alert “ALERT! Decompose Gas detected,” which indicates the release of harmful gases during spoilage. This shows the effectiveness of the system in early spoilage detection. The gas alert allows users to detect the biochemical spoilage even before it causes damage. Immediate alert ensures timely action, thus preventing further spoilage. This shows the reliability of the system in monitoring spoilage-related gas emissions.


ALERT! Sunlight detected

Fig 21. Sunlight DetectionThe mobile notification, which is given in the figure, is “ALERT! Sunlight detected.” This notification proves that the system has successfully detected the presence of light and has notified the user accordingly. This notification is very important in ensuring that the product does not remain in contact with excess amounts of light, which could cause the chemicals to degrade quickly.

5. CONCLUSION

Although several monitoring systems exist for managing food quality, predicting shelf life in real time and detecting spoilage accurately remains a significant challenge for large-scale use in real-world situations. Changes in storage conditions, sensor noise, and limited decision- making often lead to incorrect predictions and slow responses. This project tackles these issues by introducing a Smart IoT-Based Shelf-Life Monitoring and Spoilage Prediction framework that combines real-time sensing, cloud intelligence, and adaptive alert systems. The proposed system uses an intelligent prediction method to constantly analyze environmental conditions. It looks at factors like temperature, humidity, gas concentration, and light intensity. A mixed approach, combining rule-based logic and machine learning models, estimates spoilage risk and remaining shelf life.

The system evaluates freshness levels using learned data patterns instead of just relying on fixed thresholds. This allows for better detection of early spoilage signs. A cloud-based monitoring module oversees the entire process. It verifies sensor data to support reliable decision-making. Only confirmed sensor data is used for predictions and alerts, which improves system reliability. The addition of a real- time dashboard for visualization and automated alert notifications on mobile devices enhances responsiveness. This ensures that timely actions can be taken. Experimental results show that the system effectively detects unusual conditions, such as high temperatures, sunlight exposure, and the presence of decomposition gases. The alerts generated quickly confirm the system’s reliability in real-life scenarios. The framework also supports better storage management, extends shelf life, and reduces food waste compared to traditional manual monitoring methods. In the future, the performance of this framework could be improved by adding more sensors, such as pH and ethylene sensors, and using more advanced machine learning models for better prediction accuracy. The system might also expand to support large-scale implementation across various storage units and connect with blockchain systems to increase transparency in food supply chains.

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