A Review Paper on ”Freshness of Food Detection using IoT and Machine Learning”

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***Abstract*—This review explores innovative strategies to combat the pervasive issue of food spoilage by employing sensor technology, gas monitoring, and Internet of Things (IoT) connectivity. The proposed system utilizes a microcontroller to issue timely alerts upon detecting spoilage indicators, offering a technological alternative to manual food detection processes in industries. Additionally, the integration of machine learning enhances the model's predictive capabilities, estimating the likelihood and duration of food spoilage based on vendor-specific factors. This approach not only addresses consumer safety concerns but also has the potential to instigate healthy competition among retailers, encouraging the sale of fresher and safer food products. The review aims to provide a succinct overview of advancements in food spoilage detection systems, catering to researchers, practitioners, and stakeholders seeking insights into cutting-edge technologies for ensuring food safety.**

***Index Terms*—Food spoilage detection, Sensor technology, Gas monitoring, Internet of Things (IoT), Microcontroller, Machine learning**

I. INTRODUCTION

In the contemporary landscape of the 21st century, the food sector stands as a significant pillar of our economy. Amidst its multifaceted challenges, a prominent issue demanding attention is food spoilage, particularly affecting perishable items such as meat, fruits, and vegetables. Compounding this challenge is the pervasive occurrence of undetected spoilt items reaching consumers. Across various fruits and vegetables industries, the quality-check process remains predominantly manual, relying on human inspection along conveyor belts. Introducing an automated system not only promises enhanced accuracy in detecting spoilt food but also heralds a reduction in manual manpower. [1][4] This review envisions the automation of this critical process through the integration of intelligent sensors, notably the Node Mcu microcontroller. Upon the identification of spoilt or stale food items, an audible alert system is activated, while concurrently transmitting data to the cloud through Internet of Things (IoT) applications. This interconnected framework not only improves detection efficiency but also establishes transparency by enabling authorities to monitor the frequency of spoilt food occurrences.

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II. PRINCIPLE OF SENSING

The detection of food spoilage hinges on a nuanced understanding of pivotal principles, each illuminating distinct facets of spoilage indicators.

a) Oxygen Level Detection: Central to this principle is the premise that the presence of germs within a food item, whether fruits or meat, induces a discernible alteration in the ambient oxygen levels. As these microorganisms metabolize, they deplete the oxygen content in their immediate vicinity, resulting in a measurable reduction compared to the norm. The proposed sensing mechanism aims to capitalize on this phenomenon, employing intelligent sensors to meticulously monitor and detect variations in oxygen levels. By discerning these deviations, the system can effectively identify potential spoilage, offering a proactive approach to food quality assessment. [1][3]

b) Ammonia Gas Sensing: Specifically tailored for meat items such as fish, the second principle revolves around the detection of ammonia gas emanating from stale products. When meat undergoes spoilage, it releases ammonia gases as a byproduct of bacterial degradation. To capture this distinctive spoilage marker, a gas sensor is strategically deployed to measure ammonia levels in the proximity of the food item. An aberration in these levels triggers an alert mechanism interfaced with the microcontroller, signaling potential spoilage. This dual-pronged approach, combining oxygen level detection and ammonia gas sensing, enhances the system's sensitivity and specificity, providing a comprehensive framework for reliable spoilage detection. [1][3][2]

c) Temperature Fluctuations: Beyond oxygen levels and gas emissions, an additional critical parameter for spoilage detection involves monitoring temperature fluctuations. Spoiled food items often undergo alterations in temperature due to microbial activity. Integrating temperature sensors into the detection system allows for a holistic assessment, capturing the synergistic relationship between temperature variations and spoilage progression. Real-time monitoring of temperature dynamics adds an extra layer of precision, further fortifying the efficacy of the proposed spoilage detection model. [4][6]

d) Humidity Monitoring: Recognizing the influence of moisture on food quality, humidity monitoring emerges as another indispensable facet. Spoiled food items often exhibit changes in humidity levels as a consequence of microbial growth or water release. By incorporating humidity sensors into the sensing framework, the system gains the capacity to detect deviations in moisture content, providing an additional dimension to the spoilage detection process. This multifaceted approach, encompassing oxygen levels, gas emissions, temperature fluctuations, and humidity monitoring, establishes a robust foundation for an advanced and adaptive food spoilage detection system.

III. ALTERNATIVE WORK IN THE FIELD

- **Artificial Intelligence Approach:** A burgeoning avenue in the realm of food spoilage detection involves the integration of artificial intelligence (AI). Current research explores the utilization of computer vision techniques, leveraging image analysis to discern the spoilage status of a given food item. While this method offers a non-intrusive means of inspection, a notable limitation lies in its inability to penetrate the interior of the food item. [1][3] Image capture provides only surface-level insights, posing challenges for a comprehensive assessment of spoilage. The quest for an all-encompassing solution prompts ongoing investigations into refining the capabilities of AI-based approaches in addressing the intricate nuances of food spoilage detection.

- **MIT Research:** A notable contribution to the field emerges from the Massachusetts Institute of Technology (MIT), where a research team has developed a sensor dedicated to the detection of spoilt meat items. This innovative sensor, while proficient in discerning specific gases indicative of spoilage, grapples with the limitation of potential false negatives. [1][3] The exclusive reliance on a singular gas marker poses challenges in achieving a comprehensive and foolproof spoilage detection system, thereby underscoring the need for a more nuanced and multifaceted approach.

- **Blockchain Integration:** A cutting-edge direction in food safety technology involves the integration of blockchain. Some initiatives explore the use of blockchain to create immutable records of the entire food supply chain, from production to consumption. This tamper-resistant and transparent ledger system not only enhances traceability but also ensures the authenticity and quality of food products. Incorporating blockchain technology into spoilage detection systems could provide an additional layer of security and accountability, contributing to a more resilient and trustworthy food safety ecosystem.

- **Spectral Analysis Techniques:** Advancements in spectral analysis techniques are gaining traction as an alternative avenue for spoilage detection. By examining the unique spectral signatures of food items, particularly in the infrared and ultraviolet ranges, researchers aim to uncover subtle changes indicative of spoilage. This non-invasive approach holds promise for detecting spoilage at early stages, offering a complementary perspective to traditional sensor-based methods.

- **Nanotechnology Applications:** Exploring the intersection of nanotechnology and food safety, researchers are investigating the use of nanosensors for spoilage detection. These miniature sensors can operate at the nanoscale, providing high sensitivity to changes in the composition of food items. Nanotechnology applications hold potential for enhancing the precision and efficiency of spoilage detection systems, presenting an avenue for future innovation in the field. [6]

- **Machine Olfaction:** In a novel approach, researchers are exploring machine olfaction, inspired by the human sense of smell, for detecting food spoilage. Utilizing electronic noses that mimic the olfactory system, these systems analyze the volatile organic compounds emitted by spoiling food. Machine olfaction presents a unique perspective on spoilage detection, leveraging principles from nature to enhance the sensitivity and specificity of detection systems.

- **What proposed system proposes:** In the pursuit of heightened accuracy, our proposed system pioneers a dual-sensor strategy, integrating cumulative values from both oxygen and ammonia sensors. This innovative amalgamation not only mitigates the risks of false negatives but also establishes a more resilient decision-making framework. Beyond gas-specific detection, our approach broadens its scope by incorporating an oxygen sensor, enabling the identification of germ infections across diverse food items. Furthermore, our system recognizes the significance of additional parameters, such as temperature fluctuations and humidity levels, in fortifying the robustness of spoilage detection. By encompassing these multifaceted elements, our proposed model aspires to set a new standard in comprehensive and adaptable food spoilage detection systems. Combing IoT and Machine learning only increases the interoperability and application. [1]

IV. METHODOLOGY

Our proposed methodology constitutes a multifaceted approach, intertwining sensor technology, machine learning, and cloud-based analysis to create a robust and adaptive system for food spoilage detection.

- **Sensor Monitoring and Data Acquisition:** The foundation of our methodology lies in the deployment of intelligent sensors, specifically oxygen and ammonia sensors, to measure the respective content in a given food item. These sensors act as vigilant sentinels, capturing crucial data related to spoilage indicators. The real-time data generated by the sensors serves as the fundamental input for subsequent analysis and decision-making. [1][3]

- **Machine Learning Model Utilization:** To decipher the intricate patterns within the sensor data, a machine learning model is employed. Trained on a diverse dataset encompassing various spoilage scenarios, the model utilizes the oxygen and ammonia content as key features to predict the spoilage status of the food item. This predictive capability enhances the system's discernment, enabling it to make informed decisions regarding the freshness or spoilage of the monitored food items. [1]

- **Node Mcu Implementation and Cloud Integration:** The Node Mcu microcontroller takes on a pivotal role in the practical implementation of our spoilage detection system. Upon encountering a spoilt food item, the microcontroller triggers a sound alert, drawing attention to the potential spoilage event. Simultaneously, the data collected from the sensors is transmitted to a cloud platform for comprehensive analysis and storage. [1][3]

- **Cloud Platform Integration - Leveraging ThingSpeak:** Our methodology integrates with popular cloud platforms, exemplified by ThingSpeak, to facilitate in-depth analysis of the accumulated data. In the context of food industries, this cloud-based approach offers valuable insights such as the occurrences of spoilt food items throughout the day, identifying peak durations of spoilage incidents (e.g., day, afternoon, evening). [1] Furthermore, the system provides metrics on the successful separation of spoilt food items, contributing to a more nuanced understanding of operational efficiency. A sample plot on ThingSpeak illustrates the dynamic tracking of spoilt food items on different days of the month, offering a visually intuitive platform for comprehensive data analysis. [3]

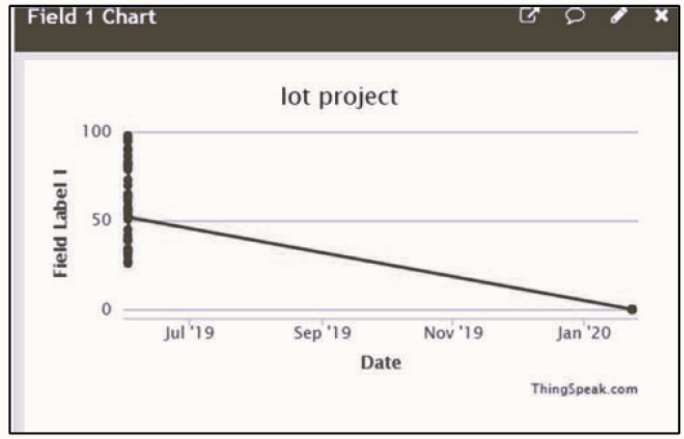

Fig. 1. Sample plot on Thingspeak [1]

- **Predictive Analysis and Model Refinement:** The cloud platform not only serves as a repository for real-time data but also facilitates ongoing predictive analysis. By monitoring the frequency of spoilt food occurrences over time, the machine learning model can be iteratively deployed to predict the average shelf life of various food items. This cyclical process of data analysis and model refinement ensures the adaptability and accuracy of the system, enhancing its utility in dynamic food industry settings.

In summary, our methodology seamlessly integrates sensor technologies, machine learning algorithms, and cloud-based analytics to create an advanced food spoilage detection system. This comprehensive approach not only detects spoilage in real-time but also contributes to predictive analytics and continuous improvement, setting a precedent for the future of intelligent food quality monitoring systems.

V. SCOPE OF MACHINE LEARNING: ELEVATING PRODUCTIVITY AND INSIGHT

Machine learning, the dynamic field dedicated to the acquisition of knowledge from data and the subsequent formulation of predictions, emerges as a transformative force within the ambit of our project. The diverse applications of machine learning in this context herald a new era of efficiency and insight, revolutionizing the landscape of food spoilage detection.

A. *Industrial Application: Optimizing Resource Allocation:*

In the realm of industrial application, machine learning stands as a strategic ally for enhancing productivity and resource management. Through meticulous analysis of spoilt food data, the system adeptly forecasts peak occurrences of spoilage during specific times of the day. Additionally, it discerns patterns regarding the specific food items most susceptible to spoilage. Leveraging this insight, industrial operations can dynamically adjust workforce allocation, channeling more manpower during peak spoilage periods and optimizing staffing during other times. This adaptive approach not only conserves significant manpower resources but also streamlines operational efficiency, minimizing the economic impact of spoilage incidents. [1][4][6]

B. *Commercial Application: Empowering Vendor Accountability:*

Extending its reach to commercial spheres, machine learning introduces a paradigm shift in the retail and grocery landscape. By scrutinizing collective data on the frequency of food spoilage associated with specific vendors, the system provides valuable insights into vendor-specific spoilage patterns. This information acts as a catalyst for accountability, compelling vendors to prioritize food items with extended shelf life. Simultaneously, it fosters consumer awareness, encouraging informed choices by highlighting the shelf life of products. This symbiotic relationship between vendors and consumers serves to elevate the overall quality of food products available in the commercial market. [1]

C. *Consumer Application: Ensuring Food Safety in Real Time*

At the consumer level, the integration of machine learning into refrigeration systems manifests as a pivotal advancement in food safety. The smart sensing system, seamlessly incorporating machine learning algorithms, proactively detects spoilage events and promptly sends email notifications directly to users. This real-time communication ensures that consumers, especially vulnerable groups like children, are promptly informed and safeguarded against the consumption of harmful or spoilt food. This not only enhances consumer well-being but also promotes a culture of safety and vigilance in food consumption practices. [1][3]

D. *Environmental Impact Assessment:*

Beyond its immediate applications, machine learning can be harnessed for a broader environmental impact assessment. By analyzing patterns of food spoilage data over extended periods, the system can contribute valuable insights into the ecological footprint of wastage. This knowledge can inform sustainable practices, aiding in the development of strategies to minimize food waste and its associated environmental implications. [4]

E. *Dynamic Model Refinement:*

The iterative nature of machine learning models allows for continuous refinement based on evolving data patterns. As the system accumulates more data on food spoilage occurrences, the machine learning model can be dynamically updated and fine-tuned. This ongoing refinement ensures that the system remains adaptive and responsive to changing patterns in food spoilage, reinforcing its long-term efficacy and relevance in diverse applications.

In essence, the scope of machine learning in this project transcends mere prediction; it becomes a catalyst for operational efficiency, vendor accountability, consumer safety, environmental stewardship, and ongoing model refinement. The transformative potential of machine learning in the domain of food spoilage detection lays the foundation for a paradigm shift in how we approach food quality and safety across various sectors.

VI. DEVELOPMENT OF ML MODEL

The development of our machine learning model represents a pivotal stride towards augmenting food safety through proactive spoilage detection. This section outlines the intricate process from data input to model evaluation, showcasing the efficacy of logistic regression and paving the way for future extensions.

A. *Input and Output Parameters:*

The foundational elements of our machine learning model are characterized by the input source, primarily the food item under consideration, and the binary output indicating whether the food item is deemed spoilt or not. This binary classification hinges on the nuanced analysis of oxygen and ammonia concentrations for each sampled instance. [1]

B. *Training Data and Learning Algorithm:*

The crux of our machine learning model lies in its learning algorithm, with logistic regression emerging as the chosen methodology. This model calculates the probability of a given input instance belonging to either the 'Spoilt' or 'Not Spoilt' class. Leveraging this binary output, the probabilities of spoilage are ascertained for different days, enabling consumers to anticipate the expected shelf life based on the food vendor source. Logistic regression, renowned for its versatility in binary classification tasks, serves as a powerful tool for predicting spoilage outcomes. [1]

C. *Evaluation of Machine Learning Model:*

To assess the performance of various machine learning models, a sample dataset comprising instances of spoilt and non-spoilt foods, along with corresponding ammonia and oxygen gas concentrations, was meticulously crafted. Rigorous evaluations were conducted on three distinct models: Linear Regression, Support Vector Machine, and Logistic Regression. The evaluation metrics, including mean-squared errors, were employed to gauge the models' proficiency. Remarkably, Logistic Regression emerged as the frontrunner, boasting a mean-squared error of zero. This compelling performance solidified the choice of Logistic Regression as the model of choice for our spoilage detection system. [1]

Food Item	Oxygen Concentration (ppm)	Ammonia Concentration (ppm)	Spoilage Status
Apple	20	2	Not Spoilt
Banana	18	1	Not Spoilt
Chicken	15	5	Spoilt
Carrot	22	1	Not Spoilt
Salmon	14	8	Spoilt
Tomato	21	2	Not Spoilt
Beef	16	6	Spoilt
Lettuce	19	3	Not Spoilt
Orange	17	2	Not Spoilt
Pork	14	7	Spoilt

Fig. 2. An image of sample portion of dataset

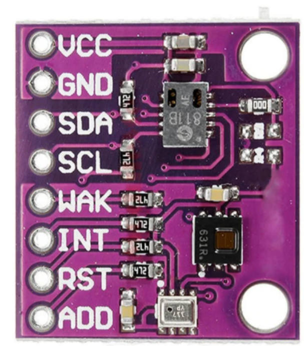

Fig. 3. TVOC

Fig. 4. MQ-135 Ammonia Gas Sensor

D. *Further Scope of Machine Learning:*

While our current machine learning model exhibits commendable accuracy, its potential for expansion remains a dynamic frontier. The model's performance is contingent upon the dataset at its disposal, and as we accrue more data, avenues for extensions become apparent. Future enhancements may encompass predictive capabilities, such as estimating the duration a food item can last based on its vendor source. This extension holds profound implications for inventory management in the food industry and can foster general awareness about food safety practices. The iterative nature of machine learning allows for ongoing refinement and expansion, ensuring the model's adaptability to evolving data patterns and reinforcing its role as a pioneering force in proactive food safety.

VII. System Architecture

A. *Sensor Array for Comprehensive Monitoring:*

At the heart of the system lies a meticulously crafted sensor array, featuring TVOC (Total Volatile Organic Compounds) sensors, specifically CCS811, and ammonia sensors. These sensors collectively monitor the volatile organic compound content of each food item under scrutiny. This granular level of sensing not only captures surface-level indicators but delves into the intricate details of organic compounds, laying the foundation for a nuanced understanding of food quality. [1][3][2]

B. *Machine Learning Model for Predictive Analysis:*

Harnessing the wealth of data from the sensor array, a robust machine learning model takes center stage. Trained on an extensive dataset comprising instances of spoilt and unspoilt food items, the model leverages TVOC and ammonia content as key features. This predictive analysis empowers the system to make real-time decisions on whether a given food item is deemed spoilt or not. The integration of machine learning augments the system's discernment, providing a dynamic and adaptive framework for spoilage detection. [1]

C. *NodeMCU-ESP32 Microcontroller: The Brains of Operation:*

The NodeMCU-ESP32 microcontroller serves as the operational nexus, seamlessly connecting the sensor array and the machine learning model. Upon encountering a spoilt food item, this intelligent microcontroller orchestrates an immediate response by sounding a buzzer. Beyond real-time alerts, the NodeMCU-ESP32 acts as a conduit for data transmission to a cloud platform, initiating a cascade of events that contribute to a holistic understanding of food spoilage patterns. [1][3][2]

D. *Cloud Platform Integration for Analytical Insights:*

The system extends its reach to the cloud, integrating with a powerful cloud platform. This integration facilitates comprehensive analysis and storage of the data generated by the sensor array and the microcontroller. The cloud platform becomes a repository for crucial insights, including the frequency of spoilt food occurrences. This wealth of data not only aids in real-time monitoring but also lays the groundwork for

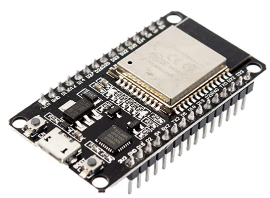

Fig. 5. NodeMCU-ESP32 Microcontroller

predictive analytics and trend analysis, contributing to a more informed understanding of food quality dynamics. [1][3]

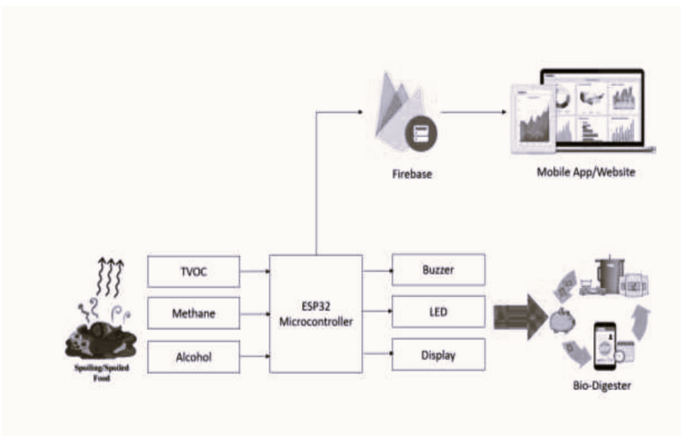

Fig. 6. Architecture [3]

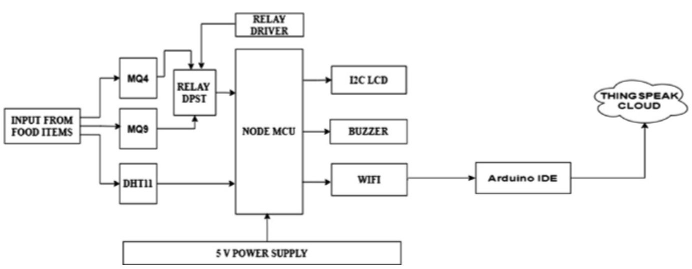

Fig. 7. Flowchart [2]

E. Predictive Analytics for Shelf Life Estimation:

A distinctive facet of the system lies in its predictive analytics capabilities. By continuously monitoring the number of spoilt food occurrences, the machine learning model can be iteratively deployed to predict the average shelf life of given food items. This forward-looking dimension introduces a proactive element, enabling stakeholders to anticipate shelf life trends and optimize inventory management practices. [1]

F. Feedback Loop for Continuous Improvement:

The system embraces a feedback loop mechanism, crucial for continuous improvement. As the machine learning model processes new data and refines its predictive capabilities, the insights gained from cloud-based analytics inform future iterations. This iterative process ensures that the system remains adaptable to evolving patterns, setting a precedent for ongoing advancements in smart food spoilage detection.

In essence, the system architecture represents a symbiotic amalgamation of sensor precision, machine learning prowess, microcontroller intelligence, and cloud-based analytics. This orchestrated synergy not only elevates the accuracy of spoilage detection but also establishes a foundation for predictive insights, contributing to a paradigm shift in how we approach food quality monitoring in the modern era.

VIII. **IMPLEMENTATION**

The practical implementation of our advanced spoilage detection system unfolds across various sectors, ushering in a new era of efficiency and precision. Each deployment scenario capitalizes on the unique features of our sensor array, machine learning model, and microcontroller, showcasing the versatility and impact of our innovation.

- **Retail Stores: Revolutionizing Inventory Management**

  In the dynamic landscape of retail stores, our system finds a natural fit within the intricate web of shelves and containers. The strategic placement of our array of ammonia and oxygen sensors within these storage units transforms them into vigilant sentinels for food quality. As soon as a spoilt food item is detected, an immediate alert is relayed to the management. The real-time monitoring capabilities extend beyond mere detection; they empower the management to prioritize the sale of items with shorter shelf lives, optimizing inventory turnover and minimizing potential losses. This nuanced approach to inventory management heralds a paradigm shift, offering retail stores a dynamic tool to enhance operational efficiency. [1]

- **Food Industry: Enhancing Conveyor Belt Operations**

  In the vast expanse of the food processing industry, our system integrates seamlessly into the bustling operations along conveyor belts. The array of sensors is strategically positioned across the conveyor belt, forming an unobtrusive yet powerful network for spoilage detection. This deployment enables management to track and analyze the temporal patterns of spoilt food occurrences throughout the day. Armed with this insightful data, proactive measures can be taken to address specific timeframes where spoilage is most prevalent. The real-time feedback loop not only bolsters food safety measures but also contributes to operational optimization, establishing our system as an invaluable asset within the industrial landscape. [1][3][4]

- **Household: Empowering Personalized Food Safety**

  At the intimate level of households, our system takes residence within refrigerators, becoming the guardians of individual food safety. The array of sensors seamlessly integrates into the refrigeration environment, constantly monitoring the volatile organic compound content of stored items. Upon detecting a spoilt food item, the microcontroller orchestrates a dual-response – sounding a buzzer within the household and triggering an email alert to the owner. This personalized notification system ensures swift action, preventing the inadvertent consumption of harmful or spoilt food. The household deployment not only enhances food safety practices but also cultivates a culture of awareness and proactive engagement among consumers.

- **Transportation: Ensuring Quality Throughout the Supply Chain**

  Extending the reach of our system, transportation scenarios within the food supply chain benefit from the integration of our sensor array. Placing sensors within transport containers enables real-time monitoring of food quality during transit. Alerts can be generated if spoilage is detected, allowing for prompt intervention and minimizing the risk of compromised food safety. This application ensures the integrity of food items throughout the supply chain journey, reinforcing the commitment to delivering fresh and safe products to end consumers. [4][1]

- **Integration with IoT-enabled Smart Appliances:**

  Expanding the horizon, our system seamlessly integrates with IoT-enabled smart appliances. Refrigerators, storage units, and transportation containers equipped with IoT capabilities can leverage our sensors to not only detect spoilage but also communicate with other smart devices. This interconnected ecosystem facilitates dynamic adjustments, such as temperature control or isolation of spoilt items, optimizing the entire food storage and transportation process. [1][3][2]

IX. CONCLUSION

In culmination, our exhaustive research highlights the profound impact of integrating sensors, IoT, and machine learning within the food industry. Beyond revolutionizing food quality monitoring, this synergy fuels a competition among manufacturers to prioritize healthier products, fostering consumer awareness and a culture of informed consumption. The interconnected ecosystems facilitated by IoT, coupled with predictive insights from machine learning, usher in a new era of efficiency and sustainability. Beyond immediate applications, the model holds economic benefits by minimizing food waste and building consumer trust. This dynamic framework, continuously refined through iterative feedback, positions itself at the forefront of technological innovation, promising a future where technology not only transforms industry practices but also cultivates positive cultural and environmental change.

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