International Journal of Advanced Technology in Engineering and Science
Vol. No. 11, Issue No. 12, December 2023
www.ijates.com
ijates
ISSN 2348 - 7550

Smart Nose: Detection of Food Decay using Machine Learning

Shivanand V. Manjaragi[1], Akhila Rajendra Sadalagi[2],

Varsha Huchchannavar[3]

[1, 2, 3] Department of Computer Science and Engineering, Hirasugar Institute of Technology, Nidasoshi, Karnataka, India

[1]shiva.vm@gmail.com email; [2]akhilasadalagi28@gmail.com; [3]varshahuchchannavar@gmail.com

ABSTRACT

Researchers are striving to extend the lifespan of food by exploring innovative approaches to preserve its quality. Food grains are particularly prone to decay owing to factors like weather conditions, moisture, and temperature fluctuations. Thus, effective methods to track food spoilage are crucial to maintain food quality. We've developed a prototype that monitors food quality and manages storage at home. Initially, a Convolution Neural Network (CNN) is used to identify fruits and vegetables. Subsequently, our system employs sensors and actuators to track gas emissions, humidity, and temperature levels in fruits and veggies, gauging their spoilage. This system helps regulate the environment, reducing spoilage risks. Customers receive alerts on their phones regarding the food's freshness and condition. The model we used boasts an impressive 95% accuracy rate. Ultimately, our experiment successfully increased the shelf life of select food categories by an additional 2 days.

Keywords— *Machine learning for health, smart system, food spoilage detection, food spoilage prevention, sensors, IoMT*

1. Introduction

In recent years, there has been increasing concern about food wastage, prompting research into novel approaches to minimize it. This issue is seen as critical for the long-term sustainability of food production, demand, and supply chains. Given that meals are fundamental for all living organisms, the quality and safety of food have remained in high demand. The Internet of Things (IoT) has the capacity to connect everything, everywhere, and at any time [1–4], and its integration into Food Supply Chain (FSC) management offers potential to enhance food shelf life by constantly assessing food conditions and exchanging data with consumers. However, the full utilization of IoT technologies in FSC is still in its early phases and has considerable progress ahead [5, 6]. Prioritizing food sanitation and safety is crucial to combat food wastage. The consistency of food should be carefully regulated, and implementing quality control systems in grocery stores can significantly reduce waste and help prevent diseases [7]. These systems actively monitor environmental conditions that affect food quality. Traditionally, techniques like refrigeration and vacuum storage were used to manage atmospheric effects. Food contamination can stem from manufacturing processes, yet it predominantly arises due to inadequate handling during transportation and storage in unsuitable environmental conditions.

1.1. Process of Food Spoilage

Food spoilage denotes the point when a food item becomes unsuitable for consumption. This process is influenced by several external factors, such as the nature of the food, its packaging, and processing methods. Each year, approximately one-third of the world's produced food, intended for human consumption, is lost due to wastage [8, 9]. Figure 1 illustrates that when bacteria begin affecting fresh apples, gas emission initiates, and within a few hours, the apple undergoes complete spoilage.

Microbes like bacteria, viruses, protozoa, and fungi contribute to food spoilage. While these elements can pose risks to consumers, implementing preventive measures can safeguard the longevity and standard of food. Generally, bacteria themselves might not cause food poisoning, but many of the microorganisms responsible for food borne illnesses remain undetectable by smell or taste, except through mycotoxins and microbial by products. Consequently, consuming spoiled food is always advised against. Among the pathogenic bacteria, Clostridium perfringens and Bacillus cereus are notable agents of food spoilage.

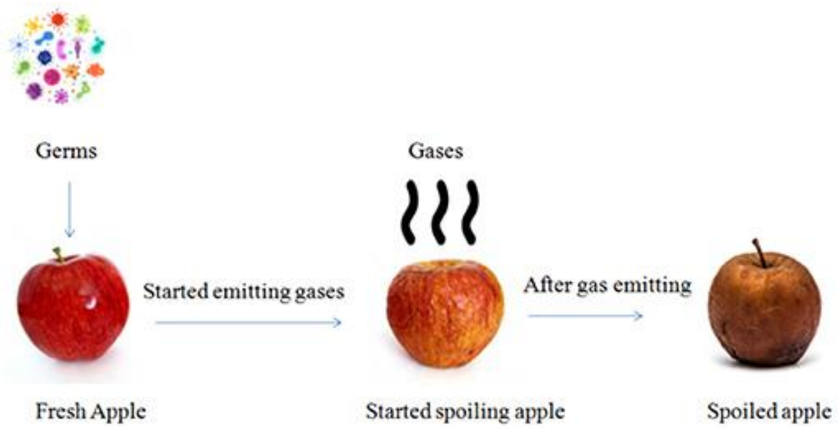


FIGURE 1. Food spoilage process.

1.2. Key Component of Food

One crucial element in food production is the seed itself, as the vitality and health of fruits and vegetables heavily rely on it. Seeds come in two main types:

- Hybrid seeds: These seeds result from cross-pollination in cultivated and garden plants. Hybrids are selected to enhance specific traits in resulting plants, like yield, uniformity, color, and disease resistance.
- Non-hybrid seeds: Also known as heirloom or open-pollinated seeds, these originate from naturally pollinated plants that have existed for centuries.

Hybrid seeds yield hybrid produce, while non-hybrid seeds yield non-hybrid fruits and vegetables. Non-hybrid varieties generally have a longer lifespan compared to their hybrid counterparts. Distinguishing between hybrid and non-hybrid produce isn't always easy, underscoring the importance of understanding this aspect in day-to-day activities.

Food spoilage can stem from various factors, including humidity and temperature fluctuations. Hence, there's a need for devices capable of measuring these differences during food preparation and transportation [10]. In our daily diets, beyond junk food, inconsistency in canned vegetables and other items arises due to varying oxygen, temperature, and moisture levels. Smart home devices now detect food wastage and alert caregivers. However, repetitive measurements and tracking for improvements don't ensure nutritional consistency [11]. Collected data should be scrutinized and delivered for policy research, trend prediction, program evaluation, and planning purposes.

1.3. Reasons for Food Spoilage

Evidence of food spoilage, seen in recycling bins and waste, largely stems from office eateries, roadside stalls, gatherings, and receptions. This surplus isn't just environmentally toxic but also poses economic challenges. Globally, an estimated 1.3 billion tons of food is wasted annually, with projections indicating a potential increase, posing a significant concern [17].

Food spoilage can arise from various human, chemical, and biological factors, including plant enzymes, insects, parasites, and microbes [18]. Microbial degradation is the most common and serious cause. When microbes proliferate, they invariably contaminate food.

Figure 2 depicts factors that can deteriorate fruits and vegetables. Heat, humidity, moisture, temperature, and oxygen levels have threshold values; once surpassed, food spoilage begins. Maintaining these thresholds can extend the lifespan of fruits and vegetables.

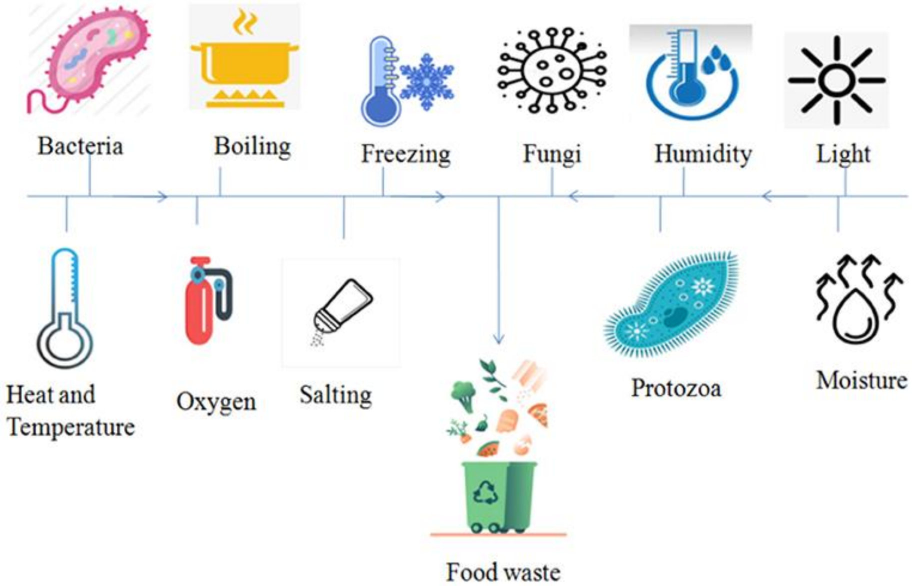


FIGURE 2. Factors of food spoilage.

1.4. Motivation

The purpose of employing Machine Learning for monitoring and analyzing food spoilage is to oversee and regulate food items, aiming to prevent spoilage resulting from changes in climate and atmosphere. Concerns about food wastage primarily revolve around promoting healthy dietary practices and ensuring food quality, given past instances of discovering harmful chemicals in fruits and vegetables. Utilizing Machine Learning for monitoring and analyzing food spoilage offers time efficiency and delivers precise and dependable outcomes.

1.5. Our Contribution

Upon reviewing literature on food wastage, we've identified several endeavors aimed at prolonging the shelf life of food. Consequently, specific research questions have emerged in this domain. Notably, our study makes significant and innovative contributions:

- Devising a smart monitoring system employing gas, humidity, and temperature sensors to assess food quality.
- Creating an alert system that notifies users about food quality and deterioration timelines.
- Crafting a system that enhances food shelf life by regulating the environment to suit specific food requirements.

2. Literature Review

Numerous studies in the field of food spoilage detection have been reviewed, focusing on diverse methodologies to identify potential hazardous situations in a smart home. One such concern is food deterioration, the primary focus of this study [19]. In this study, the authors examined the scent signatures of two common foods (milk and yogurt) stored at 25°C for a week using a metal-oxide sensor (MOS) based electronic nose. Analyzing the highest sensor responses produced feature vectors whose components showed consistent trends as the data aged. Principal component analysis (PCA) revealed distinct trajectories for the two chemicals as they spoiled.

Rajesh Megalingam et al. introduced a novel method for detecting food spoilage by integrating image classification with machine learning techniques and artificial intelligence [20]. Utilizing AI, deep CNN networks, computer vision, and ML techniques like the k clusters method for color classification in images and HSV values for spoilage detection, they identified food spoilage. The project was executed using the Anaconda prompt on the Jupyter notebook platform. Similarly, Iwendi et al. employed an AI-based approach for security analysis in IoT using a network classifier, showcasing impressive accuracy. This illustrates the wide applicability of AI across various domains.

Green et al. presented an electronic nose (e-nose) composed of four gas sensors employing functionalized single-walled carbon nanotubes (f-SWNTs) and polymer nanocomposites. This e-nose aimed to serve as a simple monitoring device for detecting microbiological spoilage and pollutants in canned food [21]. The gas sensor signals were utilized as early indicators of spoilage to mitigate potential health risks. The sensors were particularly sensitive to ammonia, a gas produced by microorganisms, making them suitable for detecting microbial deterioration in canned food.

Food spoilage occurs due to various factors, like insufficient temperature control, leading to rapid bacterial growth in warm and humid conditions [22]. If consumed, deteriorated food may cause foodborne illnesses. In response, a wearable RFID patch for monitoring food spoilage using smart packaging and NFC technology has been designed and simulated.

Different individuals have varying perceptions of food spoilage, potentially resulting in inaccurate conclusions about its condition [23]. To address this, an electronic nose system is sought to accurately categorize spoiled food. A study focused on detecting food deterioration in tomato-based Filipino dishes using an array of sensors and Artificial Neural Network algorithm for classification. This system aims to identify gases emitted by spoiled dishes, particularly those made from tomatoes, with a 3.85% error rate.

Benjamin et al. described a flexible UHF RFID sensor for assessing food quality [26]. The sensor utilizes the interaction between inter-digital capacity in an RFID antenna and a coating of vegetal biopolymer to gauge food deterioration by altering the adaption coefficient between the chip and antenna based on changes in the food's condition.

Post-harvest food losses, attributed to microbial degradation during transportation and storage, account for 10 to 30% of food losses [27]. Several bacteria produce toxins that render food unfit for consumption. This study proposes electrostatic spray technology and a processing-line prototype for postharvest food protection, demonstrating significant deposition advantages for food protection.

Milk is susceptible to microbial spoilage, prompting the development of an electronic nose system (e-nose) with gas sensors to monitor its freshness and spoilage [28]. Gas sensors made of various polymers and f-SWCNTs respond to volatile organic compounds (VOCs) in milk, allowing for the assessment of spoilage levels.

The study of crop quality and assessment has become increasingly crucial in contemporary society [29]. Utilizing fuzzy logic and advanced agricultural technologies, the evaluation of crop quality has evolved from labor-intensive methods to more efficient, consistent approaches.

Ensuring food safety in the food industry is a pressing concern [30]. A proposed solution involves utilizing blockchain technology and smart contracts for quality monitoring in fruit juice manufacturing, offering a highly automated and reliable system.

As globalization progresses, the quality of food is deteriorating due to various preservation methods involving chemicals, prompting a desire for healthier food options [31]. Sensors like pH sensors, gas sensors, and temperature sensors are employed to assess food quality in various settings, including restaurants, homes, and small businesses.

3. Existing Methods and Solutions

The primary objective of the intelligent food monitoring device is to oversee and manage food items to mitigate potential damage caused by fluctuations in atmospheric or climatic conditions. Inadequate food storage practices can also contribute to food wastage. By monitoring and controlling various aspects related to food items, the smart food monitoring system emphasizes the importance of maintaining healthy food storage. This device utilizes storage units embedded with diverse electronic sensors capable of interpreting the parameters influencing food products.

3.1. Methods of Food Preservation

The fundamental aim of food preservation is to prevent food from spoiling, enabling its consumption over an extended period. Often, gardeners produce an excess of food that surpasses immediate consumption, leading to spoilage. Food preservation facilitates enjoying a wide array of foods throughout the year. Figure 3 illustrates the four techniques employed for food preservation [32].

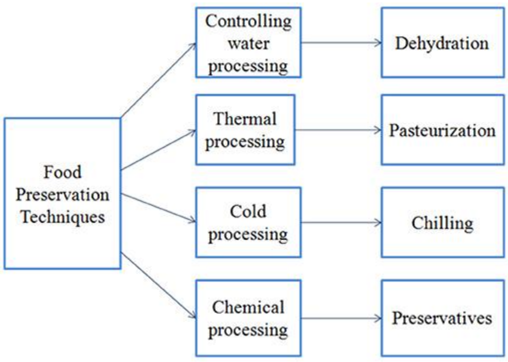


FIGURE 3. Food preservation techniques.

3.2. Alternatives of Artificial Preservatives

Various natural preservatives sourced from plants, insects, fungi, and alloys have exhibited antioxidant, antimicrobial, and anti-enzymatic properties in research. Extracts like neem, basil, rosemary, and clove are promising alternatives to their synthetic counterparts [33].

Studies highlight that chemical antioxidants used in manufacturing processes might trigger hyperactivity in individuals who were previously not prone to it. Natural compounds derived from plants, organisms, or alloys could serve as viable replacements. These compounds might find applications as preservatives in meats, cosmetics, pharmaceuticals, and even in diverse roles such as flavoring, binding, disintegrating, gelling, thickening, suspension agents, and potentially in automotive applications. Researchers have explored the use of extracts from natural sources such as green tea, grape seed, and nisin (a bacteriocin known for its nutritional food preservation properties) in trials for making chicken and turkey hot dogs [34]. Table 1 provides information on various food preservatives used with different fruits and vegetables, while Table 2 outlines diseases associated with preservative usage.

TABLE 1. Different types of food containing various kinds of preservatives.

Preservatives	Food
Sorbic acid	Syrups, sweets, dairy products, fruit products, fermented products, beverages
Tert butyl hydroquinone (TBHQ)	Fats, oils, snack foods
Tocopherols (vitamin E)	Oils
Ascorbic acid (vitamin C)	Fruit and acidic products
Butylated hydroxyanisole (BHA) and Butylated hydroxy -toluene (BHT)	Fats and oils, bakery products, cereals
Sodium sorbate	Mayonnaise, processed meats, dairy products, fermented products
Sodium and calcium propionate and Potassium propionate and propionic acid	Breads and other baked goods
Benzoic acid and sodium benzoate	Fruit products, margarine, and acidic foods
Calcium lactate	Olives, frozen desserts, jams, jellies, and dairy products
Calcium sorbate	Mayonnaise, dairy products, syrups, and margarine
Ethylene diamine tetra acetic acid (EDTA)	Dressings, canned veggies, and margarine
Methylparaben	Relishes, dressings, and beverages
Propylparaben	Cake, pastries, beverages, and relishes
Sodium nitrate and nitrite	Cured meats, fish, and poultry

3.3. Importance of Food Preservation

- Preservation methods prevent bacterial growth and other forms of spoilage, ensuring food remains safe for consumption.
- Pickling competes with freezing, canning, and drying as a means of preserving produce. Fermented foods commonly contain antioxidants, amino acids, and beneficial bacteria.
- Food preservation techniques slow the breakdown of fats prone to becoming rancid while also inhibiting the growth of microorganisms, including yeasts and other harmful microbes.
- Food storage expands the available food supply.
- Food storage contributes to minimizing food waste. Surplus foods that might have been discarded otherwise are processed, stored, and added to available stocks, reducing wastage [35].

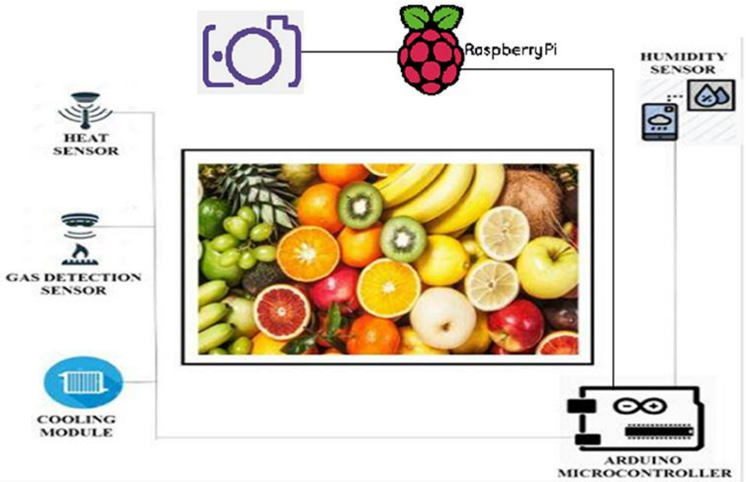
- Storing food helps alleviate dietary deficiencies by introducing variety into diets. In certain arid regions of the Middle East where plantations are limited, the shortage is compensated for by importing dried and preserved fruits and vegetables.

TABLE 2. Dangerous food preservatives cause various diseases.

Columns	Description	Value	Type
Names of fruits and vegetables	Different types of fruits and vegetables	NA	String
Minimum optimal storage temperature	Minimum temperature in which fruit or vegetable remain fresh	Multiple minimum optimal temperature values	Numeric
Maximum optimal storage temperature	Maximum temperature in which fruit or vegetable remain fresh	Multiple maximum optimal temperature values	Numeric
Freezing point	This cooling point in which fruit or vegetable remain fresh	Multiple freezing point values	Numeric
Minimum optimal humidity	Minimum humidity in which fruit or vegetable remain fresh	Multiple minimum optimal humidity values	Numeric
Maximum optimal humidity	Maximum humidity in which fruit or vegetable remain fresh	Multiple maximum optimal humidity values	Numeric
Minimum approximate storage life	At least number of days in which fruit or vegetable remain fresh	Multiple minimum approximate storage life values	Numeric
Maximum approximate storage life	At most number of days in which fruit or vegetable remain fresh	Multiple maximum approximate storage life values	Numeric
Average shelf life	Average of minimum (start spoiling) spoilage time and maximum (after spoiled) spoilage time	Multiple average shelf life values	Numeric

4. Architecture

The proposed solution involves a revised device architecture tailored to specific requirements. This updated device architecture integrates a humidifier to regulate device humidity and a cooling module to maintain the temperature for stored food items. Figure 4 illustrates the prototype of this device. Various electronic instruments have been employed for monitoring purposes, and the recorded values serve as monitoring data [36]. The data collected from diverse sensors can be compared against preset target values. If sensor readings deviate from these critical parameters, the speed control mechanism intervenes, interpreting the provided instructions to ensure the system operates correctly. This concept lays the groundwork for a method designed to safeguard perishable foods. This architectural setup comprises the following components:



International Journal of Advanced Technology in Engineering and Science
Vol. No. 11, Issue No. 12, December 2023
www.ijates.com
ijates
ISSN 2348 - 7550

FIGURE 4. The architecture of Monitoring and analysis of food spoilage using Machine Learning.

- Microcontroller: The Arduino serves as the microcontroller in this setup.
- Gas detection sensor: This sensor measures gas levels within a specific environment and is commonly employed as part of safety systems. When a leak occurs, this sensor alerts operators in the affected area [37].
- Humidifier: An electrical appliance that elevates humidity levels in a room or an entire house. Point-of-use humidifiers are commonly utilized in households to humidify a single room, while they are also integrated into medical ventilators for enhanced patient comfort.
- Heat sensor: Primarily designed to detect ambient heat, this sensor triggers an alert when the surrounding temperature surpasses its predetermined threshold, safeguarding devices from potential damage [38].
- Humidity sensor: This sensor detects and translates humidity levels into an electrical current. Available in various sizes and configurations, humidity sensors detect moisture in fruits or vegetables and relay this information to the microcontroller. If moisture content is detected, an alert message is sent to a mobile device; otherwise, it continues monitoring.
- Cooling module (TEC1-12715-Thermoelectric Cooler 15A Peltier Module): Comprising a heater, condenser, and fan, this module regulates temperature. It includes both a heater and condenser.
- Light sensor: These electronic devices gauge natural or artificial light intensity, converting light energy into an electrical signal. Commonly employed in diverse manufacturing applications.

Figure 5 illustrates the Gas detection sensor, which identifies any gas or air emitted by the fruits or vegetables. It transmits data to the microcontroller; if gas content is detected, an alert is triggered for the user. Alternatively, if no gas content is detected, the microcontroller continues to gather and process values.

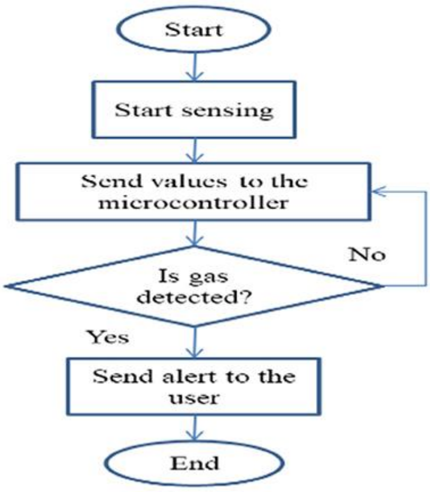


FIGURE 5. Gas detection sensor.

In Figure 6, the Humidity sensor initially detects any moisture present in the fruits or vegetables, relaying this information to the microcontroller. If moisture content is detected, it triggers an alert for the user. If no moisture content is detected, the microcontroller continues to receive and process values.

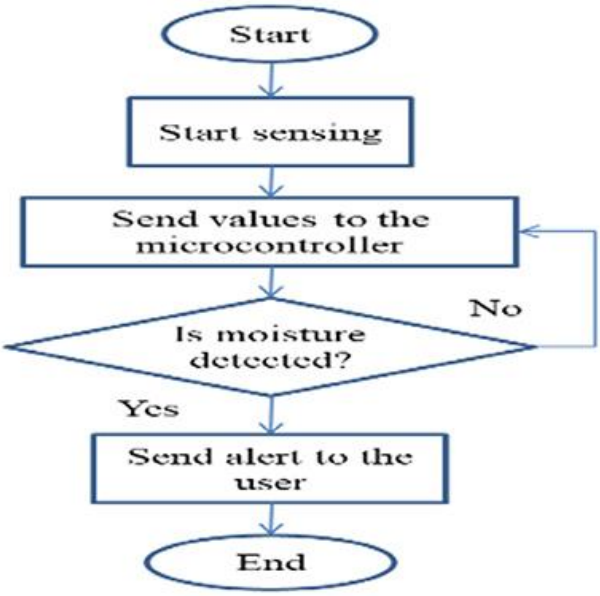


FIGURE 6. Humidity sensor.

. Figure 7 demonstrates the Heat sensor and Cooling module, which identify any heat emanating from the fruits or vegetables and transmit this data to the microcontroller.

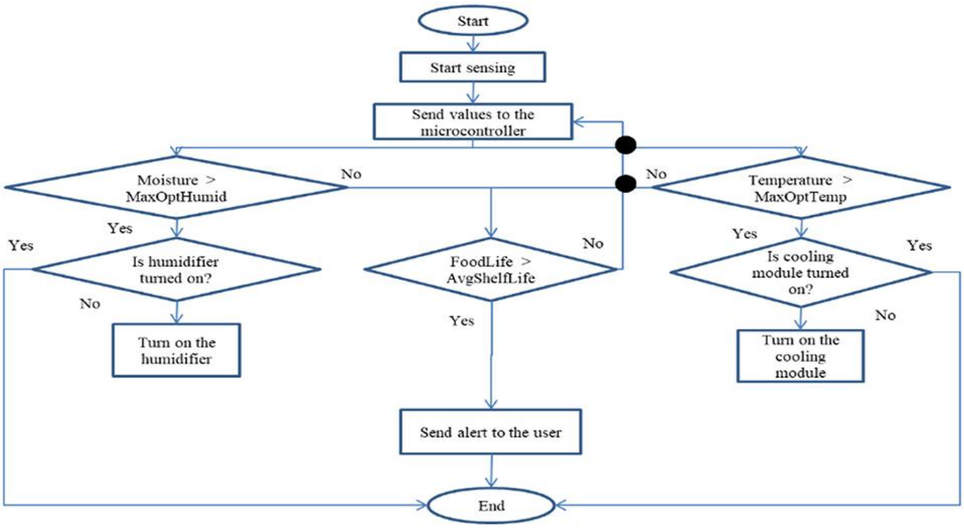


FIGURE 7. Heat sensor and cooling module.

The entire procedure is outlined in Algorithm 1.

ALGORITHM 1 : Process (object).

```
1:  Turn on the device
2:  Capture the image of fruit or vegetable
3:  Turn on the Cooling module
4:  Turn on Humidifier
5:  Store the optimal values of parameter according to captured
    object
6:  Read the values of sensor for monitoring process of fruits or
    vegetables
7:  if Gas content is detected then
8:      go to step 20
9:  else
10:     go to step 21
11: end if
12: if Moisture content is detected AND moisture > maximum
    optimal humidity of object AND Humidifier is off then
13:     Turn on the humidifier
14: else if heat content is detected AND temperature >
    maximum optimal storage temperature of object AND
    cooling module is off then
15:     Turn on the cooling module
16: else if life of object > average shelf life of object then
17:     go to step 20
18: else
19:     go to step 21
20: end if
21: Send alert to the user
22: Capture an image of fruit or vegetable
23: go to step 7
```

5. Working Principle

We employ various sensors crucial for detecting and overseeing food spoilage, such as the camera sensor, humidity sensor, gas sensor, and heat sensor. The camera sensor captures images of fruits or vegetables, while the humidity sensor monitors the surrounding moisture levels. If it falls below a set threshold, the humidifier adjusts the humidity to match this value. Simultaneously, the temperature sensor tracks temperature variations against predefined thresholds managed by the Arduino. The Arduino is directly linked to the Raspberry Pi, serving as a mini-computer with its processing unit and memory. When the temperature surpasses the designated threshold, the cooling module activates. Additionally, the gas sensor identifies early spoilage by detecting minimal gas emissions from the food items, relaying this data to the Arduino, which subsequently uploads the values to the cloud. The web application then notifies the user, utilizing methods such as a buzzer, voice-activated commands, or display messages.

6. Smart Food Life Prediction

The food life cycle involves distinct stages: Fresh Food, Onset of Food Spoilage, and Spoiled Food. For prediction purposes, we've trained a model encompassing 50 varieties of fruits and vegetables across these three classifications. Our proposed approach employs a Convolutional Neural Network (CNN) for object detection and prediction. This CNN model has been trained on these diverse categories.

Object detection poses a challenge within computer vision, but with machine learning models trained on extensive photo datasets, identifying and distinguishing objects becomes feasible. To identify the specific fruit or vegetable, our CNN calculates threshold values for various parameters like gas, temperature, and heat, as these values differ among different food types. Our supervised learning approach trains the CNN model using images of fruits, correlating them with corresponding tags, enabling the model to accurately predict fruit labels post-training.

We've utilized a deep learning methodology to train our model using datasets of fruits and vegetables, particularly leveraging the Fruits360 dataset, accessible on GitHub or Kaggle [41]. This dataset comprises approximately 90,380 high-resolution images across various categories, essential for an effective classifier.

Our model consists of a total of 11 layers, including a SoftMax output layer, four convolutional layers, four max pooling layers, and two fully connected layers. The initial layer is a convolutional layer with a 16, 5 x 5 x 4 filter and a 2 x 2 max-pooling layer with stride = 2. The fourth convolutional layer comprises parameters of (5 x 5 x 64) and a dimension of 128. Trained on 50 different fruit and vegetable types, this model excels in identifying multiclass images.

7. Results and Discussion

Gathering information is a vital and time-intensive endeavor across various fields of study. Precise data collection is indispensable for maintaining coherence and accuracy. Presently, food spoilage is a pressing concern as it's pivotal to maintain a robust immune system, and there's currently no comprehensive solution to prevent spoilage to a certain degree. For this study, the Fruit360 dataset, obtained from the Kaggle dataset website, served as the primary dataset. This dataset comprises images featuring a variety of fruits and vegetables, utilized for training the CNN model and conducting object detection.

In the domain of fruits and vegetables, a meticulous dataset was meticulously curated through thorough research. This dataset encompasses 50 distinct types of fruits and vegetables, accompanied by their respective optimal storage temperature range, humidity range, estimated storage life, and freezing point (42). This collection of data is employed for generating alert messages regarding spoilage on mobile devices. Table 3 presents a detailed breakdown of the dataset attributes, their values, types, and descriptions. Each column's values are primarily numeric or floating-point, except for the initial column.

TABLE 3. Description of the fruits and veggies dataset.

Columns	Description	Value	Type
Names of fruits and vegetables	Different types of fruits and vegetables	NA	String
Minimum optimal storage temperature	Minimum temperature in which fruit or vegetable remain fresh	Multiple minimum optimal temperature values	Numeric
Maximum optimal storage temperature	Maximum temperature in which fruit or vegetable remain fresh	Multiple maximum optimal temperature values	Numeric
Freezing point	This cooling point in which fruit or vegetable remain fresh	Multiple freezing point values	Numeric
Minimum optimal humidity	Minimum humidity in which fruit or vegetable remain fresh	Multiple minimum optimal humidity values	Numeric
Maximum optimal humidity	Maximum humidity in which fruit or vegetable remain fresh	Multiple maximum optimal humidity values	Numeric
Minimum approximate storage life	At least number of days in which fruit or vegetable remain fresh	Multiple minimum approximate storage life values	Numeric
Maximum approximate storage life	At most number of days in which fruit or vegetable remain fresh	Multiple maximum approximate storage life values	Numeric
Average shelf life	Average of minimum (start spoiling) spoilage time and maximum (after spoiled) spoilage time	Multiple average shelf life values	Numeric

Figure 8 illustrates the correlation among attributes such as the minimum optimal storage temperature, maximum optimal storage temperature, freezing point, minimum optimal humidity, maximum optimal humidity, minimum approximate storage life, and maximum approximate storage life of 17 distinct fruits and vegetables. Out of the 50 fruits or vegetables available, we specifically chose 15 for our experimental purposes. This visual representation allows for a comparison of the standard parameter settings across different food items. Subsequently, these food items were placed within the proposed device, which conducted an analysis of each item and adjusted the parameter values accordingly. The proposed approach was then employed to continually monitor the item and regulate the environment as required. As a result of this experiment, we aimed to prolong the maximum approximate storage life of these fruits and vegetables, as outlined in Table 4.

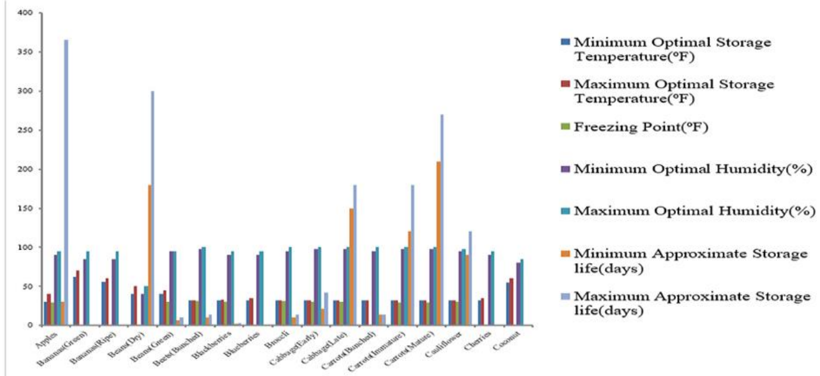


FIGURE 8. Comparison among different fruits and vegetables with respect to their various attributes.

TABLE 4. Experimental analysis of fruits and vegetables.

Name of fruits or vegetables	Minimum temperature (°F)	Maximum temperature (°F)	Average shelf life (days)	Maximum approximate storage life (days)	After experimental analysis (days)
Broccoli	32	32	11	14	16
Cabbage (Early)	32	32	41	42	44
Carrots (Immature)	32	32	35	180	181
Cauliflower	32	32	14	120	122
Cherries	30	31	6	14	15
Grapes	31	32	6	56	55
Kohlrabi	32	32	7	90	91
Gooseberries	31	32	3	28	29
Leeks	32	32	11	90	91
Parsley	32	32	6	90	91
Plums	31	32	4	35	36
Eggplant	46	54	2	7	9
Blackberries	32	33	6	3	4
Corn (Sweet)	32	32	7	8	9
Cucumbers	50	55	11	14	15

The average shelf life of fruits or vegetables denotes the duration during which they remain suitable for consumption. Beyond this period, consuming these items might pose health risks due to potential spoilage that could have occurred before reaching the average shelf life. Each fruit or vegetable has a distinct minimum optimal storage temperature, below which they begin to spoil. Hence, maintaining this minimum optimal storage temperature is crucial to prevent premature spoilage.

Regarding our model's performance, we've plotted graphs illustrating the training and validation data. These graphs showcase the model's training data loss versus validation data loss, as well as the training data accuracy and validation data accuracy for the CNN model used in object detection for fruits and vegetables. These performance plots demonstrate how accuracy improves with the increase in epochs and whether our model has been adequately trained. Figures 9 and 10 display the CNN model's training data loss versus validation data loss, along with the training and validation data accuracy. These graphs help determine whether the model is overfitting, underfitting, or perfectly fitting the data.

- Overfitting: This happens when the Training loss is significantly lower than the Validation loss.
- Underfitting: It occurs when the Training loss surpasses the Validation loss, meaning Training loss > Validation loss.
- Perfect fit: This scenario arises when Training and Validation losses are nearly equal or gradually coming together, signifying that the model is performing optimally.

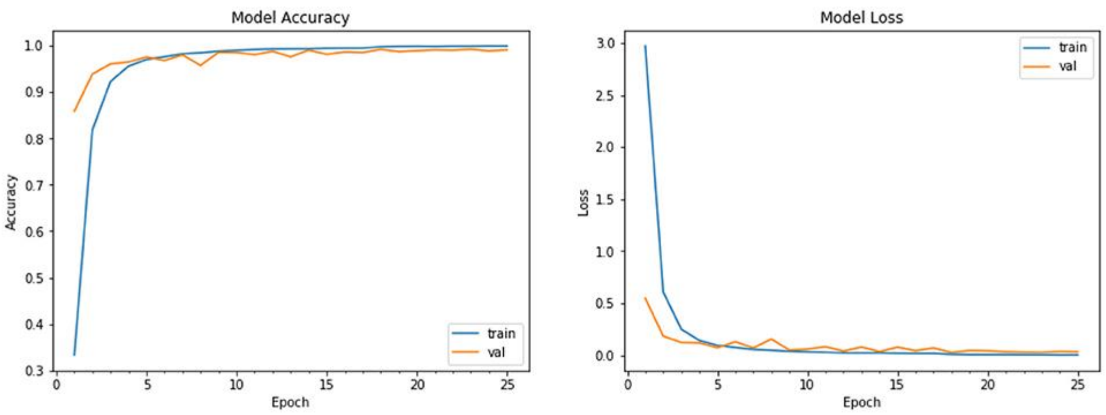


FIGURE 9. Performance graph of Training Loss vs. Validation Loss.

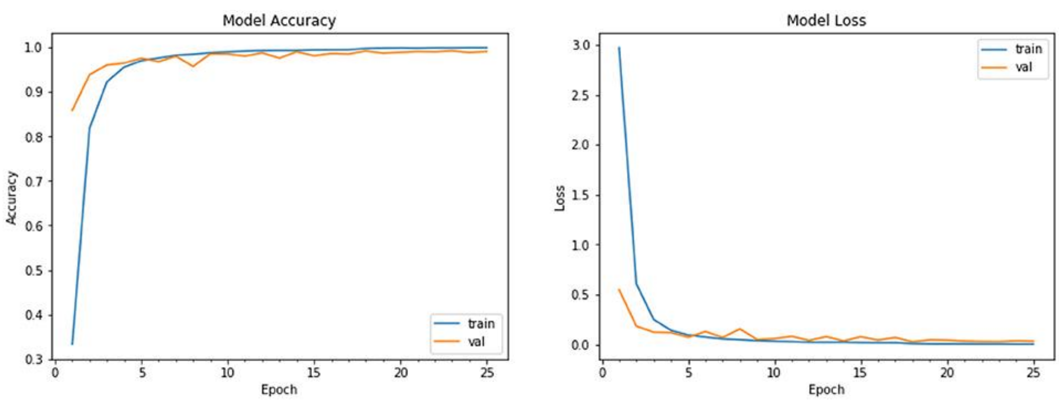


FIGURE 10. Performance graph of training accuracy vs. validation accuracy.

In Figure 9, the graph demonstrates a near convergence, suggesting that our model is void of both overfitting and underfitting. Figure 10 exhibits the training and validation accuracy after each epoch, showcasing an almost ideal scenario where the validation and training accuracies closely align. Consequently, our model boasts a 95% accuracy rate, a commendable achievement enabling it to discern various types of fruits and vegetables from images. It performs well not only with individual items but also excels in predicting the class of multiple objects. Across 50 different categories, the method performs exceptionally, delivering highly accurate results for the images processed by the model.

8. Conclusion

This research introduces an innovative method employing a sensor-based system for monitoring and analyzing food spoilage. The device proposed here is designed to extend the shelf life of food, thereby preventing premature spoilage and increasing the duration for which food remains preserved. It actively monitors food quality, providing user alerts through voice commands or display notifications, along with predicted time frames for spoilage. With an accuracy rate of 95%, this device ensures reliable performance.

REFERENCES

[1] Dhanamjayulu C, Nizhal U, Maddikunta PKR, Gadekallu TR, Iwendi C, Wei C, et al. Identification of malnutrition and prediction of BMI from facial images using real-time image processing and machine learning. IET Image Proc. (2021). 1–12.

[2] Ahmad P, Jin H, Alroobaea R, Qamar S, Zheng R, Alnajjar F, et al. MH UNet: a multi-scale hierarchical based architecture for medical image segmentation. IEEE Access. (2021).

[3] Arul R, Alroobaea R, Mechti S, Rubaiee S, Andejany M, Tariq U, et al. Intelligent data analytics in energy optimization for the internet of underwater things. Soft Comput. (2021) .

[4] Anajemba JH, Tang Y, Iwendi C,Ohwoekevwo A, Srivastava G, Jo O. Realizing efficient security and privacy in IoT networks. Sensors. (2020).

[5] Gadekallu TR, Khare N, Bhattacharya S, Singh S, Maddikunta PKR, RaIH, et al. Early detection of diabetic retinopathy using PCA-firefly based deep learning model. Electronics. (2020).

[6] Gadekallu TR, Khare N, Bhattacharya S, Singh S, Maddikunta PKR, Srivastava G. Deep neural networks to predict diabetic retinopathy. J Ambient Intell Humanized Comput. (2020) .

[7] Ayoub A, Mahboob K, Javed AR, Rizwan M, Gadekallu TR, Abidi MH, et al. Classification and categorization of covid-19 outbreak in pakistan. Comput Mater Continua. (2021).

[8] Jedermann R, Nicometo M, Uysal I, Lang W. Reducing Food Losses by Intelligent Food Logistics. London: The Royal Society Publishing (2014).

[9] Brody AL, Bugusu B, Han JH, Sand CK, McHugh TH. Innovative food packaging solutions. J Food Sci. (2008).

[10] Pang Z, Chen J, Zhang Z, Chen Q, Zheng L. Global fresh food tracking service enabled by wide area wireless sensor network. In: 2010 IEEE Sensors Applications Symposium (SAS). Limerick: IEEE (2010). p. 6–9.

[11] Drago E, Campardelli R, Pettinato M, Perego P. Innovations in smart packaging concepts for food: an extensive review. Foods. (2020).

[12] Bourouis S, Alroobaea R, Rubaiee S, Andejany M, Almansour FM, Bouguila N. Markov chain monte carlo-based bayesian inference for learning finite and infinite inverted beta-liouville mixture models. IEEE Access. (2021).

[13] Iwendi C, Khan S, Anajemba JH, Bashir AK, Noor F. Realizing an efficient IoMT-assisted patient diet recommendation system through machine learning model. IEEE Access. (2020).

[14] Hebbar N. Freshness of food detection using IoT and machine learning. In: 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE). Vellore: IEEE (2020).

[15] Kumar A. An arduino sensor-based approach for detecting the food spoilage. Int J Eng Appl Sci Technol. (2020).

[16] Chander BR, Kumari G. Food quality monitoring system by using arduino. J Eng Sci. (2020).

[17] Ishangulyyev R, Kim S, Lee SH. Understanding food loss and waste–Why are we losing and wasting food? Foods. (2019).

[18] Yousefi H, Ali MM, Su HM, Filipe CD, Didar TF. Sentinel wraps: real-time monitoring of food contamination by printing DNAzyme probes on food packaging. ACS nano. (2018).

[19] Green GC, Chan AD, Goubran RA. Tracking food spoilage in the smart home using odour monitoring. In: 2011 IEEE International Symposium on Medical Measurements and Applications. Bari: IEEE (2011).

[20] Megalingam RK, Sree GS, Reddy GM, Krishna IRS, Suriya L. food spoilage detection using convolutional neural networks and k means clustering. In: 2019 3rd International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE). Noida: IEEE (2019).

[21] Green GC, Chan AD, Goubran RA. Monitoring of food spoilage with electronic nose: potential applications for smart homes. In: 20093rd International Conference on Pervasive Computing Technologies for Healthcare. London: IEEE (2009).

[22] Yuan M, Ghannam R, Karadimas P, Heidari H. Flexible RFID patch for food spoilage monitoring. In: 2018 IEEE Asia Pacific Conference on Postgraduate Research in Microelectronics and Electronics (PrimeAsia). Chengdu: IEEE (2018).

[23] Caya MVC, Cruz FRG, Blas PJR, Cagalingan MM, Malbas RGL, Chung WY. Determining spoilage level against time and temperature of tomato-based Filipino cuisines using electronic nose. In: 2017IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM). Manila: IEEE (2017).

[24] Ponnan S, Saravanan AK, Iwendi C, Ibeke E, Srivastava G. An artificial intelligence based quorum system for the improvement of the lifespan of sensor networks. IEEE Sens J. (2021).

[25] Jorge-Martinez D, Butt SA, Onyema EM, Chakraborty C, Shaheen Q, De-La-Hoz-Franco E, et al. Artificial intelligence-based Kubernetes container for scheduling nodes of energy composition. Int J Syst Assurance Eng Manag. (2021).

[26] Saggin B, Belaizi Y, Vena A, Sorli B, Guillard V, Dedieu I. A Flexible Biopolymer based UHF RFID-Sensor for food quality monitoring. In: 2019 IEEE International Conference on RFID Technology and Applications (RFIDTA). Pisa: IEEE (2019).

[27] Law SE, Cooper SC. Air-assisted electrostatic sprays for postharvest cont rolof fruit and vegetable spoilage microorganisms. IEEE Trans Ind Appl. (2001).

[28] Phukkaphan N, Eamsa-ard T, Chairanit C, Kerdcharoen T. The application of gas sensor array based electronic nose for milk spoilage detection. In: 2021 7th International Conference on Engineering, Applied Sciences and Technology (ICEAST). Pattaya: IEEE (2021).

[29] Goel P, Goel S, Bhatia S. Food quality assessment using fuzzy logic. In: 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom). New Delhi: IEEE (2015).

[30] Yu B, Zhan P, Lei M, Zhou F, Wang P. Food quality monitoring system based on smart contracts and evaluation models. IEEE Access. (2020).

[31] Prajwal A, Vaishali P, Sumit D. Food quality detection and monitoring system. In: 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). Bhopal: IEEE (2020).

[32] Considine KM, Kelly AL, Fitzgerald GF, Hill C, Sleator RD. Highpressure processing-effects on microbial food safety and food quality. FEMS Microbiol Lett. (2008).

[33] Raveau R, Fontaine J, Lounès-Hadj Sahraoui A. Essential oils as potential alternative biocontrol products against plant pathogens and weeds: a review. Foods. (2020).

[34] Bastos DH, Saldanha LA, Catharino RR, Sawaya A, Cunha IB, Carvalho PO, et al. Phenolic antioxidants identified by ESI-MS from yerba mate (Ilex paraguariensis) and green tea (Camelia sinensis) extracts. Molecules. (2007).

[35] Anand G, Prakash L. IoT based novel smart refrigerator to curb food wastage. In: 2018 3rd International Conference on Contemporary Computing and Informatics (IC3I). Gurgaon: IEEE (2018).

[36] Chanthini B, Manivannan D, Umamakeswari A. Perishable food quality monitoring–an internet of things (IoT) approach. Int J Pure ApplMath. (2017).

[37] Ilie AM, Vaccaro C. Design of a smart gas detection system in areas of natural gas storage. In: 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). Fort Worth, TX: IEEE (2017).

[38] Jain P, Kushwaha R.Wireless gas sensor network for detection and monitoring of harmful gases in utility areas and industries. In: 2012 Sixth International Conference on Sensing Technology (ICST). Kolkata: IEEE (2012).

[39] Jovanovi´c U, Jovanovi´c I, Manˇci´c D. Overview of temperature sensors for temperature measurement of PV modules. In: 2018 26th Telecommunications Forum (TELFOR). Belgrade: IEEE (2018).

[40] Benabdellah N, Bourhaleb M, Benazzi N, Dahbi S. Design of temperature and humidity sensors for an electronic nose used in rotten food. In: 2016 International Conference on Electrical and Information Technologies (ICEIT). Tangiers: IEEE (2016).