GIET UNIVERSITY JOURNAL, 2026, VOL. 6, NO. 1, PP. 86-91
Manuscript received 10th August 2025; revised 21st December 2025;
Accepted 15th January 2026

*ISSN: 2583-5955*

# SMART AGRITECH FOR MONITORING FOOD QUALITY USING SENSOR-BASED INPUTS

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**Abstract- In this evolving technological era, various agricultural technologies are used to ensure food quality and address safety concerns. Nowadays, there is an increase in the demand for food safety, which combines challenges in post-harvest handling as well as in transportation, with the monitoring of intelligent solutions. The Smart Agritech paper presents the features that leverage data-driven insights to evaluate the quality of food as well as fruits. This can be possible with the help of physical and chemical sensors based on the input parameters. The input parameter contains the key features like moisture content, color intensity, texture, odor intensity, pH level, nutritional value, sugar content, presence of additives, and shelf life. The smart Agritech system provides real-time predictions on the quality of food, which enables the stakeholders, including farmers, wholesalers, and retailers, to make informed decisions on storage and transportation. Integrated AI models with sensors reduce human error as well as subjectivity in the quality evaluation of the feed by using sensors. This system helps to increase the supply chain and make it more beneficial for the farmer because if the quality of the food increases, then its demand also increases, which helps the farmer to make more profit. There is no involvement of any third party who takes the food at their price from the farmers and sells it in the market at a higher price; this system also reduces the involvement of any third party. Here we are using advanced data visualization techniques, which are scatter plots, histograms, box plots, and correlation. Here we use the heatmap to explore the relationship between input features and the quality of the food.**

**Key Word – Quality Parameters, pH level, and real-time predictions**

## 1. Introduction

Demand for food is rapidly growing due to the increasing global population. At the present time, food is wasted in very large amounts because of its poor handling, delays in detecting the diseases, and its improper storage. in fruits and vegetables. This problem is especially common; it is highly sensitive to changes in environmental conditions. Ensuring the quality of the food and safety from the harvested time until it reaches the consumer is more important than anything. The food quality and safety are checked by the farmers and suppliers manually by looking at physical signs like food color, its smell, and its texture. This manual process is slow and also inaccurate. Also, for this, a highly skilled and experienced person is required for checking its quality. As a result, it happened that some of the food that looked good might actually be spoiled, and some food was rejected whose actual quality was good. To overcome this problem, there are a lot of sensors available. There's a smart sensor that continuously monitors the important features like temperature, humidity, moisture, and pH levels. By the use of this smart sensor, we can predict whether the food is fresh or spoiled. This system collects the input data, like moisture content, sugar levels, color intensity, texture, and freshness indicators, and food quality is classified and analyzed with the help of various ML models. By using this system, it helps the farmers, retailers, and storage centers, and it is beneficial for the consumer also to get the real-time update on the food quality.

## 2. Literature Survey

Y. Liu et al.'s work aim is to track the freshness of the fruits during transportation; when the temperature exceeds the safe limits, then this system provides the alert, but it has fewer

ISSN: 2583-5955

decision-making features involving AI-based classification [1]. Kaur et al. has developed an IoT-based system for the food supply chain whose aim is to enhance the traceability of the food chain [2]. Their approach is to collect the real-time data from different sources, like from farms to retail outlets, with the aim of improving product tracking and logistics. It mainly focused on capturing the location of the food product and its movement rather than having to concentrate on its actual freshness and quality [2]. Mahmood Rehman et. al. aim is to classify the vegetable freshness based on their images, which are analyzed for classification [3]. While these projects have various limitations because they use deep learning for visualizing the data. it will be dependent on visuals, so the system may not reflect the internal spoilage or freshness of the vegetables. As well, it is image-based classification that has a much greater chance for error because of image lighting conditions, its background, and angles; it reduces the accuracy in the real world [3]. Chen et al. aim is to detect the spoilage in dairy products and meat. These systems have many limitations for some specific foods, and they don't integrate the multiple sensor inputs, and they offer the user a real-time dashboard [4]. On the other hand, our proposed system addresses these limitations by integrating machine learning algorithms and sensor-based monitoring, and it offers a more comprehensive solution. By combining these technologies, we can achieve a higher level of precision in assessing the quality of produce. We propose integrating multiple sensors that track the food quality based on the humidity and temperature, and incorporate pH as well as gas sensors to capture a complex set of data that indicates the food spoilage. We have also integrated multiple ML algorithms for classification, like SVM and Random Forest. Our model classifies the food quality in three categories, which are fresh, spoiled, or moderate. Our system goes beyond with less focus on traceability by integrating multiple sensors, like our sensors that monitor the temperature, pH levels, humidity, and gas emissions, which help our model to evaluate the real-time quality prediction for the food and its freshness. This holistic approach not only enhances the reliability of our evaluations but also provides valuable insights for improving supply chain management. Our sensors continue to collect the data that enables real-time prediction for food quality that detects the food spoilage and its condition.

## 3. Proposed Methodology

The proposed system is designed to monitor, analyze, and evaluate the food quality as well as the fruit quality by combining multiple sensor data and machine learning methods. The Smart Agritech is built in mainly four main stages:

### A. Sensor Integration

Sensors are used to collect data from the environment where food is stored in order to monitor and maintain food quality. Smart sensors continuously evaluate important parameters that influence the condition of stored food. These include temperature, where excessively high or low values can reduce food quality and lead to spoilage; humidity, as excessive moisture can promote mold growth and rotting; pH levels, where changes may indicate chemical spoilage or fermentation; and gas emissions, such as ethylene and ammonia, which can signal rapid food deterioration and a decline in quality. Continuous monitoring of these factors helps ensure

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better storage conditions and reduces food wastage.

### B. Data Preprocessing and Feature Engineering

When the sensor collects the data, then this data needs to be preprocessed and cleaned, and also needs to reduce nulls or duplicates before it is going to be used in the ML model. The collected data is preprocessed by removing missing values and correcting possible errors to ensure accuracy and reliability. The data is then normalized so that readings from different sensors are represented on a common scale. Finally, relevant features such as temperature levels, moisture range, and gas concentrations are extracted for further analysis.

### C. Machine Learning Models

After data preprocessing, machine learning algorithms are trained and tested using the processed dataset. Random Forest is applied to improve prediction accuracy by constructing multiple decision trees, while Support Vector Machine (SVM) is used to create a decision boundary that separates different quality levels. The primary objective of these models is to predict food quality and classify it into categories such as Fresh, Moderate, and Spoiled. To make real-time decisions, this model used to learn from the past unseen data or input features, which are given by the smart sensors.

### D. User Interface (Dashboard)

A simple dashboard is developed to make the system user-friendly and easily accessible to users. Through this interface, users can monitor the current quality status of their stored food in real time. If a decline in food quality or spoilage is detected, the system generates an alert notification. The dashboard also presents charts and analytics based on sensor data and model predictions, enabling users to make informed decisions regarding food storage and consumption. Additionally, it provides recommendations for optimal storage conditions to help maintain food freshness and reduce waste.

## 4. Results & discussion

To know how well our system predicts the accurate output, we used a real-time dataset that consists of the collection of food, vegetable, and fruit data. The datasets contain the various values that are recorded under different storage conditions, like low and high temperatures, different humidity levels, and changes in pH and moisture. We selected that condition to reflect real-world scenarios where food quality is changed over time.

**Table 1. Performance different models**

| Model | Accuracy (%) | MSE | RMSE |
|---|---|---|---|
| Random Forest | 96.0 | 0.063 | 0.251 |
| SVM | 91.5 | 0.085 | 0.291 |
| Decision Tree | 89.2 | 0.108 | 0.328 |

Random Forest performance is quite good compared to all three models. Random Forest has 96% accuracy, its lowest MSE (0.063), and its lowest RMSE (0.251). This model works in

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ensemble learning, where multiple decision trees are made to make predictions to get better results. It is also good at handling null and missing values and also helps to overcome the over-fitting problem. It makes this system highly reliable for real-world applications like food quality monitoring. SVM also gives a better result with 91.5 % accuracy, but it was less efficient compared to the random forest because SVM is good for classification and also performs well on small datasets, but it is not flexible for more complex and large datasets; it will be slow while dealing with a large dataset, and in our case, it became slow while taking multiple sensor inputs.

The decision tree performance is not good for this model; it had the lowest performance among all these models, with 89.2% accuracy and high errors. Decision trees are simple algorithms that suffer from over-fitting conditions, and they also do not perform as well as ensemble methods. After evaluating the performance of all the models, Random Forest was selected for the smart agritech system due to several advantages. It provided higher accuracy compared to other models, indicating fewer prediction errors in determining food quality. The model also exhibited lower error values, meaning its predictions were closer to the actual outcomes. Additionally, Random Forest is highly scalable, making it suitable for handling large datasets and diverse sensor inputs from different environments. It is also more robust in dealing with noisy and missing data, which further enhances its reliability for real-world applications.

After successful data preprocessing, machine learning models were trained and evaluated to predict the quality status of stored food. The trained model analyzes sensor data and classifies the predicted food condition into three categories: Fresh, Moderate, and Spoiled. The Fresh category indicates that the food is in good condition, safe for consumption, and retains its original quality. The Moderate category represents food that is still usable but may begin to lose freshness over time and therefore requires careful monitoring. The Spoiled category indicates that the food has deteriorated and is unsafe for consumption, potentially posing health risks. Such automated classification systems help improve food safety and reduce wastage by enabling early detection of spoilage and timely decision-making.

In this model, we used algorithms like Random Forest and Support Vector Machine (SVM) for this task. Also, the Random Forest model gave the best results with 96% accuracy for correctly predicting the quality of the food based on the input features and the sensors that sense the input parameters. This means out of 100% of the food, the system was able to correctly predict the condition of 96% of the food items. **Fig. 1** shows the relation between the color intensity, and fruit quality. The charts and graphs in **Fig. 2** and **Fig. 3**, shows 75% of Median with good (IQR), as well as predicting output, which is our result, clearly show that our system can be a powerful and helpful tool for analyzing and monitoring the food. Based on this, it will predict its quality. **Fig. 4** show which factor contribute most when predict the food quality. Based on the Random Forest model analysis, Shelf Life (days), Color Intensity, and Freshness were identified as the most influential features contributing to the prediction of food quality. This system helps to identify early signs of spoilage and take quick decisions to reduce food waste and improve safety, which makes it beneficial to both the farmer and the consumer.

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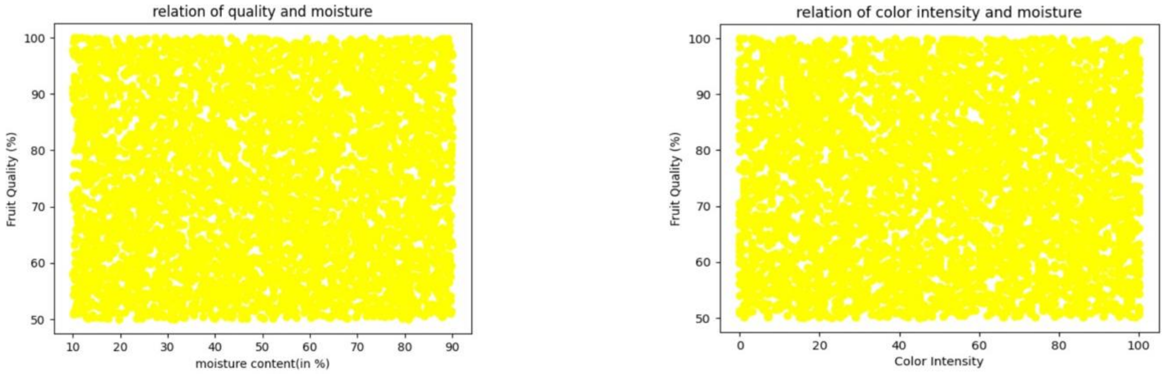


**Fig. 1. Relation between moisture content (%) and fruit quality (%) relationship between color and fruit quality**

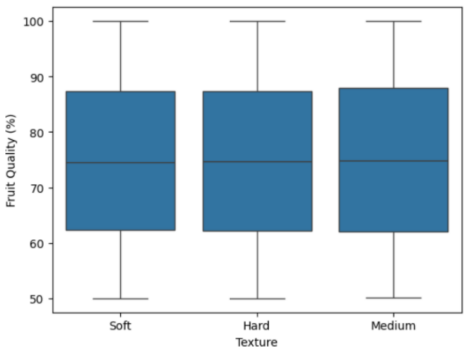


**Fig. 2. Fruit quality by Texture**

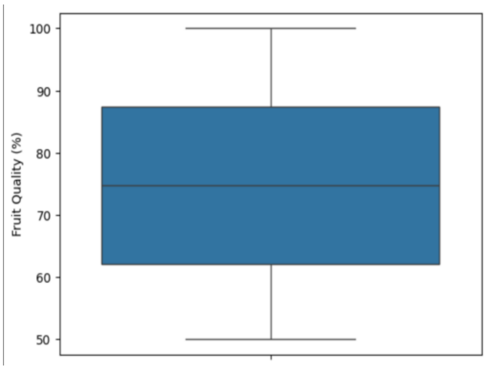


**Fig. 3. Overall fruit quality**

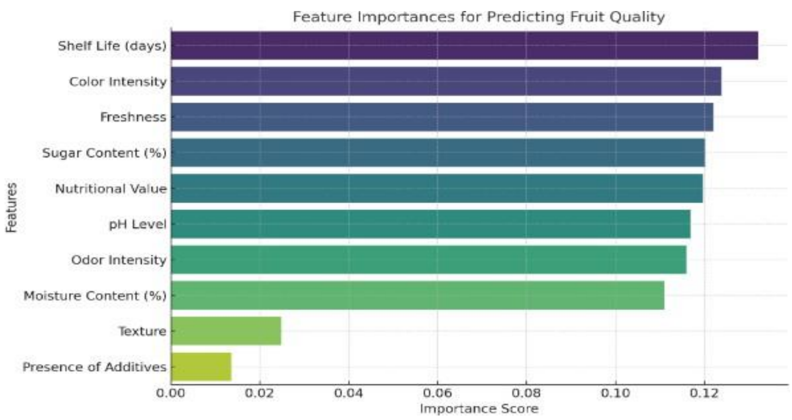


**Fig. 4. Feature importance for fruit quality**

## 5. Conclusion

In conclusion, our Smart Agritech system, clearly shows that it is possible to use modern AI and smart sensors to monitor the food and predict the quality of the food with 96% accuracy of our model. Instead of depending on the expert to predict the quality by manually analyzing, we directly used this automated system, which takes the input parameters with the help of sensors like temperature, humidity, pH, and gas and gives us the quality of the food with better accuracy and also tells us if it is safe for us or not or how much longer fruits and vegetables will stay fresh. This system accurately tells us if the food is now fresh, getting spoiled, or already spoiled. By utilizing different machine learning models, this system enables farmers,

***ISSN: 2583-5955***

food suppliers, and retailers to take the right step at the right time, such as adjusting storage conditions or removing spoiled food before it affects other food or deteriorates, causing it to spoil and smell worse. As a result, it saves money, reduces food wastage, and ensures that customers receive safe and healthy food that has a positive impact on their health.

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