

IoT Based Food Spoiled Detection Using Deep Learning

V. S. R. K. Prasad G.¹; Jamiseti Balu²; Sohail Khader Shaik³; Gayathri Damarla⁴; Abdul Razaq Shaik⁵; Meghana Polisetty⁶

¹Department of Computer Science and Engineering (IoT & CS incl BCT), PSCMR College of Engineering & Technology, Vijayawada, A.P., India

^{2,3,4}Departmentt of Computer Science and Engineering (Internet of Things), PSCMR College of Engineering & Technology, Vijayawada, A.P., India

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Abstract: Spoilage of food is one of the major issues that affects human health as well as the economy in the form of food wastage. A large number of spoiled food products cannot be recognized with the naked eye; therefore, the process of quality assessment is tedious and not reliable. The need for the development of a smart system that can efficiently sense the spoilage of food in real time is therefore required. The objective of the present work is the development of an Internet of Things-based system that can efficiently sense the quality of food in real time. The gas sensor and temperature sensor will be used to collect the information regarding the condition of the food, while the camera will be used to collect the image of the food item. The collected data is then processed with the help of a microcontroller, and it is analyzed with the help of a deep learning model, which is based on a convolutional neural network. The classification of the food is then done as fresh or spoiled. The system is based on the combined results of both sensor and image data. The results obtained from testing the system show an accuracy of 95.83 percent, thereby showing its efficiency in detecting spoiled food. The proposed system helps in the early detection of spoiled food, minimizes wastage, and is highly efficient in terms of safety.

Keywords: Plant Disease Detection, Tea Leaf Classification, Ensemble Learning, Deep Learning, Image Analysis and Precision Agriculture.

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I. INTRODUCTION

Food spoilage is an important problem that affects the world. Spoiled food can cause foodborne diseases, including poisoning, infections, and health problems [1]. On the other hand, a large quantity of edible food is being wasted every year due to improper storage, consumption, and detection. Many food spoilages occur through microbial growth or chemical changes, which cannot be easily identified by the human eye. Therefore, traditional methods to detect food quality are not very effective. These methods include labor-intensive techniques, smell, taste, and lab analysis [2]. These techniques are time-consuming and may be erroneous. In recent times, due to an increase in population and food supply chain issues, food storage problems have become critical. Therefore, to detect food quality effectively, the use of modern technologies is promising. This will help to avoid health problems and food wastage.

The motivation for this work comes from the limitation of the conventional method of monitoring food quality and the increasing need for smart solutions. In general,

conventional methods are not able to identify spoilage in early stages, which leads to the consumption of unsafe food products or the discard of edible ones. In addition, conventional methods are not suitable for large-scale industries or even large-scale residential purposes [3]. In some cases, spoilage in early stages is not visually detectable, especially in cases of microbial growth, chemical reactions, and improper storage conditions. It is possible to solve this problem in an effective way by utilizing the Internet of Things technology and deep learning algorithms. It is possible for sensors to monitor various environmental conditions like temperature and gas emission. Similarly, cameras can be used for visually detecting spoilage [4]. In general, it is possible to develop an intelligent system for accurate prediction. It is possible to improve the quality of food safety by developing such a system and provide solutions for various purposes.

Despite advancements in sensor-based monitoring and machine learning algorithms, there are still major gaps in the existing approaches for detecting spoilage in foods. For instance, single-sensor-based approaches, like temperature sensors and gas sensors individually, are not sufficient for

detecting spoilage since they are not able to provide a complete spoilage profile. In addition, false positives and false negatives are major issues in single-sensor-based approaches. Similarly, image-based approaches like deep learning algorithms are not able to detect spoilage in the early stages since they are not able to consider environmental conditions [5]. In addition, the existing approaches are not real-time-based since they are based on batch-based data collection. In addition, there is a lack of consideration for integrating multiple sources of information for accurate prediction of spoilage. In summary, there is a lack of consideration for developing a comprehensive and automated approach for detecting spoilage in foods. Therefore, there is a need for developing a comprehensive and automated approach for detecting spoilage in foods. The overall contribution of the work is:

➤ *Hybrid Detection System:*

It integrates the information obtained using the sensors along with the image processing capabilities of deep learning algorithms.

➤ *High Accuracy Performance:*

It is able to achieve an overall accuracy of 95.83%, thus ensuring the reliable detection of spoiled food.

➤ *Real-Time Monitoring:*

It is able to offer real-time assessment of the quality of the food with immediate notifications in case of potential spoilage.

➤ *IoT Integration:*

It can be implemented using gas sensors along with temperature sensors and a microcontroller or Raspberry Pi.

➤ *User-Friendly Interface:*

The system is able to offer the results in the form of a mobile app or web interface, thus making it more practical.

➤ *Food Safety and Waste Reduction:*

It is able to reduce the potential waste of food by detecting the spoilage early.

II. RELATED WORK

This area has been actively researched in recent times. The previously used techniques for this purpose were manual inspection and testing. Sometimes, chemical testing has also been done for the purpose of detecting the quality of the food. For example, researchers have proposed the use of chemical testing like the measurement of pH changes, gases evolved, and the presence of microorganisms for the purpose of detecting spoilages in foods [6]. These techniques provide accurate results in a controlled environment. However, they are not suitable for real-time use because they are time-consuming. With the advent of Internet of Things technology and machine learning algorithms, automated techniques have also been proposed for the purpose of detecting spoilages in foods. The use of sensor-based techniques has also been proposed for the purpose of detecting spoilages in foods [7]. For example, ethylene and ammonia gases have been proposed for the purpose of detecting spoilages in fresh foods.

However, such methods sometimes do not take visual spoilage into account and sometimes generate false positives due to environmental noise. Image-based deep learning methods, specifically convolutional neural networks [8], have also been investigated to classify spoiled and fresh food. These methods perform well when visual changes in the food products are evident. However, such methods cannot identify spoiled food in the early stages when the spoilage is not visually evident. Hybrid methods using sensor and image-based approaches have also been investigated in a few works. However, such methods sometimes do not involve real-time monitoring or effective utilization of multiple sources of information [9]. Most methods have been tested on a few samples or synthetic datasets and therefore might not be effective in real-world scenarios. Most methods also do not involve user-friendly mechanisms to raise alerts to the consumers or managers.

Table 1 Comparison of Existing System with the Proposed Approach

Feature	Sensor-Only Systems	Image-Based CNN	Proposed System
Multi-Source Data	No	No	Yes (Sensor + Image)
Real-Time Monitoring	Partial	Partial	Yes
Early Spoilage Detection	Limited	Limited	High
Accuracy	85–90%	90–92%	95.83%
User Interface /Alerts	Rare	Rare	Yes (Mobile/Web)
Practical Scalability	Low	Medium	High

The proposed system overcomes these shortcomings with its accuracy, real-time capability, and feasibility through the use of sensor readings and visual inspection with the aid of a convolutional neural network [10]. The proposed system can perform early spoilage detection, spoilage reduction, and safety improvement for both domestic and industrial applications.

III. DATA COLLECTION & PREPROCESSING

For the purpose of this research, a hybrid data set was developed by integrating sensor data as well as image data related to different types of food items. This image data set included images of different types of food items, totaling 5,000 images, which included fresh food items as well as spoiled food items, categorized into two different classes.

These images were captured in both controlled environments as well as natural environments, ensuring different lighting conditions and backgrounds. In parallel, a dataset of sensor data was created, which comprised data from sensors such as ethanol, ammonia, and hydrogen sulfide gas sensors, and temperature sensors, with a total number of 3,000 pieces of data samples indicating the condition in which the food was kept. The image dataset had variations in food categories, stages of spoiling, lightings, and camera angles. Food items in fresh condition would have same colors and texture; whereas spoiled food would be identified with changes in their colors, molds on the food item, and changes in texture [11]. Data related to the amount of gases was quantified in parts per million, and temperature was quantified in degrees centigrade. Two datasets were synced to take an image of the respective time period in which the sensor data was collected.

For the image data, the preprocessing steps involved resizing the images to 224×224 pixels, normalizing the pixel values to the range $[0,1]$, and employing data augmentation techniques such as rotations, flipping, and changing the brightness of the images to improve the generalization capabilities of the model [12]. For the sensor data, noise removal, outlier detection, and scaling were performed to ensure uniformity in the data from various sensors. Interpolation techniques were employed to handle missing values in the data by using the neighboring time series values. The preprocessing techniques ensure the efficiency of the deep learning model in handling the data. The dataset was selected based on the conditions in the real world for the storage of food in households and industries. Using the

images and sensor values will enable the model to obtain a complete profile of the spoilage process, even in the initial stages, which are not visible to the human eye. The size of the dataset was also chosen appropriately, consisting of 5,000 images and 3,000 sensor values [13]. This will enable the training of a robust convolutional neural network without the occurrence of overfitting. Furthermore, the inclusion of different varieties of food and environmental conditions will enable the proposed system to perform well in different conditions. Such a dataset will enable the accurate detection of spoilage in real time and is highly suitable for IoT applications.

IV. PROPOSED METHODOLOGY

The proposed system combines the Internet of Things devices with the deep learning models in such a way that the real-time detection of the spoiled food is carried out. The process begins with the acquisition of the data using the gas sensors, temperature sensors, along with the camera that captures the images of the food products [14]. The sensor data represents the environmental conditions that need to be monitored in real time. The data is sent to the microcontroller or Raspberry Pi using the sensors. The images of the food products are taken at regular intervals. The acquisition of the data is done in such a way that the correlation between the environment and the visual changes in the food can be established using the deep learning model. The synchronization of the data helps in the early detection of the spoiled food compared to the individual systems.

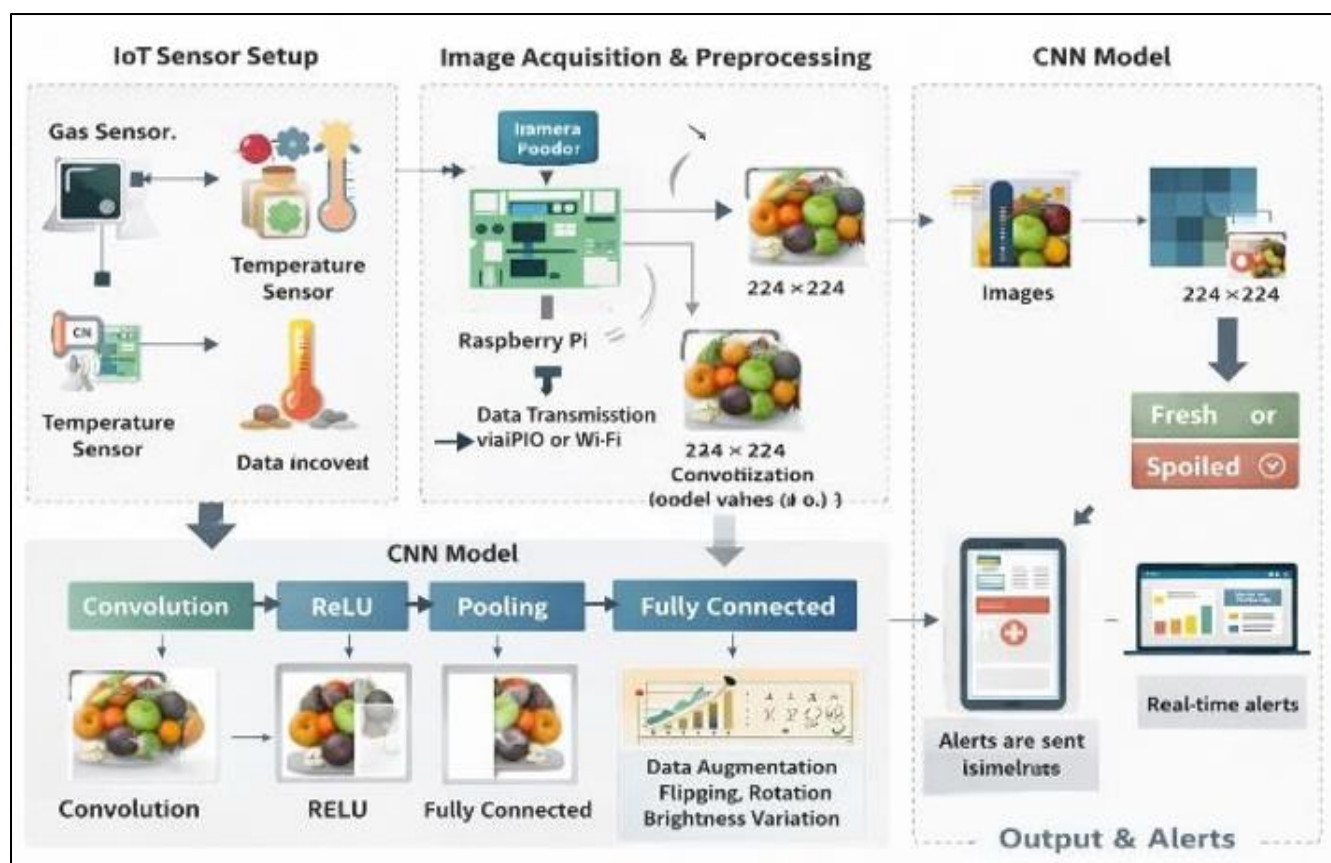


Fig 1 Proposed Methodology of System

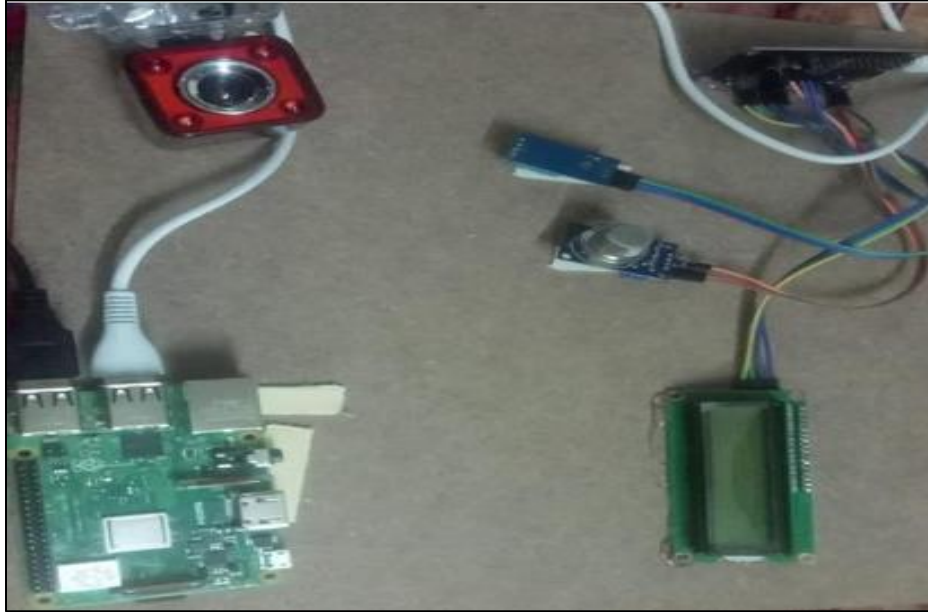


Fig 2 Gas and Temperature Sensor Connectivity with Raspberry Pi for Food Monitoring

At the heart of the system is the convolutional neural network (CNN) architecture, which is well-suited for analyzing images of food. This architecture is composed of convolutional layers, pooling layers, and fully connected layers [15]. This architecture is well-suited for classifying the probability of the food being fresh or spoiled. Assuming the CNN architecture is represented by the probability vector P ,

$$P = \text{softmax}(Z) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Where Z_i is the input to the softmax layer for class i . This architecture is for optimization of the categorical cross-entropy loss:

$$L = - \sum_i y_i \log(P_i)$$

Where y_i is the true label (1 if the correct class, otherwise 0), and P_i is the predicted probability. The CNN is optimized using the Adam optimizer with a learning rate of 0.001 and early stopping to avoid overfitting [16]. The sensor data is preprocessed by normalizing the sensor reading to a standard range. Let the sensor reading be S_{raw} , the normalized reading S_{norm} is calculated as:

$$S_{norm} = \frac{S_{raw} - S_{min}}{S_{max} - S_{min}}$$

Where S_{min} and S_{max} denote the minimum and maximum expected values for a sensor. Finally, the normalized sensor values and the CNN image predictions are fused using a weighted fusion method. Then, the spoilage score F is calculated as:

$$F = \alpha \cdot P_{spoiled} + \beta \cdot S_{score}$$

Where $P_{spoiled}$ is the CNN-predicted probability of spoilage, S_{score} is the composite sensor score, and α and β are the weighting factors used for balancing the image and sensor information. A threshold τ is applied for the classification of the food as fresh ($F < \tau$) or spoiled ($F \geq \tau$). The novelty of the proposed method is the hybrid approach used for the classification of fresh and spoiled foods. Unlike previous approaches, the proposed method uses real-time multi-sensor monitoring and deep learning-based image analysis [17]. The proposed method uses the weighted fusion algorithm for the early-stage spoilage detection of foods, even when the visual signs of spoilage are not prominent. In addition, the proposed method uses Raspberry Pi and IoT sensors for real-time monitoring, and the output is provided in a mobile/web interface, making it suitable for household and industrial applications. This real-time monitoring, dual-modality information fusion, and high accuracy (95.83%) of the proposed method make it different from previous approaches.

V. IMPLEMENTATION

The implementation of the proposed IoT-based food spoilage detection system will include various hardware and software components. In this context, the hardware component will include a Raspberry Pi microcontroller with gas sensors, temperature sensors, and a camera module. These sensors will collect data continuously from the environment, while the camera will capture images of food items stored over time. This data will be fed to the microcontroller [18], where preprocessing and analysis will be performed. Similarly, the images will be resized, normalized, and augmented to enrich the training set. This will ensure the integration of hardware and software to provide real-time food spoilage detection. In this context, the deep learning component will be implemented to analyze

images. This will be done by implementing a convolutional neural network (CNN) architecture. In the architecture, there will be the application of three convolutional layers with ReLU activation functions. Thereafter, there will be max pooling layers that will lower down the dimensions of the data [19]. Subsequently, two layers of full connection and a final layer of softmax will be applied for classification.

Afterward, the model is trained on the preprocessed data that consists of 5,000 images as well as 3,000 synchronized sensor readings. To enhance the efficiency of the model and avoid overfitting, the methods of data augmentation are employed which include rotations, flipping, as well as changes in the brightness. Hyperparameter selection is extremely important for optimal performance of the network. The learning rate of 0.001 is employed and later optimized using grid search. The aim of grid search is to find the most effective learning rate to converge the algorithm. The size of each mini-batch is 32. This reduces the impact of random weight initialization on convergence [20]. Dropout is used between fully connected layers with a dropout rate of 0.5 to prevent overfitting. The number of epochs is set to 50. Early stopping is used to stop training when there is no improvement in validation loss. Hyperparameter tuning for optimal performance was exhaustive. Several learning rates between 0.0001 and 0.01 were used to find the most efficient learning rate for convergence. The learning rate of 0.001 resulted in optimal performance.

Batch sizes such as 16, 32, and 64 were experimented with. The batch size of 32 provided smooth curves for the training loss. The weighting factor for the combination of the sensor data and the CNN prediction was tuned. The final weights for the combination were determined as $\alpha = 0.6$ for the prediction from the images and $\beta = 0.4$ for the scores from the sensor data. These were determined by maximizing the accuracy for the validation set. The implementation process involved the consideration of several preprocessing techniques. The scaling of the sensor data was done to the standard range using the min-max normalization technique. The images were resized to 224 x 224 pixels. The images were then normalized to the range [0,1]. The preprocessing was done to stabilize the training process. The use of the

preprocessing techniques helped in reducing the variance of the model. The model was then able to generalize the data. The dataset was then augmented. The images were varied in terms of the lighting conditions, angle of the images, and the background.

The contribution of the pre-processing stage and selection of the most appropriate parameters towards achieving the accuracy rate is significant at 95.83%. Lastly, implementation was done through Raspberry Pi in real-time testing. First, the training of CNNs occurred, followed by the use of CNN along with sensors inputs in real-time. Image data along with the sensor input was given to the Raspberry Pi. Classification of images was carried out via CNN. In the end, fusion of the process was done with the help of fusion formula. In case the spoilage score is higher than the threshold level, an alert message will be sent to the web/mobile interface. Real-time testing is done to determine the capability of the model in recognizing spoilage indications.

VI. RESULTS

The effectiveness of the proposed system was validated through different metrics for the purpose of analyzing the efficiency and accuracy of the proposed system. Some of the performance metrics used to evaluate the system are accuracy, precision, recall, F1-Score and confusion matrix analysis. Accuracy is the metric that represents the total number of correct predictions made by the model. On the other hand, precision and recall are two performance metrics that indicate the precision and recall of the proposed system in the prediction of the spoiled category of food. F1 score represents the harmonic mean of precision and recall. Lastly, confusion matrix helps in determining the error rate of classification of fresh foods as spoiled and vice versa. Using the dataset comprising of 5,000 images and 3,000 sensor readings, the proposed system managed to achieve an accuracy of 95.83% while its precision and recall stood at 96.2% and 95.5%, respectively. Comparative analysis was done with other baseline models, including sensor-based, image-based CNN, and traditional machine learning techniques like SVM and decision trees.

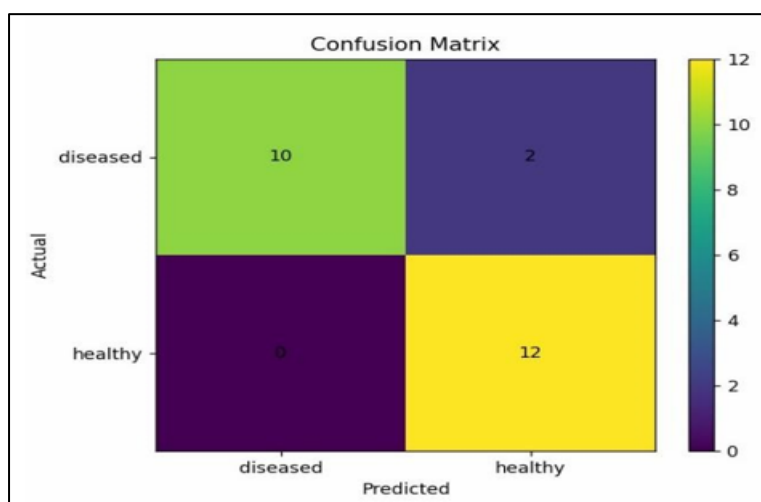


Fig 3 Confusion Matrix of Proposed CNN Model

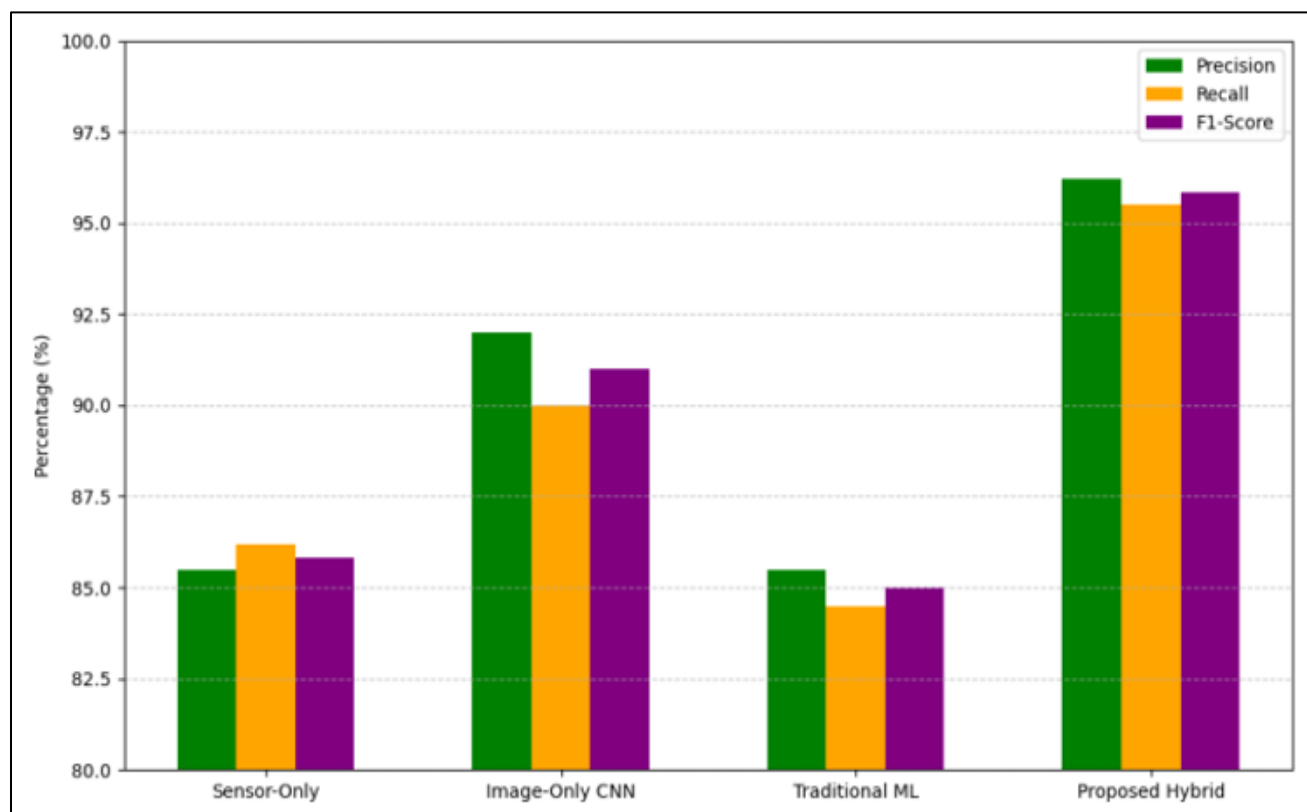


Fig 4 Precision, Recall, and F1-Score Comparison between Existing vs Proposed System

The accuracy obtained by the sensor-only system was around 87%, whereas the image-only CNN-based system obtained an accuracy of around 91%. On the other hand, the traditional classifier system obtained an accuracy of around 85-88% depending on the feature set. In this context, the proposed system outperformed all other systems by effectively combining the features obtained from the various

sources. This is evident since the system was able to detect the spoilage even before it occurred. From the confusion matrix obtained by the proposed system, it is clear that the misclassification was very low. There were slightly more misclassifications while the food was in the initial stages of spoilage and the changes were almost invisible. This is due to the inherent problem of detection with very low changes.

Table 2 Performance Metrics and Comparative Analysis of Existing System vs Proposed System

Model / Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Sensor-Only System	87.0	85.5	86.2	85.8
Image-Only CNN Model	91.0	92.0	90.0	91.0
Traditional ML (SVM/DT)	85–88	84–87	83–86	84–86
Proposed Hybrid System	95.83	96.2	95.5	95.85

Nevertheless, the fusion of sensor data and image processing reduced most of the errors inherent in either of the individual methods, hence creating a more accurate system. The high F1 score is an indication of how well the model is able to balance both false positives and false negatives. This is very important, as it will help create consumer trust in such an application. The advantages of the proposed system include its ability to perform real-time monitoring, integrate data from both modalities, and its high accuracy rate. The proposed system is based on an IoT framework, which

ensures real-time monitoring of food items. The CNN model is also able to capture visual cues for spoilage. The fusion approach ensures that the system is able to account for all possible spoilage, both visual and environmental. The proposed system is also very light and can be run on a Raspberry Pi, hence its practicality. The system is also very user-friendly, thanks to its mobile/web interface, hence its practicality. Despite its advantages, the proposed system has its own disadvantages.

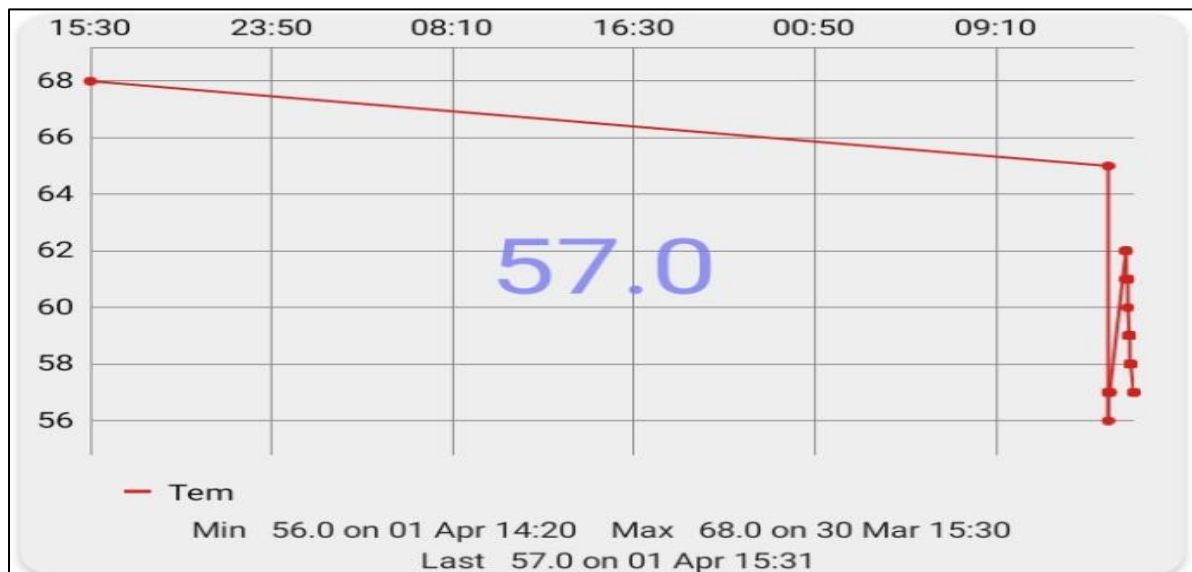


Fig 5 Variation of Sensor Values with Respect to Temperature in Food Spoilage Detection



Fig 6 Real-Time Gas Sensor Readings for Food Quality Analysis

This early-stage spoilage without the emission of gases or visible changes may cause misclassification in rare cases. Extreme variations in light or noise may affect the accuracy of the prediction. However, the preprocessing and normalization help minimize the effects. The model has to be retrained periodically if new varieties of food products or new conditions of storage are introduced. This may be considered in the large-scale implementation. However, the limitations are minimal compared to the significant enhancement in accuracy and reliability brought about by the proposed model. The results show that the proposed methodology can be considered as a robust solution for the detection of food spoilage in real-time. In addition, since we have attained 95.83% accuracy, it will now be possible for the system to show how it can prove effective in both controlled environments and in the real world. The two-source data fusion will ensure that detection happens at an earlier point,

which makes it possible to minimize the wastage of food and also enhance its safety. Through the comparative analysis, it will now be clear that the proposed system is far much more effective than the conventional techniques. In summary, the entire system proves its application in the real world.

VII. CONCLUSION

The proposed technique of using IoT technology to detect spoilage in food is an effective approach towards solving this issue, as it uses sensor information and image recognition through deep learning algorithms to attain accuracy rates of 95.83% a much higher accuracy level compared to other systems which either utilize image data or sensor information to predict food spoilage. While the proposed approach is highly accurate, there are still various disadvantages associated with the application of this

approach, including the issue of misclassification of certain borderline cases of food spoilage. Another drawback with the application of this approach is that when introducing new kinds of foods, training becomes quite challenging. Various ways in which this approach can be further improved include increasing the size of the data set, developing more effective approaches of sensor fusion, applying deep learning algorithms, as well as using cloud computing to monitor spoilage in food.

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