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A Real-Time IoT-Enabled Machine Learning for Quality Prediction of Perishable Beef Product

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Abstract

The cold chain industry in Indonesia is experiencing rapid growth, especially for perishable products such as beef. Ensuring product quality during distribution requires accurate monitoring of storage environmental factors, including temperature, humidity, and gas exposure. This study aims to develop an IoT-based quality monitoring system for perishable beef products and implement a machine learning approach for quality prediction. An IoT-enabled e-Sense device was developed to collect real-time environmental parameters and RGB colour information as quality parameter from tenderloin beef samples. The collected data were analysed using three regression-based machine learning algorithms: Random Forest (RF), Decision Tree (DT), and Support Vector Regression (SVR). Data preprocessing and hyperparameter tuning were applied to improve model performance. The results show that SVR consistently outperformed RF and DT in predicting RGB colour in presenting beef quality based on prescribed parameters. SVR achieved an R^2 of 0.973 for RED and 0.992 for both GREEN and BLUE channels. These findings confirm the effectiveness of integrating IoT technology with machine learning for real-time perishable products quality prediction. This research contributes to combining real-time multi-sensor IoT data with regression-based models to provide improved continuous quality monitoring compared to previous single-parameter or offline approaches.

Keywords: Cold Supply Chain; Regression; Machine Learning; Perishable Product; Quality.

1. Introduction

The global demand for perishable food products such as beef, dairy, and fresh produce continues to increase, driving the expansion of cold chain logistics. Ensuring product freshness and safety throughout transportation and distribution has become a critical challenge, particularly due to the rapid changes of perishable products to environmental conditions. Any failure in maintaining optimal storage conditions can lead to rapid quality degradation, economic loss, and health risks.

Among various perishable goods, fresh beef stands out as one of the most frequently consumed items. However, this high consumption rate is not supported by adequate microbiological quality control in product storage along the supply chain and distributions, as many beef products fail to meet established safety and quality standards during distribution. This issue is challenged by the length and complexity of the supply chain, from upstream producers to end consumers. Currently, monitoring of product quality during transportation is generally limited to measuring environmental parameters such as temperature, humidity, and gas exposure. While such monitoring aims to prevent spoilage, it is often conducted manually or with devices lacking real-time data transmission capabilities, causing delays in detecting degradation [1].

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Several studies have shown that food degradation can be modeled using kinetics reaction, where microbial spoilage in beef products often follows first-order reactions, while fruits and vegetables tend to follow zero-order kinetics [2]. Although various predictive models and quality decision-support systems are already provided [3], the integration of IoT-based monitoring and machine learning for predictive quality control, particularly in fresh beef logistics, remains limited.

Predicting beef quality in real-time is a major challenge due to the dynamic nature of beef degradation which is influenced by many factors. Unlike non-perishable products, fresh beef is highly sensitive to fluctuations in temperature, humidity, and the accumulation of gases such as ammonia (NH_3), hydrogen sulfide (H_2S), and carbon dioxide (CO_2), which can accelerate microbial activity and biochemical changes [4-6]. Previous studies generally still rely on periodic sampling or laboratory-based evaluations that do not reflect the actual real-time condition of the product, making them inadequate for rapid decision-making in cold chain logistics. Moreover, many existing models simplify the prediction process by focusing on a single variable or using linear approaches without considering the complex interactions among various factors affecting quality [7]. Therefore, an integrated approach is needed that not only can collect real-time data through IoT sensors but also utilize multivariate analysis via machine learning algorithms to model the complex relationships between environmental conditions and beef quality indicators such as color, pH, and gas composition.

Previous studies have emphasized that the quality of perishable meat is strongly influenced by environmental conditions and modelled using mathematical approach. Luong et al. [8] demonstrated that microbiological degradation in beef tends to follow first-order reaction behavior. In terms of environmental monitoring, Afreen & Bajwa [9] developed a basic IoT system to monitor temperature and humidity, although it lacked real-time gas monitoring capabilities. Other studies have explored alternative sensing approaches, for example, a study using a TCS3200 colour sensor demonstrated that meat colour changes during storage can be monitored kinetically [10]. Another work employed a colorimetric sensor array to detect spoilage in meat and fish by monitoring volatile compounds, with colour changes analysed in RGB space [11]. Recently, a colorimetric indicator for beef spoilage was developed that changes colour in response to biogenic amines, with spoilage progression tracked via RGB analysis [12].

In quality prediction, conventional approaches such as linear regression [13], have been shown to be insufficient for capturing the nonlinear relationships among sensor variables. Machine learning methods have begun to gain traction, where Decision Trees offer good interpretability [14], Random Forests improve prediction accuracy through ensemble techniques [15], and Support Vector Regression (SVR) demonstrates strong capability in modeling nonlinear patterns in perishable products [16]. Nevertheless, most of these studies focus on a single quality parameter, do not incorporate multivariate data from diverse environmental sensors, and do not provide real-time predictive capabilities within the context of fresh-meat logistics.

Multivariate analysis is essential for modeling the complex relationships among various environmental conditions that affect beef quality. By considering multiple variables simultaneously, this approach can capture the interactions between product quality parameters and influences factors such as temperature, humidity, and gas composition. In this case, three machine learning models, Decision Tree (DT), Random Forest (DF), and Support Vector Regression (SVR) were chosen due to their proven effectiveness in handling complex and nonlinear relationships as well as their robustness in predictive analysis. Decision Tree offers a simple yet interpretable structure that can capture important decision rules in data. Random Forest, as an ensemble method, improves prediction accuracy by aggregating multiple decision trees and reducing overfitting. SVR, on the other hand, is well-suited for regression problems with high dimensionality and can model nonlinear patterns through kernel functions. These models have been successfully applied in various food quality prediction studies, demonstrating their ability to process multivariate sensor data and provide reliable forecasts. Therefore, the combination of these three is expected to leverage the strengths of each method to achieve accurate and practical quality prediction of products.

Further to provide symmetrical information for all supply chain stakeholders, a mobile-dashboard is required. Overall, the literature highlights a significant gap: there is still no comprehensive system that integrates real-time multi-sensor IoT monitoring with multivariate machine-learning prediction models to characterize the complex relationships among temperature, humidity, gas concentration, color, and other quality indicators in beef during distribution. To fill the gap, a comprehensive and systematic approach is needed to define the required features in perishable product quality monitoring, design the predictive quality models and presents in a smart dashboard for real-time monitoring.

Therefore, this study aims to develop an IoT- and machine learning-based system to predict the perishable product quality. By using regression-based machine learning algorithms, the proposed system is expected to provide an accurate and easily interpretable quality insights. This approach not only enhances traceability and reduces quality uncertainty during distribution but also supports informed decision-making for producers and improves consumer trust.

This paper is organized as follows: Section 2 presents the related work on food quality monitoring using IoT technologies and machine learning. Section 3 describes the research methodology, including the development of the IoT sensor system, data acquisition process, preprocessing steps, and prediction model design. Section 4 provides the experimental results and discusses the performance of the models in predicting beef quality based on RGB parameters. Finally, Section 5 concludes the paper by summarizing the key findings and outlining potential directions for future research.

2. Related Work

Several studies have focused on leveraging modern technology to improve the efficiency and sustainability of supply chains for perishable goods, Kumar & Agrawal [17] proposed an image processing-based architecture in the era of Industry 4.0 for monitoring and assessing product quality during distribution. Rong et al. [18] offered an optimization approach to managing fresh food quality throughout the supply chain by balancing cost efficiency and product quality. Meanwhile, Sourav et al. [19] and Suryaningrat et al. [20] developed IoT-based monitoring systems to oversee the distribution of perishable foods, such as tomatoes, to enhance efficiency and reduce potential waste. These four studies discuss the design of a more efficient and sustainable supply chain for perishable products using modern technology. In addition, Stephan et al. [21] introduced a federated learning–driven IoT architecture for real-time freshness monitoring in resource-constrained environments, highlighting the advancement of modern supply chain digitalization using scalable and privacy-preserving IoT systems.

Another stream of research emphasizes the development of sensor-based and IoT-enabled systems to monitor product quality in real time, particularly for perishable food items, Wijaya et al. [22] developed a portable electronic nose as a tool for monitoring beef quality, enabling early detection of quality degradation before the product reaches the consumer. Nerkar et al. [23] applied a combination of IoT and machine learning to monitor the quality of fresh fruits and food in real time. Their focus is on the use of IoT and machine learning for product quality monitoring. Further, Veličković et al. [5] introduced a multi-gas detector capable of monitoring CO_2, NH_3, and H_2S concentrations in minced beef, demonstrating the importance of gas-sensing technology for assessing meat freshness in real-time IoT applications.

In addition, multiple works have explored advanced signal processing techniques and the use of electronic noses for evaluating the quality of fresh beef products, Sarno & Wijaya [24] highlighted developments in electronic nose data processing used for assessing beef quality. Wijaya & Afianti [25] researched the stability of feature selection algorithms on sensor arrays for optimizing product quality detection. Wijaya et al. [26] proposed an ensemble machine learning approach to improve accuracy in processing signals from the electronic nose. These studies focus on signal processing and sensor data for perishable product quality. Further advancements include Iqbal et al. [27], which introduced a multi-sensor fusion framework combining electronic-nose data with spectral information to enhance spoilage prediction, and Kodogiannis & Alshejari [28], which integrated electronic nose signals with multispectral imaging, showing that multimodal signal fusion significantly improves the detection of meat deterioration.

Alaya et al. [29] developed a color sensor-based solution used for sorting products in the food industry automatically, enhancing accuracy and efficiency in food sorting processes. This research emphasizes the implementation of sensor technology in the food industry as the basis for product classification. Additionally, Seilov et al. [30] provided a comprehensive review of emerging innovations in electronic nose technology, IoT-based sensing, and machine learning applications for spoilage detection in perishable food products, strengthening the relevance of colour, gas sensing, and multi-sensor approaches for modern quality assessment.

This research focuses on the use of an IoT-based system to collect real-time data that accurately reflects the current condition of the product. The real-time data obtained from various sensors will then be processed using regression algorithms to predict the color of the beef, which serves as the most easily observed and widely recognized indicator of quality by the supply chain stakeholders. By leveraging continuous data acquisition through IoT, the system enables timely and precise quality assessment, improving the ability to monitor perishable products effectively.

The theoretical foundation of this study aligns with established principles in meat science and food deterioration kinetics. Environmental variables such as temperature, humidity, pH, and volatile gases (NH_3, H_2S, CO_2, CH_4) accelerate microbial growth and biochemical degradation, thereby altering meat colour over time. These scientific relationships justify the selection of RGB values as the dependent variable and sensor-based environmental parameters as the independent variables. Moreover, regression-based machine learning models are theoretically well-suited for capturing the nonlinear interactions among these variables, enabling reliable prediction of beef colour within an IoT-driven monitoring framework.

3. Method

3.1. Research Stage

The research flow is depicted in Figure 1. The research begins with a literature study on monitoring perishable products. The results of the literature review are expected to provide a gap between previous research and the research to be conducted, thus maintaining the novelty of the resulting research. Further, we also design IoT for real-time data collection, data preprocessing for modelling preparation. This research also contributes to beef quality prediction using several regression-based machine learning model. Further, the detailed step of the research is explained in the following subsections.

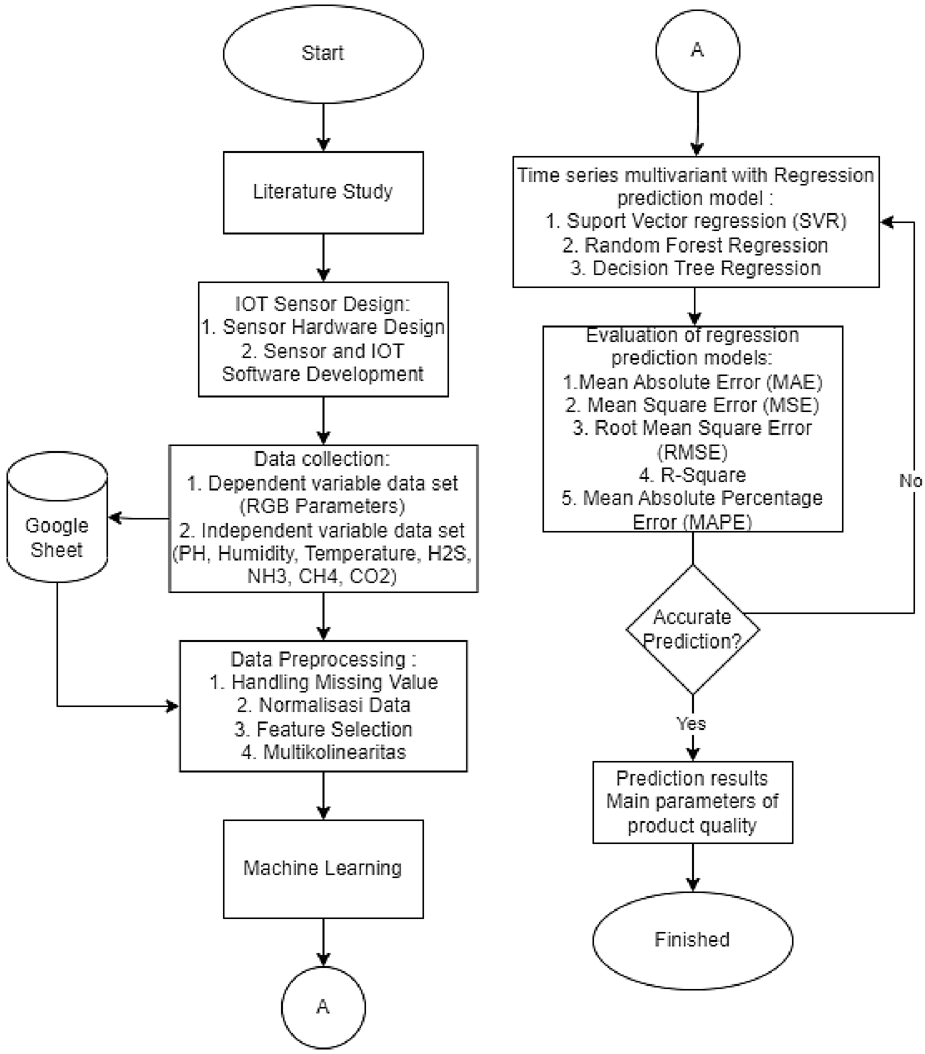


Figure 1. Research Flow Chart

3.2. Data Collection and Acquisition

The IoT Sensor Development

An Internet of Things (IoT)-based system enables real-time data collection through low-cost sensor devices connected to cloud platforms such as Firebase and Blynk, allowing continuous monitoring and responsive action to changes in critical parameters [31]. The data collection and acquisition process begins with the development of the IoT sensor monitoring product device. This device consists of a series of sensors connected to a microcontroller, which is integrated with a Wi-Fi module to transfer the sensor data to a Google Sheets database.

All the sensors used in this system are placed inside a portable hardcase to facilitate the monitoring of product quality at various locations. The design of this hardcase is intended to protect sensors, such as color sensors, temperature, humidity, gas, and pH sensors, while still allowing them to capture data with high accuracy as shown in Figure 2.

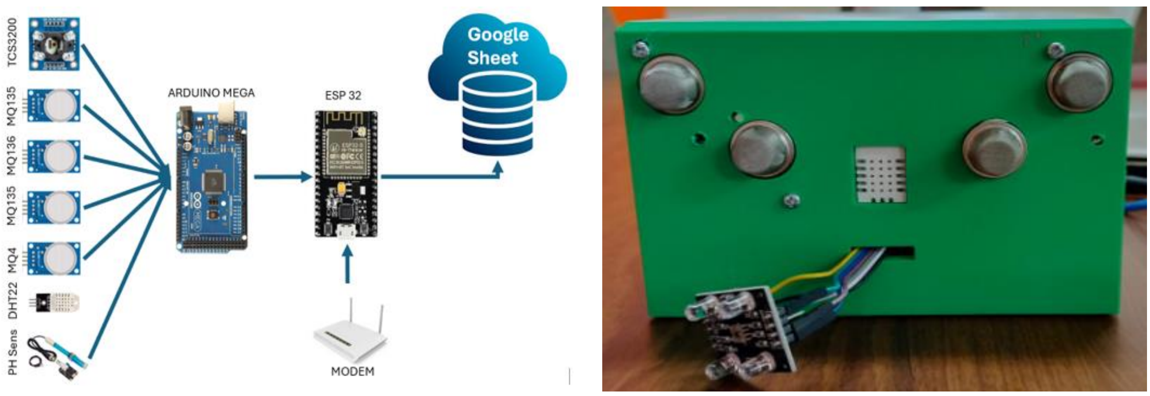


Figure 2. The design of IOT for data acquisition (E-sense)

All these components are designed to work integrally, where the data generated by each sensor will be sent to the IoT platform in real-time. This data will then be modeled to predict the quality condition of perishable products which is represented by RGB, based on the monitored environmental parameters. This system is expected to assist in decision-making and provide information throughout the product distribution process.

Data Acquisition

The data acquisition framework is designed in Figure 3. The IoT-based sensors collect the environmental conditions of Tenderloin cuts until it loses it freshness. The collected data will be sent to Google Sheets within a certain period. Once the data is gathered, the data preprocessing and modeling is deployed in Phyton.

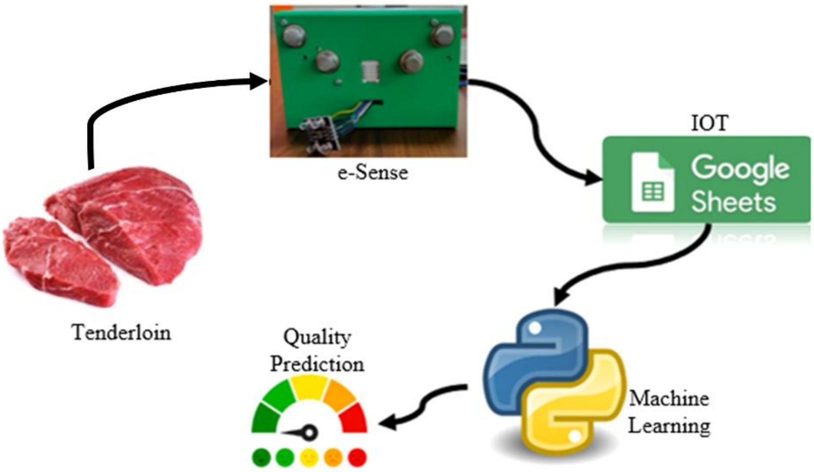


Figure 3. Data Collection, Acquisition, and Processing

During the product quality parameter collection, which is represented by product's color, the e-Sense sensor utilizes an internal LED-based light source from sensor RGB, ensuring that illumination conditions remain constant and are not affected by ambient light. Therefore, the RGB readings do not require additional correction for environmental lighting variability. The use of an integrated LED source guarantees that the light intensity remains stable throughout the entire data collection period. For the MQ-Series, Calibration of the MQ-series gas sensors was performed through a 24-hour preheating process prior to the experiment to stabilize the baseline sensor response, following standard MQ sensor operating procedures. The sensors were not calibrated against absolute gas concentrations but were instead used as relative indicators of changes in volatile compounds. pH measurement was conducted using a pH meter with a direct-contact probe applied directly to the surface of the beef sample, a commonly applied method for evaluating the pH of fresh meat without requiring liquid extraction.

The data collection was carried out for approximately 32.5 Hour, where observations were made from the fresh beef (immediately after leaving the slaughterhouse) until the beef was no longer fit for consumption, as illustrated in the Figure 4. The data was recorded at 1-minute intervals. A total of 1950 data points were collected from the observations. The data collection process was conducted at room temperature, with an initial recorded temperature of 32.4°C and a relative humidity of 89.5%.

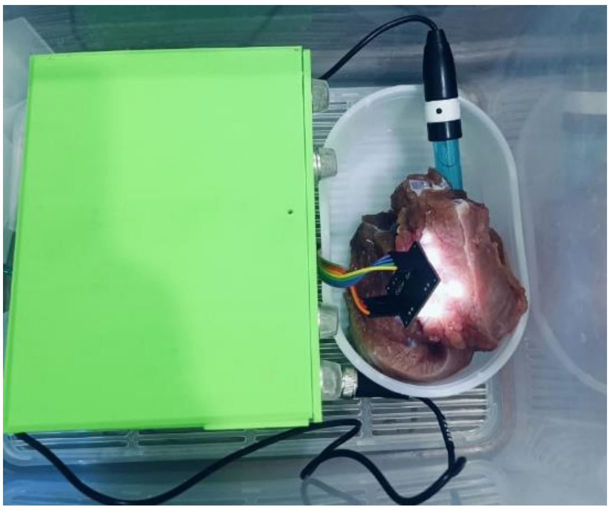


Figure 4. Data Acquisition Process

For the experiment, the beef samples were stored at room temperature to allow the spoilage process to progress more rapidly, enabling measurable variations to be captured within the experimental timeframe. The samples were placed in a closed container to maintain a consistent microenvironment throughout the experiment. This closed-container setup promotes the natural accumulation of volatile gases around the meat, allowing the sensors to detect changes in gas concentration more effectively while minimizing interference from ambient air. The 32.5-hour duration provides adequate coverage of the early to mid-stage spoilage dynamics at ambient temperature, during which substantial changes in color, volatile gas emissions, and pH typically occur. This timeframe also aligns with previous rapid-spoilage studies conducted under non-refrigerated conditions, where significant deterioration becomes apparent within 24–36 hours.

3.3. Feature Selection for Prediction Modelling

Table 1 describes the sensor system and data processing methods used in a study for monitoring and predicting beef quality using Internet of Things (IoT) and Machine Learning approaches. Each sensor has a specific function in detecting environmental or biological parameters that influence beef quality during storage.

Table 1. Features and a target of beef quality

No.	Sensor	Input	Process	Output	Variable Types	Definition	Ref.
1	RGB Sensor	Object Light Intensity	Color filter (R, G, B) → Intensity to frequency conversion	Frequency Digital Value Color	Target	Beef color (R, G, B) is the main visual indicator of beef quality, reflecting freshness and oxidation level.	Zhou et al. [32]
2	PH Sensor	H^+ Ion (acidity/basicity of solution)	Voltage → pH scale	Analog PH Value	Feature	pH reflects the acidity level of beef, influencing microbial activity and biochemical reactions that affect freshness and shelf life.	Koutsoumanis et al. [33]
3	MQ135 Sensor 1	Carbon dioxide gas	Resistance → Voltage → Gas concentration	CO_2 Gas Concentration	Feature	CO_2 indicates microbial respiration and packaging conditions that impact beef quality and shelf life.	Yang et al. [34]
4	MQ135 Sensor 2	Ammonia gas	Resistance → Voltage → Gas concentration	NH3 Gas Concentration	Feature	NH_3 is a microbial metabolism product and spoilage indicator that reduces sensory quality and safety.	Lin et al. [35]
5	MQ4	Methane gas	Resistance → Voltage → Gas concentration	CH_4 Gas Concentration	Feature	CH_4 may indicate anaerobic microbial activity; its presence correlates with the spoilage process in vacuum or modified atmosphere packaging.	Thamsborg et al. [36]
6	MQ136	Hydrogen gas	Resistance → Voltage → Gas concentration	H_2S Gas Concentration	Feature	H_2S is produced by protein decomposition and contributes to bad odor, indicating beef spoilage.	Zhou et al. [32]
7	DHT22	Temperature and humidity	Thermistor & capacitance elements → Digital data	Temperature (°C) and humidity (%) (digital)	Feature	Temperature and humidity are key environmental factors influencing microbial growth and biochemical changes in beef.	Freitas et al. [37]

The RGB sensor is used to capture the colour intensity of the beef surface based on red (R), green (G), and blue (B) components. Beef colour is a primary indicator of freshness, making RGB values the dependent variable in this study. These values are influenced by various environmental parameters recorded by other sensors and therefore serve as the target in the regression modelling. Prior to data collection, the sensor was initially calibrated using colour reference paper to ensure consistent baseline readings. After this preliminary calibration, a conversion function was implemented in the Arduino code to translate the sensor's output frequency into RGB intensity values. The mapping function applied a linear transformation to convert the red, green, and blue frequency signals into corresponding RGB values within the 0–255 scale.

Other sensors such as pH, MQ135 (CO_2 and NH_3), MQ4 (CH_4), MQ136 (H_2S), and DHT22 (temperature and humidity) act as independent variables, providing data on environmental conditions and chemical compounds produced during the degradation process of the beef. The pH sensor detects acidity levels associated with microbial activity. MQ sensors detect gases resulting from biological decomposition, which are important indicators of beef spoilage. Meanwhile, the DHT22 sensor records temperature and humidity, which are key external factors influencing the rate of degradation. The integration of such environmental sensors within an IoT-based system has been demonstrated to be effective for continuous and responsive quality monitoring of perishable products such as beef during distribution [38].

All data from these sensors are then analyzed using regression based machine learning methods for knowledge extraction of the relationships between features and the quality of beef which is represented by the RGB. This system enables automated monitoring of beef quality and allows real-time prediction of its freshness level, supporting better decision-making in the cold supply chain of beef products.

3.4. Data Preprocessing and Feature Extraction

Data preprocessing was thoroughly performed to prepare the dataset before model development. The initial steps included data cleaning by removing rows containing missing values (NaN). Then, time series feature creation was carried out using three main techniques: lagging, rolling mean, and differencing. Lagging was applied up to 12 previous time steps for each feature and target (RGB), rolling mean was calculated with two window sizes (3 and 7) to capture short- and medium-term trends, and differencing was used to reduce seasonal trends and enhance data stationarity. These techniques are commonly used in time series analysis to help the model understand temporal dynamics [39]. Additionally, the Interquartile Range (IQR) method was applied to detect and remove outliers, ensuring that extreme values did not adversely affect model training. These techniques are commonly used in time series analysis to help the model understand temporal dynamics [40]. The basic outlier detection using IQR model with quartile 3 (Q3) and quartile 1 (Q1) is explained in Equation 4.

$$\mathrm{IQR} = \mathrm{Q3} - \mathrm{Q1} \tag{4}$$

Additionally, feature engineering was conducted to generate new derived features such as Temp_x_Humidity, CO2_x_CH4, NH3_x_H2S, along with logarithmic and squared transformations of several sensor variables. This strategy aimed to enrich data representation and capture nonlinear relationships among variables, which is crucial for improving machine learning model performance [41]. After generating all features, any remaining NaN values resulting from transformation processes were removed, and the index was reset to ensure chronological order. This approach is vital for maintaining time sequence integrity in time series data, allowing the model to consistently learn from historical patterns.

3.5. Model Development

The analysis process in this research requires a prediction model capable of accurately estimating the product's condition based on measurable features. This prediction model is designed to utilize data generated by various sensors, such as temperature, humidity, air quality, and pH, to estimate the product quality degradation during storage and distribution. By using machine learning methods and time series analysis, this model is expected to provide real-time predictions to consumers and enhance confidence in the receiving products.

To ensure a reliable model evaluation, the dataset was divided into training and testing subsets using a 70% and 30% split based on temporal order. This proportion is widely adopted in machine learning as it provides a balanced allocation, where 70% of the data is sufficient for the model to learn underlying patterns, while 30% offers an adequate portion for evaluating forecasting performance. Because the dataset represents time-dependent observations, random shuffling not applied to prevent data leakage. Instead, the first 70% of the sequential data was used for model training, and the remaining 30% was reserved for testing as unseen future data.

The machine learning approach in this research employs regression-based machine learning models including Decision Tree Regression, Support Vector Regression, and Random Forest. A decision tree (DT) is an efficient algorithm for classification and regression problems. The basic idea of the decision tree algorithm is to split a complex problem into several simpler problems, which might lead to a solution that is easier to interpret [42]. Decision tree regression was chosen because of its ability to build models that are easy to interpret and able to handle non-linear relationships between input and output variables. Suppose that N as number of samples in parent node, N_L and N_R as number of samples include in left and right node, respectively, and MSE as mean square error, then the decision tree is explained by Equation 1.

$$Impurity\ Split = \frac{N_L}{N} \times MSE_L + \frac{N_R}{N} + MSE_R \tag{1}$$

The support vector regression enables to address the non-linear relationship between variables, with a focus on producing accurate predictions related to color changes that represent product quality. The SVR hyperparameter settings and the selection of the right kernel will be optimized for achieving maximum accuracy. Suppose that $f(x)$ as the prediction result which depend on weight vector (w), non-linear feature mapping function $\varphi\ (x)$ and bias (b) and the basic SVR model is highlighted in Equation 2.

$$f(x) = W^T \varphi\ (x) + b \tag{2}$$

Meanwhile, random forest regression (RFR) is a tree-based ensemble method and was developed to address the shortcomings of traditional Classification and Regression Tree (CART) method. RFR consists of a large number of weak decision tree learners, which are grown in parallel to reduce the bias and variance of the model at the same time [42].

The random forest regression prediction model was chosen because of its ability to reduce the risk of overfitting by utilizing the ensemble approach. Suppose that x as input vector, $h_i\ (x)$ as decision tree prediction result on $-i^{th}$ tree, k as number of tree, then the result of RF prediction $H(x)$ is explained in Equation 3.

$$H(x) = \arg max_y \sum_{i=l}^{k} l(h_i(x) = y) \tag{3}$$

Table 2 shows the hyperparameter configurations used for each regression algorithm: Decision Tree, Support Vector Regression (SVR), and Random Forest Regression (RFR) in predicting RGB colour values (Red, Green, Blue). Model parameters such as max_depth, min_samples_split, n_estimators, along with SVR-specific parameters like C, gamma, and kernel, were adjusted according to the characteristics of each target colour to improve model accuracy and performance. A hyperparameter tuning was carried out using RandomizedSearchCV, where parameter combinations were randomly sampled from a predefined search space. The tuning process consisted of 30 iterations and utilized a 5-fold cross-validation scheme with negative mean squared error as the optimization metric. The parameters optimized included the number of trees (n_estimators), maximum tree depth (max_depth), minimum samples required for node splitting and leaf formation (min_samples_split, min_samples_leaf), and the number of features considered at each split (max_features). The best-performing parameter set from the cross-validation process was then selected as the final model for evaluation on the test dataset.

By using input data from sensors such as MQ135, MQ4, MQ136, DHT22, and the pH sensor as independent variables, and RGB values as dependent parameters, it is expected to establish a strong relationship between the independent and dependent parameters. For the model evaluation, three regression models are exercised using several performance metrics, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), R-Square (R^2), and Mean Absolute Percentage Error (MAPE), as stated in Equation 5-9. This evaluation aims to assess the accuracy and reliability of each model in predicting product quality. The model that demonstrates the best performance based on these metrics will be selected as the main model for forecasting in the upcoming period.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_l}| \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_l})^2 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \ |y_i - \widehat{y_l}|} \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y_l})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y_l}}{yi}\right| \times 100 \tag{9}$$

Table 2. Parameter Configuration Prediction Model

Algorithm	Parameter	Value
Random Forest	n_estimators	[100, 200, 300]
	max_depth	[5, 10, 20, None]
	min_samples_split	[2, 5, 10]
Decision Tree	max_depth	[5, 10, 20, None]
	min_samples_split	[2, 5, 10]
SVR	C	[0.1, 1, 10]
	Gamma	[scale, auto]
	Kernel	[rbf, linear]

4. Results and Discussion

4.1. Result

To understand the quality changes of fresh beef products during the observation period, trend graphs are presented to illustrate the variation of parameters measured by the sensors in the IoT system, such as temperature, gas concentration, pH, and color (RGB). These graphs show how the values of these parameters changed over the 32.5-hour observation period with data acquisition every minute. These trend changes are important for analyzing beef quality degradation, where environmental factors such as temperature, humidity, pH, and Concentration gas have a significant impact on the product's condition. This degradation is also visually observable in Figure 5, which presents a comparison of the beef condition from fresh to spoiled throughout the observation process.

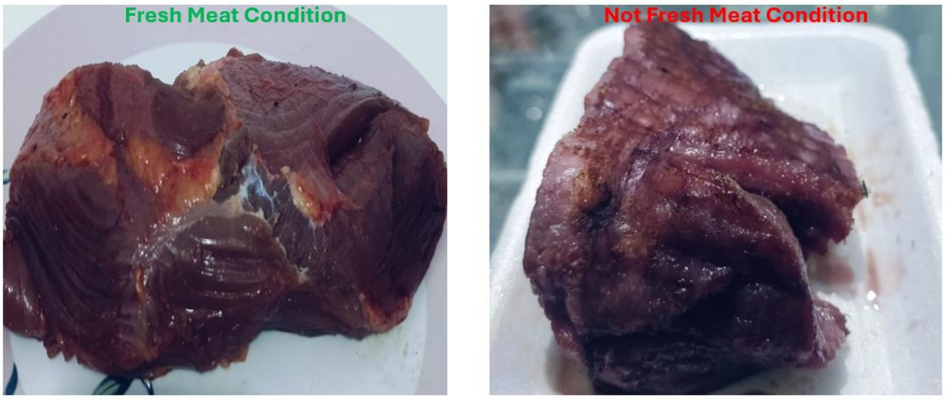


Figure 5. Beef Condition during Observation

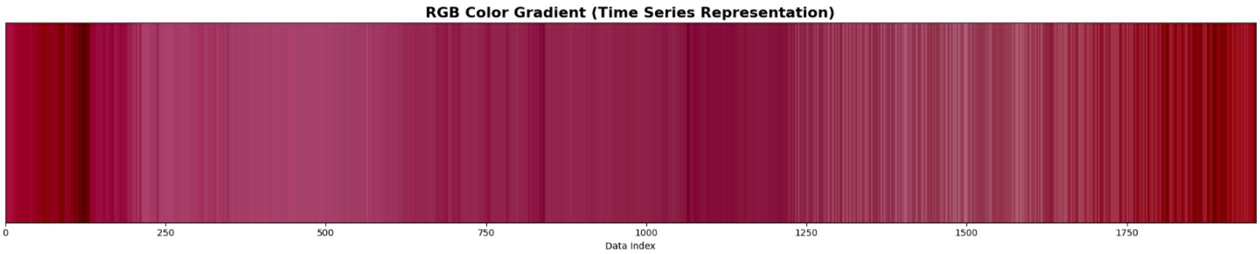


Figure 6. RGB Color Change Trend during the Monitoring Process

Figure 6 shows the trend graph of fresh beef color changes during the three-day monitoring period using the RGB sensor. This graph illustrates the changes in color intensity across the red (Red), green (Green), and blue (Blue) channels, each reflecting the visual condition of the beef, which can be used to monitor product quality. The color variations detected by the RGB sensor play a crucial role in assessing the freshness level and potential degradation of the product based on environmental factors such as temperature and humidity. This graph provides a clear representation of the relationship between color changes and environmental factors related to beef quality.

Figure 7 shows the trend of changes in various environmental and chemical parameters during the monitoring process of fresh beef in the cold supply chain from May 18 to 19, 2025. This graph includes seven main parameters: temperature, humidity, pH, as well as the concentrations of volatile gases such as CO_2, CH_4, NH_3, and H_2S.

The temperature graph shows significant fluctuations with several sudden spikes, reflecting instability in temperature during storage. Humidity exhibits a sharp increase at the beginning of monitoring, reaching nearly 100%, then remains relatively stable, indicating a very humid environment that poses a risk of accelerating the growth of spoilage microorganisms. The pH value gradually decreases, indicating increased acidity due to microbial activity and natural decomposition processes.

The concentration of CO_2 consistently increases throughout the monitoring period, reflecting microbial respiration activity and the degradation of organic matter in the beef. A significant increase in CH_4 is also observed, especially in the middle of the monitoring period, indicating the activity of anaerobic microbes. Additionally, the concentrations of NH_3 and H_2S gradually rise, both of which result from protein decomposition commonly occurring in beef beginning to spoil. The interactions occurring among these parameters correspond to the explanations in Table 1 along with the supporting research.

Overall, the pattern of changes in all these parameters indicates a decline in the quality of fresh beef over time, heavily influenced by the environmental conditions during storage. Therefore, real-time monitoring of these parameters is crucial to ensure the freshness and safety of beef within the cold supply chain system.

Data Statistic Descriptive

Table 3 provides an overview of the distribution and characteristics of the data. The meaning for each parameter represents the typical value during the observation period, while the standard deviation (std) indicates the level of data variation. The minimum and maximum values reflect the extreme conditions observed, while the first quartile (25%) and third quartile (75%) provide insights into data distribution. The median (50%), as the central value, shows the midpoint of the data, which can offer more stable information compared to the mean in the presence of outliers.

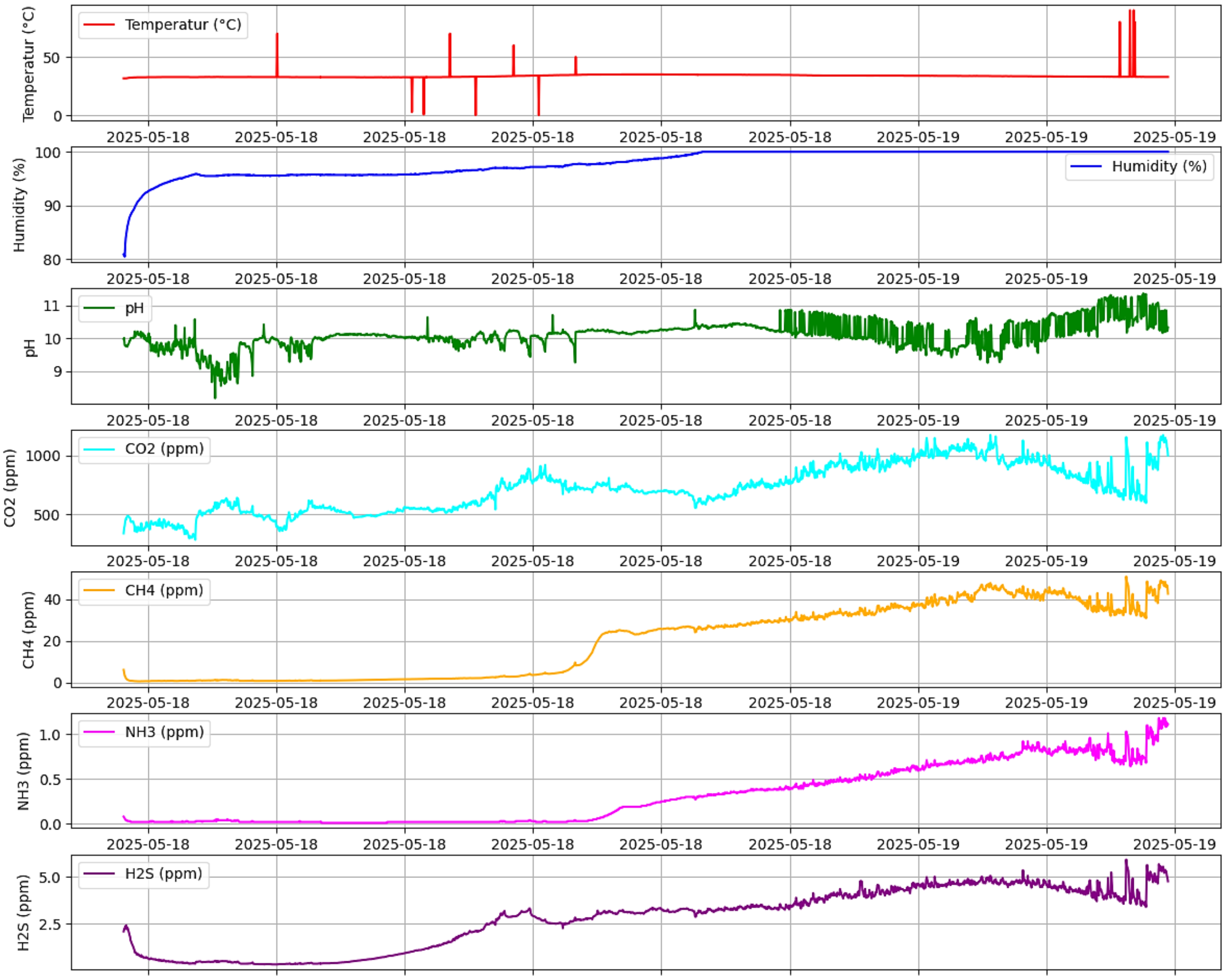


Figure 7. Feature trend during observation

Table 3. Statistic Descriptive Before Preprocessing

	Temp.	Humidity	CH_4	CO_2	H_2S	NH_3	pH	RED	GREEN	BLUE
count	1950	1951	1951	1951	1951	1951	1951	1951	1951	1951
mean	33.60	97.91	19.74	717.82	2.73	0.31	10.11	147.50	40.06	73.22
min	0.00	80.50	0.64	285.45	0.31	0.01	8.17	66.00	0.00	0.00
25%	32.70	95.80	1.52	548.21	0.86	0.02	9.89	139.00	22.00	62.00
50%	33.40	98.60	24.78	713.82	3.14	0.20	10.11	147.00	39.00	76.00
75%	34.20	100.00	34.64	884.77	4.12	0.60	10.31	160.00	61.00	96.00
max	90.00	100.00	50.83	1175.82	5.94	1.18	11.37	174.00	99.00	123.00
Std.	3.20	2.44	16.83	196.77	1.60	0.32	0.41	13.59	24.21	27.58

Pre-Processing: Data Cleaning and Outliers Removal

The data cleaning process and outlier removal were carried out by eliminating incomplete entries and removing outliers based on the Interquartile Range (IQR) method applied to ten numerical parameters, to improve data quality before model training. The initial dataset, consisting of 1,950 rows and 10 features, was reduced to 1,698 rows after the cleaning process, without any reduction in the number of features. The removed data points were identified as extreme or invalid values that could potentially affect the performance of the predictive model.

As shown in Table 4, after data cleaning and outlier removal, the quality of the temperature demonstrated a significant improvement. For instance, the minimum temperature increased from 0.00°C to 32.40°C, effectively eliminating unrealistic readings and measurement errors. The average temperature remained stable around 33.6°C, indicating that the central tendency of the data was preserved. Moreover, the standard deviation significantly decreased from 3.20°C to 0.84°C, reflecting reduced variability due to the removal of extreme values. These improvements confirm that the cleaned dataset more accurately represents the actual environmental temperature conditions during the observation period.

Table 4. Data statistic descriptive after preprocessing

	Temp.	Humidity	CH_4	CO_2	H_2S	NH_3	pH	RED	GREEN	BLUE
count	1698	1698	1698	1698	1698	1698	1698	1698	1698	1698
mean	33.61	98.05	19.89	732.20	2.78	0.30	10.11	149.06	44.66	79.67
min	32.40	89.50	0.64	333.54	0.31	0.01	9.27	118.00	0.00	17.00
Std.	0.84	2.09	16.68	195.06	1.57	0.30	0.32	11.69	21.93	20.48
50%	33.60	98.60	24.80	725.87	3.14	0.21	10.11	148.00	43.00	79.00
75%	34.40	100.00	34.33	903.07	4.16	0.54	10.28	160.00	62.75	98.00
max	35.00	100.00	50.83	1175.82	5.94	1.18	10.94	174.00	99.00	123.00
25%	32.70	95.80	1.70	552.44	1.06	0.02	9.93	140.00	30.00	68.00

Feature Extraction and Transformation

The application of feature engineering techniques such as the creation of interaction features (products between parameters) including Temp_x_Humidity, CO2_x_CH4, NH3_x_H2S, comparison or ratio features such as CO2_per_CH4, NH3_per_H2S, logarithmic and quadratic transformations such as log_CO2, log_CH4, log_H2S, log_NH3, Temperature2, Humidity2. This strategy aimed to enrich data representation and capturing nonlinear relationships among variables, which is crucial for improving machine learning model performance [41]. Interaction features are constructed to accommodate potential combined effects between parameters that cannot be captured using only the original features, while ratio features are employed to highlight proportional relationships between parameters, which are often more meaningful than their absolute values. Logarithmic and quadratic transformations are applied to address issues of non-normal data distribution and to enable the model to recognize hidden non-linear patterns within the data. By implementing these various feature engineering techniques, it is expected that the information obtained from the data becomes richer, more relevant, and can enhance both the performance and interpretability of the analytical model used.

In addition to the above transformations, the dataset also incorporates time series-specific features such as lag features, rolling statistics, and differencing. Lag features (252 in total) capture the values of variables from previous time steps, allowing the model to learn temporal dependencies and patterns over a substantial historical window. Rolling features (42 in total) represent moving averages computed over fixed-size windows, which help smooth out short-term fluctuations and highlight longer-term trends in the data. Differencing features (21 in total) calculate the change between consecutive observations, assisting the model in detecting trends and making the time series more stationary, which is often beneficial for predictive modeling. By combining these time series transformations with other engineered features, the dataset becomes richer and better equipped to model complex temporal dynamics in addition to cross-variable relationships. Overall, the model utilizes a total of 336 features as inputs to predict the RGB values of the beef, as illustrated in Figure 8.

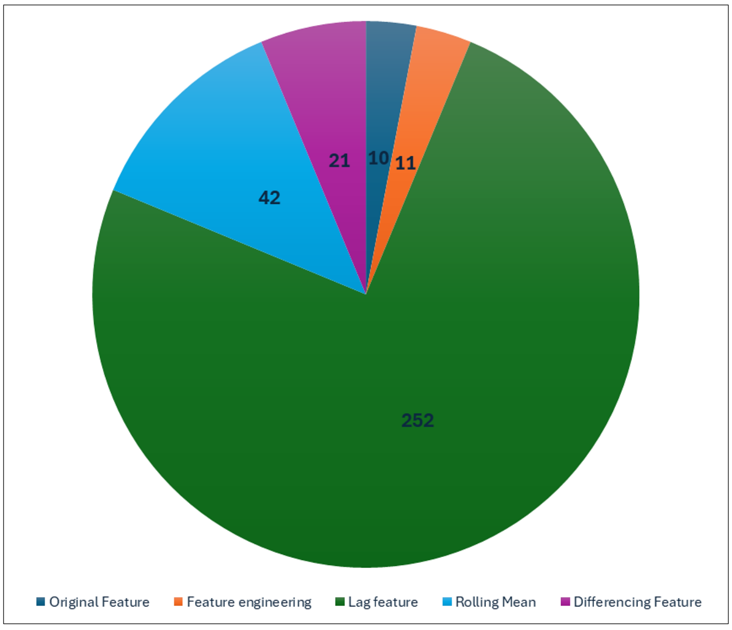


Figure 8 Number of Features After pre-processing

Machine Learning Model Development for Quality Prediction

The decision to use regression based on classical time series models is based on several key considerations. First, regression models like Random Forest and SVR capturing complex non-linear relationships between multiple input variables and output targets, a capability that traditional linear models such as ARIMA and VAR are lack of this competency [43]. Second, the flexibility to include exogenous variables (e.g., sensor interactions and engineered features) enables a more holistic understanding of the dynamics affecting beef quality, which is crucial in real-world supply chain applications [44]. As shown in Figure 9 and Table 5, the evaluation results of the regression models without using exogenous variables indicate a very poor prediction performance. This is clearly reflected in R2 values that are mostly below 50%, with many even being negative, signifying that models such as Random Forest, Decision Tree, and SVR are completely unable to explain the variability of the target data (RED, GREEN, BLUE) and are even worse than merely predicting the mean. Furthermore, very high MAE, MSE, RMSE, and especially MAPE values (particularly for GREEN and BLUE targets, exceeding 100%) confirm that the prediction errors generated are very large and unacceptable for practical applications. In summary, without input from exogenous variables, these regression models utterly fail to capture the relevant relationships for predicting beef quality.

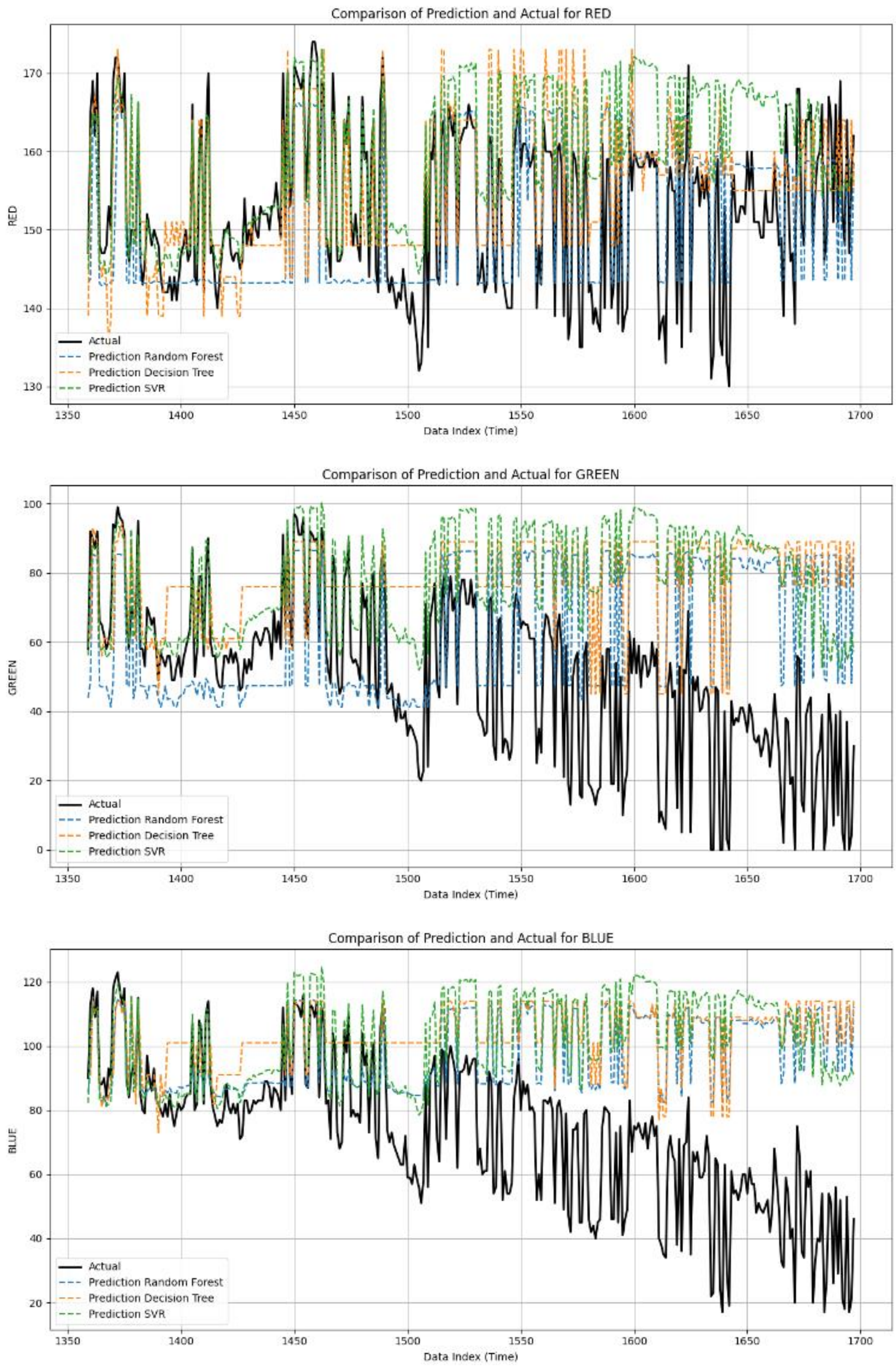


Figure 9. Comparison between prediction value and Actual Value Random Forest, Decision three, SVR without Lag, Roll, Differencing

Table 5. Evaluation models Without Lag, Roll and Differencing

Model	Target	MAE	MSE	RMSE	R^2	MAPE
Random Forest	RED	6.13	67.40	8.21	0.33	3.98
Random Forest	GREEN	24.11	844.02	29.05	-0.56	91.39
Random Forest	BLUE	26.95	1175.39	34.28	-1.21	56.75
Decision Tree	RED	6.66	76.07	8.72	0.24	4.49
Decision Tree	GREEN	29.80	1304.78	36.12	-1.40	125.21
Decision Tree	BLUE	31.67	1460.12	38.21	-1.75	64.73
SVR	RED	8.18	110.13	10.49	-0.10	5.51
SVR	GREEN	28.10	1251.83	35.38	-1.31	125.86
SVR	BLUE	29.50	1390.59	37.29	-1.62	61.51

Based on the scatter plots shown in Figure 10, it can be concluded that the addition of lag, rolling, and differencing features consistently improves the performance of regression models across all targets (RED, GREEN, and BLUE). This is evident from many points lying above the identity line in the R^2 plots, indicating that the R^2 values of models with lag/rolling/differencing features are higher than those without. In other words, the model can explain the data variance more effectively after the inclusion of these time series features. This improvement is also consistent across other error metrics such as RMSE and MAPE, where error values tend to be lower when using lag, rolling, and differencing features. In general, feature transformation is crucial for enhancing the accuracy and reliability of multivariate prediction models on time series data.

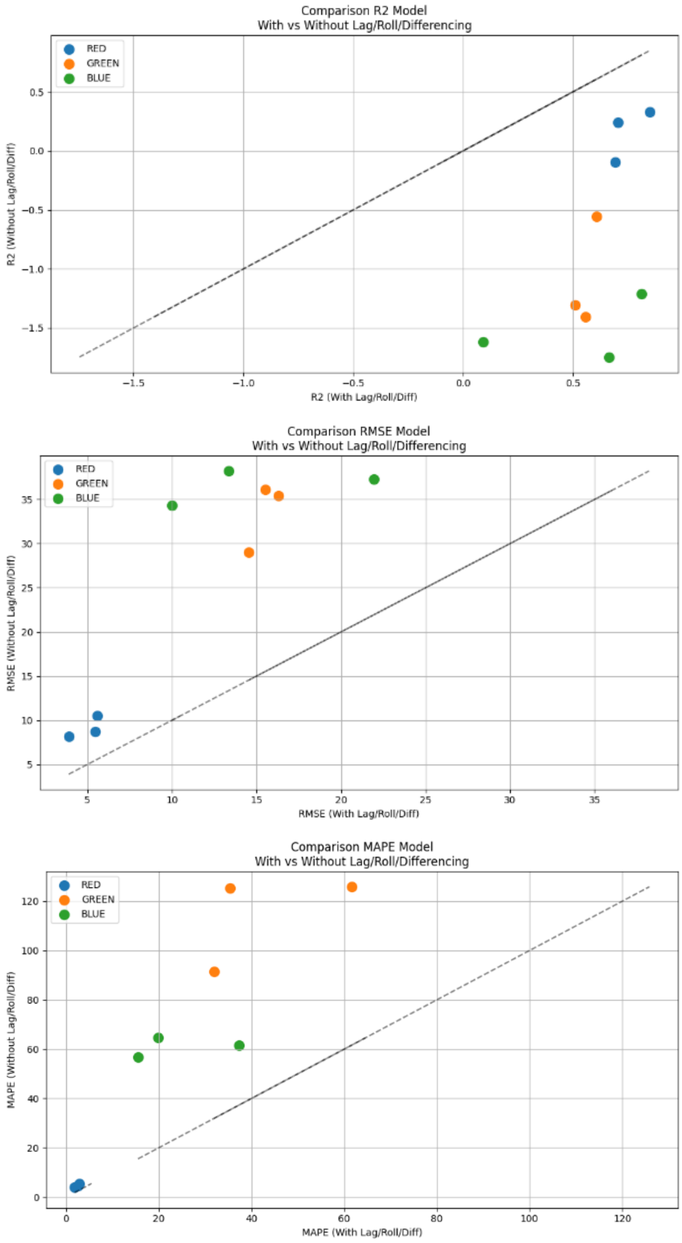


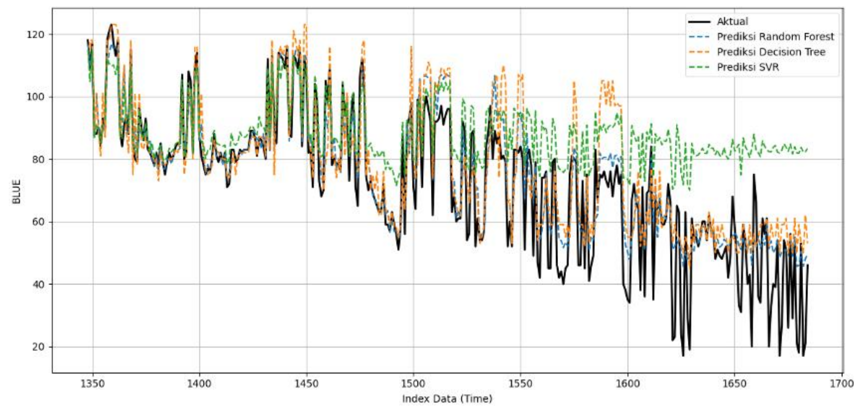
Figure 10. Scatter Plot With vs. Without Lag, Rolling, Differencing R2, RMSE and MAPE

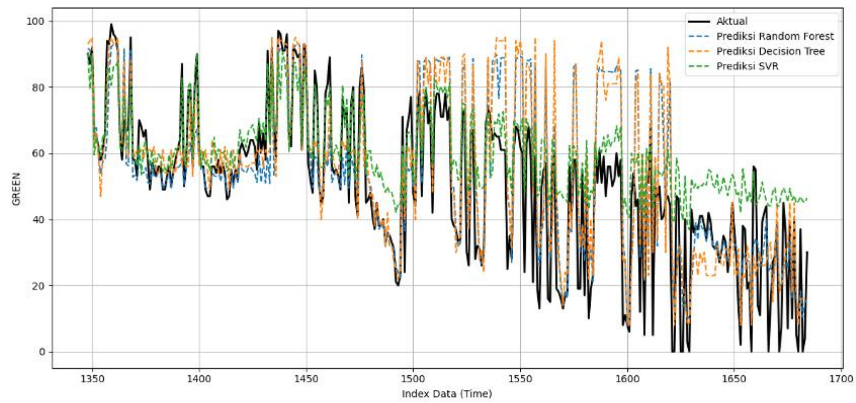
Moreover, machine learning regression models support multi-target prediction, allowing the RGB values to be forecasted simultaneously within a single framework. This approach is not only enhances prediction coherence across channels but also reduces model complexity. Empirical studies also show that multivariate regression approaches tend to outperform traditional time series models in high-dimensional, real-time forecasting scenarios [45, 46], making them suitable for predictive monitoring in cold supply chains. Therefore, in this research we employed the multi-target prediction model to simultaneously predict the product quality which represented by red, green and blue parameters.

According to the results in Table 6, the Random Forest model consistently outperformed the others across all targets. Specifically, for the RED component, Random Forest achieved a Mean Absolute Error (MAE) of 2.812, Root Mean Squared Error (RMSE) of 3.909, and a coefficient of determination (R^2) of 0.848, indicating a strong predictive capability. For GREEN, although the MAE and RMSE increased to 10.783 and 14.562 respectively, Random Forest still maintained better accuracy ($R^2 = 0.608$) compared to Decision Tree and SVR. The BLUE target followed a similar trend, with Random Forest yielding an MAE of 7.191, RMSE of 9.986, and R^2 of 0.812. Decision Tree and SVR models demonstrated comparatively higher errors and lower R^2 values, particularly SVR, which exhibited the poorest performance for the BLUE component ($R^2 = 0.091$). Additionally, the Mean Absolute Percentage Error (MAPE) results showed that Random Forest produced the lowest relative errors across all targets, with values of 1.839% for RED, 31.944% for GREEN, and 15.522% for BLUE. These findings suggest that Random Forest provides a more reliable and accurate prediction of the RGB color parameters within this dataset based on Figure 11.

Table 6. Evaluation models With Lag, Roll and Differencing

Model	Target	MAE	MSE	RMSE	R^2	MAPE
Random Forest	RED	2.812	15.281	3.909	0.848	1.839
Random Forest	GREEN	10.783	212.065	14.562	0.608	31.944
Random Forest	BLUE	7.191	99.724	9.986	0.812	15.522
Decision Tree	RED	3.994	29.733	5.453	0.704	2.616
Decision Tree	GREEN	11.864	240.469	15.507	0.555	35.416
Decision Tree	BLUE	9.733	178.920	13.376	0.662	19.855
SVR	RED	4.450	31.117	5.578	0.690	2.894
SVR	GREEN	12.028	265.045	16.280	0.510	61.637
SVR	BLUE	16.226	481.122	21.934	0.091	37.325





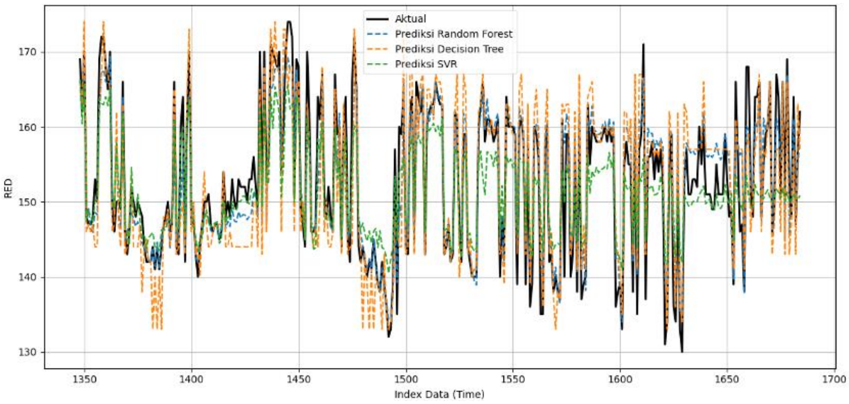


Figure 11. Comparison between prediction value and Actual Value Random Forest, Decision three and SVR

Although the Random Forest model demonstrated the best performance compared to the other models, the coefficient of determination (R^2) values remained below 0.85 for several targets, particularly for the GREEN component (R^2 = 0.608) and BLUE (R^2 = 0.812). Evaluation parameters R^2 values below 0.85 is considered relatively low, as they indicate that the model has not yet captured the data variability optimally. Therefore, a hyperparameter tuning process is necessary for all related parameters to improve the model's accuracy and generalization capability in predicting RGB values more precisely and consistently.

By performing hyperparameter tuning using optimal parameter combinations, the performance of all models increased significantly. In the Random Forest model, tuning was carried out by adjusting parameters such as n_estimators, max_depth, and min_samples_split, while for the Decision Tree model, the tuning focused on max_depth and min_samples_split. For the SVR model, performance improvement was achieved through the adjustment of C, gamma, and kernel parameters like Table 7.

The evaluation results after tuning showed an increase in R^2 values and a significant reduction in error metrics such as MAE, RMSE, and MAPE across all color targets (RED, GREEN, and BLUE). Among the three models, SVR demonstrated the best performance, with R^2 values reaching 0.973 for RED and 0.992 for both GREEN and BLUE, as well as very low MAE values, all below 1.5. In contrast, although Random Forest still maintained good performance, the improvement was not as significant as that of SVR, especially since the R^2 value for GREEN remained below 0.85. Based on the results in Table 8, SVR was selected as the preferred model due to its more reliable and accurate ability to map complex relationships among variables in the RGB color data.

In addition to showing significant improvements in evaluation metrics such as MAE, MSE, RMSE, R^2, and MAPE, which indicate that the model is capable of accurately capturing and predicting data pattern. The analysis of the residual plot in Figure 12 also reveals that the prediction errors (residuals) of the SVR model are randomly scattered around zero without any clear pattern. This indicates that the model does not exhibit systematic bias and has successfully mapped the relationship between input and output variables.

Table 7. Selected Parameter Configuration Prediction Model

Algorithm	Target	Selected Parameter
Random Forest	RED	max_depth: 20, min_samples_split: 10, n_estimators: 300
	GREEN	max_depth: 20, min_samples_split: 5, n_estimators: 300
	BLUE	max_depth: 20, min_samples_split: 10, n_estimators: 300
Decision Tree	RED	max_depth: 20, min_samples_split: 10, leaf: 245, node: 489
	GREEN	max_depth: 5, min_samples_split: 2, leaf: 31, node: 61
	BLUE	max_depth: 10, min_samples_split: 5, leaf: 225, node: 449
SVR	RED	C: 1, gamma: 'scale', kernel: 'linear'
	GREEN	C: 0.1, gamma: 'scale', kernel: 'linear'
	BLUE	C: 0.1, gamma: 'scale', kernel: 'linear'

Table 8. Evaluation Models After hyperparameter tuning

Model	Target	MAE	MSE	RMSE	R^2	MAPE
Random Forest	RED	2.852	15.640	3.955	0.844	1.864
Random Forest	GREEN	10.683	209.249	14.465	0.613	31.782
Random Forest	BLUE	7.256	101.755	10.087	0.808	15.657
Decision Tree	RED	3.684	26.436	5.142	0.737	2.406
Decision Tree	GREEN	12.037	257.498	16.047	0.524	36.288
Decision Tree	BLUE	8.993	155.448	12.468	0.706	18.742
SVR	RED	1.260	2.709	1.646	0.973	0.832
SVR	GREEN	1.484	4.581	2.140	0.992	6.647
SVR	BLUE	1.510	4.130	2.032	0.992	3.185

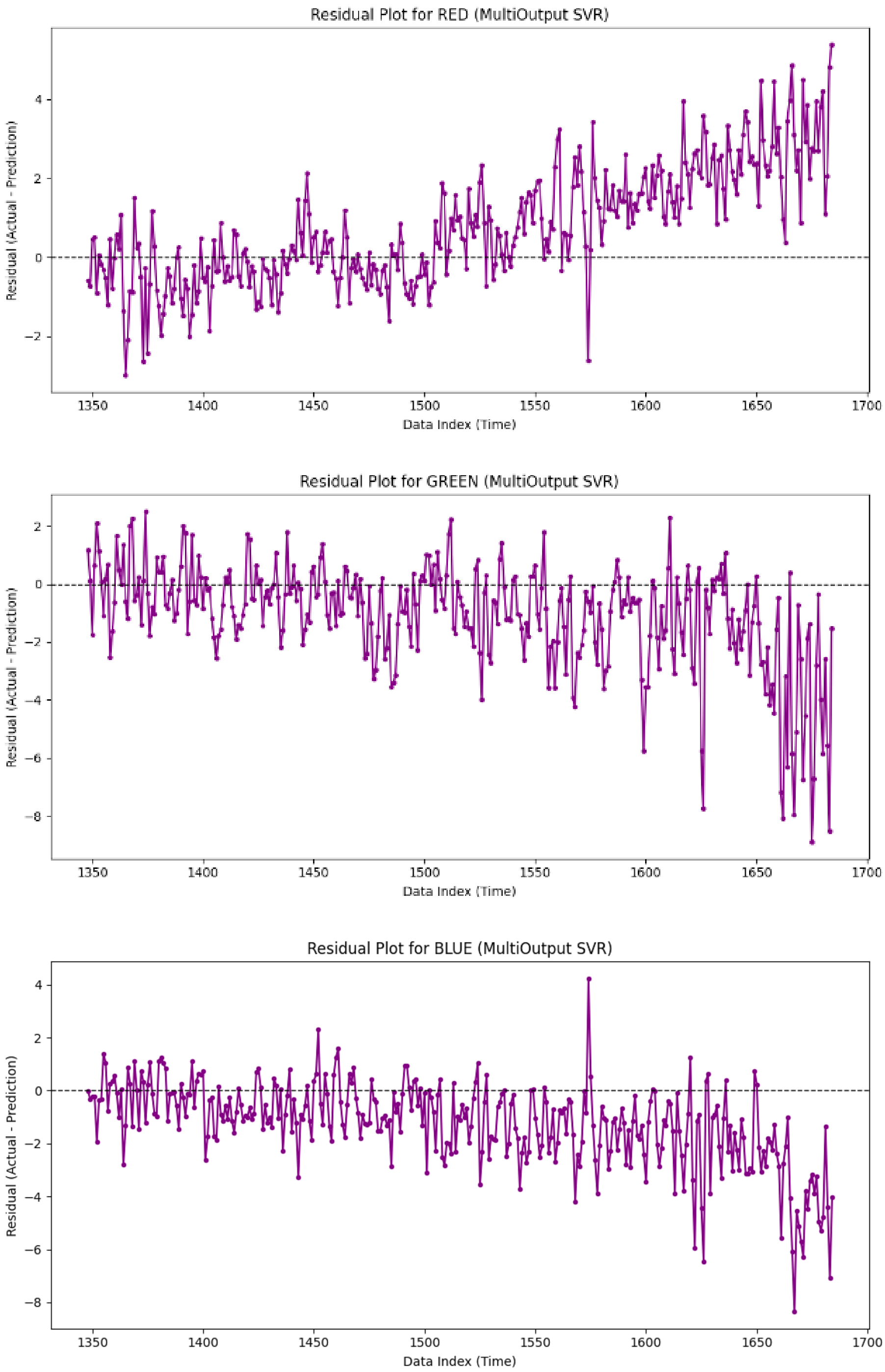


Figure 12. Residual Plot SVR

4.2. Discussion

The Support Vector Regression (SVR) model demonstrated the best overall predictive performance after hyperparameter tuning, particularly in predicting all three-color components (RED, GREEN, BLUE). With proper tuning, SVR significantly reduced prediction errors (MAE, RMSE, MAPE) and produced very high R^2 values which indicating excellent accuracy and stability in modeling complex and dynamic sensor data.

For example, in predicting the RED color component, the SVR model's MAE drastically dropped from 8.18 to 1.26, RMSE from 10.49 to 1.646, and R^2 sharply increased from -0.10 to 0.973. Similarly, for the GREEN component, MAE decreased significantly from 28.10 to 1.484, RMSE from 35.38 to 2.140, with R^2 rising steeply to 0.992. A similar trend was observed for the BLUE component, where MAE dropped from 29.50 to 1.510, RMSE from 37.29 to 2.032, and R^2 also reached 0.992 after tuning. This performance improvement is visually illustrated in Figure 13, which compares evaluation metrics across models before and after feature engineering and hyperparameter tuning. This result also confirm that the proposed model is better than previous research with R^2 85% using fuzzy inference system [47], also using SVR and LDA by Wijaya et al. [48] with R^2 0.924 and 0.852, respectively. These previous research also predict the tenderloin quality which data collected by IoT sensors.

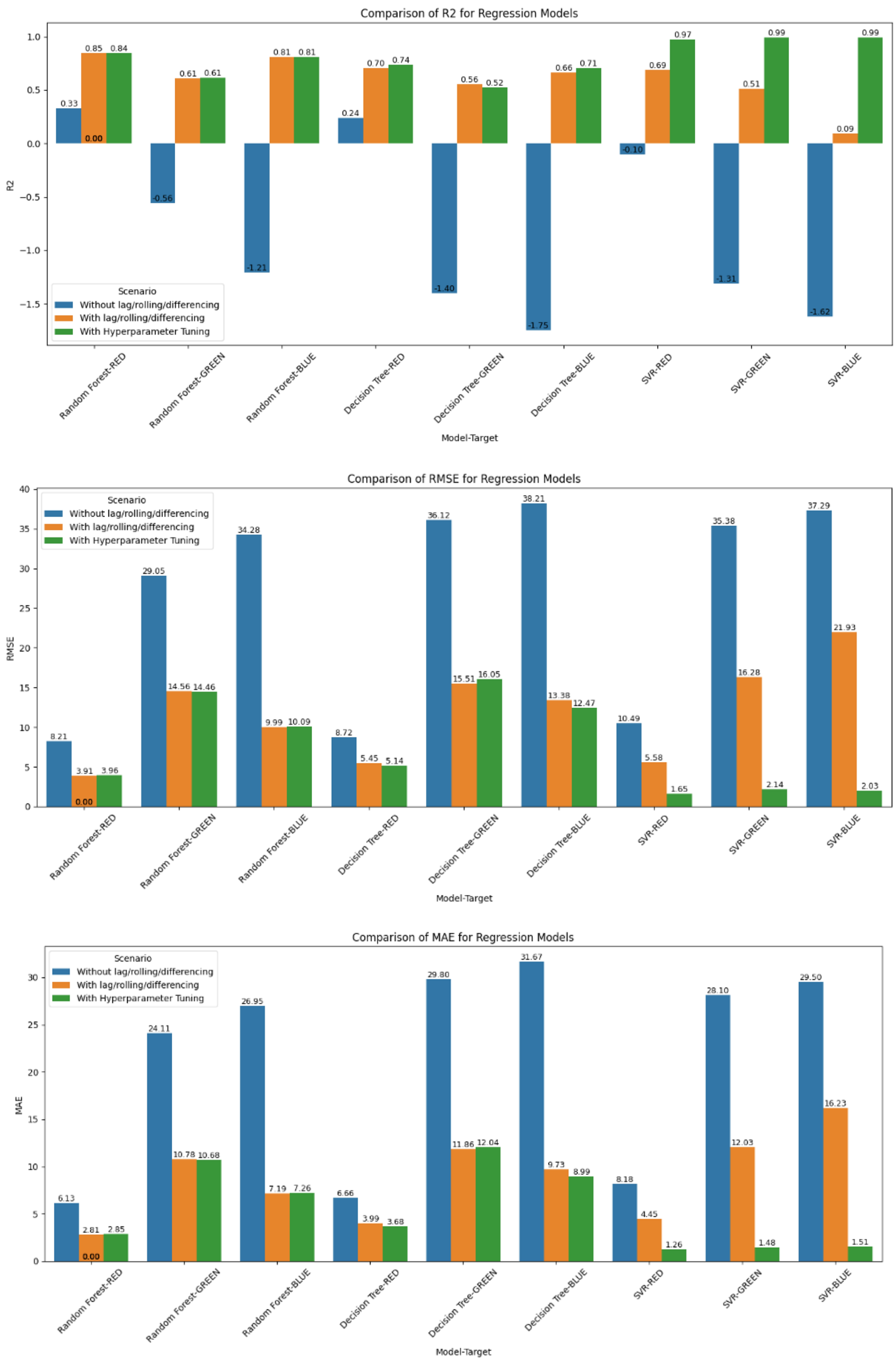


Figure 13. Evaluation Metrics R2, MAE, RMSE for all developed regression models

Although Random Forest and Decision Tree also showed improved performance after the addition of features such as lag, rolling mean, and differencing, along with parameter tuning, their results remained below SVR, especially in terms of precision and stability across all color targets. Random Forest still excels in interpretability through feature importance analysis, but SVR outperforms in terms of prediction accuracy and consistent performance across targets.

Beyond numerical performance, several important patterns emerge from the prediction behaviour of the models. The SVR model consistently yielded lower errors for the RED and GREEN channels compared to the BLUE channel. This aligns with meat discoloration theory, where the dominant visual changes during spoilage, primarily influencing the red and green components of meat surface colour. The BLUE channel tends to be less sensitive to biochemical degradation, which explains why prediction errors are slightly higher for this component.

A closer look at the prediction curves reveals that the model performs more accurately during the early stages of storage, while deviations increase gradually as the beef approaches advanced spoilage. This is consistent with the nonlinear acceleration of microbial activity and gas production at later stages, which introduces sharper fluctuations in sensor readings. Similar behaviour has been reported in prior studies in Veličković et al. [5] and Kodogiannis & Alshejari [28] where late-stage spoilage exhibits higher variance due to rapid biochemical reactions.

Model performance also varies depending on the type of sensor signal. NH_3 and H_2S concentrations display the strongest correlation with RGB colour shifts, confirming their role as primary indicators of protein degradation. This result aligns with the multi-gas spoilage monitoring findings in Veličković et al. [5], and the multi-sensor fusion studies in Iqbal et al. [27]. Meanwhile, temperature and humidity contribute to long-term drift in colour values, acting as moderators of reaction kinetics rather than direct indicators of spoilage.

Overall, the results demonstrate that integrating IoT-based sensing with machine learning enables accurate mapping of environmental parameters to visual freshness indicators. This provides strong evidence of the feasibility of automated real-time quality monitoring systems in cold chain applications. However, the model still shows sensitivity to sudden environmental fluctuations, suggesting potential enhancements through more advanced architectures such as LSTM-based time-series models or fusion with image-based inputs to further stabilize predictions and capture mid-spoilage nonlinearities.

The success of SVR in handling multivariate data shows that this model is highly suitable for applications involving product quality prediction based on environmental sensor data. In an industrial context, this opens opportunities for automatic and real-time quality monitoring, such as predicting changes in beef color as an indicator of freshness. With the high accuracy offered by SVR, companies can accelerate decision-making, reduce errors from manual inspections, and improve both the efficiency and consistency of product quality throughout the cold supply chain.

5. Conclusion

This research successfully developed an integrated quality monitoring and prediction system for perishable beef products using an Internet of Things (IoT) architecture combined with machine learning–based regression models. The proposed system employs an e-Sense sensor module which capable of continuously capturing essential environmental parameters, including temperature, humidity, pH, and concentrations of volatile gases (NH_3, H_2S, CO_2, CH_4) also as real-time RGB values that reflect surface discoloration of the beef. All acquired data is transmitted automatically to cloud storage, enabling seamless and efficient monitoring throughout the storage period. Based on the comparative evaluation of three machine learning models, Support Vector Regression (SVR) demonstrates superior predictive performance across all metrics. After applying feature engineering and hyperparameter optimization, SVR achieves exceptional accuracy, with R^2 scores of 0.973 for RED, 0.992 for GREEN, and 0.992 for BLUE. These results significantly outperform the Random Forest and Decision Tree models.

The integration of these sensory indicators with SVR-based prediction models demonstrates the potential for deploying automated, sensor-driven monitoring systems that can replace conventional visual inspections, which are often subjective and inconsistent. The proposed system offers significant benefits for industrial cold-chain operations, including improved decision-making, early detection of quality deterioration, and reduced dependency on manual assessment processes. However, certain limitations remain, particularly the model's reduced stability during the advanced stages of spoilage, when environmental fluctuations become more extreme and sensor variance increases. Future work should explore the incorporation of multimodal data, such as high-resolution imaging and advanced time-series models like LSTM, to further improve predictive robustness and capture complex spoilage dynamics. Expanding the system to cover various meat types and diverse storage conditions would also enhance its practical applicability. Overall, this study provides a strong foundation for the development of intelligent, automated freshness monitoring technologies for perishable products within modern supply-chain environments.

6. Declarations

6.1. Author Contributions

Conceptualization, M.A.; methodology, M.A. and A.P.; software, A.P.; validation, M.A.; formal analysis, A.P.; investigation, A.P. and M.A.; resources, M.A.; data curation, A.P; writing—original draft preparation, A.P. and M.A.; writing—review and editing, M.A.; visualization, A.P., and M.A.; supervision, M.A.; project administration, M.A.; funding acquisition, M.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are openly available, with permission, at DOI:10.5281/zenodo.18168229

6.3. Funding

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6.5. Institutional Review Board Statement

Not applicable.

6.6. Informed Consent Statement

Not applicable.

6.7. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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