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Sensor, IoT-based post-harvest shelf life determination of tomato (*Lycopersicon esculentum*) through machine learning predictive analysis for intelligent transport

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Abstract

Aim: The current research explores the potential of machine learning predictive models in optimizing the storage conditions of tomatoes. This is achieved through Internet of Things (IoT) technology, sensors, cameras, and microprocessors integrated into refrigerators along the supply chain.

Methodology: Controlling temperature and humidity inside the refrigerated container was accomplished by implementing the Arduino microcontroller and supplementary hardware components, including the ESP32 module relay, an advancement over the ESP8266 microcontroller. The Arduino Integrated Development Environment (IDE) was used as software platform for this experimentation. Various parameters, including humidity, oxygen, carbon-di-oxide, and shelf life, were recorded at different temperatures and on different days. Subsequently, the collected data was analyzed employing machine-learning models to determine the most effective prediction model for these variables.

Results: From the results it has been revealed that apolynomial of degree 4 is the best-fit regressor model for the data on humidity. Polynomials of degrees 2, 2, and 3 are the best models for the target variables oxygen, carbon-di-oxide, and shelf life.

Interpretation: During analysis, This result suggests that different polynomial degrees are optimal for modeling different variables in the dataset. Polynomials of degrees 2, 2, and 3 are the best ML models for the target variables oxygen, carbon-di-oxide, and shelf life, respectively,to enhance the effectiveness of our predictive models.

Key words: Io T sensors, ML models, Quantile loss, Supply chain, Tomato

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Introduction

India stands as one of the globe's megadiverse nations, covering 2.4 percent of the world's land area and yielding 351.92 million tons of horticultural crops, all while utilizing a mere 28 million hectares of land. This achievement secures India's position as the second-largest producer of horticultural crops worldwide. The significance of horticulture in ensuring food and nutritional security cannot be overstated (Panwar, 2019). Given the prevalent vegetarianism among Indians, vegetables are crucial in fulfilling nutritional needs (Amit *et al.,* 2023). Culturing these vegetables ensures nutritional adequacy and provides economic stability, potentially supplanting subsistence farming across various horticultural zones (Noopur *et al.,* 2021). However, numerous challenges, including social factors (Gautam and Jha, 2022), production constraints (Gautam and Jha, 2022), post-harvest losses, and transportation and marketing hurdles (Goyal and Goyal, 2022), impede the per capita availability of vegetables and threaten vegetable farming sustainability.

Among horticultural crops, tomato crops are prominent, contributing significantly to India's GDP, accounting for approximately 218 billion Indian rupees in 2018 (Statista, 2022). Nevertheless, the short shelf life of tomatoes due to their climacteric nature poses a significant challenge, necessitating precise temperature and humidity control during post-harvest storage (Arun, 2017). Inadequate knowledge about post-harvest handling and deficient transport infrastructure result in substantial losses, with estimates suggesting that 20-40% of tomatoes are wasted in India. Addressing post-harvest losses, especially in tomatoes, is imperative. Conventional storage methods contribute significantly to overall losses in India, with post-harvest periods particularly vulnerable (Kader, 2005; Spang *et al.,* 2019). Detecting spoilage promptly is critical to prevent further contamination and decay during storage. Early identification of spoilage indicators such as discoloration, mold growth, or unusual odors enables growers and distributors to take immediate action, thus preserving the quality and safety of stored produce Mohan *et al.* (2023). Proactive measures include removing spoiled items, mitigating microbial proliferation, extending the marketable lifespan of unaffected fruits and vegetables, reducing overall losses, and ensuring consumer health.

Research indicated a steady rise in Artificial Intelligence applications in post-harvest agriculture over three decades, with notable growth in the last ten years (China, the USA, and India lead in productivity (Fadiji, 2023). However, the Internet of Things (IoT), cold chain logistics, and decision-making remain underdeveloped areas. This review study underscores the importance of AI in reducing post-harvest losses, improving food quality, and addressing food insecurity, offering valuable insights for scholars and guiding future research endeavors. In a traceability system, IoT (Internet of Things) sensors can reduce perishable food supply chain losses (Abha, 2022). This data-driven analysis highlighted Deep Learning (DL), Machine Learning (ML) (Singh *et al.,* 2022) and IoT's impact on precision agriculture. Various ML models utilizing Red, Blue and Green (RBG) and infrared and hyperspectral images are compared for accuracy and efficiency in fruit quality control, aiding cost-effective measures. The study assessing strawberry quality utilized color space coordinates alongside multiple linear regression (MLR) models and artificial neural networks (ANNs) (Amoriello, 2022).Their work revealed the inefficiency of MLR and strong predictive capability of ANN, notably for antioxidant activity and total monomeric anthocyanin. Their study underscores the effectiveness of color coordinates paired with ANN for assessing strawberry quality. The article delves into applying picture segmentation and ML techniques for food inspection (Hemamalini, 2022). It outlined a process capable of identifying and evaluating fruits, including detecting signs of spoilage. The authors used Gaussian elimination to filter out image noise, followed by histogram equalization to enhance image quality. Subsequently, they performed image segmentation using K-means clustering to isolate fruit regions. Building upon the ongoing efforts of researchers to address these challenges, the current study focus its attention on leveraging IoT technology to detect spoiled vegetables within refrigerated containers. We employed Machine Learning models were employed to evaluate vegetable freshness and predict shelf life, with the objective to enhance supply chain efficiency to mitigate post-harvest losses.

Materials and Methods

Tomatoes were selected as the focal commodity for this study due to their representative nature. Being climacteric vegetables, tomatoes offer an ideal model for understanding post-harvest physiological behavior, respiratory patterns, ethylene emission, and optimal storage conditions. Experimental trials were conducted utilizing a simulated refrigerated environment integrated with IoT technology to assess vegetable quality. In the case of poor quality, data was transmitted to a server via HTTP protocol, alerting users through a provided link about the commodity's suitability for consumption. Initially, data capture involved using cameras and sensors, including humidity sensors, to gather information transmitted to a processor linked to the sensors via cable connection. The processor employed image analysis and algorithms based on sensor inputs to ascertain food quality within the refrigerator. Subsequently, the system's sensors were deployed within a refrigerated container loaded with mature tomatoes, monitoring variations in temperature, humidity, and gas composition. Upon detecting subpar quality, data was relayed via Arduino to the HTTP protocol and subsequently, to the users via a dedicated app or message.

The project utilized a computer as the processing unit, pertinent sensors, and an Arduino board equipped with Wi-Fi connectivity. A flowchart detailing the data acquisition process via various sensors is illustrated in Fig 1. Although the ideal temperature for enhancing the shelf life of mature, firm tomatoes is approximately 7-12 ºC, the experiments were conducted at 20 ºC to evaluate quality degradation. The tests, conducted under constant temperature and relative humidity, facilitated the

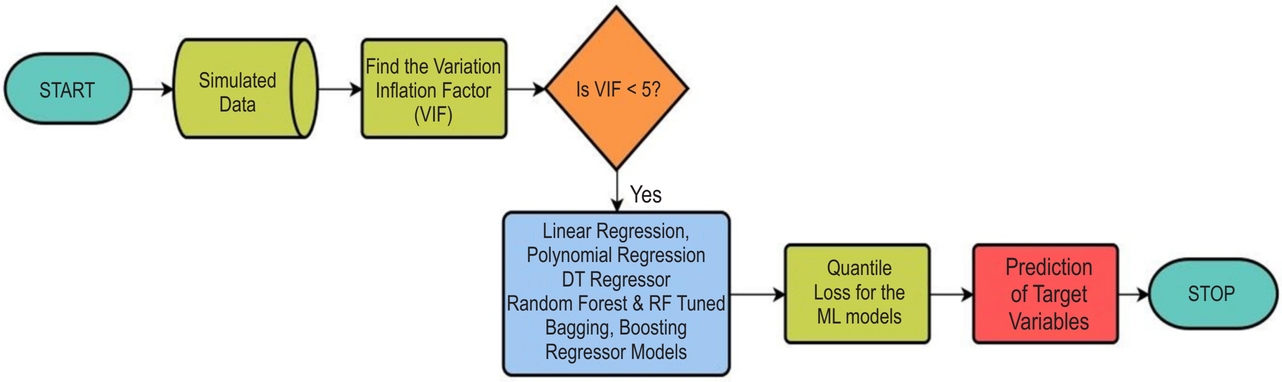

Fig. 1: Illustrates the workflow chart for performing data analysis.

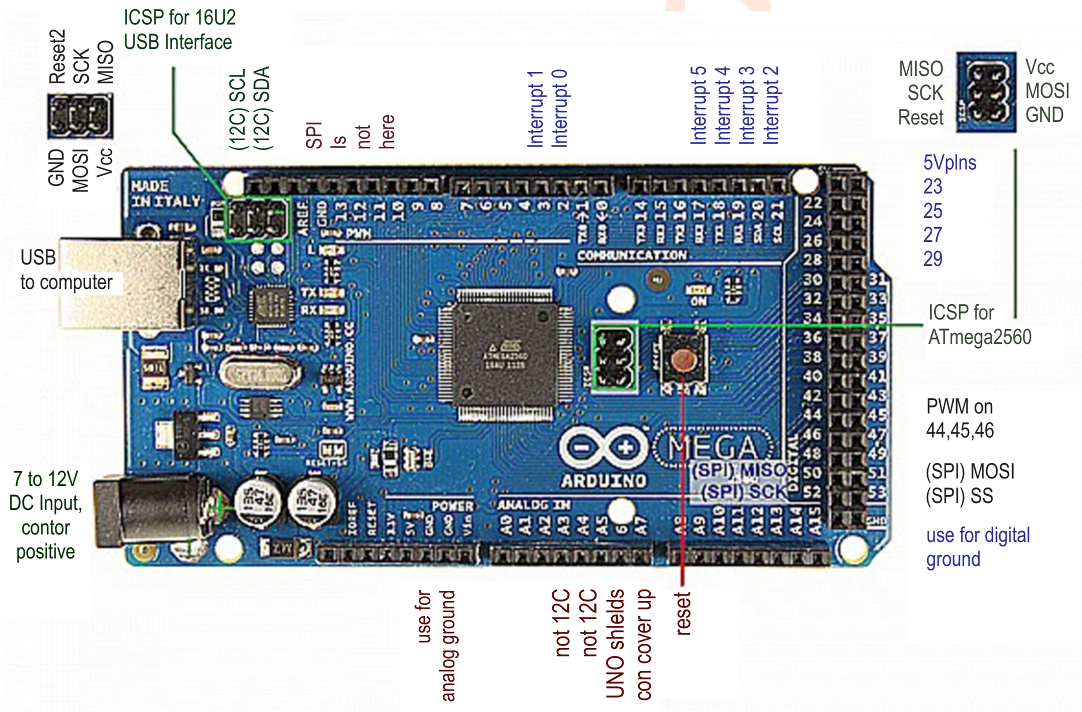

Fig. 2: Arduino Uno Board.

correlation between storage temperature and product shelf life. Therefore, assessing temperature variations throughout the post-harvest ripening period is crucial for determining commodity quality from storage to retail, ultimately ensuring consumer satisfaction.

System overview: Various IoT tools were employed to facilitate the efficient distribution of vegetables. In this experiment, the objective of controlling temperature and humidity within the refrigerated container was achieved using the Arduino Uno microcontroller and additional hardware, such as the Espressif32 (ESP32) module relay, which is a successor to the ESP8266 microcontroller. The Arduino Integrated Development Environment (IDE) served as the software platform for this experiment. These components are illustrated in Fig. 2, 3, 4 and 5, respectively. The experiment was conducted using a small cabinet-sized model (Fig. 5), with a camera installed inside the refrigerator cabinet to monitor the condition of the products and assess the extent of deterioration during storage. Inside the refrigerator, the Digital Temperature And Humidity Sensor (DHT11) sensor was positioned alongside the Arduino Uno, ESP32 module, breadboard, and relay components.

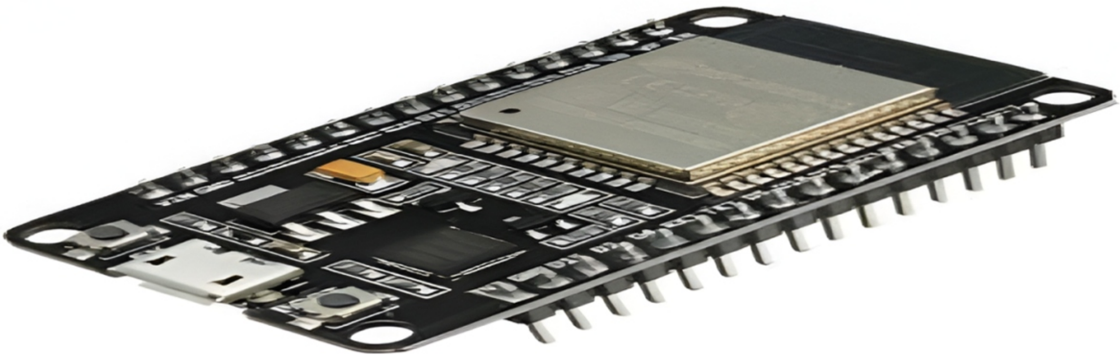

Fig. 3: ESP32 Wi-Fi Module.

Fig. 4: Small cabinet model.

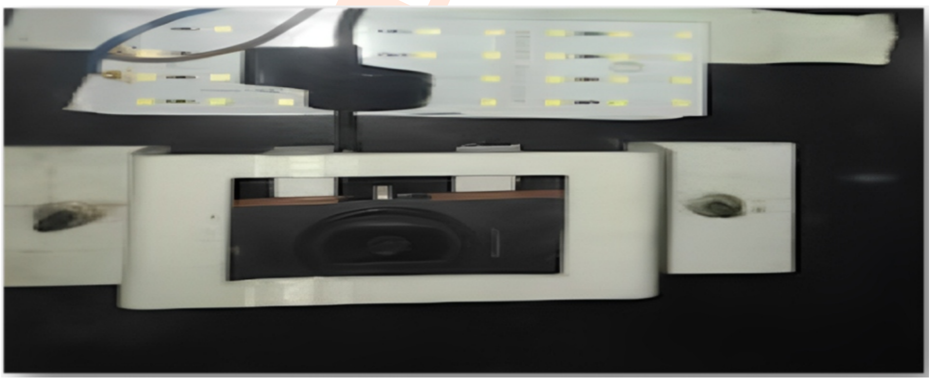

Fig. 5: Camera set up to detect the deterioration process of the commodity during storage.

Software simulations: The temperature set point was configured to 20 ºC. Whenever the temperature fell below this threshold, the humidity dropped below 95%, or the sensor detected any fluctuations, the camera captured subsequent physiological changes in the stored commodity to analyze post-harvest physiology. In CODE-1, the sensors incorporated included the DHT11 sensor to measure the temperature and humidity of the food. Additionally, sensors were utilized to detect the presence of ethylene gas emitted by decaying food and to monitor oxygen levels. These sensor data were aggregated and

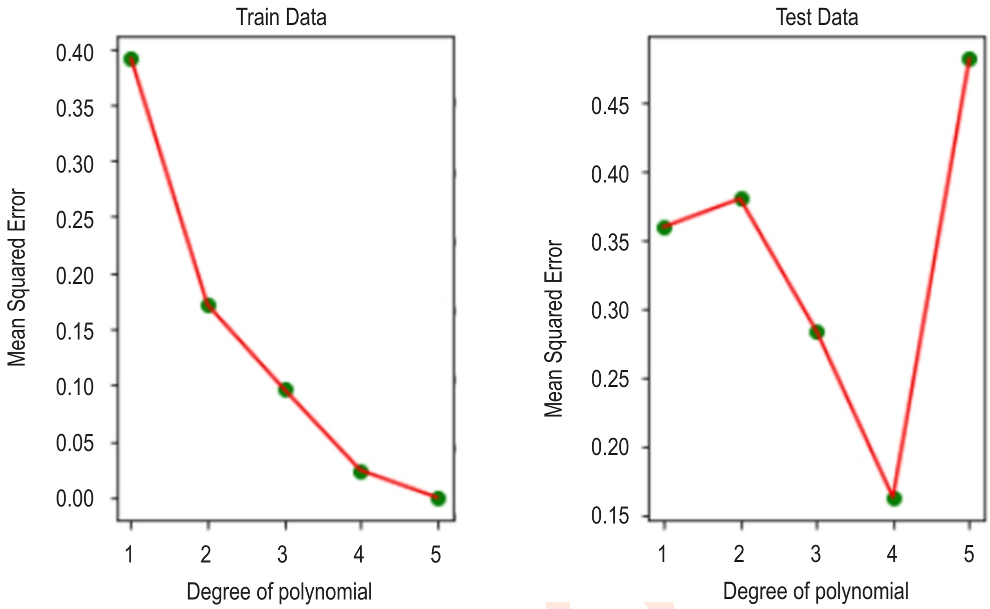

Fig. 6 (a): Target variable: Humidity.

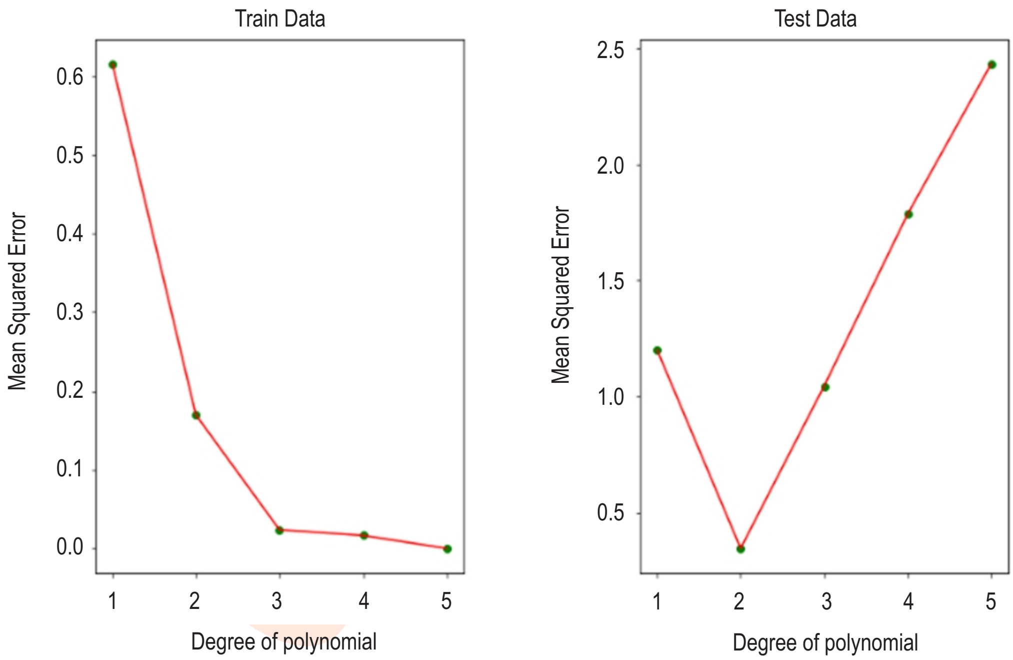

Fig. 7(b): Target variable: Oxygen.

processed by an Arduino MEGA processor. CODE-2 involved comparing the sensor output values with predefined threshold values. If the output value was lower than the threshold, the controller triggered the transmission of information to the ESP32 Wi-Fi module. Subsequently, the ESP32 module transmitted the food quality information to theHypertext Transfer Protocol (HTTP) protocol. This code facilitated communication between the ESP32 module and a personal computer for processing.

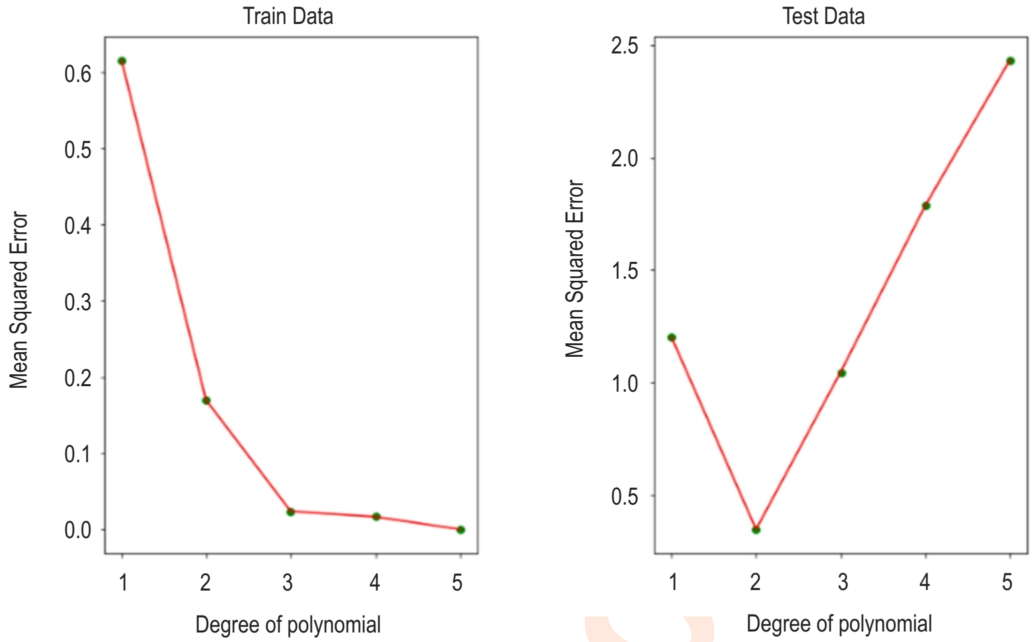

Fig. 7(c): Target variable: CO_2

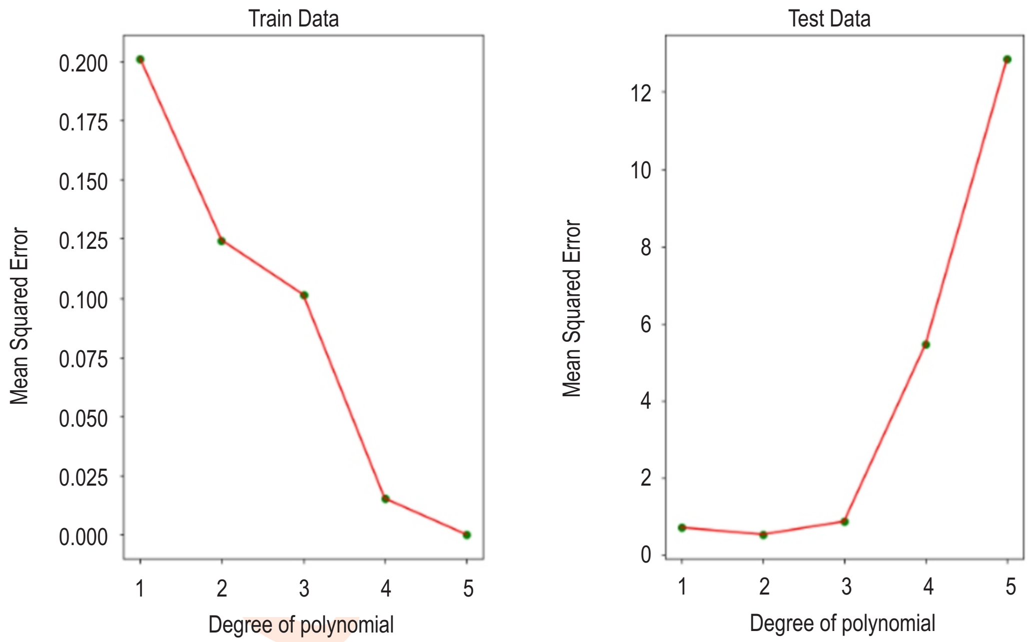

Fig. 7(d): Target variable: Shelf life.

Data Analysis: Data generated using simulations was recorded in the format is shown in Table 1. Firstly, the dataset, features, and target variables taken for the study was introduced.

Features: Temp-Temperature at which tomatoes are stored (°C) Day -Day of stay in the refrigerator.

Target variables: Humidity – Percentage of relative humidity in 24 hrs; Oxygen – Level of oxygen in the refrigerator in ml kg^{-1} hr; CO_2 – Level of carbon-di-oxide in the refrigerator in ml kg hr^{-1} and Shelf life – Recommended shelf life of tomatoes in days. An initial univariate analysis was conducted to explore the dataset's characteristics, comprising an assessment of the range and

Table 1: Data Collection Format

Temp	Day	Humidity	Oxygen	CO2	Shelf life
Features		**Target variables**			
Temperature at which tomatoes are stored (°C)	Day of stay in the refrigerator	Percentage of relative humidity in 24 hrs	Level of Oxygen in the refrigerator in ml kg hr^{-1}	Level of Carbon-di -oxide in the refrigerator in ml/kg/hr	Recommended shelf life of tomatoes in days

Table 2: Descriptive Statistics

Descriptive statistics parameters	Temperature	Day
Count	20	20
Mean	11.75	3.0
Std	4.940435	1.450953
Min	8.0	1.0
25%	8.75	2.0
50%	9.50	3.0
75%	12.50	4.0
Max	20.0	5.0

central tendencies. Additionally, descriptive statistics for the features were examined to detect any potential outliers is presented in Table 2. Notably, it was observed that the maximum and 75th percentile values of the features displayed marginal differences, suggesting the absence of outliers within the dataset. Subsequently, a univariate analysis was performed on the target variables, utilizing bar charts, which revealed a lack of skewness in the data. Following this, we moved forward to the subsequent analysis stage-a multivariate examination. This phase investigated multiple dependent variables or features influencing a single outcome or target variable.

The degree of correlation among features was evaluated by computing the Variance Inflation Factor (VIF) score. It became apparent that these features did not exhibit correlation, as evidenced by each feature's VIF score being less than unity. Thus, in the first step of constructing an machine learning model, a linear regression model was developed, incorporating 'Temp' and 'Day' as features and 'Humidity' as the target variable. Performance evaluation metrics were computed for training and testing datasets, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 scores.

Results and Discussion

Based on the metrics (MAE, RMSE, R^2) presented in Table 3, it is evident that the linear model's performance is unsatisfactory. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values are significantly high, indicating that the model's predictions deviate considerably from the actual values. High MAE and RMSE values suggest that the model has significant prediction errors, failing to capture the underlying patterns in the data accurately. Additionally, the R-squared (R2) value is low and, in some cases, negative, which means that the linear model explains only a small fraction of the variance in the dependent variable. An ideal R^2 value is close to 1, indicating that the model accounts for most of the variability in the response variable. However, the low R^2 value here points to the model's poor fit and inability to capture the complexity of the data (Bonnin, 2017; Chicco, 2021; Plevris, 2022; Varoquaux, 2023; Rainio, 2024). Thus, these metrics collectively highlight the inadequacy of the linear model for this dataset, suggesting that it does not perform well in predictive accuracy or explaining the variance in the data. Subsequently, a non-linear regression model, specifically the polynomial regressor model, was applied to the data.Analysis of the Mean Squared Error (MSE) plotted against the degree of the polynomial (depicted in Fig. 7a) revealed that a polynomial of degree 4 yielded the best fit for the data. Further, Table 3, shows that the polynomial model demonstrates superior

Table 3: Performance Metrics

Target Variable	Model	Performance metrics for test dataset			
		MAE	RMSE	R2	Adjusted R2
Humidity	Linear	0.298	0.359	0.842	0.529
	Polynomial	0.149	0.027	0.967	0.902
Oxygen	Linear	1.018	1.201	-ve	-ve
	Polynomial	0.32	0.12	0.744	0.232
CO2	Linear	0.951	1.016	-ve	-ve
	Polynomial	0.111	0.014	0.945	0.836
Shelflife	Linear	0.486	0.723	0.509	-ve
	Polynomial	0.375	0.293	0.725	0.176

Table 4: Quantile prediction for humidity

Temperature	Day	Humidity			
		Actual	0.1 quantile	0.5 quantile	0.9 quantile
8	5	18.80386464	18.80386382	18.80386382	18.80386382
21	2	37.27146974	37.27147326	37.27147326	37.27147326
9	2	22.90777779	22.90777705	22.90777705	22.90777705
10	1	19.82984088	19.82984211	19.82984211	19.82984211

Table 5: Quantile prediction for oxygen

Temperature	Day	Oxygen			
		Actual	0.1 Quantile	0.5 Quantile	0.9 Quantile
8	1	29.85798087	170.1363865	170.1363865	170.1363865
21	3	20.40660696	154.7467107	154.7467107	154.7467107
21	1	36.1588968	180.3961703	180.3961703	180.3961703
8	2	29.22788927	169.1104081	169.1104081	169.1104081

Table 6: Quantile prediction for CO_2

Temperature	Day	CO_2			
		Actual	0.1 Quantile	0.5 Quantile	0.9 Quantile
8	1	129.87141	129.8714073	129.8714073	129.8714073
21	3	141.1571656	141.1571689	141.1571689	141.1571689
21	1	124.7415168	124.7415158	124.7415158	124.7415158
8	2	131.9233602	131.923364	131.923364	131.923364

Table 7: Quantile prediction for Shelf life

Temperature	Day	Shelf life			
		Actual	0.1 Quantile	0.5 Quantile	0.9 Quantile
8	1	11	11	11	11
21	3	3	3	3	3
21	1	6	6	6	6
8	2	11	11	11	11

performance compared to linear model. This conclusion is drawn from the fact that the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values for the polynomial model were lower than those of the linear model. Lower MAE and RMSE values indicate that the polynomial model's predictions were closer to the actual observed values, thereby reducing the magnitude of prediction errors. Furthermore, the R-squared (R^2) value for the polynomial model was relatively higher than that of the linear model. This indicates a better fit for the data, as the model captures more underlying relationships and patterns. In addition to the polynomial model, we worked on other non-linear machine learning models such as support vector machines, decision trees, and ensemble models, including random forest, bagging, and boosting algorithms. However, these models exhibited signs of overfitting to the data. Consequently, the findings related to these models were omitted from the paper. A similar analysis was carried out for other target variables, and the performance metrics are presented in Table 3. From Fig. 7(b) – (d), we understand that polynomials of degrees 2, 2, and 3 are the best ML models for the target variables, Oxygen, CO_2 and shelf life, respectively.

Following our prior findings, we have arrived to the concluding phase of our analysis, which is dedicated to examining the inherent uncertainty in the predictions generated by these models. To accomplish this, we employed the Quantile loss function, a tool that allows us to delve into the varying levels of uncertainty associated with individual point predictions (Agarwal, 2019; Xu, 2023; Nair, 2024). Through this method, we sought to gain insight into the extent and distribution of uncertainty surrounding the predicted outcomes produced by our models and presented them in Tables 4 to 7. In Table 4, we found the quantile predictions for the target variable 'humidity.' It displayed the actual value alongside the 0.1, 0.5, and 0.9 quantile values of humidity, all associated with specific sets of 'Temp' and 'Day' feature values. The values suggest that on comparing the actual value of the target variable (in this case, humidity) with the predicted quantile values (0.1, 0.5, and 0.9 quantiles), there was a notable proximity between them. Essentially, it implied that the actual observed humidity values tend to align closely with the predicted quantile values, indicating the reliability or accuracy of the predictive model. Tables 5, 6, and 7 contain quantile predictions for Oxygen, Carbon dioxide, and shelf life. Like Table 4, these tables display actual and predicted quantile values for these variables under specific conditions or feature sets. The values in these tables suggest that the predicted quantile values for Oxygen, Carbon dioxide, and shelf life closely match the observed values. This alignment between predicted and actual values across multiple variables indicates the overall reliability and accuracy of the previously developed predictive models for these variables.

The data in these tables affirm our models' effectiveness despite a significant limitation: the relatively small dataset utilized in constructing the machine learning (ML) model. While acknowledging this limitation, it's notable that our models still demonstrate notable efficiency and performance. This underscores the robustness and adaptability of our methodologies, even when confronted with constraints such as dataset size. This research aimed to create an Internet of Things (IoT) integrated supply chain system capable of tracking and adjusting to market fluctuations. Through rigorous testing, we successfully generated a sample dataset and employed machine learning techniques to evaluate the quality of vegetables by predicting humidity, gas composition, and shelf life within the established framework. Despite constraints in dataset size, our findings indicate the effectiveness of machine learning models, highlighting promising prospects of the proposed methodology.

Hence, future endeavors will focus on expanding the scope of this research by generating larger datasets encompassing a broader range of features. This will involve systematically varying the parameters to capture a more comprehensive representation of the underlying phenomena. By doing so, we aim to enhance the robustness and effectiveness of our predictive models, enabling them to accurately capture and adapt to a broader array of scenarios and conditions.

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