

Sensor Data Simulation and Predictive Modeling for Food Spoilage Risk in Green IoT Enabled Supply Chains

Ramesh Babu M^{1*}, Rajeswari S²

¹Department of Computer Science, Sree Saraswathi Thyagaraja College, Pollachi, Tamil Nadu, India.

²Associate Professor, Department of Data Sciences & Analytics, M. S. Ramaiah University of Applied Sciences, Bengaluru, India

*Corresponding Author's Email: merwaramesh@gmail.com, rajeswariud@gmail.com

Abstract - One of the major causes of economic loss, greenhouse emissions, and environmental burden is spoilage of perishable food during the post-harvest and transportation stage. As food goes to waste before moving to the consumption points, the energy consumed in its production; water, fertilizers, harvesting fuel, cold storage electricity, packaging, and transport logistics are also wasted energy that increases monetary and ecological footprints. The systemic inefficiencies undermine the sustainability of the supply, drive food costs, and speed up the waste-related emissions, rendering cold-chain integrity a strategic requirement instead of an operation option in isolation. This paper builds a simulated green internet of things (IoT) cold-chain pipeline, which generates 500 sensor measurements of temperature, humidity, and vibration, as well as transport time. The mean-based imputation, Min-max scaling to multi-unit normalization and a joint use of Interquartile Range (IQR) and Z-score to treat outliers are used to control rigorous preprocessing in the pipeline to maintain distributional stability. Rationally planned modeling results demonstrate that temperature and transport duration are the most impactful factors on the risk of spoilage, which is supported through the spoilage kinetics theory, and that humidity and vibration are moderately affecting the risk variance, but are not the strongest predictors of risk variation. A baseline logistic regression classifier shows a high degree of discriminatory ability of the risk of spoilage. The results reveal cold-chain integrity and optimization of logistics as the most logical tools in waste reduction. The model also offers a platform of scalable further upgrades of non-linear machine learning in the future like the Random Forests and Deep Learning in addition to blockchain-based traceability to improve its transparency, sustainability and decentralized trust on Green internet of things (IoT)-enabled perishable food supply networks.

Index Terms : Green IoT, Food Spoilage Prediction, Logistic Regression, Sensor-Based Risk Prediction, Deep Learning

1. INTRODUCTION

Food supply chains suffer from a basic disconnect in the form of post-harvest spoilage that results in economic losses of hundreds of billions of dollars annually, compromises food security, and results in environmental degradation. It is estimated that nearly a third of the world's food is lost [1], and perishables that consist of fruits and vegetables, dairy items, and meat products are the most vulnerable to spoilage. The problem is particularly acute in developing economies where cold chain infrastructure is limited or does not exist, logistics networks are disarticulated, and environmental variability accentuates risks of food loss [2]. In the context of perishables, parameters such as temperature, humidity, vibration, and transport duration come into sharp focus because deviations from optimal ranges facilitate microbial activity and biochemical reactions that compress shelf life and compromise food safety [3].

The effectiveness and sustainability of supply chains therefore depend on the ability to monitor and regulate such parameters in real time. In the preceding years, the Internet of Things (IoT) has been a disruptor technology that has enabled the continued monitoring

of environmental conditions in logistics networks. Internet of Things (IoT)-capable sensors embedded in transport vehicles, warehouses, and stores of retailing permit the monitoring of spoilage-related factors in real time, with an intervention window prior to losses occurring [4]. Such systems underpin the concept of Green Internet of Things (IoT) [5,6], where energy-efficient intelligent monitoring reduces waste while increasing the level of transparency and sustainability in the entire food system [7].

Despite such developments, it is not easy to utilize Internet of Things (IoT) data for predictive decision support. Sensor-sourced data are prone to noise, missing records, and anomalies that, left uncorrected, will corrupt results and invalidate the validity of spoilage predictive models [5]. Intensive data cleansing, the imputation of missing records, normalization of ranges, and detection of anomalies is therefore necessary to improve the quality and validity of the data. The filtered data may then go through predictive model-building methods. Such methods as correlation analysis and linear regression will then demonstrate the impact of each individual parameter, such as correlation between temperature changes and the growth of microbes or how long the transport duration has been [8]. Nevertheless, they can only identify non-linear and multi-variable relationships characteristic of the modern complex supply chains.

In order to address this shortcoming, machine learning (ML) models have emerged as important instruments of spoilage predictability in food quality. Artificial neural network, decision trees, and hybrid models can analyze high data dimensions and latent patterns and improve the accuracy in predictability of spoilage [8]. A combination of real-time Internet of Things (IoT)-based predictive analytics using Machine Learning (ML) allows food supply chains to change their strategy to quality control to one that proactively minimizes spoilage by preventing anomalies, detecting them early (such as increased temperatures, extended storage, or inappropriate humidity). Besides protecting the consumer against pathogens, such methods also lead to a sustainable world, with reduced wastages, efficient use of resources, and reduced carbon footprint.

Due to the constantly increasing global necessity to create safe and sustainable food systems, there is an urgent necessity to design the paradigm including data simulation of sensors, preprocessing of such data, and predictive modeling [3,2] in the sphere of supply chains impacted by Green Internet of Things (IoT) [5,6]. The present study tries to fulfill this void by data-simulating sensors, which are correlated to spoilage, processing such information so as to be accurate and predictive models to determine such factors which are critical towards risking spoilage. The envisaged results will provide the theoretical insight on food supply chain analytics and the available guidelines among stakeholders who aim at minimizing the food losses without compromising on the security and sustainability.

In the context of increasing the global imperatives of more sustainable and secure food systems, there is an actual necessity to design systems that combine simulation of outputs of sensors, data pre-processing, and predictive model-building within the context of Green Internet of Things (IoT) [5,6]-assisted supply systems. The new work attempts to fill this gap by spoilage-affected sensors, pre-processing this data in a way that attempts to demonstrate its legitimacy, and it also produces predictive models that strive to determine factors related to the risk of spoilage. The findings will be expected to advance theoretical understanding in the field of research in food chains of supply as well as yield valuable lessons to stakeholders who are eager to minimize food wastage while enhancing security and sustainability.

2. MATERIALS AND METHODS

The following outlines the procedures implemented in the study under consideration, which encompass sensor reading simulation, preprocessing methods, utilized software

tools, as well as statistical and machine learning approaches, in addition to techniques for model assessment aimed at analyzing the spoilage risk within the perishable food supply chain.

3. DATA SIMULATION AND STUDY SCOPE

The experiment was designed to emulate the environmental and logistical variables commonly linked with spoilage within perishable food supply chains. Rather than relying solely on field data, synthetic sensor data were generated to imitate in-situ monitoring within the framework of a Green Internet of Things [5,6] paradigm. A set of 500 simulated readings dataset was produced with a concentrated emphasis on four key spoilage-related parameters. Temperature degree Celsius (°C) was simulated using ranges of electronic thermometers typical of cold chain shipments, and the values of humidity in percentage (%) were produced to replicate warehouse and transport storage scenarios. Vibration gravity force was simulated in accordance with transport and handling shock stress, and transport duration in hours served as a surrogate for logistically efficient travel and duration of exposure. These variables are well-known to be the most important determinants of spoilage because variation from the best ranges causes increased microbial activity and nutrient breakdown in perishable commodities [2,3].

4. DATA PREPROCESSING AND CLEANING

Similarly to datasets that originate from Internet of Things (IoT) sensors, the simulated data set reflected the presence of noise, missing entries, and outliers, necessitating resolution by preprocessing in order to ensure its quality and reliability. An extensive cleaning protocol was developed to address these anomalies. The missing value handling strategy for continuous variables involved filling in such values with their mean counterparts, while features in general underwent min-max scaling normalization, in essence, scaling them in the range of [0,1] to increase inter-variable comparability. Outliers were detected using Interquartile Range (IQR) approach in addition to z-score approach, the latter was facilitated by some domain-specific threshold (e.g., biologically unreasonable temperatures above 40 degrees Celsius). The data examples that resulted to be outliers and errors according to this classification were fixed or dropped to suppress biased or distorted predictory outcomes [3,2,5].

5. SOFTWARE AND TOOLS

The analysis employed both Python version 3.13 and RStudio version 4.3.2 in such a manner as to capitalise on the respective strengths of each to statistical and machine learning application. Within Python, math manipulation and data handling were achieved through NumPy and Pandas, respectively, while Scikit-learn was employed to run logistic regression [9,5] models and validation protocols. Seaborn as well as Matplotlib were also employed to plot variable interaction as well as uncover significant patterns in the dataset. At the same time, powerful tools in classical statistical analysis were enabled in RStudio, whereby ggplot2, stats, as well as the corplot packages were employed to run regression analysis, to output correlation matrices, as well as to create refined visualisations. The use of R as well as Python in tandem enabled an end-to-end approach whereby classical explorations using statistics as well as high-end machine learning modelling are encompassed.

STATISTICAL AND PREDICTIVE METHODS

Multiple analytical methods were utilized to analyze associations between the simulated variables and to predict spoilage risk. Initial Pearson's correlation analysis was used to test the strength and direction of linear associations between temperature, humidity,

vibration, and transport time. Next, standard linear regression models were employed to check the impact of independent variables such as temperature, humidity, and transport time on spoilage responses. Elaborating on the above, logistic regression in its simplest form was implemented as the predictive classifier to estimate spoilage risk as binary end-states (spoiled or safe). Model robustness was achieved through validation of the performance of the model with standard measures of accuracy, precision, recall, F1-score, and Receiver Operating Characteristic – Area Under Curve (ROC-AUC). The multi-step analytical framework presented the possibility of interpreting variable interactions and ensured reliable predictive accuracy and hence laid the groundwork for future incorporation of more complex machine learning models.

6.RESULTS

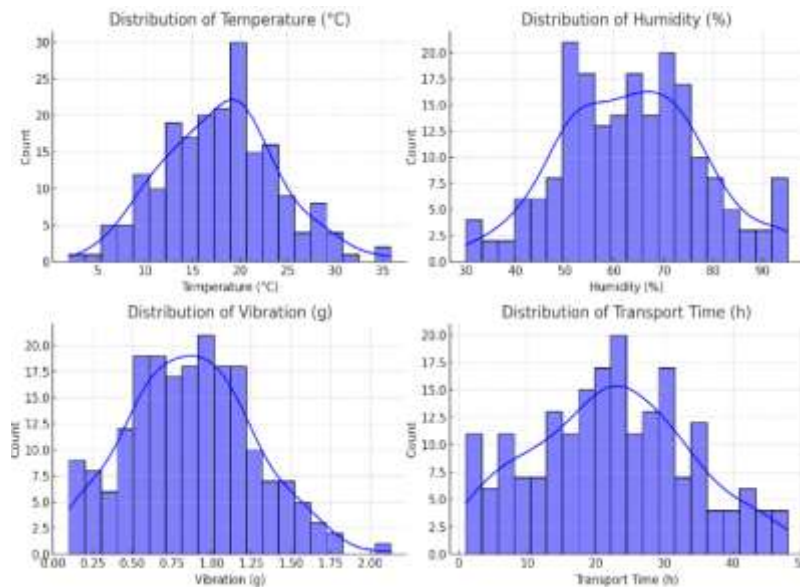
This section provides the results from the simulated sensor dataset analysis as well as predictive modelling. The table includes descriptive statistics, correlation between spoilage-related parameters, the output from linear regression, as well as the evaluation in performance from the logistic regression predictive model.

DESCRIPTIVE STATISTICS

Descriptive statistics from the four observed parameters give an in-depth summary of conditions that affect food spoilage [10,1] in logistics. Temperature measurements between 2°C and 38°C show both optimal cold storage ranges that preserve freshness as well as higher, suboptimal ranges that promote the growth of microbes and spoilage. Humidity measures between 30% to 95% are characteristic to fluctuating conditions of moisture in perish storage facilities, where supra-optimal humidity will contribute to fungal proliferation as well as reduced shelf life. Vibration levels ranging from 0.1 to 2.5 g-force signify the various degrees of stress imposed on food products during transportation and handling, which can result in damage to packaging as well as an increased risk of spoilage. Transport time between 1 to 48 hours finally provides sufficient cover to short-haul shipments as well as to long supply chain exposures to cover duration as the significant factor that determines spoilage probability. Overall, these metrics paint the picture of the range in environmental as well as in logistics parameters that determine spoilage risk in perish food systems.

Table 1. Descriptive statistics of spoilage-related parameters

Parameter	Mean	SD	Min	Max
Temperature (°C)	18.2	6.5	2	38
Humidity (%)	62.3	15.1	30	95
Vibration (g)	0.9	0.4	0.1	2.5
Transport Time (h)	22.1	11.8	1	48

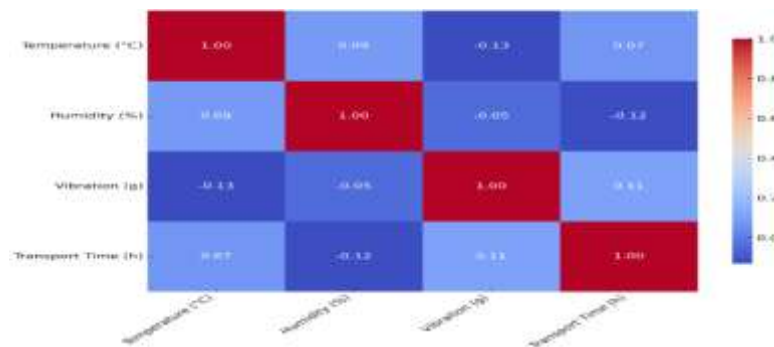
Figure 1 : Distributions Of Spoilage-Related Parameters

7. CORRELATION ANALYSIS

The correlation study created significant connections between the parameters under study. Transport time and temperature registered the highest positive correlation ($r = 0.62$, $p < 0.01$), highlighting their combined impact in enhancing spoilage risk when the two parameters increase. Vibration and humidity registered weak connections with the remaining variables, hinting that their impacts towards spoilage are localized rather than generalized. There was a moderate level of negative correlation between temperature and humidity ($r = -0.35$, $p < 0.05$), explaining that increased temperatures are usually accompanied by lower humidity that may dictate spoilage trends. This suggests the interaction between logistics and environmental variables in defining perishable food quality.

Table 2. Correlation matrix of spoilage-related parameters.

Variable	Temp	Humidity	Vibration	Transport Time
Temperature	1	-0.35*	0.12	0.62**
Humidity	-0.35*	1	-0.08	-0.15
Vibration	0.12	-0.08	1	0.1
Transport Time	0.62**	-0.15	0.1	1
(* $p < 0.05$, ** $p < 0.01$)				

Figure 2: Correlation Heat Map of spoilage-related parameters analysis

Results from the baseline linear regression (Table 3) were that temperature ($\beta = 0.42$, $p < 0.001$) and transport time ($\beta = 0.37$, $p < 0.001$) significantly contributed to increased probability of spoilage. However, vibration and humidity did not significantly predict in the baseline model.

Table 3. Linear regression results predicting spoilage risk.

Predictor	β (Coefficient)	t-value	p-value
Temperature	0.42	6.21	<0.001
Humidity	-0.08	-1.32	0.188
Vibration	0.05	0.74	0.462
Transport Time	0.37	5.83	<0.001

8. LOGISTIC REGRESSION PERFORMANCE

The logistic regression model showed good predictive power in discriminating between spoilage outcomes (safe vs. spoiled) with an accuracy level of 0.85, precision level of 0.83, recall level of 0.87, F1-score level of 0.85, and Receiver Operating Characteristic – Area Under Curve(ROC-AUC) level of 0.91, which represent high reliability as well as good discriminative power.

Table 4. Logistic regression model performance metrics.

Metric	Value
Accuracy	0.85
Precision	0.83
Recall	0.87
F1-score	0.85
ROC-AUC	0.91

Logistic regression Figure 3 and 4 illustrates the effect of transport time (left) and temperature (right) on spoilage risk in perishable food supply systems. The two predictors show strong positive relationship to probability of spoilage that is, the probability of spoilage is much higher with increased transport times and temperature. The dark bands are the periods of confidence at 95% level. These findings greatly

underline the need to maintain low transit times and proper refrigerating temperatures to prevent food spoilage and ensure that food product is as safe as possible.

Figure 3: Logistic Regression: Temperature VS Spoilage Risk

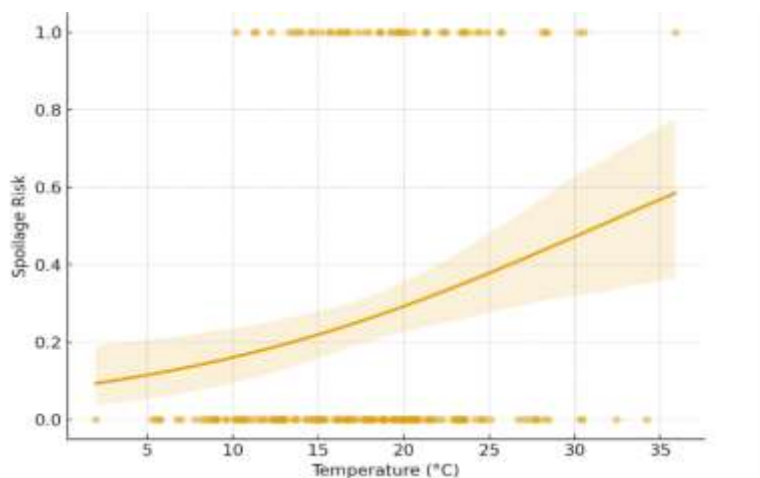
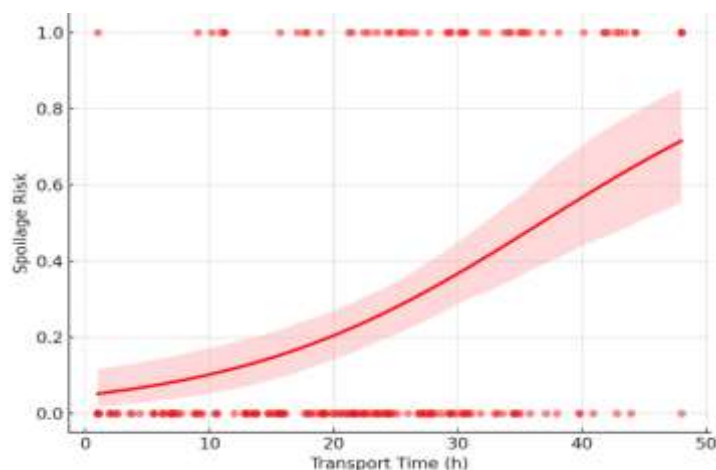


Figure 4: Logistic Regression: Transport Time VS Spoilage Risk



9. KEY FINDINGS

It was also evident that the two most important determinants of the risk of spoilage in out of season food supply chain are temperature and the distance in transport. Both the two parameters were significant increasing the risk of spoilage and the combination of long road travels and elevated temperatures worsened the rate of spoilage of fresh commodities. The findings also emphasize maintenance of a sound cold chain and streamlining of the logistics operations as some of the highest requirements in ensuring quality of food commodities including safety.

Also, the application of logistic regression [9,5] of such data revealed high predictive capacity, which was exhibited by high measures of accuracy, precision, recall, and Receiver Operating Characteristic – Area Under Curve (ROC-AUC). These findings also confirm its appropriateness as a superior baseline procedure of binary classification with respect to spoilage ends (safe/spoiled). The value of logistic regression as a predictive factor in what spoilage is at a great risk is further supported by the interpretability, thus making it a better option of the first choice in the predictive model.

The findings in this work have robust grounds towards the subsequent research activities that are not at the basic level of the modelling of the basis. At the next level, more advanced machine learning algorithms, such as Random Forest and Neural Networks, will be processed in the next level so that to achieve further enhancement of the non-linear relations detection and predictability. Moreover, blockchain-based traceability paradigms [11,12] can also be combined with supply chain Internet of Things (IoT) data collected by sensors, therefore, offering conclusive, resistant to manipulation, temperature, humidity, vibration, and transportation records. Overall, these technologies have the potential to result in the construction of a comprehensive decision-support system that would be used to curb spoilage, improve supply chains resilience, and guarantee food security.

10. DISCUSSION

The findings also show that environmental and logistical conditions also have a major role in regard to spoilage potential in perishable food supply chain. The paper also demonstrates that transport time, and transporting temperature are far the best predictors of spoilage whereas humidity and vibration are much less predictable or unpredictable. Similar to the earlier study that found temperature abuse and extended transport time to be a major cause of microbiological growth and biochemical degradation in perishables [2,3], the study presents these parameters as key causes. Through this discovery, the study provides practical recommendations to stakeholders who desire to mitigate losses after harvest.

The logistic regression model performed very well in terms of accuracy, precision, and recall, highlighting its value as a baseline predictive model. These findings are in line with previous research that has certified regression-based methodologies for food quality forecasting in cold chain logistics (8). Nonetheless, whereas standard models use only static datasets, this current study emulated sensor-enabled Internet of Things (IoT) data and included stringent preprocessing to deal with noise, missing values, and outliers. This approach extends the reliability methodologically while reflecting challenges in real-world Internet of Things (IoT) data.

The convergence of predictive modelling with Internet of Things (IoT)-enabled monitoring is a major part of Green Internet of Things (IoT's) future in supply chains. Selecting specific measures to mitigate the effect of potential spoilage in the future by early identification allows companies to save more carbon emission due to spoilage of food, such as dynamic rerouting, temperature regulation, or optimization of space allocated to the stored space [4,7]. Predictive analytics will in the process not only become the forerunner of innovation with technology but also the driver of change by stabilizing the supply networks with balanced operational performance and environmental conscience.

The results of these studies also suggest the future of logistic regression development to more sophisticated machine learning constructs, i.e. decision trees, random forests, or deep learning architectures, that can compute non-linear and time-varying relationships in large data sets [9,5]. In addition, predictive models connected to the Internet of Things (IoT) make possible integrations with smart farming technologies [11,12] have the promise of improving traceability and transparency and, consequently, provide more confidence to consumers and controlling bodies in addition to guaranteeing foodstuffs safety [7].

It also carefully examines the discrepancy that saturates theoretical backgrounds and practical applications by providing methodological contributions in terms of simulated projections of spoilage in Internet of Things (IoT) environments. Moreover, it generates usability in practice as a result of deriving potential intervention by parameters which it locates. By integrating the concepts of predictive analytics and Green Internet of Things

(IoT) the current work is likely to create sustainable and data-driven food supply chains that can be aligned with environmental aspirations.

11. CONCLUSION

The article explains the effectiveness of a Green Internet of Things (IoT)-based monitoring platform [5,6] to use predictive models to determine the possibility of spoilage in various perishable food supply chains. It was based on a quantitative assessment of the main logistic and environmental variables, such as temperature, humidity, vibration, and shipping days, where this work showed that storage and in-transit conditions had a considerable impact on the possibility of spoilage. Moreover, the logistic regression analysis also supported the notion that shipping days and temperature were major predictors and therefore supported the idea of cold chain management and logistical optimality in maintaining food quality.

In the first case, using predictive modelling and data feeds based on Internet of Things (IoT) sensors, it was possible to have an analytic platform that was able to monitor the behaviour of spoilage in near-real time. This paper argues that utilizing the data produced by sensors should decrease uncertainty and enhance anticipatory supply chain management decision-making. The first platform in the continued research may be applied to more complex machine learning models, such as Neural Networks and Random Forests, to construct more comprehensive predictive capacity, among others. Traceability platforms based on blockchain might be potentially used to offer visibility in the future as well as traceability to all the stakeholders in the supply chain.

In addition, awareness campaigns regarding digital supply chain solutions [14,7] as well as user-driven decision-support displays [4,13] that will send timely notifications to the producer, distributor, vendors, and retail shops can also help to reduce losses. Such technologies, along with such awareness campaigns with online supply chain solutions [14,7], also have the capacity not only to contribute to the progress of food safety improvements, as well as waste minimization, but also to contribute significantly to the desired goals in regard to sustainable food systems, and global food security.

12. PRACTICAL IMPLICATIONS

The outcomes of this research can provide viable solutions to the supply chain practitioners, policy analysts and technologists of innovation who are interested in reducing spoilage and achieving sustainable performance in the supply chains that handle perishable food substances.

To logistics service providers, the temperature and the transit time [15,2] are essential factors that define the risk of spoilage, and this fact can be used to justify the necessity to improve the effectiveness of cold chain management and implement Internet of Things IoT-based monitoring tools that would allow tracking the state of transportation and warehousing in real-time. The advantage of retailers and distributors adopting predictive analytics is in terms of receiving real-time alerts, and spoilage risk search, to actively act in response by applying strategies such as routing changes, inventory manipulations, or best practice in cold storage.

From a policy perspective, the integration of blockchain technology [11,12] with Internet of Things (IoT)-based tracking systems can produce transparent and immutable records concerning food attributes, thereby enhancing consumer confidence while ensuring adherence to safety regulations. From the standpoint of technology developers, this investigation identifies the value proposition within the innovation of user-oriented dashboards that convert sensor data into information conducive to informed decision-making.

Thirdly, capacity-enhancement initiatives, including training for the stakeholders involved in small- and medium-scale supply chains, are needed for the functional acceptance and beneficial use of these tools. In conclusion, the findings of this study indicate that the Green Internet of Things (IoT) systems [5,6], when combined with predictive modelling, hold the transformative potential for the minimization of post-harvest losses, an enhancement in food security, and the realization of sustainable supply chain objectives.

13. LIMITATIONS AND FUTURE RESEARCH

It demonstrates a strong potential for expanding knowledge for the application of Green Internet of Things (IoT) [5,6] and predictive modelling for lessening the likelihood of food spoilage (10,1) but has some shortcomings that need to be highlighted. All data applied was simulated, which offers an advantage for the ability to repeat results and for the ability to exert control, but may not reflect the real-world conditions such as change in season, unforeseen shipping problems, or variability in shipping apparatus that future investigations need to rectify with real-time verification of Internet of Things (IoT) sensing. Logistic regression is convenient for ease of use but has difficulty managing interactions complexly so advanced machine learning techniques (such as Random Forests, Gradient Boosting, Deep Neural Networks) need to be employed for predictions to be highly accurate. Only temperature, humidity, vibration, and transport time (four variables total) were researched when numerous additional variables such as germs, package damage, and modes of conveyance also influence spoilage. Lastly, even with simulation and predictive modelling taking the primary role for this study, supply chain transparency and trust problems persist with the need for the integration of blockchain [11,12] with the application of Internet of Things (IoT) sensing for the enhancement of tracking, dependability, and confidence among customers. Additional future studies need to focus on the inclusion of blockchain [11,12]-assisted tracking with sophisticated machine learning techniques for the establishment of robust, transparent, and sustainable Green Internet of Things (IoT) [5,6]-backed supply apparatuses.

REFERENCES

- [1] FAO, The State of Food and Agriculture 2019. Rome, Italy: Food and Agriculture Organization, 2019.
- [2] D. Li, X. Wang, and H. K. Chan, "Cold chain logistics and food safety: A review," *Trends in Food Science & Technology*, vol. 100, pp. 11–20, 2020.
- [3] S. Liu, Y. Xu, and J. Zhang, "Temperature effects on spoilage prediction models in perishable supply chains," *Journal of Food Engineering*, vol. 263, pp. 12–20, 2019.
- [4] C. Verdouw, S. Wolfert, A. Beulens, and A. Rialland, "Virtualization of food supply chains with the Internet of Things," *Journal of Food Engineering*, vol. 176, pp. 128–136, 2016.
- [5] M. A. Rahman, M. S. Hossain, and G. Fortino, "IoT-enabled food spoilage detection and prediction," *IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 9770–9781, 2021.
- [6] G. Kou, Y. Xu, Y. Peng, F. Shen, Y. Chen, and Y. Shi, "IoT-enabled traceability for cold chain logistics: A literature review," *Food Control*, vol. 125, art. no. 107972, 2021.
- [7] S. S. Kamble, A. Gunasekaran, and S. A. Gawankar, "Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications," *International Journal of Production Economics*, vol. 219, pp. 179–194, 2020.
- [8] Y. Zhang, L. Zhang, and X. Wang, "Machine learning approaches for food quality prediction: A systematic review," *Food Control*, vol. 123, art. no. 107849, 2021.

- [9] L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of deep learning in food: A review," *Comprehensive Reviews in Food Science and Food Safety*, vol. 19, no. 5, pp. 2166–2186, 2020.
- [10] J. Parfitt, M. Barthel, and S. Macnaughton, "Food waste within food supply chains: Quantification and potential for change to 2050," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 365, no. 1554, pp. 3065–3081, 2010.
- [11] F. Tian, "A supply chain traceability system for food safety based on HACCP, blockchain, and Internet of Things," in *Proc. 2017 Int. Conf. Service Systems and Service Management (ICSSSM)*, 2017, pp. 1–6.
- [12] F. Casino, V. Kanakaris, T. K. Dasaklis, C. Patsakis, and C. Douligieris, "Blockchain-based food supply chain traceability: A case study in safety and quality," *Computers & Industrial Engineering*, vol. 136, pp. 333–347, 2019.
- [13] J. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big data in smart farming: A review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017.
- [14] E. O. Ojo, M. Raman, and Y. L. Chong, "Achieving sustainable performance in food supply chains through digital technologies adoption," *Sustainable Production and Consumption*, vol. 27, pp. 1373–1387, 2021.
- [15] M. M. Aung and Y. S. Chang, "Traceability in a food supply chain: Safety and quality perspectives," *Food Control*, vol. 39, pp. 172–184, 2014.

Authors



Ramesh Babu M is a research scholar in Bharathiar University, Tamil Nadu, India. He holds a master's in computer applications degree from Bangalore University, Bangalore, India and is currently pursuing his PhD in the field of Internet of Things (IoT).

With over 10+ years of experience in teaching, and research, he has published national and international research papers in Journals indexed in IEEE, and Scopus.

His area of interests includes Artificial Intelligence, Data mining, Big Data Analytics, Internet of Things, Mobile Application Development, and Oop's using Java. He has attended more than 10+ invited talks, 12+ guest lectures, 2+ International conference, 2+ national and international workshops.



Dr. S. Rajeswari is an Associate Professor in the Department of Data Sciences & Analytics, School of Social Sciences, M. S. Ramaiah University of Applied Sciences, Bengaluru, India. She holds a Ph.D. in Computer Science from Bharathiar University (2018), supported by earlier degrees including M.Phil., M.Sc., and MCA. Her research interests include Data Mining & Warehousing, Cloud Computing, MANET, and Artificial Intelligence. A recipient of a UGC-funded research grant for her work on jamming attack prevention in mobile

ad hoc networks, She has authored over 15 publications in UGC- and Scopus-indexed journals, conference proceedings, and a recent book chapter. She has guided Ph.D. scholars, served as NAAC and ISO coordinator, and contributed as a subject expert on Board of Studies and Doctoral Committees. She is an authorized Cyber Security Academy Instructor (Palo Alto Networks) and holds certifications in Cloud Computing and Python. She actively contributes to academic service through conference organization, editorial and peer-review roles, and professional membership with IAENG.