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Development of a Food Safety Monitoring System Using IOT Sensors and Data Analytics

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Abstract

The food area has long faced the project of monitoring meals satisfactory. making sure food safety is a primary problem inside the global meals quarter. Rotten meals could be very risky for humans and should in no way be eaten. it's far crucial that national government and international organizations can perceive emerging meals protection concerns and trouble speedy early caution signals to growth the resilience of meals structures towards meals protection dangers. As a end result, cutting-edge strategies for nucleofection (e.g., turning in CRISPR-CAs9 riboproteins) or transfection of plasmids or RNA into CD34+ cells are nevertheless linked to considerable toxicity in the target. extraordinary styles of liposomes are also nevertheless being developed. improvements in non-viral transport would facilitate the challenging project of circumventing the GMP production of surprisingly luxurious viral vectors. advanced information analytics techniques and IoT sensors are used to analyze the collected data, identify styles, traits, anomalies, and increase predictive fashions to forecast potential threats.

Keywords: Food Safety, Monitoring, IoT Sensors, Data Analytics, OGSA-HSV (Open Grid Service Architecture-Hash Based Validation).

1 INTRODUCTION

The food business has always faced the difficulty of monitoring food quality. The only method of checking food quality in the past was manual inspection, which was labour-intensive and prone to mistakes. The monitoring of food quality has grown more precise and environmentally friendly with the introduction of IoT and machine learning technology (Donaghy et al., 2021). Real-time food tracking and data analysis to forecast food freshness are made possible by these technologies. The performance of system learning algorithms in food quality monitoring has been widely demonstrated. These algorithms use information from sensors, like fuel levels, temperature, humidity, and others, to forecast the freshness of food. Machine learning algorithms have been demonstrated in numerous studies to be a promising approach for monitoring food quality since they can reliably forecast the freshness of food.

Previously, the simplest method of checking meals high-quality become manual inspections, which is probably hard and prone to errors. the appearance of IoT and gadget getting to know generation has progressed the accuracy and efficiency of meals nice monitoring (Adisa et al., 2024). those technology permit statistics evaluation to forecast meals freshness and real-time food item monitoring. sample records is to be had to reveal how properly system studying structures monitor the fine of food. these algorithms can examine sensor data, which includes temperature, humidity, and fuel concentrations, to forecast the freshness of food (Elufioye et al., 2024). numerous statistical strategies primarily based on texture and fragrance characteristics, facts mining, and device gaining knowledge of were proposed to reap early tracking and electronic evaluation of meals exceptional. all these processes are able to sufficiently resolving a part of the difficulty.

An internet of factors (IoT)-based totally system that video display units critical food protection parameters in actual-time, along with temperature, humidity, and the presence of pathogens, can offer stakeholders with a level of visibility and control over food product great and safety that has in no way been feasible earlier than. This concept paper presents an implementation method that gives a street map for imposing IoT sensors, putting in place infrastructure for records collecting and transmission, analysing records insights, integrating with modern-day systems, and supporting applications for potential building and schooling. Adopting real-time tracking and control structures powered by way of the internet of factors (IoT) has several advantages, such as higher patron confidence, lower contamination incidences, higher efficiency and value savings, and advanced protection requirements. through proactively coping with meals protection risks and making sure compliance with regulatory requirements, corporations can protect public health, shield brand recognition, and enhance their aggressive function within the marketplace (Fan, 2019). As we move towards a destiny wherein generation plays an increasingly pivotal position in meals protection control, collaboration and collective motion from enterprise gamers, regulatory businesses, and era vendors can be vital to realise the entire ability of IoT-based answers. the primary contributions of this paper are:

- Creating sensor networks and IoT devices that can track important variables like temperature, humidity, pH, and pollutants at different points during the manufacturing, processing, storage, and transportation of food.
- Real-time food inventory data can be obtained from the system, which improves food supply chain management, minimises food waste, and enables better stock management.

The rest of the paper is structured as follows. Section II, which follows, reviews related work. The suggested framework for this work is presented in Section III. Section IV presents the outcome of the framework architecture. Presenting the study's outcomes and discussing potential avenues for future investigation

2 RELATED WORK

When developing food safety systems, it is important to take into account the increasing body of scientific information indicating that new food safety concerns are influenced by climate change. The timely development and implementation of solutions aimed at mitigating the effects of climate change may be facilitated by the early detection of climate change-related issues through the monitoring of environmental health parameters, food safety, and diseases affecting humans and animals. Reduced production, more irrigation, modified agricultural methods, less alternatives for land management, and more insect pressure are the causes of these effects (Hasan et al., 2023). Decision support systems and big data analytics can be used together to forecast hazards related to climate change and make decisions to keep them from materialising into actual risks. These authors propose a number of scenarios that would be especially well-suited to the eventual development of such a system. For example, (i) the dairy industry, which is vulnerable to effects of climate change on the safety and quality of its products and where a wealth of data is being collected along the production chain that could be used as big data to inform potential control measures could be considered.

A smart food stock gadget that manages the supply chain using blockchain and net of factors technologies. meals waste is reduced and food protection is ensured by using the device, which tracks meals motion from farm to consumer (Iftekhar & Cui, 2021). The system tracks food's journey from farm to plate by fusing blockchain technology with Internet of Things sensors. To guarantee food quality and safety, the system makes use of smart contracts. Advanced technology and resources are needed for system deployment. Blockchain technology utilisation inside the system can potentially be constrained by concerns about security, scalability, and regulations. Wireless sensor networks with system learning for monitoring food quality (Ilugbusi et al., 2020; Jabbar et al., 2019). The system gathers information on food-friendly characteristics including pH, temperature, and humidity and uses machine learning to forecast food-friendliness. It is built around a wireless sensor network that gathers data in real-time on attributes that make food safe. To produce predictions, the pre-collected data is combined with a machine learning model.

An intelligent cloud-based and Internet of Things-based food safety management solution. The system gathers information on temperature, humidity, and gas concentrations—all of which are indicators of food safety and utilises cloud computing to analyse the information to deliver real-time alerts about food safety infractions (Jagtap & Rahimifard, 2019). The system is made up of numerous IoT devices and sensors that gather data in real-time. For analysis and real-time warnings, the data is sent to the cloud. The system is constrained by the requirement for cloud computing resources and the availability of a dependable internet connection. Furthermore, the system does not take into account other aspects like microbial development and is only capable of forecasting food safety breaches based on a few environmental factors (Halim-Lim et al., 2023; Mohammed et al., 2022). Analysis, effectiveness of decision-making, stability, and dependability. To enhance the decision-making process, the framework incorporates a two-player game-theoretic model with inspectors and food managers (Olusola, 2017; Tolcha et al., 2021). We demonstrate through comparison simulations that the suggested model performs better than current approaches in terms of statistical categorisation analysis, decision-making efficiency, dependability, and stability as well as data assessment efficacy. By utilising the ideas of Industry 4.0 and the Internet of Things, this study advanced the assessment of food quality and offered a novel strategy to enhance food quality control in the sector (Ukoba & Jen, 2023; Vincent et al., 2021). This paper's drawback is the lack of a thorough investigation of the computing and network needs of the suggested framework, which could make it challenging to employ in real-world scenarios.

3 METHODOLOGY

A smart food monitoring system uses IoT and OGSA-HSV (Open Grid Service Architecture-Hash Based Validation) to guarantee food safety. In order to predict the risk of food rotting, the system uses an OGSA-HSV (Open Grid Service Architecture-Hash Based Validation) to collect data on the temperature, humidity, and weight of food products. The system consists of several Internet of Things devices and real-time data collection sensors. A significant quantity of tagged data was needed by the system to train the MLLWR (Machine Learning Leverage Weighting Regression). Moreover, this approach only considers a small number of environmental factors to predict food spoilage; additional factors such as microbial growth are ignored. Safety and food waste concerns are fully handled by the food monitoring system. Our technology gives consumers a strong tool to check food quality by combining real-time data collection, simple installation, and precise prediction. The technology recognises changes in food quality and notifies consumers before it spoils by gathering and interpreting data from several sensors.

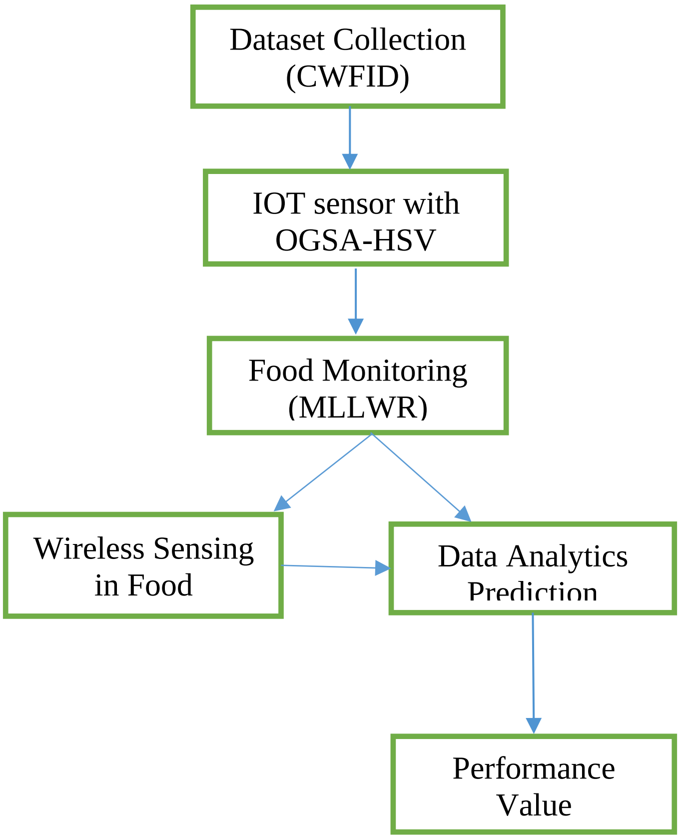


Figure 1: Proposed Work Flow

According to this suggested concept, photos are first taken with a high-resolution camera and subsequently sent via Internet of Things devices to the cloud server. After that, the principal component analysis algorithm is used to extract features. Next, a trained OGSA-HSV (Open Grid Service

Architecture-Hash Based Validation) is used to classify the photos. Figure 1 displays the model's block diagram.

Algorithmic View of MLLWR

The observations that are currently available are T_1...,, T_K, where K is the current time instant ϋ. Next, as demonstrated below, we construct a length p state vector S_i = [$S_i - p_{-1}$,..., S_i] for all $I \leq K -$ L, as well as a response variable Y_i = S_i. The lag length p required to construct the augmented state is specified by this parameter, which is an integer. Small delays are more susceptible to noise and variations in dynamics. Even when the system dynamics are averaged over the same scale, large delays react to noise more robustly. The set of hyperpairs (x_i, y_i) forms a scatter plot in p + 1 dimensional space. The scatter plot represents a noisy realisation of the predictive map, assuming that the states created in this manner capture all the information regarding the system dynamics.

Algorithm 1

Let us specify the Prediction map: g
Scatter plot: p
Neighborhood space $\boldsymbol{X_k}$
Begin
For any state vector $\boldsymbol{S_i} \in \boldsymbol{S_i} - \boldsymbol{p_{-1}}$
then
Prediction of Time;
for (ŋ ≤ L + ψ)
then
$\dot{\boldsymbol{y}}_{\boldsymbol{i}}$ = g($\boldsymbol{x_i}$)
end

Here, g is the predictor, a smooth function of yÌ_i = g(x_i). This is a reasonable model considering that the designers assume that the predictions smoothly follow historical trends. To anticipate the target's location, we aim to estimate ẏ_i at time ((Å ≤ L + Ï) seconds. If (p + 1) is the dimension of the distributed space, then r is the size of the neighbourhood whose members estimate.

The rth lowest integer between the distances between x_i,where i = 1, 2,...,K − L, and x_K is denoted by $h_K h_K$. In the p-dimensional subspace, let k(·) be the Euclidean distance. Let k(·) be a symmetric kernel function meeting the specified requirements.

$$k(x) > 0 \, for \, |x| < 1 \, and \, k(x) = 0 \, for \, |x| \, 1,$$

$$k(-x) = \kappa(x),$$

k(x) is a non-increasing function for x_0.

We select local inference weight according to

$$w_i = k \, (h_K^{-1} \, ||x_i - x_K||). \tag{1}$$

The weighting technique is based on the distance in the state space. A delayed tap (p = 2) is chosen for simplicity, leading to the state x_i= [S_i]. The objective is to utilise the available covariate-response pairs (x_i, y_iin I K L to estimate the response y_k for the current state vector $x_K x_K$. Keep in mind that the foundation of K–L is the idea of weighting according to distance within the state space. A delayed tap (p = 2) is chosen for simplicity, leading to the state x_i = [S_i]. The kernel function (3) is used to calculate the regression weights w_i and estimate the distance between the current state x_K and x_i. The weights that are mentioned highlight these training examples in equation 1.

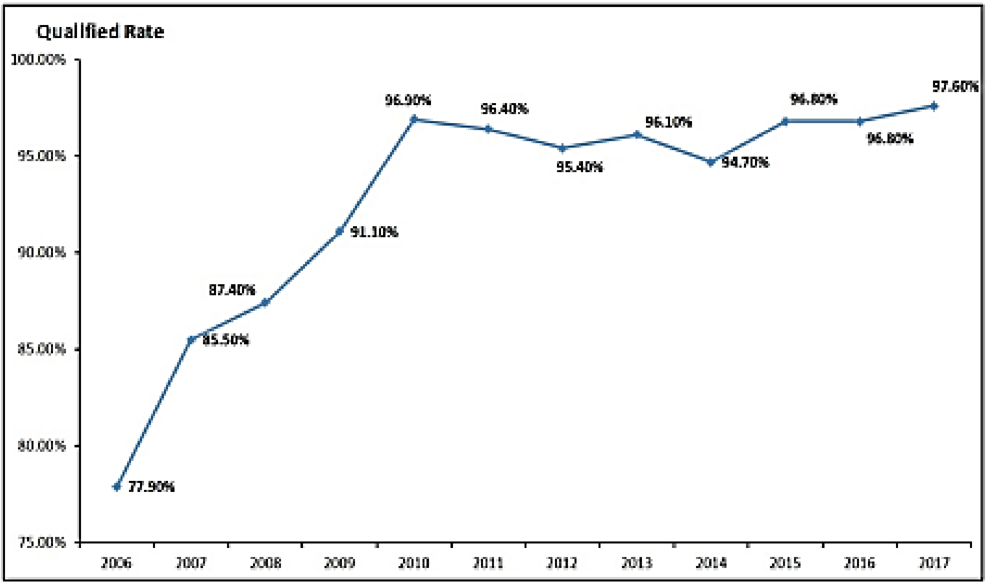
Due to the limited bandwidth h_K of the local weights w, as stated in (2), the weight matrix W only contains r nonzero diagonal elements. In a similar vein, it is possible to specify that the outer $\sum_{i=1} K - L$ $\sum_{i=1} K - L$ can only be sustained in a local environment with radius h. $\sum || x_i - x_K || <$ h $\sum || x_i - x_K || <$ h. Consequently, rather than K → L, the length of the related data vectors is r → K → L. To reduce computational costs, it is desirable to choose a small environment size r, but it cannot be as small as the regularity d. h. As a result, the invertibility of Z_T WZ is compromised. The polynomial coefficients calculated according to equation (2) are used for the next prediction from a given observation x_K.

$$y\grave{}\_i = \sum\_(q=1)▒〖Q (\beta\_(qZ\_q))\grave{}〗(x_K) \quad (2)$$

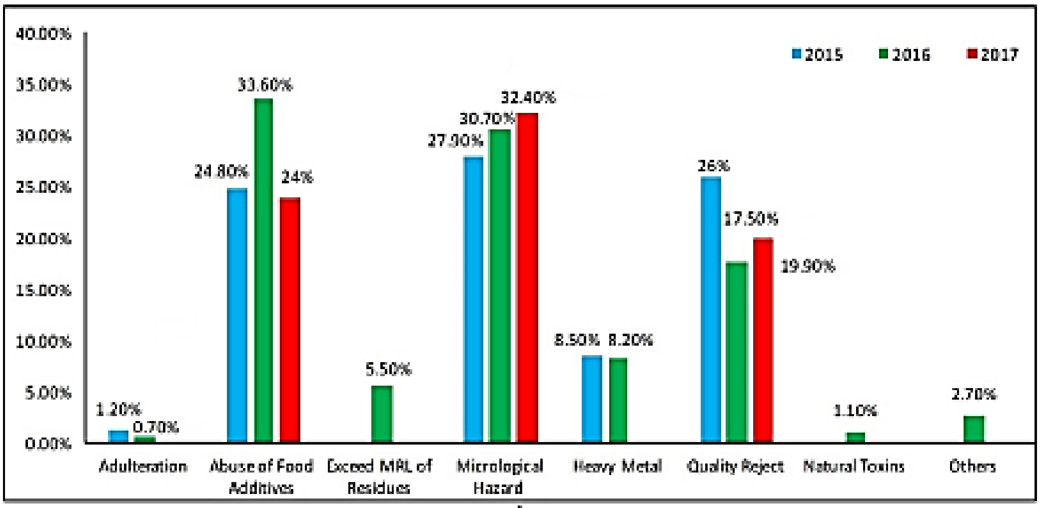
Utilise a predictor of the type (x_K) coefficients of the local polynomial to estimate Q locally using a polynomial of degree Z. This can be done by minimising the weighted local squared error, as the equation above illustrates:

4 RESULT ANALYSIS

One exciting technology development that has the potential to increase food safety and decrease food waste is an intelligent food monitoring system built on the Internet of Things and machine learning. The system is made up of sensors that are mounted in kitchen and food storage appliances to gather information on temperature, humidity, and other elements that can have an impact on food quality. We describe an empirical analysis of an IoT- and machine learning-based intelligent food monitoring system in this article. The conventional approaches to guaranteeing the freshness and quality of food still rely heavily on manual testing and human observation. We suggest an intelligent food monitoring system that leverages deep learning to automate the process of detecting foods and forecasting their quality and freshness in order to address these issues. To solve these difficulties, we propose a smart food monitoring system that automates the process of detecting food and forecasting its quality and freshness using deep learning. In this work, we provide a deep learning method trained on a dataset containing sensor readings and pertinent rotting levels for different fruits and vegetables. Sensors are installed in food storage facilities and kitchen equipment to collect data on temperature, humidity, and other variables that may impact food quality.



(a)



(b)

Figure 2: The Statues of Food Safety Risk Monitoring (a) Trend of Quality Rate by Monitoring (b) Identifying the Main Risk

The certification rate is the primary criterion used to assess the efficacy of food safety monitoring (Figure 2). Next, using the monitoring data to identify the primary risks, dietary control priorities are established. There are a number of reasons behind this, the most significant of which is the dearth of comprehensive and insightful data. Furthermore, because there are insufficient sentinel hospitals and epidemiological investigations at FBD sites frequently fail to gather unconsumed food samples in a timely manner, active FBD surveillance networks are not completely utilised. The majority of significant species of bacteria, but also a small number of viruses and parasites, are biologically active elements in food. Plans for monitoring include parasites such liver rot, which are particularly significant.

A major problem in monitoring chemical risks is integrating food and environmental monitoring, especially for heavy metals and POPs, as the source of most food contamination is likely to be environmental. High concentrations of cadmium in rice as a result of mining or metallurgical industry soil contamination and POPs in animal flesh as a result of electronic waste being deposited in the soil are two prominent instances.

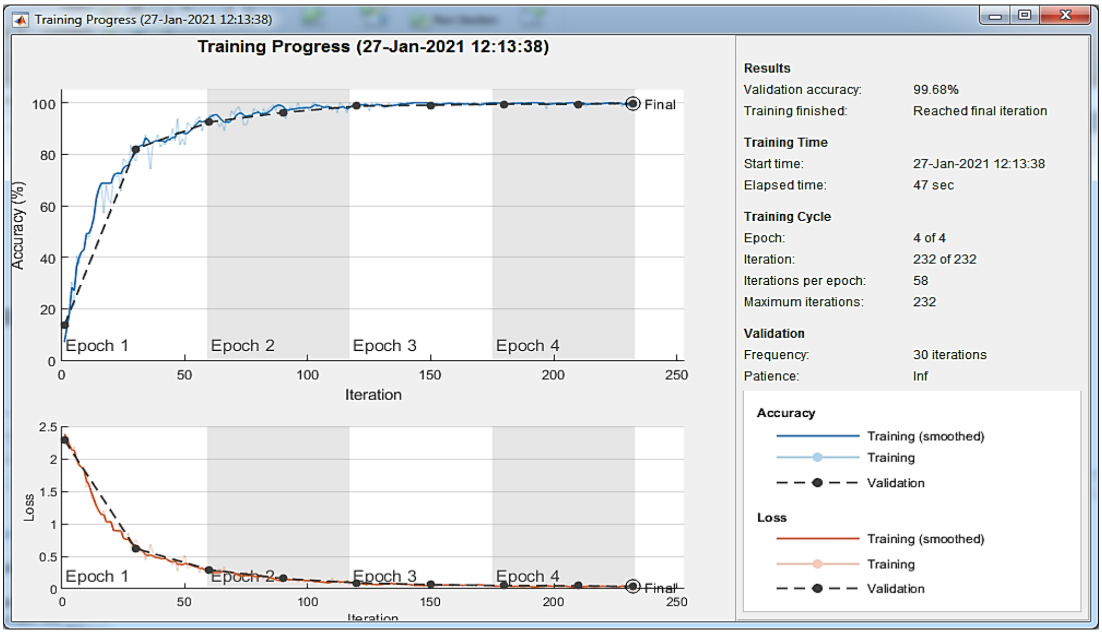


Figure 3: Training Process

The above figure 3 specifies Training process of the validation, time, Accuracy, Loss and elapsed time, on the time basis the elapsed time with respect to Changes.

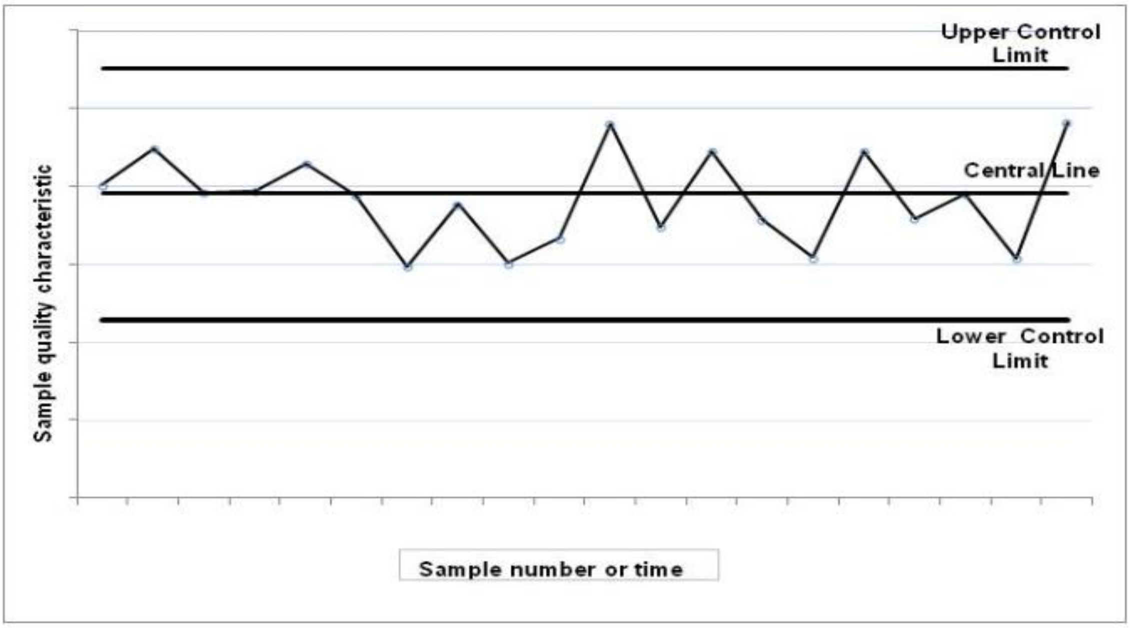


Figure 4: Sample Quality Characteristic

The Central Line (CL), the Upper Control Limit (UCL) and Lower Control Limit (LCL) of the control chart, as well as the characteristic values displayed on the graph, are displayed in Figure 4. The process is considered under control if there is no obvious trend and these values fall within reasonable boundaries. If the points relate outside of the control bounds or are arranged strangely, the process is perceived as being out of control. The confusion matrix is shown in Figure 5. Hardware requirements for the suggested model include an NV GTX, 1 TB HDD, Windows 10 OS, and a Ryzen 5/6 series CPU. The effective deployment of the IoT-based real-time monitoring system is possible if this implementation strategy is followed.

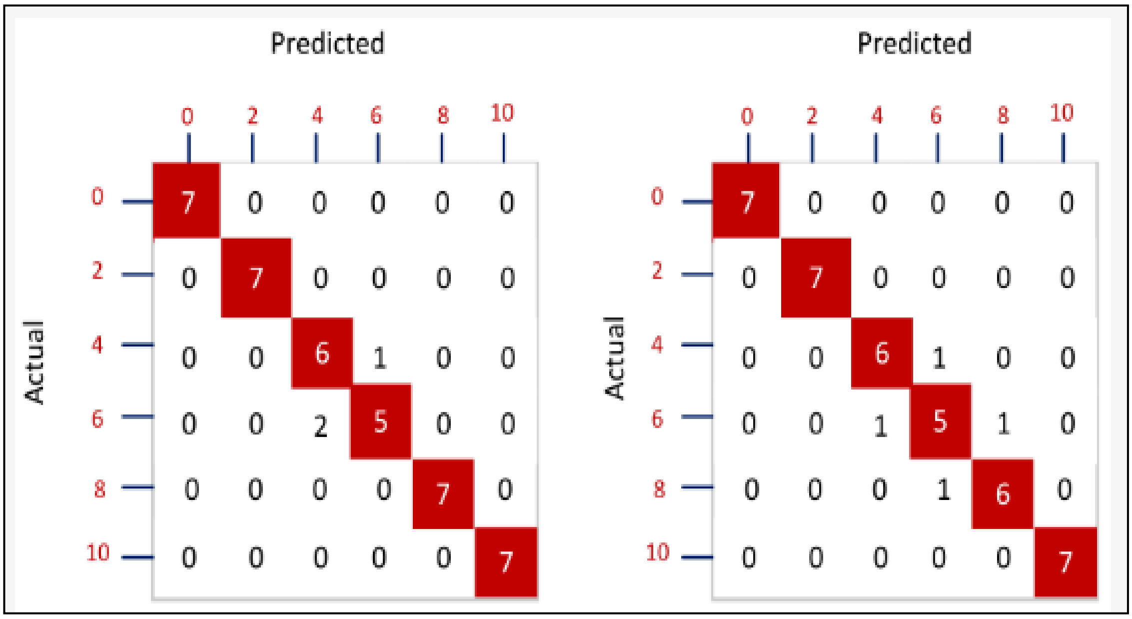


Figure 5: Confusion Matrix

Including other variables generated by data sources outside the food safety industry that could affect food safety, including the mycotoxin climate, could improve the model's performance. In the future, the comparison of DLs and the integration of more data sources may be considered.

5 CONCLUSION

In conclusion, by utilising wireless communication technology, microcontrollers, and sensors to identify and track the quality and freshness of fresh food, smart food monitoring systems can greatly improve food safety and reduce food waste. These systems lessen the risk of foodborne illness and the negative effects of food waste on the economy and environment by assisting consumers and professionals in the food business in making educated decisions about when to consume or reject food. The proliferation of Internet of Things (IoT) technology has led to the increasing accessibility, affordability, and suitability of smart food monitoring systems for integration into various organisational and individual operations. These systems can be modified to meet various needs and specifications in order to create a food monitoring and control system that is more comprehensive and efficient. They can also be integrated with other intelligent devices and services.

REFERENCES

[1] Donaghy, J. A., Danyluk, M. D., Ross, T., Krishna, B., & Farber, J. (2021). Big data impacting dynamic food safety risk management in the food chain. *Frontiers in microbiology*, *12*, 668196. https://doi.org/10.3389/fmicb.2021.668196

[2] Adisa, O., Ilugbusi, B. S., Adewunmi, O., Franca, O., & Ndubuisi, L. (2024). A comprehensive review of redefining agricultural economics for sustainable development: Overcoming challenges and seizing opportunities in a changing world. *World Journal of Advanced Research and Reviews*, *21*(1), 2329-2341.

[3] Elufioye, O. A., Ike, C. U., Odeyemi, O., Usman, F. O., & Mhlongo, N. Z. (2024). Ai-Driven predictive analytics in agricultural supply chains: a review: assessing the benefits and challenges of ai in forecasting demand and optimizing supply in agriculture. *Computer Science & IT Research Journal*, *5*(2), 473-497. https://doi.org/10.51594/csitrj.v5i2.817

[4] Fan, H. (2019). Theoretical basis and system establishment of China food safety intelligent supervision in the perspective of internet of things. *IEEE Access*, *7*, 71686-71695. https://doi.org/10.1109/access.2019.2919582

[5] Hasan, I., Habib, M., & Mohamed, Z. (2023). Blockchain database and iot: a technology driven agri-food supply chain. *International Supply Chain Technology Journal*, *9*(3), 40-45. https://doi.org/10.20545/isctj.v09.i03.01

[6] Iftekhar, A., & Cui, X. (2021). Blockchain-based traceability system that ensures food safety measures to protect consumer safety and COVID-19 free supply chains. *Foods*, *10*(6), 1289. https://doi.org/10.3390/foods10061289

[7] Ilugbusi, S., Akindejoye, J. A., Ajala, R. B., & Ogundele, A. (2020). Financial liberalization and economic growth in Nigeria (1986-2018). *International Journal of Innovative Science and Research Technology*, *5*(4), 1-9.

[8] Jabbar, W. A., Kian, T. K., Ramli, R. M., Zubir, S. N., Zamrizaman, N. S., Balfaqih, M., ... & Alharbi, S. (2019). Design and fabrication of smart home with internet of things enabled automation system. *IEEE access*, *7*, 144059-144074. https://doi.org/10.1109/access.2019.2942846

[9] Jagtap, S., & Rahimifard, S. (2019). Unlocking the potential of the Internet of Things to improve resource efficiency in food supply chains. In *Innovative Approaches and Applications for Sustainable Rural Development: 8th International Conference, HAICTA 2017, Chania, Crete, Greece, September 21-24, 2017, Selected Papers 8* (pp. 287-301). Springer International Publishing. https://doi.org/10.1007/978-3-030- 02312-6_17

[10] Halim-Lim, S. A., Baharuddin, A. A., Cherrafi, A., Ilham, Z., Jamaludin, A. A., David, W., & Sodhi, H. S. (2023). Digital innovations in the post-pandemic era towards safer and sustainable food operations: A mini-review. *Frontiers in Food Science and Technology*, *2*, 1057652. https://doi.org/10.3389/frfst.2022.1057652

[11] Mohammed, M., Riad, K., & Alqahtani, N. (2022). Design of a smart IoT-based control system for remotely managing cold storage facilities. *Sensors*, *22*(13), 4680. https://doi.org/10.3390/s22134680

[12] Olusola, A. O. (2017). Rural-Urban migration in Nigeria. *International Journal of Management Sciences (IJOMAS)*, *10*(1), 79-87.

[13] Tolcha, Y., Kassahun, A., Montanaro, T., Conzon, D., Schwering, G., Maselyne, J., & Kim, D. (2021). Towards interoperability of entity-based and event-based IoT platforms: The case of NGSI and EPCIS standards. *Ieee Access*, *9*, 49868-49880.

ISSN: 3049-1282

[14] Ukoba, K., & Jen, T. C. (2023). *Thin films, atomic layer deposition, and 3D Printing: demystifying the concepts and their relevance in industry 4.0*. CRC Press.

[15] Vincent, A. A., Segun, I. B., Loretta, N. N., & Abiola, A. (2021). Entrepreneurship, agricultural value-chain and exports in Nigeria. *United International Journal for Research and Technology*, *2*(08), 1-8.