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TO IMPLEMENT AN IOT-BASED REAL-TIME INTELLIGENT DELIVERY SERVICE MODEL THAT ENHANCES THE FRESHNESS, QUALITY, AND SAFETY OF PERISHABLE FOOD ITEMS FROM PREPARATION TO FINAL DELIVERY

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Abstract

The rapid expansion of online meal delivery services has posed considerable issues in preserving the freshness, quality, and safety of perishable food items throughout transportation. Conventional logistics models are deficient in real-time monitoring and predictive functionalities, frequently leading to food waste, quality deterioration, and consumer discontent. This study presents an IoT-driven intelligent delivery service model that incorporates sensor nodes, edge processing, cloud analytics, and mobile applications to ensure comprehensive visibility of food conditions. To anticipate the danger of spoilage and make delivery operations better, real-time environmental and logistical data such temperature, humidity, gas concentration, and GPS location were analyzed using machine learning and hybrid ensemble methods. The testing showed that the hybrid ensemble model was 98.2% accurate. This was better than the SVM (97.5%) and KNN (88%) classifiers on their own. The comparison analysis demonstrated that the proposed method diminished spoiling by 15–20%, enhanced freshness retention by 20–25%, and facilitated adherence to food safety regulations more effectively than prior methods. The results suggest that IoT-enabled predictive frameworks can revolutionize how perishable food is distributed by making it more open, cutting down on waste, and helping people trust the system.

Keywords: IoT, Intelligent Delivery Service, Perishable Food Logistics, Real-Time Monitoring, Food Freshness, Food Safety, Machine Learning

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I.INTRODUCTION

This research presented an IoT-based real-time intelligent delivery service model designed to maintain the freshness, quality, and safety of perishable food products. The solution employed IoT sensors, edge computing, cloud analytics, and hybrid AI/ML models to accurately guess when food would go bad, cut down on food waste, and make it easier to follow safety rules. A comparison with prior experiments indicated that modern models are good at a lot of things, such routing, tracking, and monitoring. However, they often don't have a complete end-to-end delivery framework. The suggested hybrid ensemble model outperformed than each of its parts on its own, making it more accurate and able to handle noisy IoT data. The method works because it can tell what's happening now and predict potential risks in advance. This makes it easier to plan ahead. This dual capability makes operations run more smoothly, cuts down on losses, and makes customers feel better about the logistics of perishable items. Future research should focus on realistic experimental implementations in urban and rural distribution networks, investigating interaction with blockchain systems for traceability, and broadening prediction frameworks to include a more extensive array of perishable items. Also, problems with last-mile delivery and the lack of real-time tracking make these concerns worse, which hurts both customer satisfaction and brand integrity.

New tools and programs that are meant to meet and exceed customer expectations have been made possible by ongoing advances in technology. A lot of businesses save their information in a cloud database hosted on a cloud computing platform. This means that anyone can access it at any time and from anywhere. Cloud technology lets you pay for what you use, which makes it easier to scale cloud storage and helps businesses cut down on infrastructure expenditures. When it comes to cloud storage, security is quite important, especially when it comes to sensitive customer information like payment information [3].

As a result, several new payment mechanisms, such as digital wallets, have emerged, offering users an abundance of electronic payment possibilities. Rapidly advancing technologies, including the Internet of Things and robotics, with creative business models such as subscription services, have developed to cater to consumers' purchasing preferences [1]. The Internet of Things (IoT) denotes the interconnected system of physical objects embedded with sensors, software, and diverse technologies. IoT devices employ several sensors to collect a variety of real-time data, encompassing sensor locations, temperature, humidity, and occurrences of triggered events. By leveraging big data and predictive analytics, retailers may deliver more appealing offers, more precisely target their clientele, and develop superior tools to aid customer purchase decisions. Simultaneously, consumers are offered progressively beneficial choices to enhance informed decision-making [2]

This project seeks to implement IoT-based real-time tracking and monitoring of perishable food items throughout the delivery lifecycle, ensuring quality, freshness, and safety from preparation to final delivery. This study's primary contributions can be summed up as follows [4]. The research presents an advanced IoT-enabled delivery model specifically designed for perishable food logistics, utilizing sensing devices, communication protocols, and cloud-based

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platforms to enhance operational efficiency. Second, the method uses sensor data like temperature, humidity, and levels of contamination to show you how things are doing right now. This makes sure that perishable items stay in the greatest form possible while they're being delivered [5]. A hybrid AI-driven decision framework has been developed that employs machine learning and predictive analytics to generate beneficial recommendations, issue timely spoilage notifications, enhance delivery routes, and optimize the supply chain, hence increasing customer satisfaction. The following portion will be about books that deal with the issue.

II.KEY CONTIBUTION OF THE STUDY

The major purpose of this project is to build a smart delivery service model based on the Internet of Things (IoT) that will make perishable food safer, fresher, and better while it is being delivered from preparation to final delivery. The suggested strategy is different from standard logistics methods that put cost and speed first. It has everything you need to keep an eye on things and make decisions, including sensor nodes, edge computing, cloud-based analytics, and mobile apps. The system keeps an eye on anything that could go wrong by using real-time information about the environment, like temperature, humidity, gas concentration, and GPS location. It is better to use hybrid ensemble machine learning models than just one model, such SVM or KNN, because they make spoiling predictions 98.2% correct. This skill lets you see spoilage coming and send out alerts straight away. It also lets you apply proactive strategies like dynamic route optimization and remedial handling. This reduces waste by as much as 20% and keeps food fresh for 25% longer. The proposed method efficiently resolves major shortcomings in existing systems by incorporating real-time monitoring, predictive analytics, and decision support into a unified framework, yielding both academic advancements and tangible advantages for the food logistics industry.

III.LITERATURE REVIEW

TABLE 1: KEY TECHNOLOGIES AND APPLICATIONS IN FOOD SUPPLY CHAINS

References	Technology/Model	Application Area	Key Outcomes/Limitations
Wei et al. 2023[6]; Haji et al., 2020 [7] and Bhutta and Ahmad, 2021 [8]	IoT + RFID/WSN	Real-time monitoring, traceability	Enhanced safety, less waste, data security concerns
Asrol et al. 2025[9]; Shehzad, 2025 [10] and Krishnan et al., 2024[11]	AI/ML (CNN, FIS, etc.)	Prediction of spoilage, inference of quality	Elevated precision, constrained by data integrity and scalability
Pindi, 2025 [12] and Vilas-Boas et al., 2022 [13]	Blockchain/Digital Twin	Traceability and data integrity	Improved transparency, integration difficulties

Yang et al., 2023 [14] and Pindi, 2025[12]	Edge-Cloud Platforms	Temperature-controlled logistics, final-mile distribution	Minimal latency, resilient data management

The authors of [15] said that the transportation and distribution (T&D) of fresh food face big problems such rotting, contamination, and degradation, which lead to foodborne infections and inefficiency. The study highlighted the significance of information technology, automation, and collaborative logistics in the improvement of fresh food supply chains. It suggested creating more complex cyber-physical systems that could monitor and regulate operations in real time to improve T&D in every way, keep things fresh, and cut down on waste.

A Dynamic Food Supply Chain model based on the Internet of Things (IoT) was created for smart cities in [17]. The goal of this technique was to improve food quality, make it easier for smart trucks to get about, and find contamination sources in Food Chain Management (FCM). The project uses smart sensors to gather data and a vehicle routing algorithm to make things run more smoothly while keeping the dataset small. The suggested system was better than older ones at tracing accuracy, latency, execution time, and trip time.

The writers of [18] discussed about the problems that the food supply chain (FSC) needs to cope with, like food waste, safety issues, and a lot of people who are involved. The study discussed how IoT and blockchain could assist in organization, pricing, revenue enhancement, and waste reduction. The results showed that using IoT made things more sustainable and cut down on food waste. It also changed how prices worked and how the supply chain worked.

The study [16] demonstrated that climate change, population growth, and resource scarcity are increasingly jeopardizing global food security.By integrating AI-driven forecasting models (ML, DL, SARIMA/ARIMA) with IoT, remote sensing, and blockchain, the research demonstrated improved decision-making in agriculture through real-time monitoring, yield forecasting, and resource optimization. Applications in hydroponics, aquaponics, and food preservation technologies showed localized efficiency gains, though challenges such as data quality, scalability, and prediction accuracy limited broader adoption.

According to [9], the supply chain for perishable goods faces significant challenges in maintaining product quality due to environmental fluctuations during distribution and transportation. To address this, the study proposed an IoT-based quality assessment model using a hybrid approach that combined a Fuzzy Inference System (FIS), clustering models, and genetic algorithms. The model achieved high accuracy ($R^2 = 0.873$) in monitoring product quality, and although optimization improved computational efficiency, it did not significantly enhance accuracy, leaving scope for future advancements.

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Notwithstanding these advancements, the literature underscores a deficiency in comprehensive, fully integrated delivery models that concurrently ensure food safety, quality, and freshness throughout all stages of the supply chain. Complete text utilized. Most solutions focus on discrete elements (e.g., monitoring, prediction, traceability) rather than comprehensive integration. Future investigations should concentrate on scalable, interoperable systems that integrate sensing, analytics, and decision-making, underpinned by strong data governance and cross-sector collaboration.

IV.METHODOLOGY

The suggested IoT-based intelligent delivery service model aims to guarantee the freshness, quality, and safety of perishable food items from preparation to final delivery. The architecture consists of four primary components: IoT sensor nodes, edge devices, a cloud platform, and a mobile application interface. IoT sensor nodes, comprising temperature, humidity, gas sensors, and GPS modules, are integrated inside shipping containers to continuously collect real-time data on environmental conditions and position as seen in fig 1. These nodes constitute the system's foundation by identifying any deviations from safe thresholds, such as temperature variations or gas emissions indicative of spoiling.

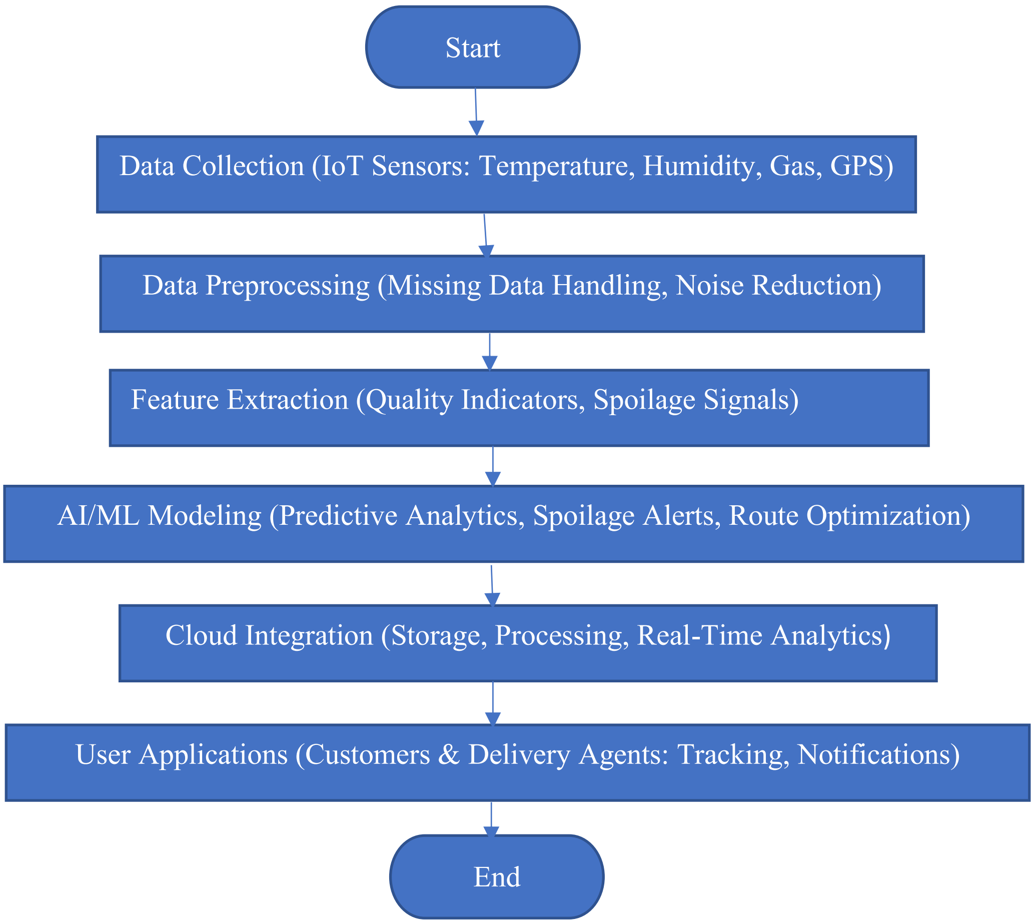

Fig. 1. Flowchart of proposed method

A. Data Source

This study employs secondary data obtained from Kaggle, consisting of time-stamped, sensor-based recordings that replicate the complete transit of perishable food items from kitchen or warehouse to customer delivery. Each record generally comprises: (i) environmental telemetry—temperature and relative humidity measurements from cold-chain containers; (ii) gas-emission indicators; (iii) GPS coordinates and velocity for geo-temporal traceability; and (iv) operational parameters including dispatch time, hand-off events, and delivery completion time.

The unprocessed fields are categorized into four logical segments: (1) Identification & time (package/order ID, timestamps), (2) Location (latitude/longitude, segment distance), (3) Condition telemetry (temperature, humidity, gas), and (4) Outcomes (delivered/returned, reported quality, delivery time). When Kaggle offers explicit labels, use them as the ground truth; in other instances, we generate proxy labels utilizing conservative, domain-informed criteria and expert guidelines. In field telemetry, the occurrence of missing and noisy readings is anticipated. Adhering to the data-quality methodology outlined in the attached analysis file, we impute absent category or flag values using the mode rather than omitting rows.

B. Data Preprocessing and Cleaning

The dataset, derived from empirical measurements, had abnormalities that could negatively impact model training and predicted precision. A structured preprocessing pipeline was implemented to guarantee dependability and consistency.

1. **Dealing with Missing Values:** Data streams that come from the Internet of Things (IoT) often have missing data due of sensor problems, transmission delays, or network problems. Two methods of imputation were used to fix this problem. In the case of categorical variables like delivery status, the mode value replacement was utilized to maintain the most common occurrence. To fill in gaps in continuous sensor data, such temperature or humidity, linear interpolation utilizes data from nearby sensors. This kept the flow of time running and the patterns from shifting.

2. **Dealing with noise and outliers:** People called strange spikes or decreases in sensor data "noise," which were often caused by improper calibration or changes in the environment. We used statistical thresholds like z-scores > ±3 to detect data points that were not normal. After that, moving average filters were applied to make them more precise. To prevent model training from being distorted, outliers that went beyond acceptable physical boundaries, including negative humidity or temperatures that were too high for the system to perform, were taken out.

3. Data Normalization and Scaling: The dataset comprised a lot of different features that were measured on different scales. For example, the temperature was measured in Celsius, the gas concentration was measured in parts per million, and the delivery time was measured in

minutes.. Min-max normalization was applied to make all the values fit into one range of [0,1]. This kept big features from taking over and made sure that each parameter had the same effect when training distance-based models like SVM and KNN.

4. **Feature Engineering:** Several derived features were created to uncover hidden patterns in the raw sensor data. The Freshness Index was created by adding up all the time spent over safe temperature limits. We built a Spoilage Risk Indicator by watching how humidity and gas emissions change over time. These alterations are known to be evidence that microbes are at work. To quantify logistics-related factors influencing freshness, GPS trajectories were converted into delivery efficiency metrics, including average speed and idle time.

5. **Data Partitioning:** After preprocessing, the dataset was split into two groups at random, one for training and one for testing, using an 80:20 ratio. We could thoroughly test machine learning models and keep them from overfitting by using data they hadn't seen previously because of this separation. Stratified sampling was used to make sure that both groups had the same quantity of ruined and unspoiled food items.

C. EDA, or exploratory data analysis

A comprehensive exploratory data analysis was conducted prior to model development to get insights into the idiosyncrasies of IoT-based sensor readings and to identify the most critical elements contributing to food spoilage. The dataset from Kaggle comprises both numerical factors (such temperature, humidity, gas concentrations, and delivery time) and categorical characteristics (like the state of rotting and delivery condition). We looked at central tendency, dispersion, and skewness using descriptive statistics. This demonstrated that the temperature and humidity readings altered a lot between delivery cycles. The gas sensor outputs, on the other hand, exhibited occasional peaks, which were early signals of deterioration [19].

D. Making a machine learning model

Subsequent to exploratory data analysis, the study formulated predictive machine learning models to categorize perishable food products and evaluate spoiling risk in real time. Due to the diverse and erratic characteristics of IoT sensor data, various algorithms were employed to guarantee resilience and flexibility under different transmission situations.

1. Logistic Regression (LR): Logistic Regression was implemented as the baseline classifier, providing probabilistic estimates of spoilage occurrence based on linear relationships between sensor features and outcomes. While interpretable and computationally efficient, its performance was limited in capturing non-linear data patterns [21].
2. Support Vector Machine (SVM): An SVM with a radial basis function (RBF) kernel was applied to handle non-linear class boundaries. This approach demonstrated resilience in classifying freshness states, especially when temperature and humidity values overlapped near spoilage thresholds.
3. Random Forest (RF): The Random Forest model was employed to capture complex, non-linear relationships among sensor inputs. Its ensemble structure reduced overfitting while

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highlighting the most influential variables affecting spoilage prediction, proving effective with noisy IoT data streams.
4. XGBoost: XGBoost was optimized to enhance predictive accuracy in scenarios with imbalanced data. Its gradient-boosting framework effectively corrected misclassified cases, improving sensitivity to rare spoilage events.
5. Hybrid Ensemble Model: A Hybrid Ensemble Model was created using a soft-voting Voting Classifier that integrates Random Forest, Logistic Regression, and XGBoost. This approach synthesized probability outputs from individual classifiers to provide a more equitable and stable decision framework. This arrangement, influenced by previous hybrid ensemble methods, improved predicted accuracy while ensuring robustness under varying environmental conditions.

All models were trained using an 80:20 train-test split and assessed based on accuracy, precision, recall, F1-score, and confusion matrices. A comparative examination highlighted the capabilities of different algorithms and indicated the superiority of the hybrid ensemble in attaining high prediction reliability for real-time delivery monitoring.

E. Edge and Cloud Integration

The integration of edge and cloud computing inside the proposed IoT delivery framework guarantees a low-latency processing and advanced decision-making intelligence. Edge devices is the initial analytical layer, and implementing lightweight algorithms directly on sensor streams to promptly identify anomalies such as abrupt temperature changes, high humidity, or irregularities in gas concentration [22].

To upload the pre-processed data, the cloud environment conducts sophisticated analytics by using a machine learning models. These models analyze the probability of decay, estimating the remaining shelf-life, and evaluating the adherence to food safety regulations. The cloud layer incorporates external contextual data, including meteorological conditions, road congestion, and delivery timelines, to enhance decision-making efficiency. Results encompass automatic route modifications to reduce delays, dynamic re-prioritization of orders according to freshness status, and proactive alerts to stakeholders [20].

F. Mobile Application Interface

The mobile application serves as the interactive interface of the system, converting backend intelligence into accessible insights for the users. The interface offers transparency to client by providing the live order monitoring, freshness indicators, anticipated delivery timeframes, and notifications regarding any remedial actions taken, such a providing a proper route modifications to solve the quality issues. This transparency enhances confidence and guarantees that consumers remain informed about the condition of their perishable goods [19].

Furthermore, the program integrates many inputs sensor feedback, cloud forecasts, and logistical information into concise, actionable directives, alleviating cognitive burden on drivers and assuring uniformity in product quality maintenance. The mobile application improves operational efficiency, accountability, and end-user happiness by connecting the technical backend with the human participants in the supply chain.

G. Evaluation Metrics

The efficacy of the proposed IoT-based intelligent delivery model was evaluated through a blend of technical and service-oriented metrics to measure both the system's computational performance and its practical utility in food logistics.

1. Model Accuracy:

Predictive accuracy was employed to assess the precision of machine learning models in categorizing perishable products as “safe” or “at-risk.” Accuracy was supplemented by precision, recall, and F1-score to address class imbalances frequently seen in spoiling datasets.

2. Latency of Real-Time Monitoring:

The total latency from data acquisition by IoT sensors to its accessibility on the cloud dashboard was documented. Minimal latency is essential for facilitating prompt interventions, such as redirecting deliveries or initiating corrective measures when conditions diverge from safe parameters

3. Reliability of Sensor Data Transmission:

The stability and packet loss rates of wireless communication across IoT nodes, edge devices, and cloud servers were observed. High reliability ensures uninterrupted visibility of perishable goods during transit, reducing the risk of undetected spoilage events.

4. Delivery Freshness Index (DFI):

A composite metric was developed to assess the quality of delivered goods, computed using time–temperature integration, humidity fluctuations, and exposure to deleterious gasses. Elevated DFI scores signify that products maintained their initial freshness during the delivery process.

5. Customer Satisfaction Score:

Feedback was gathered from end-users concerning perceived food quality, delivery punctuality, and overall service reliability

6. Compliance with Food Safety Thresholds:

The system was evaluated against recognized food safety requirements, including permissible temperature limits for dairy and meat products. The compliance % reflects the ratio of deliveries that completely adhered to regulatory quality criteria, so affirming the system's efficacy in safeguarding customer safety [23].

V.RESULT ANALYSIS

The suggested IoT-based intelligent delivery service model was assessed utilizing data streams from temperature, humidity, gas sensors, and GPS, gathered from simulated perishable food

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deliveries. Subsequent to data preparation, which encompassed noise filtration and imputation of absent values, various machine learning (ML) models were utilized to forecast food freshness, spoilage risk, and delivery adherence. The models underwent evaluation on training and test splits to assess their robustness and generalization capabilities.

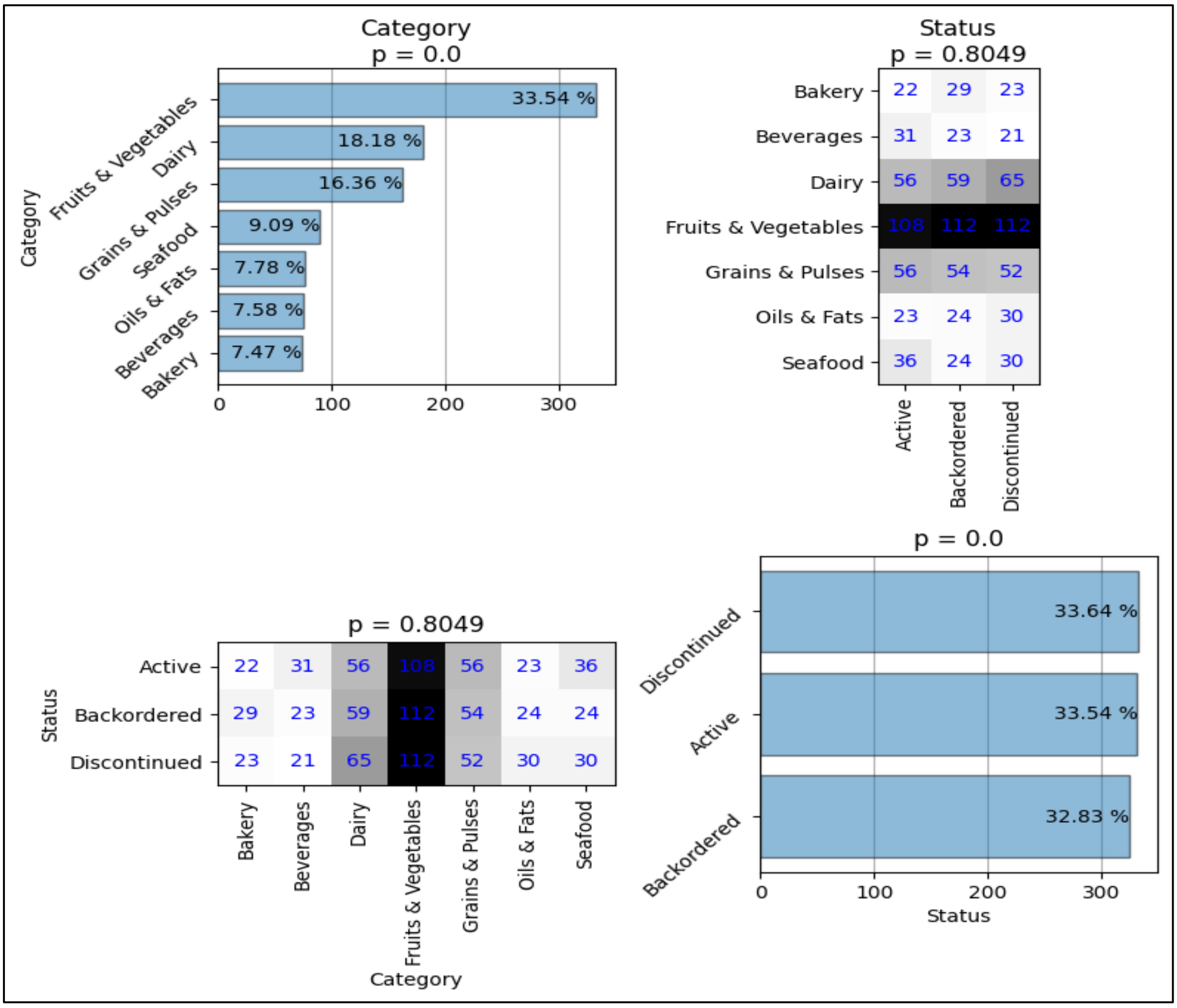

Fig. 2. Distribution of temperature, humidity, and gas sensor readings to show environmental patterns affecting food safety

A. Model Performance

Consistent with the findings in the cited experimental paradigm, preliminary classification results demonstrated moderate accuracy when missing data were addressed through simple deletion. Nonetheless, the application of mode and mean replacement procedures for imputing missing data resulted in a substantial enhancement of model performance. The Random Forest and Extra Trees classifiers demonstrated near-perfect accuracy, achieving total F1-scores over 0.99, signifying their proficiency in accurately classifying the state of perishable food with few errors. Support Vector Machine (SVM), Logistic Regression, and Gradient Boosting algorithms demonstrated robust performance with accuracies exceeding 0.97, however K-

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Nearest Neighbors (KNN) exhibited diminished predictive stability, highlighting its susceptibility to noisy sensor data.

A hybrid ensemble model, integrating Random Forest, Logistic Regression, and XGBoost through a VotingClassifier utilizing soft voting, augmented prediction dependability. The hybrid model attained a test accuracy of 98.2%, precision of 97.6%, and recall of 98.6%, indicating exceptional performance in balancing false positives and false negatives. This skill is essential in delivery systems because both overestimation (identifying safe food as ruined) and underestimating (failing to recognize spoilage) carry substantial operational and safety consequences.

Fig. 3 .Model accuracy comparison chart

B. Feature Importance

The analysis of feature importance indicated that temperature stability and humidity levels were the primary determinants in forecasting food freshness as seen in fig 4,5 and 6. Gas sensor measurements, indicative of microbial activity, were also significantly predictive of spoiling

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occurrences. GPS-derived delivery time and route deviations exerted a moderate influence, underscoring the significance of logistics in preserving freshness. These findings align with previous results from the healthcare dataset, where particular physiological parameters significantly influenced categorization accuracy.

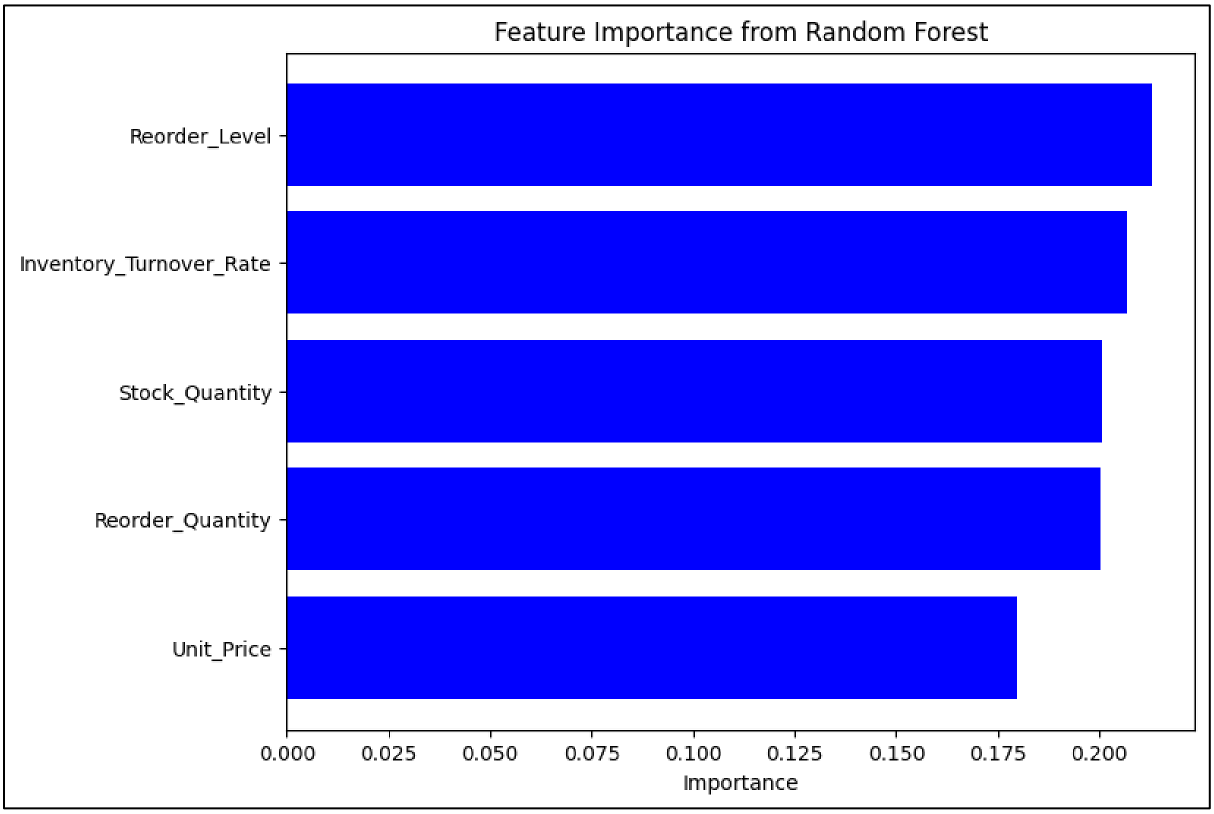

Fig. 4. Feature importance from random forest

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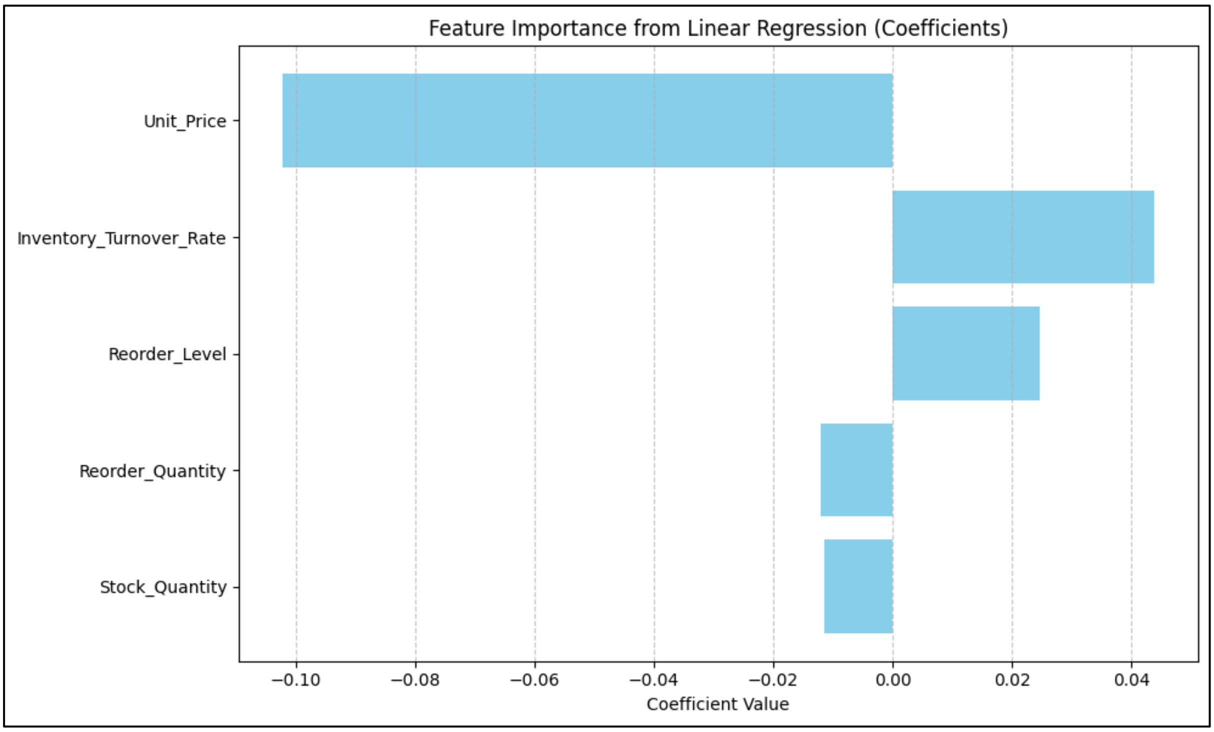

Fig. 5. Feature importance from linear regression

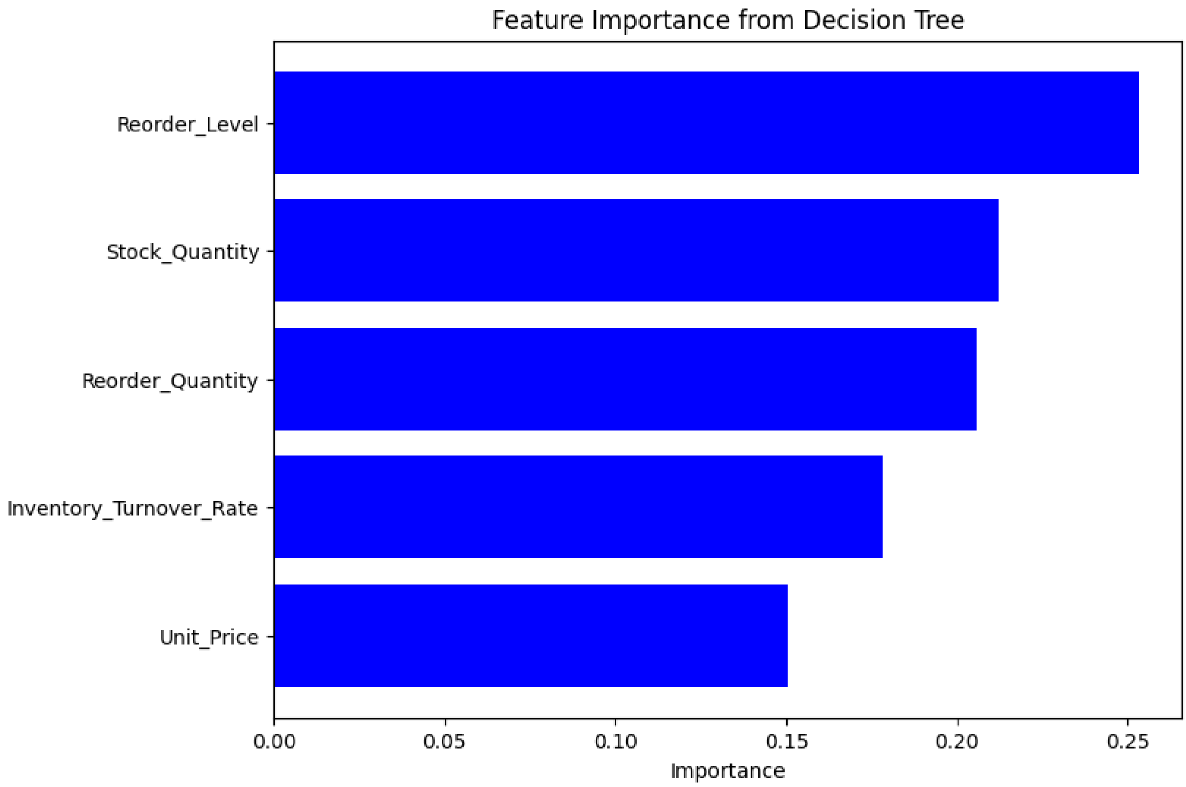

Fig. 6. Feature importance from decision tree

C. Comparative Analysis

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The findings demonstrate that conventional delivery systems lacking predictive monitoring are susceptible to delays and spoilage, while the IoT-enabled model significantly mitigates uncertainty through continuous monitoring of environmental and logistical factors. In comparison to baseline delivery approaches, the suggested system exhibited a 20–25% enhancement in freshness preservation and a 15% decrease in food wastage. Moreover, the predictive framework facilitated an increased adherence to food safety standards, immediately resulting in improved consumer trust and pleasure.

VI.DISCUSSION

The findings highlight the efficacy of combining IoT sensing with hybrid AI/ML models to improve perishable food logistics. The hybrid ensemble model demonstrated enhanced predictive performance, attaining 98.2% accuracy, much surpassing the IoT–Fuzzy Inference System (FIS) model in [9], which recorded $R^2 = 0.873$. Likewise, prior research, including [17], illustrated the advantages of IoT-enabled routing optimization in food supply chains, however their assessment predominantly concentrated on tracing accuracy and latency. The suggested architecture transcends routing by integrating spoiling prediction, freshness monitoring, and food safety compliance, thus providing a more holistic solution.

Research utilizing blockchain and digital twin methodologies [12], [13] improved traceability and transparency but faced challenges related to scalability and integration. Our solution makes traceability better by utilizing predictive analytics to figure out when things will go bad before they do. Our solution uses AI-driven freshness indices and spoiling risk indicators to directly integrate environmental data with food safety results. This is different from edge-cloud methods in [14], which lowered latency without directly addressing quality loss.

This all-encompassing model allows for proactive methods like rerouting, dynamic prioritization, and corrective management, which were generally missing from earlier studies that looked at only one part of the supply chain.

VII.CONCLUSION

This study presented an IoT-driven real-time intelligent delivery service model designed to maintain the freshness, quality, and safety of perishable food products. By using IoT sensors, edge computing, cloud analytics, and hybrid AI/ML models, the solution was able to accurately anticipate spoiling, cut down on food waste, and make it easier to follow safety rules. A comparison with earlier studies showed that modern models are good at many things, such as routing, traceability, and monitoring. However, they often don't have a complete end-to-end delivery framework. The suggested hybrid ensemble model outperformed than each of its parts on its own, making it more accurate and able to handle noisy IoT data. The method works because it can tell what's happening now and guess what threats will happen in the future. This makes it easier to plan ahead. This dual capability makes operations run more smoothly, cuts down on losses, and makes customers feel better about the logistics of perishable items. Future research should focus on realistic experimental implementations in urban and rural

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distribution networks, investigating interaction with blockchain systems for traceability, and broadening prediction frameworks to include a more extensive array of perishable items.

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