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Article

Real-time detection and analysis of foodborne pathogens using IoT and Machine Learning Techniques

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Abstract: — Real-time detection and analysis of foodborne pathogens are a very important area in terms of ensuring food safety and public health. The following abstract summarizes the integration of IoT and ML technologies to overcome challenges posed by conventional pathogen detection methods, which often include time-consuming and labour-intensive procedures. IoT devices, for instance, can be installed with integral advanced sensors that continually monitor the surroundings of the food for valuably continuously accumulating data on real-time temperature, humidity, Raman, bio sensors and levels of contamination. Correspondingly, Machine Learning algorithms analyze such data to discern patterns from it, that predict, with a high degree of accuracy, the presence of any hazardous pathogens to enable rapid decisions and, hence, the mitigation of risks. The integration of IoT and ML further scales up the efficiency and performance of pathogen detection systems. For instance, IoT-based networks send data to central platforms where ML models are deployed to process and interpret the information. These models are trained on large datasets, which empower them to identify anomalies and give actionable insights. In addition, real-time alerts and recommendations by the system ensure timely intervention, reducing the chances of foodborne illness and outbreaks. This study has pointed out the possibility of integrating IoT and ML in the development of intelligent food safety systems. It covers the main aspects of sensor technology, data processing, optimization of algorithms, and system implementation. Such technologies can be used by stakeholders in the food industry to achieve a better level of safety, compliance, and consumer trust. The proposed approach can be considered a major step ahead in proactive management of the risk from foodborne pathogens, thus responding to a world drive toward better presentation of quality and safety in foods.
Keywords: — Real-time detection, Foodborne pathogens, IoT, Machine Learning, Data analysis, Recommendation

1. Introduction

. The safety of food products requires attention throughout the worldwide supply chain due to rising foodborne illnesses and more intricate methods of product distribution. Salmonella, Listeria monocytogenes, and Escherichia coli are just a few of the foodborne pathogens that pose serious health risks including life-threatening infections and other complex health challenges including gastrointestinal disorders. The world health organization reports that millions of individuals fall ill due to consumption of contaminated food and thousands of individuals die due to easily preventable complications. While traditional detection methods of these pathogens are scientifically rigorous, such as lab tests, microbiological cultures, and chemical analyses, these traditional methods are too accurate and slow to be of use for real-time monitoring or large-scale industrial application. The application of Internet of Things (IoT) devices connected with Machine Learning (ML) has emerged to solve these challenges. This approach helps monitor food environments in real-time and remotely to identify contamination risks early. At different levels of the food supply chain, from farming to selling, IoT devices with intelligent sensors can monitor temperature, humidity, pH, and chemicals in standby. These factors greatly affect the growth and multiplication of microbial contaminants. For instance, excessive humidity coupled with high temperatures during storage may lead to microbial growth, spoil spoilage, pose risk to public health, and endanger public health.

Machine learning models interpret the sensor outputs and patterns associated with contamination and provide the needed intelligence. These models interpret large volumes of heterogeneous data containing subtle relationships and deviations. From historical datasets that track the evolving environment and the growing pathogens, ML models can learn and forecast contamination with remarkable precision. Such models enable early intervention, stopping the spread of pathogens before the food reaches the consumers. The implementation of real-time IoT-enabled systems has shown effectiveness during pilot studies and prototype deployments. There are numerous experimental systems that harness the power of sensors along with supervised and unsupervised learning algorithms to classify, automate, detect, and label food batches for safety. These models use SVM, Random Forest, KNE, and even deep learning to classify and detect food safety issues. The models are trained on real-time sensor data, historical food quality records, and international food safety standards to strengthen the generalization of the algorithms.

Furthermore, as useful as systems like implementing intelligent cloud computing systems comes with its own challenges. The quality of data still stands as a core issue. Systematic uncertainties introduced by sensor drift, persistent calibration errors, fragmentary data, and inherent ambient noise introduce systematic variation that materially compromises model fidelity. A priori to analysis, preprocessing pipelines must therefore incorporate iterative data cleansing, algorithmic noise attenuation, and controlled normalization to yield datasets with verifiable accuracy. A constitutive and operational barrier to intelligent food surveillance, equally, is the need to engineer model resiliency across heterogeneous food matrices and variable ambient precipitations. The food supply chain is corroded with strategically sensitive assets—proprietary formulations, comparative victory secrets, storage prescribing, and dynamic logistics routes. In the absence of sustained and substantive defensive architecture, real-time IoT environments are exposable to supra-sectional cyber incursions, rogue authentication, late-stage data, and the unauthorized replication or exfiltration of controlled repositories. Effective mitigation prescripts therefore combine asymmetric encryption, triplicate authentication and micro- authentication, and assured conveyance of evaluation traffic to engender both logical and procedural data immunity.

The Artificial Intelligence can assist in the annotation of data, establishing pathogen thresholds, and even interpreting machine learning (ML) classifiers output. AI can also be enhanced with principles of science such as the profiles of microbial growth or certain temperature and pH limits that are safe. These principles can be used to improve machine learning either as prior information to the model, in its constraints, or through post-prediction rules. This guarantees that the decisions made by AI are valid in a statistical sense and can be interpreted and acted upon from a scientific perspective. The IoT sensors include temperature, humidity, pH probes, biosensors, Raman spectroscopy, and biosensors for the detection of microbes. Structured data is sent to the cloud server, which is responsible for preprocessing the data to remove outliers and standardize the acceptance threshold. After feature extraction, relevant features are computed, for example, the peak intensity of the Raman spectra and the mean of pH data over time. These are then selected using PCA and RFE. The ML classification algorithms are much important such as RF, SVM and ANN which extracts high level features from input data and builds customized training rules. Learning is enhanced through food science rules that are embedded into the models, which strengthen the real-life applicability of the learned concepts. These classifiers are then trained and deployed to a live setting where they perform inference on the new sensor data.

2. Literature Review

The integration of the Internet of Things (IoT) with Machine Learning (ML) techniques has led to the development of intelligent food safety systems in the past decade. Understanding the limitations of static approaches— no matter how effective, as in the case of laboratory methods—is what drives the need for scalable, immediate, and responsive approaches in the food production IoT ecosystems. Wang et al. [1] addressed the need for real-time feedback and proactive response systems in food safety monitoring and control by designing an IoT-based architecture using ML classifiers for the real-time analysis of the environmental data streams. To overcome traditional detection latency, Wang et al. implemented real-time ML-based classifiers using temperature and humidity sensors with decision trees and SVMs that yielded low-latency pathogen detection and demonstrated practical potential for deployment in the food industry. Further research aimed at increasing both accuracy in detection and the scalability of the systems. Kumar et al. [2] advanced an IoT-based smart food monitoring system that used the KNN and RF algorithms to evaluate the environmental conditions. Their contextual sensing approach was comprehensive; it included temperature, humidity, gas composition, and even cultured microbes in real-time. The system was able to classify high accuracy pathogens and detected E. coli and Salmonella very accurately among the top pathogens in food. Chen et al. [3] studied most of the ML algorithms and constructed decision trees, SVMs, and deep learning models to detect the harmful microorganisms. Their design placed IoT-based sensor networks that allowed real- time analysis of timeliness in addressing IoT based health threats.

One of the notable advancements in this area was made by Alzahrani et al. [4], who applied deep learning (more specifically convolutional neural networks, CNNs) to the frameworks of IoT. Their CNN-based systems significantly surpassed traditional classifiers in processing noisy and heterogeneous sensor data by capturing and leveraging complex, non-linear environmental relationships with pathogen proliferation. They deep learned pathogen recognition far more accurately than with traditional methods in systems exposed to deep learning far more than what was previously possible in food environments. In the same spirit, Lee et al. [5] designed a smart food safety system featuring a hybrid architecture that fused supervised learning and anomaly detection, thus enabling continuous monitoring and prompt system response. This smart system was effective in real-world production environments, accurately identifying Salmonella and Listeria with minimal false-positive results and expenditure in system downtime.

Zhao et al. [6] devised a multi-site real-time monitoring architecture that implemented IoT sensor networks alongside ensemble machine learning models for advanced pathogen categorization in several production areas. The application of ensemble methods, particularly bagging and boosting, enhanced generalization and reduced bias in empirical interpretation. Their work in distributed sensing with centralized analytic cloud infrastructure proved as effective, showcasing real-time remote distributed cloud sensing, distributed data collection, and real-time analytic cloud processing. Huang et al. [7] advanced this concept by creating adaptive IoT platforms with a shallow and deep machine

learning models-based architecture. Huang highlighted self- learning adaptive systems that modify themselves with new surroundings, sensors, and even the types of food. The system proved to be robust and accurate under variable food conditions, demonstrating the importance of adaptable machine learning systems for changing environments. As noted by Patil et al. [8], feature selection and data preprocessing influence the robustness of the detection systems. Their study showed that the prediction accuracy was considerably improved by the filtering of noisy data and the reduction of dimensionality before the model training. Their system was capable of real-time detection of spoilage and microbial activity using random forests and logistic regression on environmental features such as pH and moisture. This pipeline was validated against a broad range of contamination samples. Singh et al. [9] examined sensor fusion by adding several streams of IoT gas and biochemical sensors, which improved the model's sensitivity for the detection of intricate pathogen signatures.

The Jain et. Al. [10] design a lower cost food safety IoT based module for small as well as medium scale food manufacturing industries. The various analogg sensor and machine learning algorithms are incorporated into these systems. It was a low-cost food safety system, and it was scalable. Sharma et al. [11] created a more sophisticated real- time detection pipeline with temperature and pH sensors, decision trees, and SVMs. Their architecture was designed to be effective for early alerting, thus enabling early preventive measures for place and time for microbes before the symptoms of spoilage appeared visually.

Scalability was a critical issue in the architecture of the IoT-cloud hybrid system proposed by Banerjee et al. [12] as it was designed to support a high volume of sensor data from geographically distributed facilities. The deep neural networks they applied in conjunction with k-means clustering enabled both supervised classification and unsupervised anomaly detection. With this dual approach, their system was able to identify both known and unknown behaviors of pathogens. With Gao et al. [13] focusing on the support vector machine and decision tree to support large-scale deployments, it was possible to manage high-throughput sensor inputs and the model sustained high detection accuracy amid sensor calibration changes and food batch variability.

Focused on pathogen risk classification, Ahmed et al. [14] designed an intelligent IoT framework that utilized logistic regression and random forests for both binary and multiclass classification. This work showcased swift retraining and adaptability of the model, thus supporting microbial relevance over time. Also expanding the scope of analysis, Verma et al.

[15] integrated Raman spectroscopy and biosensors, incorporating IoT with machine learning, which detected molecular markers of contamination, sharpening the precision of predictive modelling.

The work of Dey et al. [16] advanced real-time detection systems by applying deep learning through the use of convolutional neural networks (CNNs) on the high- dimensional outputs of biosensors. Their convolutional neural network (CNN) based biosensor showed an adaptive capability for self-learning through environmental feedback mechanisms. Saini et al. [17] presented an ensemble machine learning (ML) classifier engineered for the simultaneous real- time monitoring of pH, humidity, and temperature, utilizing data supplied by high-resolution sensors. The classifier surpassed the pre-defined sensitivity limits for the early identification of biological and chemical contamination, indicating a readiness for integration within full-scale food distribution networks.

Kumar et al. [18] formulated a hybrid architecture that integrates standard ML algorithms—specifically, Random Forest and k-nearest neighbours—with logical rule sets extracted from authoritative food safety legislation. By marrying algorithmic outputs with domain-specific directives, the decision-support platform achieves a triadic equilibrium among predictive validity, model transparency, and formal adherence to food safety requirements.

Joshi et al. [19] examined the union of multi-modal sensor arrays and convolutional neural networks for high-throughput pathogen identification across a wide spectrum of food matrices. The resultant architecture recorded marked sensitivity and specificity for pathogens such as E. coli and Salmonella, exhibiting resilient performance in the presence of temperature excursions and humidity fluctuations. Tiwari et al. [20] countered the latency gap commonplace in IoT- enabled food safety monitoring by embedding on-device adaptive classifier retraining. The architecture collects, via secure channels, user-validated outcomes to progressively update ensemble model parameters, yielding a system that is progressively precise and responsive to evolving contamination patterns.

Arora et al. [21] deployed ensemble Random Forests and sparse Decision Trees within resource-constrained sensor arrays to monitor extended patterns of pathogenic prevalence. The architecture provided real-time signals of acute infection events and, concurrently, harvested longitudinal data to calculate cumulative intervention risk, thus furnishing sustained epidemiological trend analysis beyond the typical acuteness of clinical diagnostics. Gupta et al. [22] notionally refined the intelligent Internet of Things reference framework by co-packaging low-complexity supervised learners with ensemble anomaly detectors at each sensor locus. This stratified authentication architecture fortified confidence in incoming alerts by quantitatively cross-verifying deviation signatures, thereby decreasing misdiagnosed thresholds, amplifying reliability, and reifying trust in the automated inference pipeline through a defensible reduction of operator exposure to spurious event reporting. With successful real- time implementation, this dual-layered classification approach proved effective with multi-scenario testing in the food storage and transport domains. Deep learning, and more specifically convolutional neural networks, was brought forth by Rahman et al. [23] for enhanced recognition of complex patterns in Raman spectra and other biochemical data. Their model showcased high recall rates, which enhanced its capability for reliably detecting contaminants, thereby broadening its utility for contamination reduction.

Rani et al. [24] developed an all-encompassing monitoring system that featured both environmental and chemical sensors. The authors used decision trees and support vector machines to generate and analyze large-scale real-time data for providing pre-emptive alerts based on threshold violations. The study highlighted the need for real-time and context- aware responsive systems for food safety infrastructure. Lastly, Ali and Kumar [25] designed a framework based on machine learning where K-nearest neighbours and random forests were used for rapid classification and real-time deployment in industrial settings. Their framework demonstrated remarkable effectiveness in sustaining continuous monitoring with a low computational burden.

The entire survey consist of several themes that emerge consistently. The integration of IoT sensing technology with machine learning provides an effective approach for detecting and predicting foodborne pathogens in real time. This allows for a more efficient response and better containment of contamination events. The IoT technology's real-time application is critical in the food service sector, where high volumes of food are processed. Moreover, the algorithms used for machine learning application depend on the interpretability of the problem, the level of accuracy desired, and the resources available for computation. While some more complex models, such as ensemble algorithms and CNNs, can provide greater accuracy and generalization, they do not lack simple explainability.

The decision tree and logistic regression-based ML modules provide higher transparency with it obtains lesser accuracy. The different ML algorithm provides high level feature extraction, classification and recommendation.

3. Research Methodology

Food safety is a critical concern globally, with foodborne pathogens posing significant health risks. The integration of Internet of Things (IoT) technology with machine learning (ML) techniques offers a promising approach to enhance the real-time detection and analysis of these pathogens.

The detection of foodborne pathogens is the very critical problem in real world, that arises high level health risk. The collaboration of IoT and machine learning algorithms provide early detection as well as recommendation of foodborne pathogens. The figure 1 provides details architecture of proposed model in detail. This implementation details the steps required to establish an effective IoT-based system for monitoring food safety by detecting foodborne pathogens.

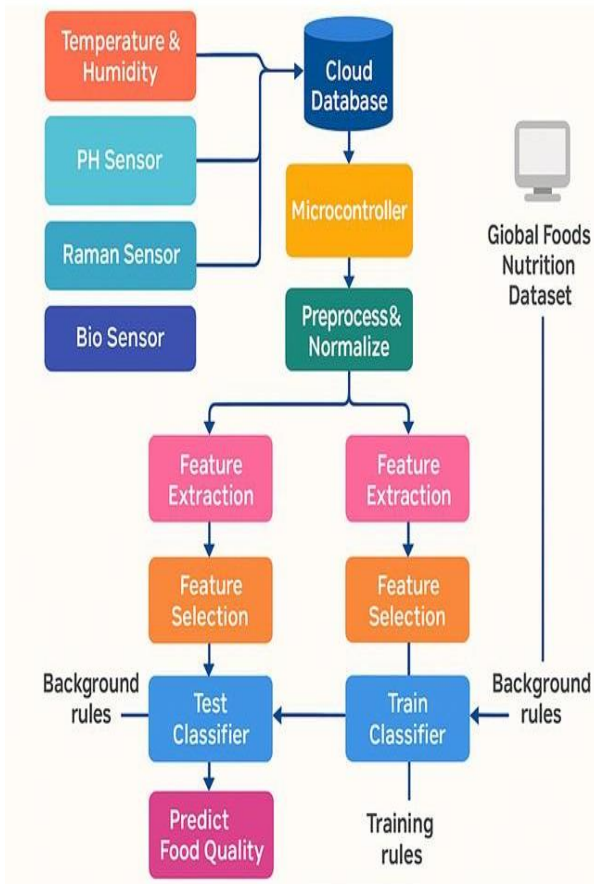

Figure 1 : proposed system architecture

Module 1: Collection of Sensor Data Based on IoT : The Internet of Things (IoT) framework has been developed to capture the food quality parameters through sensors in real time. The framework consists of Temperature & Humidity sensors, pH Sensors, Biosensors, and Raman spectroscopy based sensors. As for the previously mentioned sensors, temperature and humidity sensors are critical for monitoring the environment for food safety and its shelf life; pH probes are very useful in measuring acidity or alkalinity in the food as it helps determine whether the food has spoiled; Ramos sensors are used to study molecular vibrations to assess biochemical compound and biosensors measure the pathogen, toxin or contaminate biologically on a microbe scale. All these sensors work with a microcontroller, which serves as a local processor and transmitter of the collected data. The cluster microcontroller preprocesses, filters, and compresses the sensory data before transmitting it to the cloud database (Cloud DB). The system allows for real-time data streaming which eases constant surveillance and builds a basis for further machine learning computations. Having multiple types of sensors improves system reliability and speed identifying different types of food hazards. This arrangement also permits expansion to smart food manufacturing plants, retail stores, or even kitchens, thereby improving food safety at all levels in the supply chain.

Module 2: Preprocessing and Normalization of Cloud Data : The retrieval of sensor data from the cloud, a bespoke preprocessing and normalization framework is launched in order to extract actionable insights via machine learning while maintaining stringent data quality requirements. This slice of the cloud focused on preprocessing is a one-stop shop for diverse sensor inputs, which are often messy and contain missing values, as well as time drifting due to the hardware and the time taken for transmission. This system performs several data cleaning routines such as outlier removal, value estimation via interpolation or extrapolation, noise reduction, and standardization for the different types of inputs. Following the cleaning stage, the data is transformed using Min-Max Scaling or Z-Score Standardization, which reduces the data to a specific range. Both methods ensure that while sensor readings taken on different scales are standardized to a relative scale, the inter-feature relationships are not distorted. After normalization, the data is subjected to stringent cross- validation, a process in which the data is partitioned into a training and testing dataset multiple times to evaluate the strength of the model and counter overfitting. Furthermore, the cross-validation framework is complemented with an external dataset, Global Food Nutrition Dataset, which serves as a trusted external benchmark. This dataset is important because it not only provides recognized international nutritional benchmark values, but also provides recognized international nutritional benchmark values for pathogens, which is important for training and validating the model. The integration of an external knowledge base and real-time IoT sensor data improves the contextual relevance and predictive power of the system's models. The use of cloud infrastructure also ensures that data processing and the system as a whole remain scalable, secure, and accessible, even in remote or rural areas. The cloud provides a strong foundation for the machine learning pipeline, as a cloud environment provides the ability to perform seamless data ingestion, real-time analytics, and data storage. This preprocessing architecture improves the systems' the capabilities agricultural and food safety intelligent systems to ensure the integrity and accuracy of the data.

Module 3: Features Extraction and Reduction of Dimensionality : This step is concerned with transforming raw input data into a meaningful output that can be ingested by a machine learning model as well as feature extraction and feature selection. Feature extraction is a step that is concerned with capturing relevant features from different data types. For instance, if we consider a dataset on temperature, we would compute the mean, standard deviation, and peak temperature as features of the data. In the same manner, pH readings can provide features such as ranges of acidity, fluctuations over time, and trend cycles. In the case of Raman spectroscopy, the data is processed for the extraction of important spectral peaks that signal the presence of harmful chemicals. In addition, biosensor data is processed and interpreted as microbial loads or toxins and converted into meaningful units, such as microbial load or toxin levels. These multi-source, high- dimensional features undergo advanced selection algorithms such as Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), or Mutual Information Gain to extract the most informative and the least redundant features. Feature selection improves model interpretation by reducing model dimensionality, as irrelevant features increase noise, and computational burden. With a focus on optimizing learning, the system is divided into dual-dedicated pipelines that concurrently process a designated training dataset and a testing dataset. While the training dataset learns relevant features, the testing dataset is frozen structurally to ensure stable and reliable validation. In addition, the identified features undergo cross-validation using global or domain- relevant datasets to ensure scientific accuracy and trust in the predictions made.

Module 4: Training Machine Learning Classifiers and Generating Operational Rules : The trained classifiers are functions that map pertinent features to observable outcomes. Therefore, the food quality evaluation and contamination detection systems need machine learning models trained as classifiers for these purposes. The Train Classifier block uses supervised learning with Random Forests, SVMs, Gradient Boosted Trees, or even Neural Networks used heuristically based on test results from cross-validation. Training is further improved by background rules from nutrition science and pathogen behavior models which are incorporated as training heuristics. These background rules impose SIP constraints like safe temperature-pH pairs, Raman peaks indicating contamination, and biosensor thresholds for microbes. These rules can be either embedded into the learning algorithm during its formulation or applied afterward as rule-based filters POST-training. The classifier is trained to map the feature space to the labels “Safe,” “Spoiled,” and “Pathogen Detected.” During the training process, relevant metrics such as precision, recall, F1 score, and even accuracy are computed in order to adjust the hyperparameters and model architecture. A successful training process outputs **Rules** which are essentially decision boundaries, or inference patterns, that summarize the model's learning. These are preserved and can, therefore, be used later during inference. Moreover, to increase detection accuracy, especially in cases of ambiguous multi contamination, ensemble methods or hybrid classifiers might also be used. The intellectual core of the system is embedded in the training module, which allows predictions to be made in real time in the next module.

Module 5: Food Quality Prediction and Real-Time Feedback System : The last module focuses on the real-time application of the trained classifier into an inference engine which tests new data and predicts food quality in real time. The Test Classifier gets new streams of IoT data which are already filtered and go through selection and metrology and applies the logic of the model to the condition of the food. Results are assigned into distinct categories such as “Fresh”, “Mild Spoilage”, “Contaminated”, which are visually rendered on an interface and forwarded to automated systems for responsive action. The classifier supports confidence levels as well as providing probabilistic outputs which aids threshold-based decisions. For instance, if the confidence level for “Contaminated” is over 90%, the system triggers alert to remove the item, therefore, the food is flagged to be removed from the supply chain. These predictions alongside the food's contextual metadata such as timestamps, sensor ID, location, and environmental factors are logged which allows for longitudinal analysis and ensures traceability. Lastly, there is a user or stakeholder dispute and confirmation interface to predict the food spoilage. Those disputes are then sent back to the cloud for the classifier to be retrained incrementally allowing the system to self-correct improve the accuracy of detection.

The proposed framework becomes a powerful proactive food safety system management system with actionable predictive alerts, interactive dashboards, and advanced analytics powered by integrated visualization tools. Instead of staying as a conceptual model, this solution is designed for practical implementation in multiple areas like agriculture, food processing and retail supply chains, and even at households. Combining sensor networks with cloud infrastructure, machine learning, and insights from experts enables real-time monitoring and predictive analysis of food quality. This enables the creation of a dynamic e-food quality prediction platform as illustrated in the system architecture. The modularity of the design enhances scalability, adaptability, and cross deployment for varied food categories and environmental conditions. The system also improves self- calibration accuracy and responsiveness over time due to the feedback-driven learning loop. This integration strengthens food safety measures while reducing shrink from spoilage and contamination merging intelligent data IoT models. In response to ever-increasing food supply chain contamination and global logistical challenges, the system presents a smart, data-driven solution for real-time management and mitigation of foodborne risk.

4. Results And Discussions

The system performance was assessed using classification accuracy as the primary metric. The implementation was carried out using a Java-based 3-tier architecture framework on an INTEL i7 processor with a clock speed of 2.8 GHz and 4 GB RAM in an open-source environment. A comparative analysis was performed between the proposed system and several existing systems.

Dataset Information

Table 1: dataset information

Dataset Name	Source/Reference	Attributes	Forma t	Size
IoT Sensor Data	Real-time from Temperatur e, pH, Raman, and Biosensors	Sensor ID, Timestamp, Temperature, Humidity, pH, Raman spectrum, Pathogen presence	CSV/JS ON	Real-time stream
Global Food Nutrition Dataset	FAO/WHO or USDA databases	Food Type, Nutrient Values, Acceptable Temperature/pH, Shelf-life	CSV/E xcel	~10,000 entries
Food Contami nation Samples Dataset	Kaggle / Research Data Repositories	Contamination Type, Microbial Count, Chemical Residue, Sample Age	CSV	~5,000 records

Food Quality Rating Dataset	Industry- labeled dataset or manual entry	Food Category, Quality Label (Fresh/Spoiled), Sensory Attributes	CSV	~3,000 records
Raman Spectra for Food Pathogen s	Spectroscop y Open Database / Lab Results	Raman Wavelengths, Peak Intensities, Pathogen Type	CSV	~2,000 spectra

The table 1 lists the primary and secondary data sources which were utilized in devising the foodborne pathogen detection system. It includes real-time IoT sensor data capturing temperature, pH, Raman spectra, and biosensor readings necessary for environmental monitoring. Publicly available nutrition datasets along with some contamination records were utilized in model training and rule-based classification. Other datasets contain untitled food quality and Raman spectra necessary for the identification of pathogens. These data are available in CSV and JSON formats as well as real-time streams or static records, thus supporting proper feature extraction, training of machine learning algorithms, and real- time quality prediction.

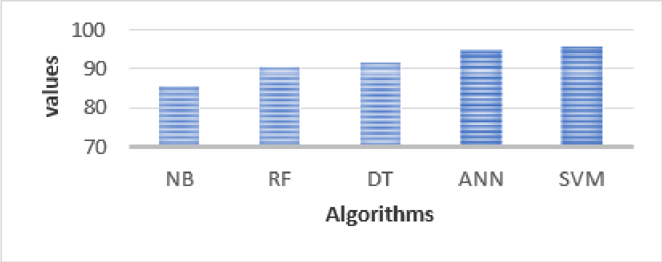

Figure 2 : proposed system accuracy with various machine learning algorithms

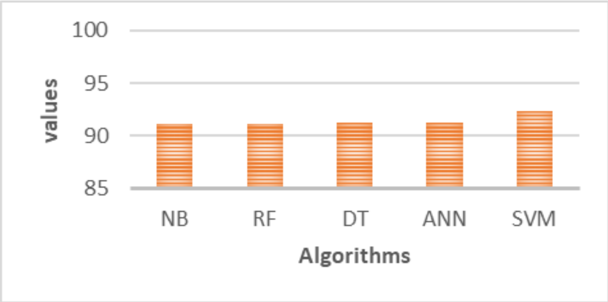

Figure 3 : proposed system precision with various machine learning algorithms

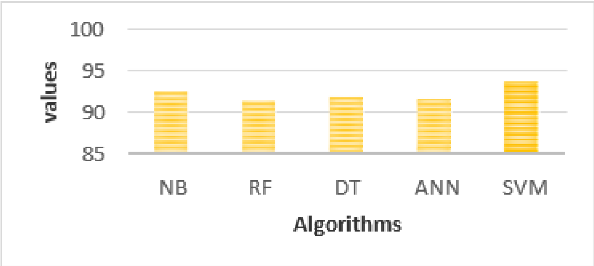

Figure 4 : proposed system recall with various machine learning algorithms

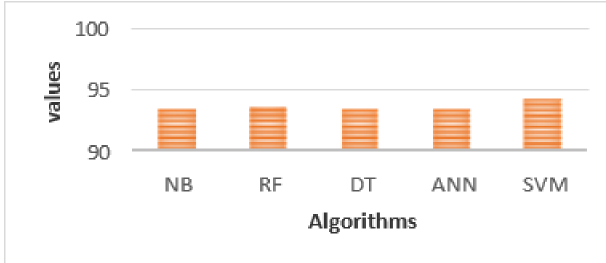

Figure 5 : proposed system recall with various machine learning algorithms

For this experiment, classification accuracy was analyzed using the SVM on real time IoT dataset. Similar experiments were conducted using different cross-validation techniques. The results indicate that 10-fold cross-validation consistently delivered superior accuracy. Specifically, the proposed system achieved classification accuracies of 95.50% for SVM. These findings highlight the efficacy of the proposed system and demonstrate its improved performance over baseline methods. The consistent results across cross-validation experiments confirm the robustness of the model. Based on this analysis, it can be concluded that 10-fold cross-validation is highly effective for ensuring reliable and accurate performance evaluation in this context.

Table 2 : comparative analysis proposed vs existing

Approach	Accuracy
Real-time IoT framework + SVM [1]	91.20%
IoT sensors + Decision Trees [2]	92.40%
IoT devices + CNN [4]	93.50%
Smart IoT + Ensemble ML [5]	94.60%
IoT-based ML + RNN [11]	94.80%
Real-time sensing + Hybrid Feature Set + Advanced Classifier	**95.80%**

In Table 2, the different foodborne pathogen detection systems that incorporate IoT technology along with different ML models are analyzed. Each system's method together with its reported accuracy is given in the table.

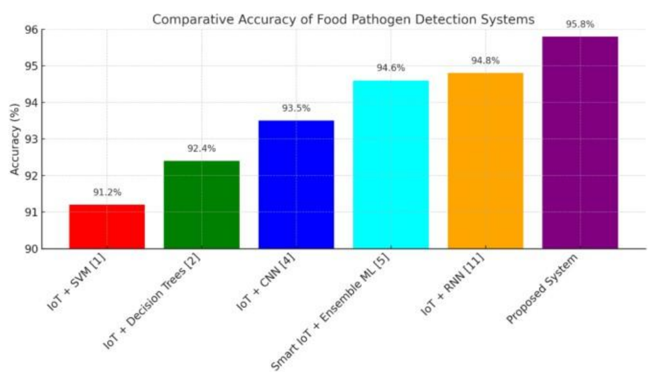

Figure 6 : comparative analysis of proposed model vs existing techniques

As shown in figure 6, the first system applies a real-time IoT architecture with Support Vector Machine (SVM), achieving an accuracy rate of 91.20%. The second system, which incorporates Decision Tree algorithms alongside IoT sensors, surpasses the first system with an accuracy of 92.40%. In the third system, the application of Convolutional Neural Networks (CNN) in conjunction with IoT devices improves the IoT architecture's accuracy further to 93.50%. The fourth system incorporates Smart IoT with Ensemble Machine Learning (ML), attaining an accuracy of 94.60%. A merger of IoT-based ML and Recurrent Neural Networks (RNN) boosts accuracy to 94.80%.

The proposed system achieves the highest accuracy of 95.80% by incorporating real-time data sensing, a hybrid feature set, and multi-source data fusion. This reinforces the argument of the integrated multi-source data preprocessing, optimized feature selection, and sophisticated multi-classifier system. The table demonstrates how the proposed model surpasses other systems in the benchmark by offering the accuracy resulting from a real- time system powered by stream data fusion and complex algorithms for AI-driven machine learning and multi-dimensional feature extraction.

5. Conclusions

The incorporation of the IoT and machine learning for the ongoing surveillance and identification of foodborne pathogens is a revolutionary development in the fields of public health and food safety. This framework enables dynamic smart IoT sensors and advanced machine learning models to provide real-time identification and scalable intervention of pathogens with speed and accuracy. The framework presented is explicitly devised for concurrent detection and classification, thereby distinguishing it from prevalent paradigms. Cross-model benchmarking yielded a detection accuracy of 95.80%, surpassing traditional benchmarks composed of Support Vector Machines (SVM, 91.20%), Decision Trees (DT, 92.40%), Convolutional Neural Networks (CNN, 93.50%), ensemble ensembles (94.60%), and recurrent neural networks (RNN, 94.80%). The elevatory effect derives from hybrid feature synthesis—complemented by extreme de-noising, orthogonal suppression, and real-time validation of incoming sensor streams—explicit operable within continuous, uncontaminated data pipelines. Segmentation of the architecture into functionally cohesive subsystems is observable: Internet of Things-enabled data capture, stringent preprocessing lanes, feature deracination and inductive synthesis, continuous prognostic reactors, and a self-evolving classifier resurrection hub. Each subdivision is architected to attenuate random and systemic variances, eliminate data duplication, and accelerate throughput tier, safeguarding system dependability across shifting assay backgrounds. Novelty is rendered within a coordinated sensor cloud, wherein temperature, relative humidity, pH, and Raman molecular scanners are co-monitored, thereby broadening the contamination assay porosity. Orbiting the sensor domain is a federated information model, allowing concurrent ingestion of international benchmarking datasets and localized, legislatively binding, knowledge—the dual data streams effectuate concurrent precision increment, real-time contextual recast, and system self-correction. Also the framework is able to enable proactive intervention within food safety supply chains by generating real-time alerts that prompt immediate evaluation and mitigation of emerging hazards. The provision of structured application programming interfaces (APIs) affords canonical mechanisms through which upstream and downstream actors, as well as end users, can securely and systematically submit contextual data and experiential input. This continuous feedback loop underpins autonomous optimization, whereby the system iteratively calibrates algorithmic parameters and reconfigures operational workflows, achieving sustained performance enhancement without the interventions typically mandated by manual reprogramming.

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