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Embedded Intelligence for Real Time Spiked Drink Detection

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Abstract - Drink spiking has become a major safety concern in social environments such as bars, clubs, parties, and public gatherings. Traditional methods for detecting harmful substances in beverages require laboratory testing and are not suitable for real-time personal safety applications. In this study, an AI-powered smart drink safety system using embedded sensors, machine learning, and mobile application integration is proposed. The proposed system analyzes beverage properties using pH, conductivity, temperature, and optical sensing modules integrated within a portable smart detection pen. The collected sensor data is processed using a machine learning model to classify beverages as Safe, Suspicious, or High Risk. The system also enables real-time wireless communication with a mobile application to provide beverage analysis and instant contamination alerts. A background notification mechanism is implemented to notify users even when the application is closed. The proposed approach provides a portable, low-cost, and real-time solution for improving personal safety and preventing drink spiking incidents.

Keywords - Drink Spiking Detection, Machine Learning, Embedded Systems, IoT, Beverage Analysis, Smart Detection Pen, Real-Time Notification System, Mobile Application Integration.

I. INTRODUCTION

Drink spiking refers to the act of secretly adding drugs, chemicals, or harmful substances into a person's beverage without their consent. Such incidents are increasingly reported in nightclubs, pubs, restaurants, college festivals, social gatherings, and other public environments. The substances used are often colorless, odorless, and tasteless, making them extremely difficult to detect through human observation alone. Victims may experience dizziness, nausea, unconsciousness, confusion, memory loss, or severe medical emergencies.

Existing detection techniques primarily rely on laboratory testing and chemical analysis methods that require sophisticated equipment, trained professionals, and significant processing time. These approaches are impractical for immediate real-world usage where rapid decision-making is critical. Therefore, there is an urgent need for a portable, intelligent, and real-time solution capable of detecting beverage contamination before consumption.

Recent advancements in embedded systems, Internet of Things (IoT), chemical sensing technologies, and machine learning have enabled the development of compact intelligent safety devices capable of performing real-time liquid analysis. By combining multiple sensor inputs with machine learning-based anomaly detection algorithms, beverages can be analyzed dynamically for abnormal chemical behavior.The proposed system introduces an AI-powered smart drink safety ecosystem consisting of a portable

detection pen and an integrated mobile application. The smart pen uses multiple sensors to analyze beverage characteristics such as acidity, conductivity, temperature variation, and strip-based chemical reactions. These sensor readings are processed through machine learning models deployed on embedded hardware and cloud-assisted services.

Unlike traditional systems that only provide local alerts, the proposed architecture introduces a real-time mobile notification framework. Once the pen detects a potentially unsafe beverage, the system automatically sends an instant notification to the user's smartphone even when the application is closed or inactive in the background. The mobile application additionally provides detailed analysis reports, contamination confidence levels, historical scan data, and intelligent safety insights.

The primary objective of this project is to create a scalable, low-cost, portable, and intelligent real-time drink contamination detection platform that enhances personal safety and prevents drink spiking incidents through proactive AI-driven monitoring.

II. RELATED WORKS

Several research works have focused on food contamination detection, intelligent sensing systems, and machine learning-based food safety analysis using embedded and IoT technologies.

Nowshad et al. studied the concentration and formation behavior of naturally occurring formaldehyde in different food products. Their work analyzed naturally occurring formaldehyde levels in fruits, vegetables, meat, milk, and beverages using spectrophotometric techniques. The research highlighted the importance of differentiating naturally formed formaldehyde from artificially added contaminants for accurate food safety analysis [1].

S. Prince Sahaya Brighty et al. proposed an IoT-based adulteration detection system for fruits and vegetables using machine learning techniques. Their system utilized HCHO gas sensors integrated with Raspberry Pi to measure formalin concentration levels and classify food samples using supervised learning algorithms such as Logistic Regression, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) [2].

Yuzhen Wang et al. presented a review on high-throughput optical sensors for food detection based on machine learning. Their study discussed intelligent optical sensing systems

using nanomaterials, hyperspectral imaging, fluorescence imaging, and machine learning algorithms including Random

Forest, CNN, and SVM for detecting contaminants, microorganisms, pesticide residues, and food freshness [3].
Abubakar Sharif et al. developed a machine learning-enabled food contamination detection system using RFID and Internet of Things (IoT) technologies. Their proposed system used RFID-based sensing with XGBoost classification models to detect contamination in food products and beverages such as soft drinks, alcohol, and milk. The system achieved approximately 90% accuracy in contamination sensing [4].

Kranthi Kumar Pulluri et al. proposed a Smart Electronic Nose (SE-Nose) system for qualitative and quantitative food adulteration detection. Their work combined intelligent sensor arrays with pattern recognition techniques and machine learning models such as Support Vector Machine (SVM) and Artificial Neural Networks (ANN) for rapid adulteration analysis. The proposed system achieved high classification accuracy with reduced detection time [5].
Aili Wang et al. reviewed the combination of machine learning and intelligent sensory systems for real-time quality control in alcoholic beverages. Their research discussed the use of Electronic Nose (E-Nose), Electronic Tongue (E-Tongue), and machine learning algorithms for fraud detection, aroma analysis, adulteration monitoring, and quality assessment in beverage industries [6].
Yan Chen et al. proposed a machine learning framework for real-time detection of microbial and chemical contaminants in food products. Their system utilized spectroscopy devices, biosensors, and smart imaging systems integrated with machine learning algorithms such as CNN, SVM, and Gradient Boosting for detecting bacterial contamination and chemical hazards with high classification accuracy [7].
Qin Ouyang et al. developed an artificial olfactory technique based on colorimetric sensor arrays for beverage quality analysis. Their research utilized RGB color feature extraction combined with Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for classification and authentication of rice wine samples [8].
Niklas Kühl et al. discussed the relationship between Artificial Intelligence (AI) and Machine Learning (ML) and proposed a conceptual framework for AI-based intelligent systems. Their work emphasized the role of machine learning in developing intelligent decision-support systems and highlighted the importance of explainable and reliable AI models [9].
Kamal Malik et al. discussed Explainable Artificial Intelligence (XAI) techniques for intelligent autonomous systems. Their work focused on improving transparency, reliability, safety, and interpretability of AI-driven decision-making systems using explainable machine learning approaches.
The study emphasized the importance of trustworthy AI models in real-time embedded applications and intelligent monitoring systems [10].
Mahanth S et al. proposed a machine learning-based formalin detection system for fruits and vegetables using IoT-enabled sensing mechanisms. Their system utilized HCHO gas detectors integrated with Arduino platforms for identifying formaldehyde concentration levels and differentiating naturally occurring and artificially added formalin using supervised learning models. [11].

Rajasathiya K et al. reviewed machine learning and IoT approaches for intelligent environmental sensing and parameter analysis. Their research highlighted the role of embedded sensors, real-time monitoring systems, cloud connectivity, and machine learning algorithms in improving automated data analysis and decision-making in sensor-driven applications [12].
Recent advancements in intelligent sensing, embedded systems, machine learning, and IoT technologies demonstrate the growing potential of automated real-time food and beverage contamination detection systems.

However, many existing approaches primarily focus on laboratory analysis or standalone sensing devices. The proposed system extends these approaches by integrating embedded intelligence, real-time beverage analysis, mobile application support, and background notification mechanisms into a unified smart drink safety ecosystem.

S.No	Research Paper	Technique / Methodology	Sensor / Technology Used	ML / AI Model	Real-Time Support	IoT / Mobile Integration	Overall Contribution
1	Nowshad et al. (2018) [1]	Formaldehyde concentration and formation analysis	Spectrophotometric analysis	Statistical analysis	Low	No	Baseline study for naturally occurring formaldehyde
2	S. Prince Sahaya Brighty et al. (2022) [2]	IoT-based adulteration detection	HCHO Gas Sensor + Raspberry Pi	SVM, KNN, Logistic Regression	Medium	Yes	Detection of artificially added formalin in fruits
3	Yuzhen Wang et al. (2026) [3]	Optical food detection using intelligent sensors	Hyperspectral & Optical Sensors	CNN, Random Forest, SVM	High	Yes	High-throughput food contamination detection
4	Abubakar Sharif et al. (2021) [4]	RFID-based contamination sensing	UHF RFID + IoT	XGBoost	High	Yes	Real-time contamination detection in beverages
5	Kranthi Kumar Pulluri et al. (2022) [5]	Smart Electronic Nose (SE-Nose)	MOS Gas Sensor Array	SVM, ANN	Very High	Limited	Fast qualitative and quantitative adulteration detection
6	Aili Wang et al. (2022) [6]	Intelligent sensory systems for beverages	E-Nose & E-Tongue	ML-based Pattern Recognition	High	Limited	Real-time alcoholic beverage quality analysis
7	Yan Chen et al. (2025) [7]	Real-time food contaminant detection framework	Spectroscopy + Biosensors	CNN, SVM, Gradient Boosting	Very High	Yes	Real-time microbial and chemical contaminant detection
8	Qin Ouyang et al. (2012) [8]	Artificial olfactory classification system	Colorimetric Sensor Array	PCA, LDA	Medium	No	Beverage authentication and quality evaluation
9	Niklas Kühl et al. (2022) [9]	AI and ML conceptual framework	Intelligent Information Systems	AI/ML Framework Models	Medium	No	Clarification of AI and ML intelligent systems
10	Kamal Malik et al. (2025) [10]	Explainable Artificial Intelligence (XAI)	Intelligent Autonomous Systems	Explainable AI Models	High	Yes	Transparency and reliability in AI decision systems
11	Mahanth S et al. (2022) [11]	Formalin detection using IoT and ML	HCHO Sensor + Arduino	Supervised Learning Models	Medium	Yes	Low-cost portable formalin detection system
12	Rajasathiya K et al. (2024) [12]	IoT and ML-based sensor monitoring systems	IoT Sensors + Cloud Systems	CNN, Regression Models	High	Yes	Real-time intelligent sensor monitoring and analysis

Table 1: Comparative analysis

III. OVERVIEW OF THE SYSTEM

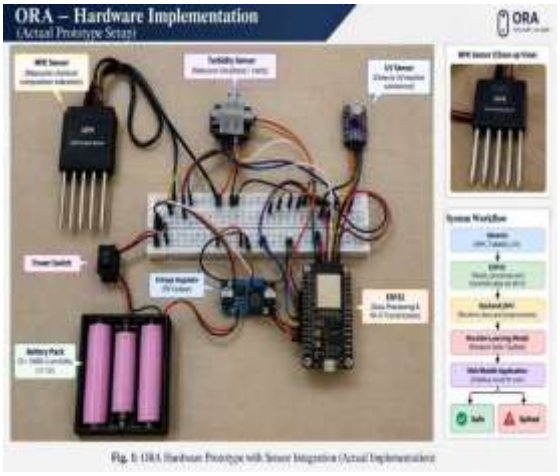


Fig 1 Hardware system

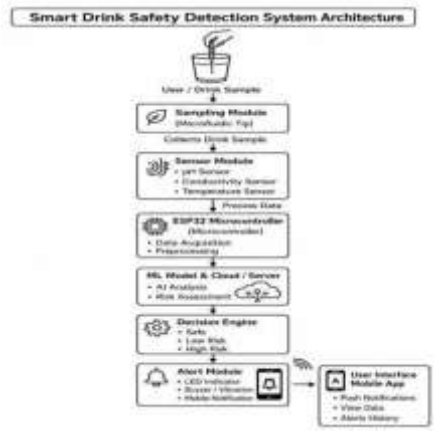


Fig 2 system design

The proposed system is an intelligent IoT-enabled beverage safety platform designed for real-time drink contamination detection and automatic user notification. The system integrates embedded sensing technologies, machine learning algorithms, wireless communication, cloud connectivity, and mobile application support to create a complete smart drink safety ecosystem. The overall architecture consists of a smart detection pen, an embedded machine learning processing unit, a cloud communication layer, and a mobile application interface.

1. Dataset Preparation and Processing

The proposed system utilizes a structured dataset containing sensor-derived beverage parameters such as pH values, conductivity readings, temperature variations, strip color intensity values, mixing ratios, and drink category labels. These parameters are used to identify abnormal chemical behavior in beverages and classify them into Safe, Suspicious, and High_Risk categories. The collected dataset undergoes preprocessing techniques including missing value handling, normalization, feature scaling, removal of data leakage attributes, and class balancing to improve model accuracy and generalization. The final dataset is divided into training and testing sets, where 80% of the data is used for training and 20% for evaluation and testing purposes.

2. Smart Hardware and Sensor Integration

The smart detection pen is designed using embedded hardware components integrated with multiple sensing modules including pH sensors, conductivity sensors, temperature sensors, and chemical strip analysis modules. When the pen is dipped into a beverage, a small liquid sample enters the sensing chamber where the sensors analyze the chemical properties of the drink in real time. The sensors continuously generate analog and digital readings corresponding to acidity levels, ionic concentration, temperature variation, and optical strip intensity.

These sensor outputs are connected to an ESP32 microcontroller which acts as the central embedded processing unit of the system. The ESP32 collects sensor readings through its GPIO and ADC interfaces and performs preliminary preprocessing operations such as filtering, calibration, and feature extraction. The processed sensor data is then forwarded to the trained machine learning model for contamination analysis. The hardware layer also includes wireless communication modules, battery management systems, and alert mechanisms to support portability and real-time operation.

3. Machine Learning-Based Beverage Analysis

The proposed system utilizes a machine learning-based classification model for beverage safety analysis. After preprocessing the sensor dataset, important features such as pH, conductivity, temperature, strip intensity values, and mixing ratios are extracted and used for training the predictive model. Multiple preprocessing techniques are applied to improve model performance and reduce false predictions. The final prediction model is developed using the XGBoost algorithm due to its ability to efficiently handle nonlinear feature relationships and multiclass classification problems.

The processed sensor values received from the ESP32 hardware unit are passed into the trained machine learning model either through embedded inference or backend server processing. Based on the analyzed sensor behavior patterns, the model classifies beverages into Safe, Suspicious, or High_Risk categories. This hardware-to-ML integration enables real-time beverage contamination analysis and intelligent decision-making.

4. IoT Communication and Mobile Application Integration

Once the classification process is completed, the prediction results are transmitted wirelessly to the mobile application using Bluetooth Low Energy (BLE) or Wi-Fi-based IoT communication protocols. The mobile application serves as the primary user interaction platform and provides detailed beverage analysis, contamination confidence scores, live sensor readings, historical scan records, safety recommendations, and a real-time monitoring dashboard. The application allows users to continuously monitor beverage safety in an interactive and user-friendly environment.

The proposed system is also integrated with a web-based monitoring platform that provides live scan simulation, analyzer interfaces, and real-time visualization of beverage safety analysis. Both the web application and mobile application communicate with the backend processing system to retrieve sensor predictions and contamination reports.

5. Real-Time Alert and Notification System

A major enhancement of the proposed system is the implementation of an intelligent background notification

mechanism. Even when the mobile application is inactive or completely closed, the backend notification service continuously listens for incoming sensor events from the smart detection pen.

If beverage contamination or abnormal chemical behavior is detected, the system immediately sends push notifications, vibration alerts, and warning messages to the user's smartphone. This ensures continuous passive safety monitoring and improves the practical usability of the system in real-world social environments.

IV. RESULT AND DISCUSSION



Fig 3 Dashboard



Fig 4 Analysis

The proposed AI-powered drink safety system was evaluated The ORA prototype was evaluated as an integrated sensor-based liquid monitoring and analysis system consisting of an ESP32-based hardware unit, multiple sensor modules, a native Android application, cloud services, and an experimental machine learning component. The system was developed to acquire selected liquid measurement parameters and make the collected information available for analysis through the application.The hardware prototype was tested using sensor modules for measuring parameters including nitrogen, phosphorus, potassium, pH, electrical conductivity, turbidity, and temperature. The ESP32 served as the central processing unit for acquiring and processing the sensor measurements. For compatible sensor modules, communication was implemented through the configured interfaces, including RS485 Modbus communication where applicable. The testing confirmed the intended integration between the microcontroller and the connected sensor modules under the experimental setup.

The Android application was developed using Kotlin and Jetpack Compose and provided the user interface for interacting with the system. The application included user registration and login through Firebase Authentication, a home interface, sensor measurement presentation, analysis-related functionality, and PDF report generation using the Android PdfDocument API. Kotlin Coroutines were used where required to perform asynchronous operations without unnecessarily blocking the main user interface.

Firebase integration provided cloud-based authentication and data storage functionality. Firebase Authentication was used for user registration and login, while Cloud Firestore was configured for storing and retrieving application-related information. The integration allowed the application to communicate with the configured cloud services without requiring a separate authentication and database infrastructure.

The machine learning component was evaluated experimentally using a customized dataset containing 14 records, consisting of six records labelled as "not spiked" and eight records labelled as "spiked". Logistic Regression was used as the initial classification algorithm to examine the relationship between the selected sensor measurements and the assigned experimental labels. The input features included nitrogen, phosphorus, potassium, pH, electrical conductivity, turbidity, and temperature.

The machine learning results are considered preliminary because of the limited dataset size and the method used to collect the samples. The records were obtained through sequential additions to the same prepared water sample and therefore do not represent a sufficiently diverse collection of independently prepared samples. Consequently, the current experimental results cannot be used to establish reliable classification performance on unseen real-world samples.

The overall testing demonstrated the integration of the hardware, sensor acquisition, Android application, Firebase services, PDF report generation, and experimental machine learning workflow within a single prototype. The results indicate that the developed system provides a foundation for

sensor-based liquid monitoring and data analysis. However, sensor calibration, independent sample collection, larger datasets, laboratory validation, and further model evaluation are required before the system can be considered suitable for reliable real-world liquid safety or pharmaceutical detection.

V. FUTURE ENHANCEMENTS

The proposed system can be further enhanced by integrating advanced Artificial Intelligence and Machine Learning models to improve contamination detection accuracy and enable better classification of harmful substances over time. Future implementations may include deep learning and adaptive learning techniques capable of continuously learning from newly collected sensor data to improve prediction reliability and support identification of a wider range of beverage contaminants.

Additionally, the hardware design can be further miniaturized to develop a more compact, sleek, and fully portable smart detection pen with reduced power consumption and faster response time. Improvements in sensor technology, embedded processing units, and battery optimization can significantly enhance the usability, efficiency, and real-world deployment capability of the system.

VI. CONCLUSION

The ORA project presents an experimental IoT-based liquid monitoring and sensor-data analysis system that integrates sensor modules, an ESP32 microcontroller, a native Android application, cloud services, and a machine learning component. The primary objective of the system is to collect selected liquid measurement parameters and provide a platform for presenting and analysing the available sensor information through a mobile application.

The hardware component uses an ESP32 microcontroller connected to sensor modules for obtaining measurements related to Nitrogen, Phosphorus, Potassium, pH, Electrical Conductivity, Turbidity, and Temperature. The ESP32 acts as the central unit for acquiring and processing sensor information, with compatible sensor modules communicating through their configured interfaces, including RS485 Modbus communication where applicable.

The Android application, developed using Kotlin and Jetpack Compose, provides the user interface for interacting with the ORA system. Firebase Authentication supports user registration and login, while Cloud Firestore provides cloud-based storage and retrieval of application-related information. The application also includes analysis-related functionality and PDF report generation using the native Android PdfDocument API. Kotlin Coroutines support asynchronous operations where required to maintain responsive application behaviour.

The project also explores the use of machine learning for analysing collected sensor measurements. A customized experimental dataset containing 14 records was prepared using normal water samples and experimentally prepared water samples containing Dolo 650. Logistic Regression was used as the initial classification algorithm to study the relationship between the selected sensor features and the assigned experimental labels.

Overall, the development of ORA demonstrates the integration of IoT hardware, sensor data acquisition, Android application development, cloud database services, and machine learning within a single prototype. The project provides practical experience in combining these technologies for experimental liquid monitoring and sensor-data analysis. However, limitations related to sensor calibration, dataset size, experimental validation, and detection capability must be addressed before the system can be considered a validated solution for identifying specific substances or determining drinking-water safety.

Future development can focus on independent sample collection, larger and more diverse datasets, improved sensor calibration, laboratory-based validation, enhanced machine learning evaluation, and more reliable real-time communication. With these improvements, the ORA prototype can provide a stronger foundation for further research and development in sensor-based liquid monitoring and analysis.

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