Development of IoT Platform for Smart Kitchen Management

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***Abstract*—This project aims to reduce the cooking hazards and the accidents that are common in the kitchen environment using the concept of IoT by using the sensor readings. An ML model is also used to detect if the kitchen environment is safe or hazardous. If the model detects that the environment is hazardous, an alert message is immediately sent and the system is automatically turned off. So, the overall goal is to monitor the kitchen environment constantly to prevent accidents and hazardous situations such as boil-overs and burning. Multiple sensors are fused to get more accurate results. In this paper, a lightweight neural network is proposed, which is trained on a synthetic dataset. Later the model is deployed on the ESP32 microcontroller using TFLite Micro to provide real-time predictions if the environment is safe or hazardous. The communication is done using WiFi, and the output is displayed on a webpage. The proposed model was able to achieve high accuracy on the unseen test data and was able to classify the two classes. This project provides a scalable, affordable, and autonomous kitchen safety solution. Further, future work aims to include edge AI and expand the diversity of sensors for better detection.**

Keywords—Internet of Things, ESP32, TensorFlow Lite Micro, Multi-Sensor Fusion, AIoT

I. Introduction

Kitchens nowadays are prone to hazards like boil-overs and burning conditions, which further lead to waste of resources and serious accidents like gas leakage. Traditional safety systems like smoke detectors are very often ignored for installation in the kitchen because of their high false alarm rates, which are also triggered by normal cooking conditions. The proposed project addresses this issue by developing an IoT platform and AI-powered automatically controlled kitchen safety system. A critical research gap is the lack of use of weight sensors to predict and further prevent the overboiling conditions and non-fire accidents in real time. The main focus of this system is modeling the cooking process rather than just detecting the smoke or fire.

The key objectives are:

- Integrating multiple sensors and calibrating four different sensor readings and modelling the complex cooking process accurately.
- Training and deploying a lightweight neural network over a synthetic dataset on ESP32 to predict if the kitchen environment is safe or hazardous.
- Implementation of secure WiFi communication to send real-time alert messages to the user.
- Automatically shut off the system when the cooking environment becomes hazardous using the relay module.

The organization of the paper is as follows: Section II reviews the related work referred to during the project completion. Section III shows the methodology, which covers the data collection, training the model, and deploying it on the ESP32 microcontroller. Section IV outlines the final results and analysis. At last the paper is concluded by Section V which highlights the future work that can be done to improve scalability.

II. Literature Review

Dakhia et al. [1] reviewed around ~160 studies with ~1500 in 2015 to ~4800 in 2024 publications. Results found that edge AI, federated learning, and blockchain are the best solutions. Almassar et al. [2] reviewed 70 studies, which showed the rising use of AIoT, with 43 using IoT and 27 using AI. The main research gaps were the use of standardized frameworks and the development of scalable architectures for real-world smart home applications. Ikram et al. [3] highlighted that the quality control of the food is enhanced by AI. AI and IoT help in improving the supply chain transparency and support the food distribution efficiently. Shukla et al. [4] developed a prototype of a smart kitchen system that provides automated alert messages when unsafe scenarios are detected. Ezugwu et al. [5] discuss how AI techniques are now embedded into smart systems. Integration of heterogeneous devices and privacy and security of data are the major challenges that are highlighted. This shows the need for better scalable models for smart home ecosystems. Vukolić et al. [6] highlighted that the demand for ML models and automated analytics dashboards are the main components in the reduction of food waste. Shouran et al. [7] outlines a general IoT architecture for a smart home. Perception, network, and application layers are featured as the building blocks of the smart home environment. Security and privacy requirements like confidentiality, integrity, availability, authentication, and authorization are identified. Very common threats that are faced can be data leakage, attacker access via wireless networks, and compromising devices. Singh et al. [8] highlights that ML, computer vision, and NLP are playing a very important role in the food quality check and safety management by using real-time monitoring. Shows the integration of IoT sensors and biosensors, blockchain, and PAT to improve food safety. Balakrishnan et al. [9] outline how AIML models like decision trees, random forests, SVMs, CNNs, RNNs, and clustering help in addressing food safety challenges like spoilage detection and monitoring food contamination. Suggested using federated learning, XAI, multimodal, and synthetic data for making food safety tools more scalable. Wang et al. [10] explains how AI tools like predictive analytics and behavior monitoring systems can promote safe food handling practices. Smart sensors and real-time data support the decision for operators and in turn reduce the risk. Challenges that are faced include data quality, employee buy-in, interpretability of AI, and regulatory acceptance. Agarwal et al. [11] showed that predictive analytics, computer vision, and smart sensors help in optimizing the production, reducing waste and increasing the food manufacturing quality. Barriers identified are legacy system integration, data and privacy issues, high costs, and workforce gaps. Clark et al. [12] outlines that the hospitality industry uses sensors along with AI to categorize and monitor food waste in real time. The complexity of the system should be reduced in order to integrate it with other smart home systems. Golshany et al. [13] found that food management has improved by monitoring freshness, automating grocery orders, and reducing waste. By enabling IoT in the cooking appliances, nutrition can be personalised and temperature can be controlled precisely. Challenges that were faced were data privacy and high costs. Saleem et al [14] use different IoT sensors in a kitchen to monitor the availability of ingredients, expiry dates, and real-time freshness tracking by feeding data into an RNN model for further taking a decision. The model predicts the optimal usage of ingredients and can recommend recipes. Murali et al. [15] developed a smart kitchen system by integrating gas leak detectors, temperature/humidity sensors, and flame/heat monitors to detect the hazard and trigger the safety actions automatically. Further, the kitchen appliances were connected to the cloud, which enabled the real-time alerts. Implementing this system included challenges like sensor reliability issues, system latency, acceptance of users, and the cost of retrofitting the kitchens, which are already existing. Kalyanam et al. [16] outlines the main use cases, which include optimizing real-time workflow, predictive maintenance of kitchen equipment, management of energy, and reduction of food waste via connected devices. Major challenges such as high upfront costs, cybersecurity risks, and integration with legacy systems are highlighted. Qian et al. [17] explained how ML, computer vision, and NLP are now being applied to food safety, including prediction of risks, detection of pathogens, and outbreak surveillance. Highlights the limitations of commercial uptake due to data sharing, standardization, and regulatory frameworks. Balta et al [18]. outlines the key AI technologies like CNNs, hyperspectral imaging, and blockchain-based traceability for enhancing the pathogen detection, supply chain monitoring, and assessment of risks. Major barriers and future work include data quality and availability, the "black box" nature of algorithms, challenges in cost and infrastructure, and the need for interdisciplinary collaboration. Odoi-Yorke et al. [19] show that the major contributions for electric cooking have been from the UK, US, Japan, Australia, and China. E-cooking was integrated with renewables such as solar PV and microgrids. Also showed the need for optimization via AIoT for smart cookers, innovative business or finance models, and research combining technical, economic, social, and policy dimensions. Yin et al. [20] show how spectral data with deep learning enhances the pests detection and spoilage; sensors with ML are used in processing, and finally blockchain with AI is used for traceability. The obstacles and future directions include standardization of data, model interpretability, edge computing, multimodal large models, and global data sharing were proposed for "Food Industry 4.0."

While the current existing AI- and IoT-based kitchen and food safety systems show strong progress, they still suffer from critical limitations:

- Most systems detect hazardous scenarios like smoke, fire, leakage or abnormal temperature. Early detection of dangerous cooking states such as boil-over, dry pot, and unattended heating is lacking.
- Previous work mainly uses the temperature, gas, or visual sensors but does not observe pot weight and liquid level changes, which are very important for hazard prevention.
- Other AI systems use cloud computing or large models, which makes them unsuitable for low-power microcontrollers.
- Systems that are existing give alert messages, but they implement autonomous actuation rarely.
- Challenges faced in the current existing systems include sensor reliability, privacy, hardware costs, and system interoperability. Very limited studies present a low-cost, embedded safety solution that can be later deployed in ordinary homes.

Our proposed system addresses some of these limitations by introducing a proactive, edge-intelligent cooking system framework. Multiple sensors are fused which including load cell, ultrasonic, temperature/humidity, and gas sensors to read the physical state transitions and detect the hazardous events. A lightweight neural network using TensorFlow Lite Micro is deployed on ESP32 to enable prediction of real-time dangerous conditions such as boilover before it occurs. As traditional models give alert-only messages, the proposed model incorporates automatic relay-based shut-off to address the issue of delayed response. This low-cost architecture is easily scalable in the existing kitchen environment. It also overcomes cloud dependency, reduces latency, and enhances reliability.

III. Methodology

A. Hardware Setup

The proposed system is built using the ESP32 Development Board. This acts as the central processing and communication unit. All incoming sensor data is managed by ESP32, then the TFLite micro model is executed for real-time inference and also handles the wireless communication via the WiFi communication module. ESP32 has a dual-core architecture; it supports lightweight ML workloads, which makes it well suited for edge intelligent monitoring applications. This prototype includes sensors such as DHT22 which measures the temperature and humidity with high accuracy, MQ2 gas sensor to detect the gas level in ppm, HC-SR04 Ultrasonic sensor to calibrate the distance which is required to detect the boil over, HX711 Load cell module to measure the weight. Together these sensors are fused to feed the input features to the neural network model to classify the condition as either safe or hazardous. This hardware design integrates a relay module, which provides a switching capability for devices that are connected externally to automatically control the system. A buzzer and an LED indicator are also included for immediate audible and visual alerts whenever the system detects hazardous conditions in the kitchen environment. For power supply, the ESP32 board is powered through both its VIN (5V) and 3.3V rails to prevent the triggering of ESP32's brownout reset, which might happen due to voltage dips. When multiple peripherals are active parallel or when the relay module switches loads, proper power supply is very important. The complete hardware setup was first simulated using the Wokwi online simulator as illustrated in Fig. 1. It was done for safe validation of pin assignments, sensor behavior, and overall system logic to prevent the damage of real components and ensure smooth transition to hardware implementation.

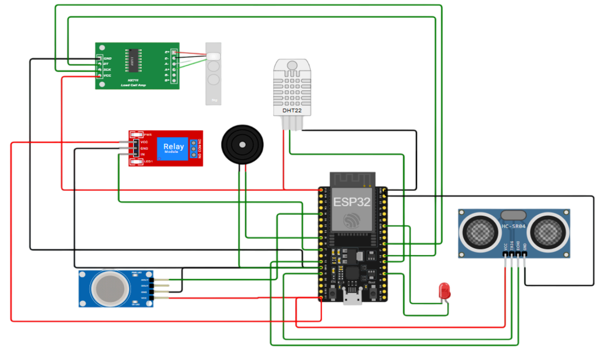

Fig 1: Hardware simulation in Wokwi simulator

B. Model training and deployment

3000 synthetic data samples are generated using NumPy and labeled as either 'safe' or 'hazard' based on logical rules. Before training, all features are normalized using the min-max scaling technique, which ensures that the dimension of each input is mapped to the range of [0,1]. This step of preprocessing helps in stabilizing and accelerating neural network training by keeping gradients well behaved. Later the processed dataset was split into separate training and validation subsets so that unbiased performance evaluation is allowed during the learning process. A lightweight neural network architecture is introduced, designed specifically with microcontroller resource constraints for binary classification, which is trained for over 50 epochs. The model includes binary crossentropy and Adam as the loss function and optimizer, respectively. The downloaded model was later quantized to int8 using TensorflowLite for hardware efficiency before it was deployed onto the ESP32 microcontroller. Fig. 2 shows the architecture of the model, which takes temperature, humidity, gas level, weight, and distance readings as input, passes through two hidden dense layers, and predicts if the kitchen environment is safe or hazardous.

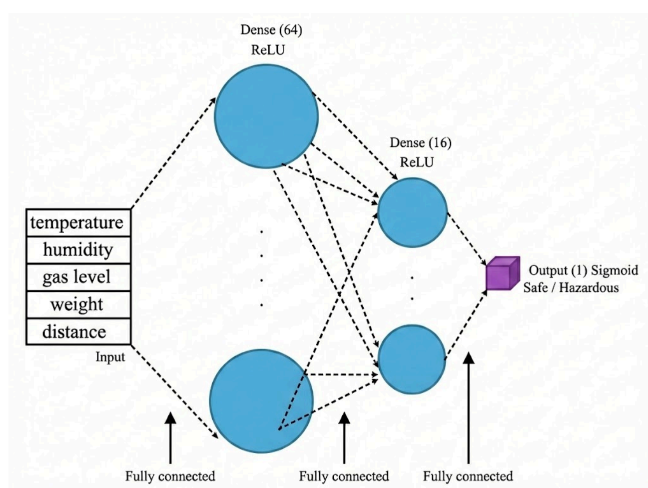

Fig 2: Lightweight neural network architecture for kitchen environment classification using multi-sensor inputs and edge deployment on ESP32.

C. Control and communication

The proposed system uses an HTTP web server on port 80 of the ESP32 microcontroller while connected to local WiFi. The IP address of ESP32 is accessed, and its respective dashboard UI is loaded on the browser. After every two seconds, the dashboard sends AJAX fetch requests. The ML inference runs on the ESP32, which reads the current sensor values and responds with a JSON object containing the latest data and status. The relay control is handled based on the output predicted by the ML model, which is run locally on ESP32. The real-time values of the sensor readings and the predicted value are displayed on the browser.

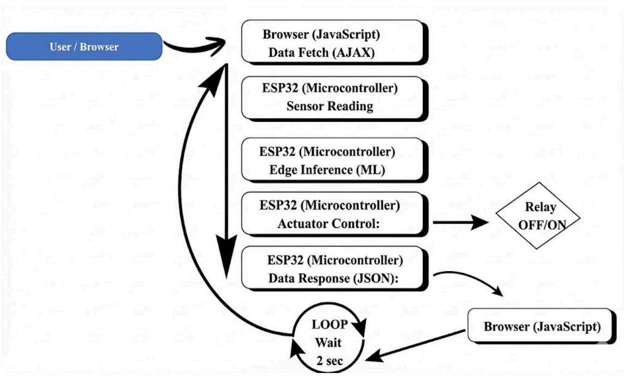

Fig 3: Control and Communication Flow

Fig. 3 illustrates the interaction, which is continuous, between the web browser of the user and the ESP32 microcontroller. Every 2 seconds the browser sends AJAX requests to read all the sensors that are connected to ESP32, run the TFLite micro model, and determine whether the kitchen environment is safe or hazardous. The relay module is controlled based on the ESP32 controls, which allow automated alarm activation. The microcontroller returns a JSON response that contains the latest sensor readings and the current real-time prediction, using this, the browser is updated continuously.

IV. Results and Discussion

The model was trained on the prepared training set and achieved an accuracy of 97.17% on the unseen test set, which demonstrates the model's strong generalization performance. Fig. 4 shows that the training and validation accuracy curves steadily converge over the course of epochs, which indicates that the model is consistently improving without overfitting. Similarly, Fig. 5 outlines the smooth and consistent downward trend of loss curves for both the training and the validation sets. This confirms that the model is able to minimize the error successfully and learn meaningful information from the data.

Complementing the accuracy analysis, the loss function's behavior was also closely monitored. The continuous reduction in loss over the training period signifies that the optimization algorithm successfully minimized the error between the model's predictions and the true labels. This sustained minimization confirms the model's ability to extract and learn meaningful, discriminatory features from the input data, thereby establishing a reliable mapping between the input and the output space. Together the high test accuracy and the stable convergence of both accuracy and loss curves validate the efficacy of the model architecture and the training methodology employed.

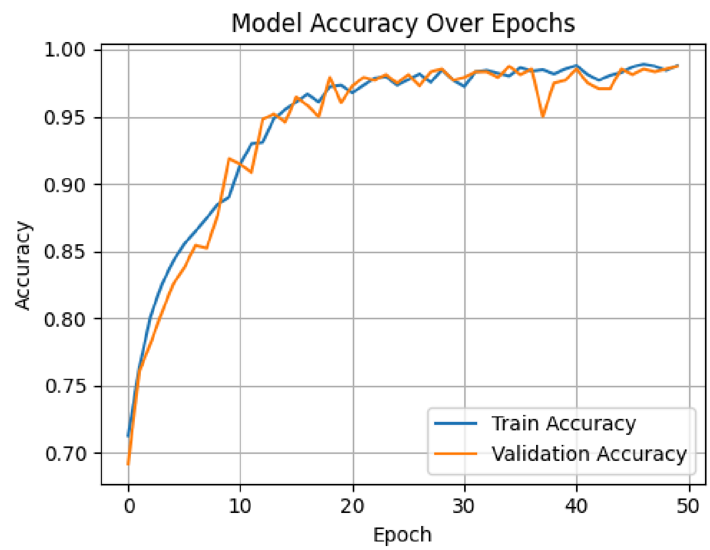

Fig 4: Accuracy of the model over epochs

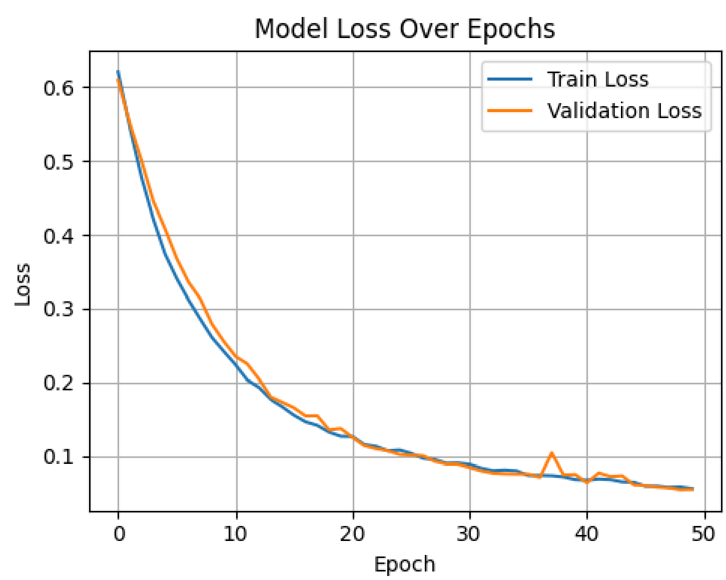

Fig 5: Loss of the model over epochs

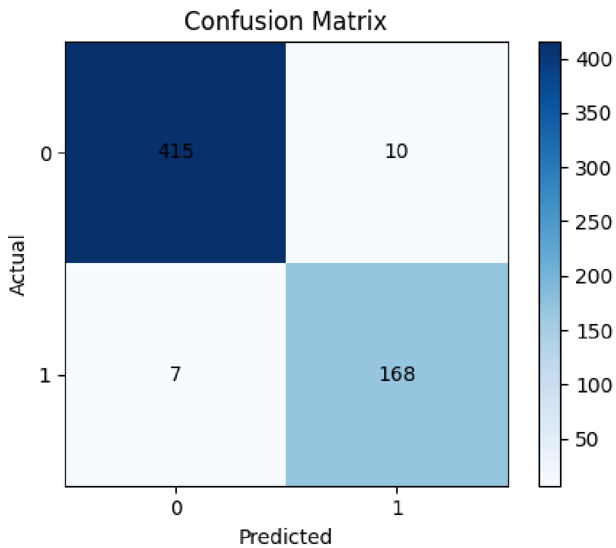

Fig 6: Confusion matrix obtained after testing the model

Further in Fig. 6 displays the confusion matrix generated from the test set evaluation, which assesses the predictive capability of the model. The matrix highlights that the model is able to successfully classify the majority of the samples from both the safe and hazard classes correctly with minimal misclassifications.

TABLE I. Metrics Table

Class / Metric	Precision	Recall	F1-Score	Support
0	0.98	0.98	0.98	425
1	0.94	0.96	0.95	175
Accuracy	—	—	0.97	600
Macro Avg	0.96	0.97	0.97	600
Weighted Avg	0.97	0.97	0.97	600

Table 1 demonstrates the model's reliable and balanced performance, as the F1 score for both macro and weighted averages is approximately 97%.

V. Conclusion and Future Scope

The proposed AIoT-enabled kitchen safety guard meets its goals effectively, ensuring a strong, reliable, and low-cost design for home safety. The readings from the four sensors are fused together to capture a comprehensive view of the kitchen environment so that it detects the dangerous conditions accurately. Their readings are processed by a lightweight neural network, and then the trained TFLite micro model is deployed on the ESP32. The model successfully achieved an accuracy rate of 97.17% on the unseen test set, showing its ability to classify the real-time sensor reading into two classes. The predicted values are then shown on the web browser over the WiFi. The system is automatically controlled using the relay module to prevent the hazardous scenarios.

Future work for this project focuses on enhancing the reliability and scalability and improving the intelligence of the system. This can further be extended by integrating other sensors such as flame detectors, CO sensors, and vibration sensors to improve hazard detection accuracy. To enable remote monitoring, long-term data storage, and automated alerts through mobile applications, cloud connectivity using MQTT or Firebase can be incorporated. To address more diverse scenarios, real-world sensor data can be collected rather than synthetic data. This way, the ML model can be improved and provide better generalization. Advanced models such as anomaly detection or edge-optimized architectures can be explored for higher performance while maintaining low computational cost.

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