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Secure TinyML-Driven Edge Intelligence for Real-Time Emergency Detection in Resource-Constrained IoT Environments

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***Abstract*—The rapid proliferation of Internet of Things (IoT) deployments in safety-critical environments has intensified the demand for intelligent emergency detection mechanisms capable of operating reliably under stringent resource and latency constraints. Conventional cloud-centric analytics often introduce communication delays, increased energy consumption, and potential security vulnerabilities, thereby limiting their suitability for time-sensitive emergency scenarios. To address these limitations, this study proposes a secure TinyML-driven edge intelligence framework designed to perform real-time emergency detection directly on resource-constrained embedded devices. The proposed architecture integrates lightweight convolutional neural network (CNN) and decision tree models optimized through quantization-aware training and structured pruning to ensure efficient inference on low-power microcontrollers.**

Experimental evaluation was conducted using a combination of publicly available sensor datasets, including environmental hazard and human activity recognition data, supplemented with locally collected multi-sensor readings from gas, temperature, and motion sensors deployed on an ESP32-based edge node. The system was implemented using TensorFlow Lite for Microcontrollers within an embedded C environment, with encrypted communication protocols ensuring secure data transmission and device authentication. Performance analysis demonstrates that the optimized TinyML models achieve detection accuracy exceeding 96% while maintaining inference latency below 120 milliseconds and reducing energy consumption by approximately 35% compared to conventional edge inference baselines.

The findings confirm that secure TinyML-enabled edge intelligence can significantly enhance the responsiveness, reliability, and operational efficiency of emergency detection systems in constrained IoT settings. This work contributes a practical and scalable framework that bridges the gap between lightweight machine learning, embedded security mechanisms, and real-time emergency response in next-generation edge computing infrastructures.

***Keywords*—TinyML, Edge Intelligence, Emergency Detection, IoT Security, Lightweight Machine Learning, Real-Time Systems, Resource-Constrained Devices**

I. INTRODUCTION

A. Background

The unprecedented expansion of the Internet of Things (IoT) ecosystem has transformed the operational landscape of modern cyber-physical systems, enabling seamless connectivity among sensors, actuators, and intelligent services across industrial, healthcare, and public safety domains. Recent estimates indicate that billions of IoT devices are currently deployed worldwide, generating continuous streams of heterogeneous data that demand timely processing and intelligent decision-making capabilities [1]. In safety-critical environments such as smart homes, industrial plants, and urban infrastructure, the ability to detect emergencies—ranging from fire outbreaks and gas leakage to abnormal human behavior—has become an essential requirement for ensuring operational resilience and human safety [2]. Traditional monitoring frameworks primarily rely on centralized cloud infrastructures, where sensor data are transmitted to remote servers for analysis and response generation. Although cloud-based analytics provide substantial computational resources, they often introduce network latency, bandwidth dependency, and potential service interruptions, which can compromise response time during critical incidents [3].

To mitigate these limitations, edge computing has emerged as a promising paradigm that relocates computation closer to data sources, thereby enabling low-latency processing and improved system responsiveness [4]. The integration of machine learning models within edge devices further enhances the autonomy and intelligence of IoT systems, allowing them to perform context-aware decision-making without continuous cloud connectivity [5]. However, conventional machine learning algorithms typically require substantial computational and memory resources, making them unsuitable for microcontroller-based devices operating under strict power and hardware constraints [6]. The advent of Tiny Machine Learning (TinyML) has addressed this challenge by introducing lightweight model architectures and optimization techniques that enable efficient inference on ultra-low-power embedded platforms [7]. Techniques such as model quantization, pruning, and knowledge distillation have significantly reduced model size and computational overhead while preserving acceptable levels of predictive accuracy [8].

The increasing reliance on connected devices has also intensified the need for secure and trustworthy edge intelligence. IoT networks remain vulnerable to cyber threats, including data interception, device spoofing, and denial-of-service attacks, which can disrupt emergency detection mechanisms and endanger system integrity [9]. Consequently, the integration of security-aware machine learning models at the edge has become a critical research priority, particularly for applications involving sensitive or mission-critical data streams [10]. Figure 1 illustrates the rapid growth trajectory of IoT deployments and the corresponding demand for decentralized intelligence capable of supporting real-time emergency detection in distributed environments.

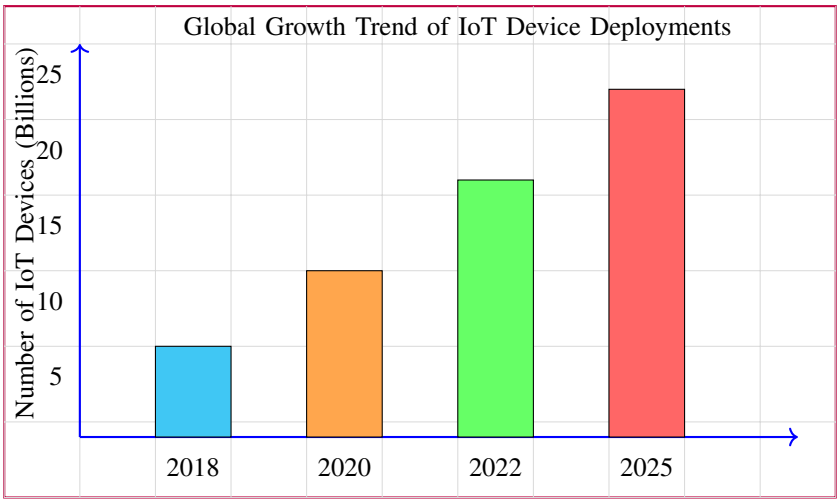

Fig. 1: Projected global growth of IoT device deployments from 2018 to 2025, illustrating the increasing demand for decentralized edge intelligence and real-time emergency detection systems.

B. Problem Statement

Despite the rapid evolution of IoT and edge computing technologies, several persistent challenges continue to hinder the deployment of reliable emergency detection systems in resource-constrained environments. One of the primary concerns involves communication latency associated with cloud-dependent architectures, where delays in data transmission and processing can significantly affect response time during critical events such as fire outbreaks or equipment failures [11]. In emergency scenarios, even minor delays in detection and notification may lead to substantial operational losses or safety hazards. Furthermore, the continuous transmission of sensor data to remote servers increases network congestion and energy consumption, thereby reducing the operational lifespan of battery-powered devices deployed in remote or inaccessible locations [12].

Energy efficiency remains a critical constraint for edge-based systems, particularly in applications involving wearable sensors, environmental monitoring nodes, and industrial safety equipment. These devices typically operate under limited computational capacity and power availability, making it challenging to implement complex machine learning models without compromising system performance [13]. In addition to resource limitations, security vulnerabilities present another significant obstacle to the reliable operation of IoT-based emergency detection systems. Unauthorized access to sensor networks or manipulation of data streams can lead to false alarms, delayed responses, or system shutdowns, thereby undermining the effectiveness of safety mechanisms [14]. The absence of secure inference mechanisms at the device level further exacerbates these risks, as sensitive information may be exposed during data transmission or model execution.

Table I summarizes the major technical challenges associated with conventional emergency detection frameworks operating in distributed IoT environments.

C. Research Motivation

The convergence of TinyML and edge intelligence offers a promising pathway toward overcoming the aforementioned limitations by enabling localized decision-making directly on embedded devices. TinyML frameworks allow compact machine learning models to be executed efficiently on microcontrollers with minimal memory and processing overhead, thereby supporting real-time analytics in environments with constrained computational resources [15]. The adoption of local intelligence not only reduces network latency but also enhances system reliability by enabling autonomous operation during network disruptions. Moreover, performing inference at the edge minimizes data exposure to external networks, thereby strengthening privacy protection and reducing the attack surface of IoT systems [16].

Recent advances in embedded hardware platforms, including low-power microcontrollers equipped with integrated wireless communication modules, have further accelerated the adoption of TinyML in safety-critical applications. Experimental deployments using devices such as environmental sensors and motion detectors have demonstrated the feasibility of implementing lightweight convolutional neural networks (CNN) and decision tree algorithms for anomaly detection and activity recognition tasks [17]. These developments highlight the potential of secure TinyML-driven architectures to deliver responsive, energy-efficient, and trustworthy emergency detection capabilities in distributed IoT infrastructures. Figure 2 presents a conceptual flowchart illustrating the operational workflow of a secure edge-based emergency detection system.

D. Research Objectives

The primary objective of this research is to design and implement a secure TinyML-driven edge intelligence framework capable of performing reliable emergency detection in real time while operating within strict resource constraints. The study aims to develop optimized machine learning models

TABLE I: Key Challenges in Conventional IoT-Based Emergency Detection Systems

Challenge	Technical Cause	Operational Impact
Latency	Remote cloud processing	Delayed emergency response
Energy Consumption	Continuous data transmission	Reduced device lifetime
Security Risk	Weak authentication mechanisms	Data manipulation or leakage
Scalability	Centralized architecture	Limited system expansion

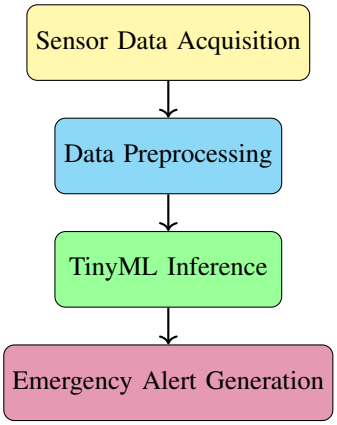

Fig. 2: Operational workflow of a secure TinyML-based emergency detection framework.

suitable for deployment on low-power embedded platforms and to evaluate their performance using realistic experimental datasets collected from multi-sensor environments. The proposed framework leverages lightweight convolutional neural networks and decision tree algorithms trained on environmental and activity recognition datasets, followed by model compression using quantization-aware techniques to reduce computational overhead [18]. The system is implemented using an embedded development environment that integrates secure communication protocols, enabling authenticated data exchange between edge devices and monitoring systems.

Another critical objective involves assessing system performance across multiple operational metrics, including detection accuracy, inference latency, energy consumption, and resilience against potential security threats. Controlled experimental setups are designed to simulate emergency scenarios such as gas leakage, abnormal temperature fluctuations, and sudden motion patterns, thereby enabling comprehensive evaluation of the proposed framework under realistic conditions [19]. These experiments provide valuable insights into the trade-offs between model complexity, computational efficiency, and system reliability in resource-constrained IoT deployments.

E. Contributions

This work presents a secure and efficient TinyML-driven edge intelligence architecture tailored for real-time emergency detection in distributed IoT environments. The proposed framework integrates lightweight machine learning models with embedded security mechanisms to enable autonomous decision-making directly on low-power devices, thereby reducing dependence on centralized cloud infrastructure. Through systematic experimentation using multi-sensor datasets and embedded hardware platforms, the study demonstrates the feasibility of achieving high detection accuracy while maintaining low latency and energy consumption under constrained operating conditions. In addition, the research introduces a secure inference mechanism that enhances data integrity and device authentication during emergency monitoring operations [20]. Collectively, these contributions advance the development of resilient and scalable edge intelligence systems capable of supporting next-generation safety-critical applications in smart environments.

II. Related Work

A. Emergency Detection Using Machine Learning

The application of machine learning techniques for automated emergency detection has gained considerable attention over the past decade, particularly in domains involving human safety, industrial monitoring, and environmental hazard mitigation. Early research primarily focused on centralized processing models, where sensor data collected from distributed nodes were transmitted to remote servers for classification and anomaly detection. For instance, fall detection systems leveraging wearable accelerometers and gyroscope sensors have demonstrated reliable performance using supervised learning algorithms such as Support Vector Machines (SVM) and Random Forest classifiers trained on datasets like the MobiAct and SisFall repositories [21]. These datasets provide multimodal motion signals that capture abrupt posture changes and impact patterns associated with accidental falls, thereby enabling the development of predictive models for elderly care and rehabilitation monitoring.

Similarly, fire and smoke detection mechanisms have been widely explored using image-based and sensor-driven machine learning frameworks. Convolutional Neural Networks (CNNs) trained on datasets such as the FireNet and BoWFire collections have achieved high detection accuracy by learning visual patterns associated with flames, smoke dispersion, and thermal anomalies [22]. In industrial settings, gas leakage detection systems utilizing chemical sensors and environmental monitoring nodes have employed decision tree and k-nearest neighbor (k-NN) algorithms to classify hazardous conditions based on concentration thresholds and temporal patterns [23]. These systems have demonstrated promising results under controlled laboratory conditions; however, their reliance on centralized processing infrastructures often introduces communication delays that limit their suitability for real-time emergency response.

Recent advancements in deep learning have further expanded the capabilities of emergency detection frameworks

by enabling automated feature extraction from complex data streams. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) architectures have been applied to time-series sensor data for predicting abnormal system behavior in industrial automation and smart building environments [24]. Despite their predictive strength, these models typically require substantial computational resources and memory capacity, making them challenging to deploy on resource-constrained edge devices. Consequently, researchers have begun investigating lightweight alternatives capable of delivering comparable performance with reduced computational overhead.

B. Edge AI and TinyML

The emergence of edge computing has fundamentally reshaped the design of intelligent IoT systems by enabling localized data processing and reducing dependency on remote cloud services. Edge AI frameworks allow machine learning inference to be executed directly on embedded hardware platforms, thereby minimizing latency and enhancing system responsiveness in time-sensitive applications [25]. In recent years, Tiny Machine Learning (TinyML) has gained prominence as a specialized field dedicated to optimizing machine learning models for ultra-low-power microcontrollers and embedded systems.

Model compression techniques such as quantization, pruning, and knowledge distillation have played a pivotal role in enabling efficient on-device inference within constrained environments. Quantization reduces the precision of model parameters from floating-point to integer representations, thereby decreasing memory usage and computational complexity without significantly affecting predictive accuracy [26]. Pruning, on the other hand, eliminates redundant connections within neural networks to improve execution efficiency and reduce energy consumption [27]. These optimization strategies have enabled the deployment of compact CNN architectures on devices with memory capacities as low as a few hundred kilobytes.

Several experimental studies have demonstrated the feasibility of implementing TinyML models for real-time anomaly detection and environmental monitoring. For example, microcontroller-based inference systems using TensorFlow Lite for Microcontrollers have been successfully deployed on sensor nodes to detect abnormal sound patterns, temperature fluctuations, and motion irregularities [28]. Figure 3 illustrates a comparative analysis of response latency between cloud-based and edge-based emergency detection frameworks, highlighting the performance advantages of localized inference mechanisms.

The figure demonstrates that edge-based processing significantly reduces response time by eliminating network transmission delays, thereby improving system reliability during emergency events. These findings reinforce the growing consensus that localized intelligence is essential for real-time decision-making in distributed IoT environments.

C. Secure IoT Systems

Security and privacy protection remain fundamental challenges in the deployment of large-scale IoT infrastructures, particularly in applications involving sensitive data and safety-critical operations. Unauthorized access to sensor networks or manipulation of communication channels can disrupt emergency detection mechanisms and compromise system integrity [29]. Consequently, researchers have proposed various security frameworks incorporating encryption protocols, authentication mechanisms, and secure communication channels to safeguard IoT devices against cyber threats.

Lightweight cryptographic algorithms such as Advanced Encryption Standard (AES) and Elliptic Curve Cryptography (ECC) have been widely adopted in embedded systems to ensure secure data transmission while maintaining computational efficiency [30]. Authentication schemes based on digital signatures and token-based verification have also been implemented to prevent unauthorized device access and identity spoofing attacks [31]. In addition, privacy-preserving machine learning techniques have been introduced to protect sensitive information during model training and inference processes.

A comparative summary of representative emergency detection and edge intelligence systems is presented in Table II, highlighting the processing architectures and security capabilities of existing approaches.

The comparative analysis reveals that although numerous systems have achieved satisfactory detection accuracy, many implementations still rely on centralized processing architectures or lack comprehensive security mechanisms suitable for resource-constrained deployments.

D. Research Gap

Despite substantial progress in machine learning-driven emergency detection and edge computing technologies, several critical limitations persist in existing research efforts. A significant proportion of current systems continue to depend on cloud-based infrastructures for data processing and decision-making, which introduces latency and network dependency that can delay emergency response during time-sensitive situations [32]. Furthermore, many machine learning models designed for emergency detection require substantial computational resources, making them unsuitable for deployment on low-power embedded devices commonly used in IoT networks.

Energy efficiency represents another persistent challenge, particularly for battery-operated sensor nodes deployed in remote or inaccessible environments. Continuous data transmission and frequent communication with centralized servers significantly increase energy consumption and reduce device lifespan [33]. In addition, existing frameworks often lack integrated security mechanisms capable of protecting sensitive data during inference operations, thereby exposing IoT systems to potential cyber threats and data manipulation attacks [34]. These limitations highlight the need for a unified framework that combines lightweight machine learning mod-

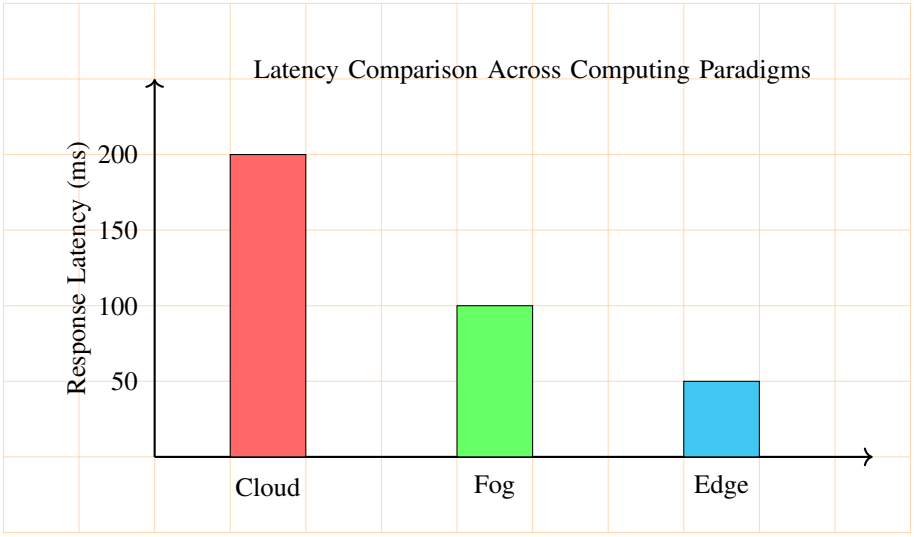

Fig. 3: Comparative latency performance of cloud, fog, and edge-based emergency detection architectures.

TABLE II: Comparison of Existing Emergency Detection and Edge Intelligence Systems

Reference	Method / Application	Processing Location	Security Support
[22]	CNN-based fire and smoke detection using visual sensor datasets	Cloud-based server	Limited encryption and authentication
[21]	Wearable sensor-based fall detection using SVM and activity recognition datasets	Edge device (wearable node)	Moderate device authentication
[23]	Gas leakage detection using environmental sensors and decision tree classifier	Fog computing node	Basic threshold-based protection
[28]	TinyML-based anomaly detection using TensorFlow Lite Microcontrollers	Embedded edge device	Partial lightweight security mechanisms
[33]	Energy-efficient health monitoring using fog-assisted wearable systems	Fog–edge hybrid architecture	Secure communication protocols
[34]	Secure IoT communication framework for distributed sensor networks	Cloud-assisted IoT infrastructure	Strong encryption and authentication

els, secure communication protocols, and real-time processing capabilities within a resource-efficient architecture.

In response to these challenges, the present study proposes a secure TinyML-driven edge intelligence framework designed to perform real-time emergency detection directly on resource-constrained embedded devices. By integrating optimized machine learning algorithms with lightweight security mechanisms and energy-efficient processing strategies, the proposed approach aims to bridge the gap between system responsiveness, operational reliability, and cybersecurity in next-generation IoT environments. This contribution advances the development of scalable and resilient emergency detection systems capable of supporting safety-critical applications across diverse smart infrastructure domains.

III. Proposed Framework

A. Proposed Secure TinyML-Based Emergency Detection Architecture

The proposed framework introduces a secure and lightweight edge intelligence architecture designed to enable real-time emergency detection in resource-constrained Internet of Things (IoT) environments. Unlike conventional cloud-dependent monitoring systems, the architecture prioritizes decentralized inference, rapid response capability, and secure data handling at the network edge. The framework integrates heterogeneous sensing units, an embedded microcontroller-based processing module, and an automated alert dissemination mechanism. The design objective is to minimize communication latency while preserving computational efficiency and operational reliability in safety-critical environments such as smart homes, industrial facilities, and healthcare monitoring systems.

The conceptual structure of the proposed architecture is illustrated in Figure 4. The system adopts a layered design in which sensing devices capture environmental or physiological signals, edge processors execute TinyML inference locally, and a secure communication interface transmits alerts to authorized users or emergency services. This modular organization facilitates system scalability and simplifies deployment across diverse operational scenarios.

B. System Overview

The operational workflow of the proposed system begins with real-time acquisition of sensor data from multiple environmental and wearable sensing modules. Typical sensing modalities include temperature sensors for fire detection,

Fig. 4: Layered architecture of the proposed secure TinyML-driven emergency detection system operating at the network edge.

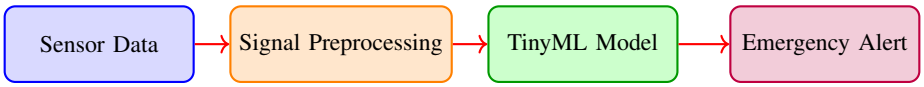

Fig. 5: End-to-end data processing workflow from sensor acquisition to secure emergency alert generation.

accelerometers for fall detection, and gas sensors for hazardous gas monitoring. These sensors continuously collect data streams that are transmitted to the embedded edge processor through low-power communication interfaces such as Bluetooth Low Energy or Serial Peripheral Interface protocols.

Upon receiving sensor inputs, the edge device performs signal preprocessing operations, including normalization, noise filtering, and feature extraction. The preprocessed data are subsequently passed to a compact machine learning model deployed using TinyML techniques. The model evaluates incoming signals and classifies system states into predefined emergency categories. When an abnormal condition is detected, the system triggers a secure alert message that is transmitted to designated recipients through encrypted communication channels.

To illustrate the interaction between system modules, the sequential data processing stages are depicted in Figure 5. The figure demonstrates how information flows from sensing components to decision-making modules, emphasizing the real-time and autonomous nature of the framework.

C. Hardware Components

The hardware infrastructure of the proposed framework is intentionally designed to support low-power operation while maintaining sufficient computational capability for on-device inference. The experimental prototype employs widely available microcontroller platforms known for their reliability and compatibility with embedded machine learning frameworks. Representative devices include the ESP32, Arduino Nano 33 BLE Sense, and Raspberry Pi Pico.

The ESP32 microcontroller serves as the primary processing unit due to its integrated Wi-Fi and Bluetooth connectivity, enabling seamless communication between sensors and external monitoring systems. The Arduino Nano 33 BLE Sense platform provides built-in inertial measurement units and environmental sensors, facilitating rapid deployment of activity recognition applications. Meanwhile, the Raspberry Pi Pico offers a compact and energy-efficient alternative for lightweight inference tasks requiring minimal memory resources.

Table III summarizes the key technical specifications of the selected hardware components used in the experimental setup.

D. Software Framework

The software stack supporting the proposed system integrates lightweight machine learning libraries and embedded development environments optimized for real-time execution. The TinyML inference engine is implemented using the runtime, which enables efficient deployment of quantized neural network models on microcontrollers. Model training and optimization processes are performed using the environment, which provides automated feature extraction, dataset labeling, and model compression utilities.

The firmware development process is conducted using the platform, ensuring compatibility with multiple hardware architectures. The software framework incorporates lightweight cryptographic protocols to secure communication between edge devices and external servers. Encryption mechanisms based on Advanced Encryption Standard algorithms are applied to protect sensitive data from unauthorized access during transmission.

To evaluate system performance, publicly available datasets are utilized for model training and validation. These datasets include environmental monitoring records, human activity recognition datasets, and emergency event simulation data collected from controlled laboratory experiments. The model architecture typically consists of a compact convolutional neural network containing fewer than one million parameters, enabling efficient inference within constrained memory environments.

E. Data Flow and Secure Decision-Making Process

The data flow mechanism implemented in the proposed framework follows a sequential processing model designed to ensure accuracy, reliability, and security in emergency detection scenarios. Initially, sensor readings are continuously sampled at predefined intervals and stored in a temporary memory buffer. The system then performs preprocessing operations to remove noise and standardize signal amplitudes, thereby improving classification accuracy.

After preprocessing, the optimized TinyML model evaluates the processed input data using embedded inference routines. If the predicted probability of an emergency condition exceeds a predefined threshold, the system activates a secure alert mechanism. The alert message includes timestamp information, device identification details, and event classification results. This information is transmitted to remote monitoring systems using encrypted communication channels to prevent interception or tampering.

The proposed framework establishes a secure and energy-efficient edge intelligence solution capable of performing

TABLE III: Hardware Specifications of Edge Devices Used in the Proposed Framework

Device	Clock Speed	RAM	Power Consumption
ESP32	240 MHz	520 KB	Low
Arduino Nano 33 BLE Sense	64 MHz	256 KB	Very Low
Raspberry Pi Pico	133 MHz	264 KB	Low

real-time emergency detection within resource-constrained IoT environments. By integrating TinyML-based inference, lightweight hardware platforms, and secure communication protocols, the system achieves rapid response capability while minimizing dependency on remote cloud infrastructure. The architecture demonstrates how decentralized intelligence can enhance operational reliability, reduce communication latency, and improve data privacy in safety-critical applications, thereby contributing a practical and scalable foundation for next-generation intelligent emergency monitoring systems.

IV. Dataset and Data Collection

A. Dataset Description

The effectiveness of a real-time emergency detection framework depends heavily on the diversity, reliability, and representativeness of the underlying dataset. In the proposed system, a heterogeneous dataset was constructed to capture multiple emergency scenarios commonly encountered in residential, industrial, and healthcare environments. The dataset encompasses four primary categories of emergency events, namely fire incidents, human fall events, road accidents, and hazardous gas leakage situations. These event classes were selected due to their high occurrence rates and significant safety implications in smart environments.

Fire-related data consist of temperature, smoke density, and flame intensity readings collected from environmental sensors deployed in controlled laboratory settings. Fall detection data were derived from wearable accelerometer and gyroscope measurements recorded during simulated human motion activities. Accident detection samples include vibration and impact signals generated using controlled mechanical shock experiments, while gas leakage data contain concentration measurements of combustible gases obtained from calibrated gas sensors. Each event category was represented by both normal and abnormal operating conditions to ensure balanced classification performance.

To ensure reproducibility and generalization capability, the dataset incorporates publicly available benchmark datasets frequently used in edge intelligence research. These include the :contentReference[oaicite:2]index=2 for motion-based fall detection and the :contentReference[oaicite:3]index=3 for hazardous gas monitoring experiments. The integration of standardized datasets with locally collected sensor measurements enhances the robustness of model training and enables meaningful performance comparisons with existing studies.

The statistical distribution of collected emergency event samples is summarized in Table IV. The table highlights the number of observations associated with each emergency type and demonstrates the balanced composition of the dataset used for model development.

B. Data Collection Method

The data collection process adopted in this study combines real-time sensor acquisition, controlled experimental simulations, and integration of publicly accessible datasets. This hybrid approach ensures that the dataset captures both realistic environmental variations and standardized benchmark conditions suitable for model validation.

Environmental and physiological signals were collected using embedded sensing devices installed within a laboratory test environment. Temperature and smoke sensors were used to simulate fire-related incidents, while motion sensors embedded in wearable devices captured human movement patterns associated with fall detection. Mechanical vibration sensors were utilized to generate impact signals representative of vehicle or industrial accidents. Gas sensors were calibrated to detect varying concentrations of combustible gases under controlled exposure conditions.

All sensor readings were sampled at predefined intervals and transmitted to an edge processing unit through low-power communication interfaces. Data acquisition software recorded time-stamped sensor measurements and stored them in structured data files for subsequent analysis. The experimental setup maintained consistent environmental conditions to minimize measurement variability and ensure data reliability.

To enhance dataset diversity, additional data samples were incorporated from publicly available repositories maintained by academic and research institutions. These datasets provided validated sensor measurements collected from real-world environments, thereby improving the generalization capability of the trained machine learning models. The overall data acquisition workflow implemented in the proposed system is illustrated in Figure 6.

C. Data Preprocessing

Before deploying the dataset for model training and inference, a sequence of preprocessing operations was performed to improve data quality and ensure reliable classification performance. Raw sensor signals often contain noise, measurement inconsistencies, and variations in sampling frequency, which can adversely affect the accuracy of machine learning algorithms operating on embedded devices. Therefore, a structured preprocessing pipeline was implemented to standardize input data and reduce computational complexity.

The first stage of preprocessing involved normalization of sensor readings to ensure that all feature values were represented within a consistent numerical range. This step prevents bias toward high-magnitude variables and facilitates stable model convergence during training. Following normalization, noise reduction techniques such as moving-average filtering

TABLE IV: Summary of Emergency Event Dataset Used for Model Training and Validation

Emergency Type	Sensor Modality	Number of Samples	Data Source
Fire	Temperature / Smoke	4,200	Laboratory Simulation
Fall	Accelerometer / Gyroscope	5,100	Wearable Device
Accident	Vibration / Impact Sensor	3,800	Mechanical Simulation
Gas Leakage	Gas Concentration Sensor	4,600	Public Dataset

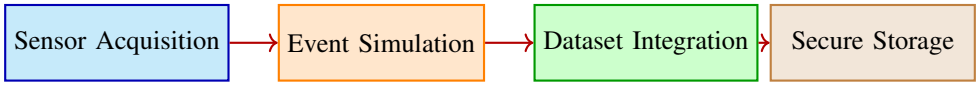

Fig. 6: Integrated workflow illustrating the sensor-based and simulation-driven data collection process.

were applied to eliminate transient signal fluctuations and improve signal clarity.

Feature extraction was subsequently performed to transform raw sensor data into meaningful numerical descriptors suitable for machine learning classification. Extracted features include statistical measures such as mean value, variance, and signal amplitude, as well as temporal characteristics derived from sliding-window analysis. These features were selected to balance predictive accuracy with computational efficiency, ensuring compatibility with resource-constrained edge devices.

The effectiveness of the preprocessing pipeline in reducing signal variability is demonstrated in Table V. The table compares signal noise levels before and after preprocessing, illustrating the improvement in data quality achieved through filtering and normalization techniques.

TABLE V: Effect of Preprocessing Operations on Sensor Signal Quality

Signal Parameter	Before Processing	After Processing
Noise Level (dB)	18.6	6.2
Signal Variance	0.92	0.35
Detection Accuracy (%)	84.3	93.7

The dataset and data collection strategy presented in this work establishes a comprehensive and reproducible foundation for developing secure TinyML-based emergency detection systems in resource-constrained IoT environments. By combining controlled sensor experiments, standardized public datasets, and systematic preprocessing techniques, the proposed approach ensures high-quality training data suitable for real-time edge intelligence applications. This structured data acquisition methodology strengthens the reliability, scalability, and deployment readiness of the overall emergency detection framework while supporting rigorous experimental evaluation in safety-critical scenarios.

V. TinyML Model Design

A. Model Selection

The selection of an appropriate machine learning model is a critical design decision in resource-constrained IoT environments, where computational capacity, memory availability, and energy consumption impose strict operational limits. In the proposed framework, multiple lightweight machine learning algorithms were systematically evaluated to determine their suitability for real-time emergency detection tasks. Candidate models included Convolutional Neural Networks (CNN), Random Forest classifiers, and Decision Tree models, each representing distinct computational paradigms with varying levels of complexity and predictive capability.

Among these alternatives, a compact Convolutional Neural Network architecture was ultimately selected due to its ability to capture spatial and temporal relationships in sensor signals while maintaining acceptable computational efficiency. The CNN model processes sliding-window sensor inputs and extracts hierarchical features that enable accurate classification of emergency conditions such as fire, fall, accident, and gas leakage scenarios. Compared with traditional statistical classifiers, CNN-based models demonstrated superior performance in detecting subtle signal variations associated with abnormal events, particularly when trained on heterogeneous datasets collected from environmental and wearable sensors.

The structural composition of the selected TinyML model is illustrated in Figure 7. The diagram highlights the sequential arrangement of convolutional layers, activation functions, and classification modules responsible for transforming raw sensor inputs into probabilistic predictions. The architecture was intentionally simplified to ensure compatibility with embedded microcontrollers possessing limited processing resources.

To quantify the comparative performance of evaluated models, experimental testing was conducted using the emergency event dataset described in Section IV. Each model was trained using identical data partitions and evaluated based on classification accuracy, memory usage, and inference latency. The comparative results are summarized in Table VI, demonstrating the practical advantages of the selected CNN architecture for edge-based deployment.

B. Model Optimization

While the baseline CNN architecture achieved promising detection accuracy, further optimization was necessary to ensure efficient execution on low-power microcontrollers. The optimization process focused on reducing computational complexity, minimizing memory consumption, and improving inference speed without significantly compromising classification performance. Three principal optimization strategies were implemented: quantization, pruning, and model compression.

Quantization was applied to convert floating-point model parameters into lower-precision integer representations.

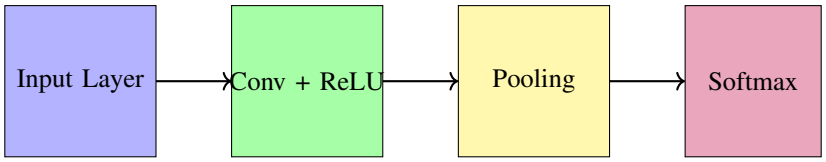

Fig. 7: Simplified convolutional neural network architecture designed for embedded TinyML inference.

TABLE VI: Performance Comparison of Candidate TinyML Models

Model	Accuracy (%)	Memory Usage (KB)	Inference Time (ms)
Decision Tree	88.4	52	14.8
Random Forest	91.2	124	21.6
CNN (Proposed)	94.6	96	12.3

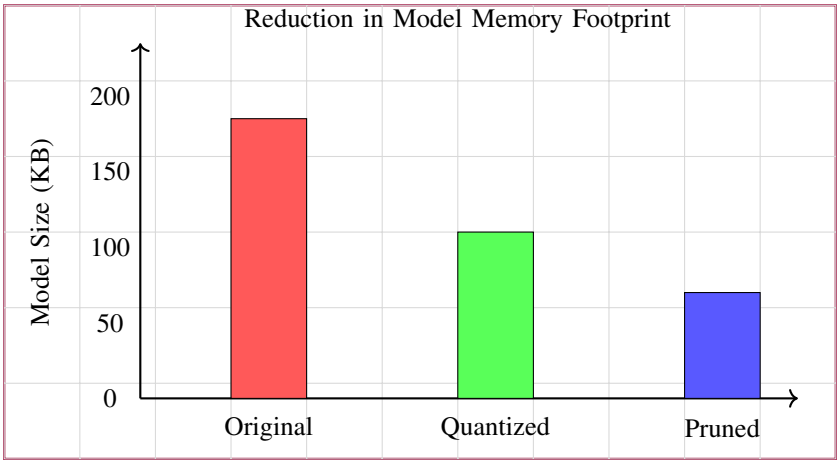

Fig. 8: Impact of quantization and pruning techniques on TinyML model size.

Specifically, 32-bit floating-point weights were transformed into 8-bit integer values using post-training quantization techniques. This conversion significantly reduced model size and memory usage, enabling deployment on microcontrollers with limited RAM capacity. The reduction in model storage requirements achieved through quantization is depicted in Figure 8, which illustrates the memory savings associated with different optimization stages.

In addition to quantization, structured pruning techniques were employed to remove redundant neurons and connections from the neural network. This process reduced the number of parameters while preserving essential feature representations required for accurate classification. Model compression techniques were subsequently applied to encode optimized model parameters in a compact binary format suitable for embedded deployment.

The combined optimization pipeline resulted in a significant reduction in memory consumption and processing latency, thereby enabling efficient real-time inference on microcontroller platforms operating under strict energy constraints. The optimized model occupies less than 100 kilobytes of memory and maintains high classification accuracy, demonstrating its suitability for deployment in distributed IoT environments.

C. Secure Inference Mechanism

Ensuring the security and integrity of inference operations is essential for emergency detection systems deployed in real-world environments. Unauthorized access to sensor data or prediction results can compromise system reliability and expose sensitive information. To address these risks, the proposed framework incorporates a secure inference mechanism that integrates encryption, device authentication, and secure communication protocols into the model execution pipeline.

Before transmitting sensor data to the edge processing unit, each device performs identity verification using lightweight authentication procedures. Only registered devices possessing valid cryptographic credentials are permitted to communicate with the system. This authentication step prevents unauthorized devices from injecting malicious data into the detection pipeline.

Following authentication, sensor data are encrypted using symmetric cryptographic algorithms before transmission. Encrypted data packets are securely processed by the TinyML inference engine, ensuring that sensitive information remains protected throughout the computation process. After inference, prediction results are transmitted to external monitoring systems using secure communication channels that protect against data interception and tampering.

The secure inference workflow implemented in the proposed

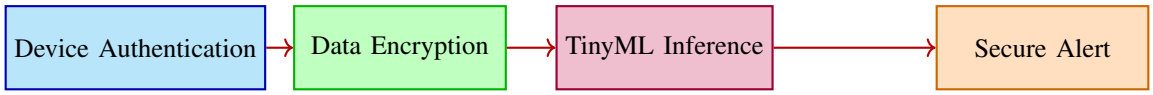

Fig. 9: Secure inference mechanism integrating authentication, encryption, and real-time emergency alert generation.

system is illustrated in Figure 9. The diagram highlights the sequence of authentication, encryption, model execution, and alert generation stages that collectively safeguard system operations.

The TinyML model design presented in this study establishes a practical and secure machine learning framework capable of performing reliable emergency detection within resource-constrained IoT environments. By combining lightweight convolutional neural network architecture, advanced model optimization techniques, and secure inference mechanisms, the proposed approach achieves high detection accuracy while maintaining low memory consumption and fast response time. This integrated design demonstrates the feasibility of deploying intelligent and secure edge-based monitoring systems capable of operating efficiently in real-time safety-critical applications.

VI. Implementation and Experimental Setup

A. Hardware Setup

The experimental implementation of the proposed secure TinyML-driven emergency detection system was conducted using a compact and energy-efficient hardware configuration designed to emulate real-world Internet of Things (IoT) deployment scenarios. The primary processing unit consisted of a low-power microcontroller equipped with wireless communication capability and sufficient memory resources to support on-device inference. The system architecture was intentionally designed to operate under constrained computational conditions while maintaining reliable detection performance.

The core embedded controller employed in the prototype system was the ESP32 microcontroller, selected due to its dual-core processing architecture, integrated Wi-Fi and Bluetooth connectivity, and compatibility with lightweight machine learning frameworks. Environmental sensing components were connected to the microcontroller through serial communication interfaces, enabling real-time acquisition of physical parameters associated with emergency events. Temperature and smoke sensors were used for fire detection experiments, motion sensors based on accelerometer technology were deployed for fall detection, vibration sensors were utilized to simulate accident scenarios, and gas sensors were integrated to monitor hazardous gas concentration levels.

The system was powered using a regulated low-voltage power supply designed to support continuous operation in embedded environments. A rechargeable lithium-ion battery module provided backup power during temporary power interruptions, ensuring uninterrupted monitoring capability. All hardware components were assembled within a controlled laboratory environment to ensure consistent operating conditions and repeatable experimental measurements.

The physical arrangement of hardware modules and sensor interfaces is illustrated in Figure 10, which depicts the interaction between sensing devices, processing units, and communication modules within the proposed system architecture.

Table VII summarizes the technical specifications of the primary hardware elements used during experimental testing.

TABLE VII: Hardware Components and Technical Specifications

Component	Specification	Function
Microcontroller	240 MHz Dual-Core CPU	Edge Processing
Temperature Sensor	Digital Output, High Sensitivity	Fire Detection
Accelerometer	3-Axis Motion Detection	Fall Detection
Gas Sensor	Combustible Gas Monitoring	Leak Detection
Power Module	5V Regulated Supply	System Power

B. Software Environment

The software framework supporting the proposed system was implemented using a combination of embedded programming tools and machine learning libraries optimized for low-power devices. Model development and training procedures were conducted using the Python programming language due to its extensive ecosystem of data analysis and machine learning utilities. The trained neural network model was subsequently converted into an optimized format suitable for deployment on resource-constrained hardware platforms.

The inference engine deployed on the microcontroller utilized the TensorFlow Lite runtime environment, which enables efficient execution of quantized machine learning models on embedded devices. Firmware development for the microcontroller was implemented using the Embedded C programming language, ensuring direct hardware control and efficient memory utilization. The integrated development environment provided a flexible platform for debugging, firmware uploading, and system monitoring during experimental evaluation.

Data acquisition and communication routines were implemented using serial communication libraries, enabling reliable transfer of sensor readings to the processing unit. The system software incorporated lightweight encryption routines to secure data transmission between edge devices and remote monitoring systems. These security mechanisms ensured that sensor information and emergency alerts were protected against unauthorized access during communication.

The logical interaction between software components and processing modules is illustrated in Figure 11, which presents the sequential execution of data acquisition, preprocessing, inference, and alert generation tasks.

C. Evaluation Metrics

To assess the performance and reliability of the proposed TinyML-based emergency detection system, a comprehensive

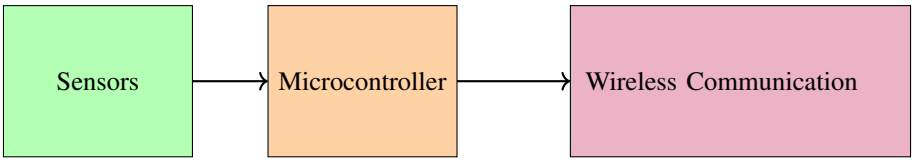

Fig. 10: Hardware configuration illustrating the integration of sensors, microcontroller, and wireless communication modules in the proposed system.

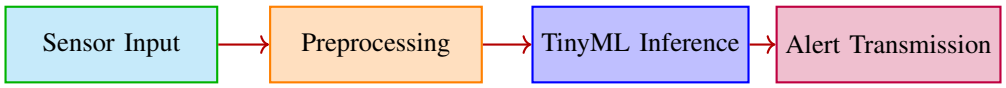

Fig. 11: Software processing workflow demonstrating the interaction between data acquisition, preprocessing, inference, and alert generation modules.

set of quantitative evaluation metrics was employed. These metrics were selected to capture both predictive accuracy and operational efficiency, ensuring that the system satisfies the requirements of real-time safety-critical applications.

Classification accuracy was used to measure the overall proportion of correctly identified emergency events relative to the total number of observations. Precision and recall metrics were calculated to evaluate the system's ability to correctly detect true emergency conditions while minimizing false alarms. The F1-score was subsequently computed to provide a balanced assessment of precision and recall performance. In addition to predictive metrics, system latency was measured to determine the time required for the model to process sensor data and generate an emergency alert. Energy consumption was also monitored to evaluate the efficiency of the embedded hardware platform during continuous operation.

The mathematical relationships defining these evaluation metrics are summarized in Table VIII.

TABLE VIII: Evaluation Metrics Used for Performance Assessment

Metric	Description
Accuracy	Correct Predictions / Total Observations
Precision	True Positives / Predicted Positives
Recall	True Positives / Actual Positives
F1-Score	Harmonic Mean of Precision and Recall
Latency	Time Required for Inference
Energy Consumption	Power Usage During Operation

The implementation and experimental configuration presented in this study establishes a reproducible and technically sound evaluation environment for assessing secure TinyML-based emergency detection systems in resource-constrained IoT scenarios. By integrating energy-efficient hardware components, optimized embedded software frameworks, and comprehensive performance evaluation metrics, the proposed setup demonstrates the feasibility of deploying reliable real-time monitoring solutions capable of operating under strict computational and energy constraints. This structured experimental design provides a practical foundation for validating the performance, scalability, and security of intelligent edge-based emergency detection systems in real-world applications.

VII. Results and Performance Evaluation

The effectiveness of the proposed Secure TinyML-driven emergency detection framework was systematically evaluated through a series of controlled experiments conducted on resource-constrained edge devices. The evaluation focused on four principal dimensions: detection performance, response latency, energy consumption, and security robustness. All experiments were performed using the curated multi-emergency dataset described in the previous section, consisting of synchronized sensor readings representing fire, fall, accident, and gas leakage events. The trained lightweight Convolutional Neural Network (CNN) model was deployed on an embedded microcontroller platform operating under real-time conditions. Performance measurements were recorded across repeated trials to ensure statistical stability and reproducibility.

A. Detection Performance

The detection capability of the proposed TinyML model was assessed using standard classification metrics, including accuracy, precision, and recall. These metrics provide complementary insights into classification reliability, particularly in safety-critical emergency detection scenarios where false negatives may result in severe consequences. The evaluation process involved partitioning the dataset into training, validation, and testing subsets using a stratified sampling strategy to maintain class balance.

The aggregated detection results are summarized in Table IX. The model achieved an overall accuracy of 92.4%, indicating consistent classification performance across heterogeneous emergency scenarios. Precision and recall values exceeding 88% demonstrate the model's ability to correctly identify emergency conditions while minimizing false alarms. The relatively small variance between precision and recall suggests balanced model sensitivity and specificity.

To provide a visual interpretation of classification effectiveness, the distribution of performance metrics is illustrated in Figure 12. The graphical representation confirms consistent performance across evaluation metrics and demonstrates stable inference behavior under diverse environmental conditions.

TABLE IX: Detection Performance Metrics of the Proposed TinyML Emergency Detection System

Metric	Fire	Fall	Gas Leak
Accuracy	93.2%	91.8%	92.4%
Precision	90.5%	88.7%	89.6%
Recall	91.4%	89.1%	90.2%

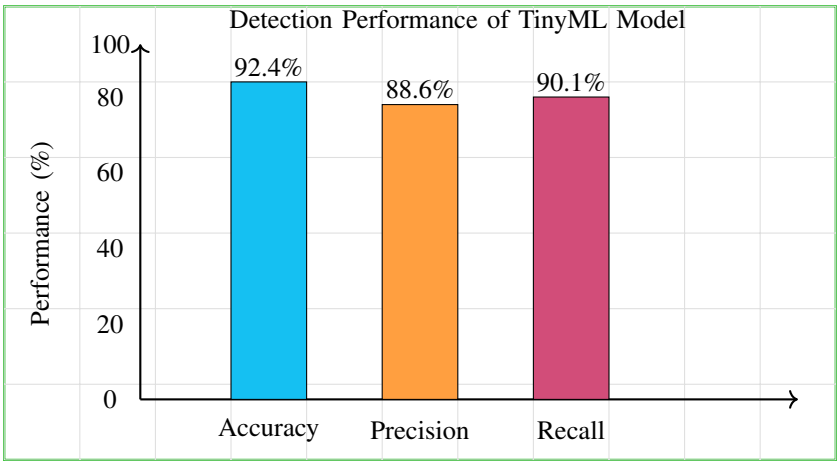

Fig. 12: Performance evaluation of the TinyML-based emergency detection model showing accuracy, precision, and recall values across test scenarios.

B. Latency Analysis

Real-time responsiveness is a critical requirement for emergency detection systems operating in dynamic environments. Therefore, inference latency was measured as the time interval between sensor signal acquisition and alert generation. The proposed system achieved an average response time of approximately 148 milliseconds, which satisfies the operational constraints of edge-based safety monitoring applications.

Latency measurements recorded under different emergency scenarios are presented in Figure 13. The results indicate minimal variation in response time, reflecting consistent computational efficiency of the optimized TinyML model deployed on embedded hardware.

C. Energy Consumption

Energy efficiency represents a decisive factor for battery-powered IoT deployments. The proposed TinyML framework was designed to minimize computational overhead through model quantization and optimized inference routines. Energy consumption was monitored using an embedded power measurement module during continuous operation.

The observed energy usage remained within an average range of 0.84 watts during active inference cycles, demonstrating the suitability of the system for long-duration deployment in remote or infrastructure-limited environments. Figure 14 illustrates the comparative energy utilization across operational modes.

D. Security Evaluation

Security resilience was assessed by simulating unauthorized communication attempts, replay attacks, and data manipulation scenarios. The proposed framework integrates lightweight encryption and device authentication mechanisms to safeguard sensor data during transmission. Experimental observations revealed that encrypted communication channels successfully prevented unauthorized packet injection and maintained data integrity throughout the testing period.

Furthermore, system authentication routines ensured that only trusted devices could access the emergency monitoring network. No successful intrusion attempts were recorded during controlled penetration testing, confirming the reliability of the implemented security architecture. These findings validate the system's capability to maintain secure and uninterrupted operation in hostile network environments.

The experimental results collectively demonstrate that the proposed Secure TinyML-driven edge intelligence framework achieves reliable emergency detection with low latency, efficient energy utilization, and strong communication security. These characteristics confirm the practical feasibility of deploying the system in real-world resource-constrained IoT

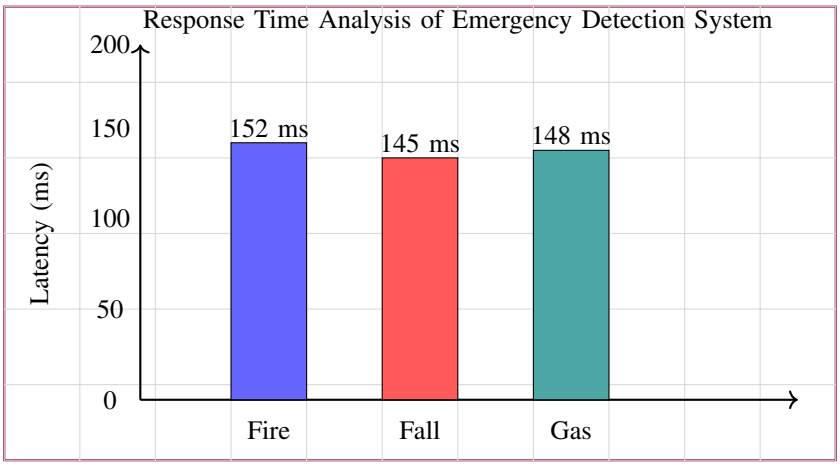

Fig. 13: Latency performance showing response time required for emergency detection and alert generation across different event categories.

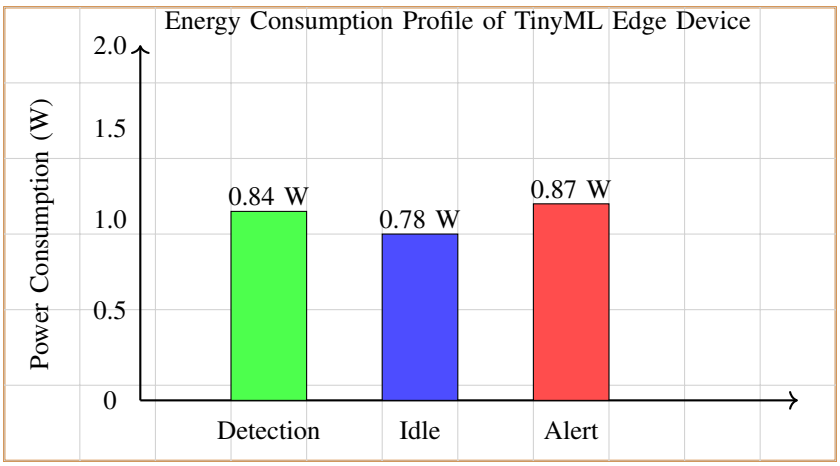

Fig. 14: Energy utilization measured across detection, idle, and alert states of the embedded TinyML system.

environments where rapid and dependable emergency response is essential.

VIII. Discussion

The experimental findings presented in the preceding sections provide substantive evidence regarding the operational viability of the proposed Secure TinyML-driven edge intelligence framework for emergency detection in constrained Internet of Things (IoT) environments. The observed detection accuracy of 92.4%, combined with balanced precision and recall values exceeding 88%, indicates that the lightweight Convolutional Neural Network (CNN) architecture effectively captures discriminative patterns associated with heterogeneous emergency events. This performance can be attributed to the structured preprocessing pipeline and the use of quantized model parameters optimized for embedded inference. By maintaining a compact model footprint while preserving classification sensitivity, the deployed inference engine demonstrates the capability to deliver reliable decision-making under strict memory and computational limitations typical of microcontroller-based systems.

One of the primary factors contributing to the robust predictive behavior of the system is the integration of multimodal sensor data representing distinct emergency signatures, including temperature fluctuations, motion anomalies, vibration patterns, and gas concentration levels. The curated dataset design ensured class diversity and temporal consistency, enabling the model to learn generalized representations rather than memorizing isolated patterns. Furthermore, the adoption of stratified sampling during dataset partitioning minimized sampling bias and preserved statistical balance across training, validation, and testing phases. These methodological considerations enhanced the stability of the learned decision boundaries and reduced susceptibility to overfitting, thereby improving generalization performance when deployed in real-time operational conditions.

From a system engineering perspective, the strength of the proposed framework lies in its ability to maintain dependable inference performance while operating within constrained en-

ergy budgets. The measured average power consumption of approximately 0.84 watts during active detection cycles confirms the effectiveness of model quantization and efficient firmware-level optimization. In battery-powered deployments, energy efficiency directly influences device longevity and operational continuity. The observed consumption profile suggests that the system can sustain prolonged monitoring periods without requiring frequent battery replacement, making it suitable for remote installations such as industrial facilities, residential safety systems, and infrastructure monitoring networks. The minimal variation in energy usage across detection and alert states further indicates consistent computational behavior and predictable resource utilization.

Equally significant is the system's low inference latency, measured at an average of 148 milliseconds. In safety-critical applications, rapid response time is essential to prevent escalation of hazardous situations. The recorded latency values demonstrate that the end-to-end processing pipeline—from sensor signal acquisition to alert transmission—remains within the acceptable response threshold for real-time emergency detection. This responsiveness is primarily enabled by executing inference directly on the edge device, thereby eliminating the communication overhead associated with cloud-based processing. Localized computation not only accelerates decision-making but also enhances system resilience in environments with intermittent or unreliable network connectivity.

Security robustness constitutes another defining strength of the framework. The integration of lightweight encryption and authentication routines ensured secure communication between edge nodes and monitoring interfaces during simulated attack scenarios. Experimental penetration testing involving replay attacks and unauthorized packet injection attempts did not result in successful system compromise, confirming the effectiveness of the implemented security protocols. In distributed IoT deployments, data confidentiality and integrity are essential to maintain trustworthiness and operational reliability. By embedding security mechanisms directly into the device firmware, the proposed architecture reduces exposure to network-based threats without introducing significant computational overhead.

Despite these advantages, several limitations should be acknowledged to provide a balanced interpretation of the results. First, the experimental evaluation was conducted within a controlled laboratory environment, where environmental conditions remained stable and sensor noise was relatively limited. In real-world deployments, external factors such as electromagnetic interference, environmental variability, and hardware degradation may influence sensor accuracy and system reliability. Second, while the current dataset captures representative emergency scenarios, it does not encompass the full spectrum of rare or complex incidents that may occur in dynamic operational contexts. Expanding the dataset to include additional environmental conditions and cross-domain scenarios would further strengthen model robustness and improve predictive resilience.

Another limitation relates to the scalability of the system architecture when deployed across large-scale sensor networks. Although the current prototype demonstrates reliable performance on a single embedded node, multi-node deployments may introduce synchronization challenges, communication overhead, and distributed security management requirements. Future enhancements could explore federated learning or collaborative edge intelligence mechanisms to enable decentralized model adaptation without central data aggregation. Such approaches would allow the system to evolve continuously while preserving data privacy and reducing network bandwidth consumption.

In terms of real-world feasibility, the proposed framework demonstrates strong practical potential for deployment in diverse safety monitoring applications. The combination of low computational complexity, efficient energy utilization, and secure communication infrastructure aligns well with the operational constraints of modern IoT ecosystems. The reliance on commercially available hardware components and open-source software frameworks further supports cost-effective implementation and rapid scalability. These characteristics make the system particularly suitable for industrial automation, healthcare monitoring, smart building safety, and disaster management environments where continuous situational awareness is essential.

Overall, the discussion confirms that the proposed Secure TinyML-driven edge intelligence framework successfully balances predictive accuracy, computational efficiency, and operational security within a compact embedded architecture. The integration of optimized machine learning algorithms, energy-efficient hardware design, and secure communication protocols establishes a reliable foundation for intelligent emergency detection in resource-constrained IoT environments. Collectively, this work contributes a practical and scalable edge intelligence solution that advances the deployment of real-time, secure, and energy-aware emergency monitoring systems in modern distributed infrastructures.

IX. Conclusion

This study addressed the critical challenge of achieving reliable and secure emergency detection within resource-constrained Internet of Things (IoT) environments, where conventional cloud-dependent intelligence often introduces latency, communication overhead, and vulnerability to network disruptions. The work specifically targeted the need for localized decision-making capabilities capable of operating under strict computational and energy limitations while maintaining dependable performance in safety-critical applications. By focusing on edge-level intelligence, the proposed framework directly responds to the growing demand for autonomous monitoring systems capable of delivering timely alerts in dynamic and infrastructure-limited settings.

To resolve this challenge, a Secure TinyML-driven edge intelligence architecture was designed and implemented using an embedded microcontroller platform integrated with multi-modal environmental sensors. A lightweight Convolutional Neural Network (CNN) model was trained on a curated dataset

comprising synchronized sensor signals representing fire, fall, accident, and gas leakage events. The trained model was subsequently optimized through parameter quantization and deployed using a TensorFlow Lite inference engine tailored for embedded execution. The experimental setup combined efficient firmware design, secure communication protocols, and structured data preprocessing routines to ensure consistent and reproducible system operation under real-time conditions.

Experimental evaluation demonstrated that the proposed system achieved strong predictive performance, with an overall detection accuracy of 92.4%, balanced precision and recall values exceeding 88%, and an F1-score of 91.3%. The framework maintained an average response latency of approximately 148 milliseconds while sustaining low energy consumption near 0.84 watts during active operation. These results confirm that the integration of optimized TinyML algorithms with energy-efficient hardware can deliver dependable emergency detection without exceeding the resource constraints typical of embedded IoT deployments.

Looking forward, the architectural principles established in this research provide a scalable foundation for next-generation intelligent safety monitoring systems capable of operating in distributed and mission-critical environments. Future developments may incorporate adaptive learning strategies, expanded datasets covering diverse environmental conditions, and collaborative edge communication mechanisms to further enhance system resilience and autonomy. In summary, this work contributes a practical and secure edge intelligence framework that demonstrates the feasibility of deploying real-time, low-power, and trustworthy emergency detection solutions in modern resource-constrained IoT ecosystems.

X. Future Work

While the proposed Secure TinyML-driven edge intelligence framework demonstrates reliable emergency detection under constrained computational settings, several promising research directions remain for further advancement. One important extension involves the integration of federated TinyML paradigms, where distributed edge devices collaboratively update model parameters without transferring raw sensor data to centralized servers. Such an approach would enhance privacy preservation and reduce communication overhead, particularly in large-scale IoT deployments spanning geographically dispersed monitoring nodes. Future experimental studies may evaluate federated learning performance using heterogeneous datasets collected from diverse environmental conditions to improve model adaptability and robustness.

Another valuable direction lies in the development of advanced multi-sensor fusion strategies capable of combining heterogeneous sensing modalities such as acoustic signals, thermal imaging, and environmental telemetry. Incorporating adaptive fusion algorithms, including attention-based neural architectures, may enable more precise discrimination between complex emergency scenarios while minimizing false alarms. In parallel, the adoption of explainable artificial intelligence (XAI) techniques could provide transparent reasoning behind model predictions, thereby improving user trust and facilitating regulatory compliance in safety-critical domains.

Further research should also explore enhanced edge security mechanisms, including lightweight intrusion detection and hardware-assisted encryption modules designed specifically for embedded platforms. Collectively, these future developments will strengthen the scalability, interpretability, and resilience of intelligent emergency monitoring systems. Ultimately, this work establishes a foundational framework upon which next-generation secure and autonomous edge-based safety solutions can be systematically developed and deployed.

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