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AI-Based Early Fire Detection & Alert System

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Abstract

In factories, bakeries and warehouses, as well as in homes, abnormal heating or smoke can trigger fires that are not caught by the fixed-threshold monitors until it is too late, especially if high temperatures are normal. The design of an AI-powered, IoT based early fire risk detection and alert system using an ESP32 microcontroller, a DHT22 temperature and humidity sensor, an MQ-2 smoke and gas sensor, an infrared flame sensor and a buzzer and LED for local alerts is presented. The system continuously takes readings from the environment, checks the conditions of the thresholds and temperature trends, determines the risk level, and uploads readings to the ThingSpeak platform for remote monitoring. To learn the normal behavior of the sensors, and detect anomalous patterns, an unsupervised algorithm called Isolation Forest is proposed, which uses time-dependent features like the speed of temperature change and the rolling statistics. The current prototype includes a pre-defined threshold-based decision logic, Wokwi simulation and data transmission to ThingSpeak, and the Isolation Forest component is still being developed and has not yet been trained and implemented. So, no accuracy, response time or false alarm rates are reported, accordingly. The paper describes the architecture, the decision logic, and the status of implementation and an evaluation plan with respect to a baseline defined only by thresholds. The system is a prototype for research purposes only and is not an alternative to certified fire-safety devices.

Keywords : Fire Detection, IoT, ESP32, Isolation Forest, Anomaly Detection, Sensor Monitoring, Machine Learning, Fire-Risk Classification

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I. INTRODUCTION

A. Background and Motivation

Fire is one of the most destructive hazards in an industrial, commercial or domestic environment and how early a first sign of a developing fire can be detected to the time a fire alarm can be heard by a person is crucial to whether a fire can be controlled. Certified fire-alarm installations are subject to codes like NFPA 72 [1] but they are expensive to install and not instrumented to provide continuous environmental data that could be analyzed site by site. Low cost network enabled sensor nodes are thus desirable as an additional monitoring layer.

Traditional monitors test one of the measured values and compare it to a predetermined threshold. Fixed-temperature and rate-of-rise principles [1] are employed in fire-alarm practice, and it is hard to determine a fixed limit for bakeries, kitchens and industrial plants where high temperatures are common: A high limit would cause a delay in alarming, while a low limit could result in nuisance alarms. A multi-signal combination approach has been proven to be useful in discriminating real fire from nuisance signals in smoke and gas sensing applications [2]–[4].

In addition to smoke and gas concentration, the flame radiation and the temperature and humidity give complementary evidence of a developing fire and Internet of Things (IoT) platforms make this evidence available remotely [5], [6]. Since actual fire outbreaks are rare on a labelled basis, unsupervised learning of normal operation mode and deviation from it, as in [7] and [8] is a very suitable method for the analysis stage.

B. Scope and Contributions

This work deals with a sensor-based system only. It does not employ cameras, image processing or vision-based method. The contributions of this paper are at the design level and are presented along with their implementation status:

- A system utilizing ESP32 microcontroller architecture with temperature, humidity, smoke/gas and flame sensing with local alarm and remote monitoring via ThingSpeak.
- A control logic that is used to derive a NORMAL, WARNING or HIGH RISK level based on the temperature rise and threshold.
- A proposed pipeline that includes the Isolation Forest anomaly detection on time-dependent features, which is identified as an ongoing work.
- A plan of evaluation that includes a baseline using a threshold-only plan, along with precision, recall, false alarm and alert latency.

The proposed sites of use include factories, bakeries, warehouses and homes, with abnormal heating or smoke possibly occurring before the fire, but also with normal operating temperatures varying throughout the different sites. The design thus prioritises transparent and explainable decision rules with an adaptive anomaly-detection stage to enable a review of the "why" of an alert by those responsible for the premises.

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There are two practical constraints on the design. First, the monitoring node should be useful even if the network is down, and this means that the local buzzer and LED are used directly by the microcontroller and are not reliant on the cloud. Secondly, the machine-learning part needs to be trainable in the field using unlabelled data from the same site, as a real fire can not be recorded on demand. The reason for this separation, the constraints, is why the system separates deterministic on-device checks from an offline analysis stage based on data.

TABLE I

PROJECT OBJECTIVES AND IMPLEMENTATION STATUS

Objective	Status
Monitor temperature and humidity (DHT22)	Completed in Wokwi simulation; physical-sensor validation planned
Monitor smoke/gas and flame conditions	Hardware testing planned
Acquire sensor data from ESP32	Completed in simulation
Analyze readings with thresholds	Threshold logic completed; temporal features proposed
Evaluate Isolation Forest for anomaly detection	Ongoing; not yet trained or integrated
Classify conditions by risk level	Defined using predefined threshold-based levels
Send and display readings on an IoT platform	Completed (ThingSpeak)
Local and remote alerts	Local buzzer/LED in design; remote push alerts planned

The rest of the paper is structured as follows: Section II introduces the problem and goals, Section III reviews related work, Sections IV to ?? describe the architecture and hardware and software, Sections VI and ?? present the Isolation Forest method and the risk classification, Sections ?? and ?? describe the data and evaluation, Sections ?? to VIII discuss limitations, further work and conclusions. The system is always regarded as a supporting research model for early warning and data collection throughout, with every statement made regarding its behavior linked to either what is implemented, simulated or only proposed.

II. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

The issue is to detect fire-risk conditions from low-cost environmental sensor data without producing false alarms due to the natural variation of the operating conditions, and alert them in a timely manner. This involves continuous monitoring, analysis of trends, identification of atypical sets of readings, levels of risk classification, and on-time local and remote alerts. It is not assumed that a method combining these elements will decrease nuisance alarms or increase the advance warning, but both may be

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beneficial and a reduction of nuisance alarms or an increase in the advance warning can occur for a method.

Follow the objective and current status of the project. Follow objective and current status of project. The project aims with their status are presented in Table I: Work that has been completed is set off against work in progress or to be done. The objectives and their implementation status are shown in Table I.

III. LITERATURE REVIEW

Conventional and Multi-Sensor Fire Detection Fire-alarm codes acknowledge the heat detectors, which can be either fixed-temperature or rate-of-temperature-rise detectors, as well as smoke and flame detectors [1]. Fixed temperature operation is easy and doesn't pay attention to the surrounding conditions for its installation. In a study by Chen et al., the use of smoke and gas sensor signals was studied, and it was reported that fusing their signals could be useful to distinguish fire from nuisance sources [2]. Chemical-sensor systems and the algorithms used for fire detection have been reviewed by Fonollosa et al. [3] and gas-sensor arrays have been calibrated and validated using multivariate models for the early detection of fire, according to Solórzano et al. [4]. The works are encouraging to using multiple complementary signals, but almost always require special sensors and calibration using test firing, which is outside the scope of a low-cost prototype.

A. IoT-Based Fire Monitoring

The IoT paradigm consists of the integration of the sensing nodes with cloud services for the storage, visualization and remote access of the information [5]. Saeed et al. [6] proposed a model for fire prevention and safety in smart homes based on the IoT concept, where they used multi-sensor data. This project takes such data and does so on platforms like ThingSpeak [9] that are easy to store and plot that data.

Anomaly Detection and Isolation Forest. Anomaly detection surveys [7], [8] categorize the anomaly detection problem into three types: supervised, semi-supervised and unsupervised. If the number of labelled anomalies is small, like fire events, unsupervised or semi-supervised methods, which model the normal behaviour, are suitable. Isolation Forest [10], [11] is based on recursive random partitioning to isolate the observations and the principle that anomalies are rare and dissimilar from other observations, thus requiring only a few partitions to isolate. It requires a small amount of memory and is linear with the sample size [10]. Some work focuses on a bias caused by the axis-parallel splits, like extended Isolation Forest [12] and some online detection work like streaming detectors—hierarchical temporal memory [13]. One of the most popular implementations is provided in scikit-learn [14].

This Work will be positioned so that it will not obstruct any exterior or internal vents. The approaches and the gap addressed by this work can be summarized in Table II: a low cost node, adding trend features, and a site-adaptive anomaly stage to threshold-based monitoring. It is not claimed that this approach is better than the ones referenced.

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TABLE II

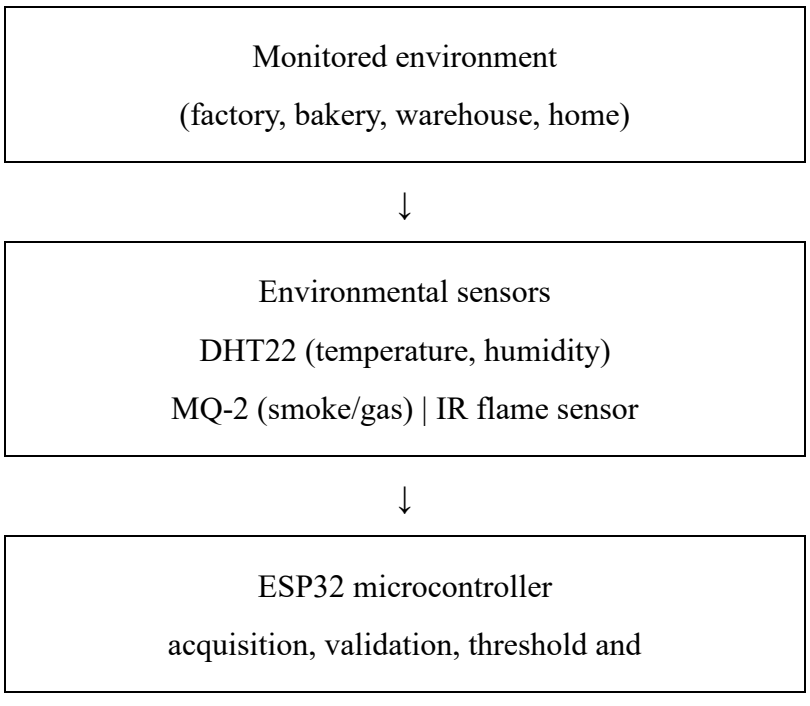
COMPARISON OF RELATED APPROACHES

Approach	Refs.	Relevance to this work
Fixed-temperature and rate-of-rise detection	[1]	Basis of the threshold and trend checks used here
Smoke and gas sensor fusion	[2]–[4]	Motivates multi-sensor evidence; uses richer sensors than this prototype
IoT fire monitoring	[5], [6]	Provides connectivity model; this work adds trend features and an anomaly stage (proposed)
Unsupervised anomaly detection	[7], [8], [10]–[13]	General methods; fire-specific decision logic must be added

IV. PROPOSED SYSTEM ARCHITECTURE

A. Overall Architecture

The architecture is displayed in the figure 1. Data from the environment is transmitted to an ESP32 microcontroller that receives and checks the data, checks threshold and rate of rise, and assesses risk. The ESP32 will activate a local buzzer and LED, and transmit the readings back to ThingSpeak where they will be stored and graphed. A separate python environment is created for downloading the stored readings, building features and offline developing of the Isolation Forest model. The ESP32 is not involved in the training or execution of the Python model, the return to the decision logic (for example, via thresholds calibrated in the ESP32, or on the cloud side, as a service) is a future design decision.



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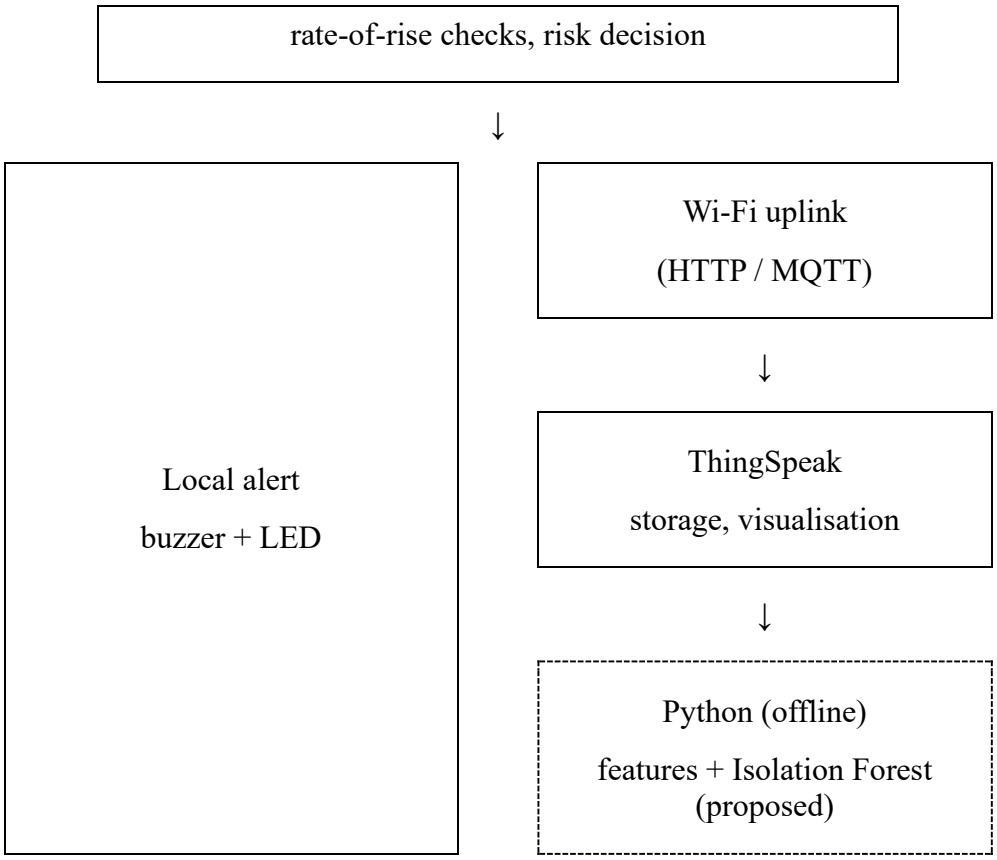
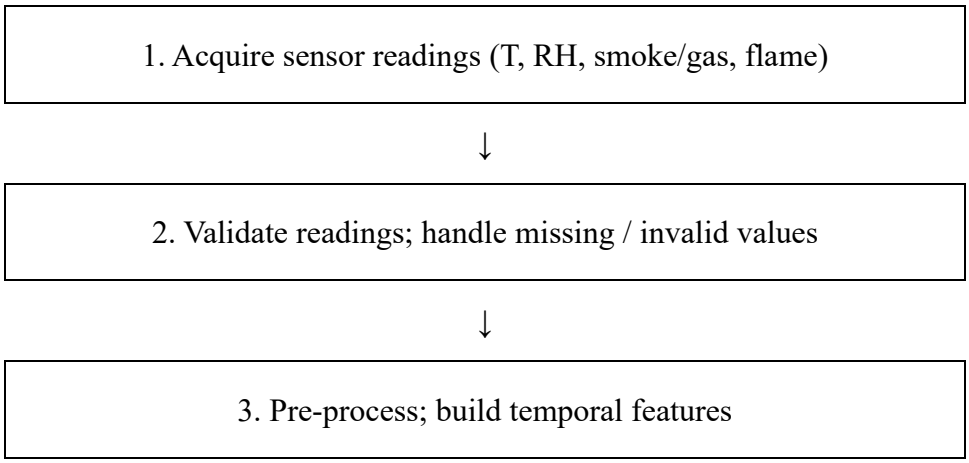


Fig. 1. Proposed system architecture. Solid blocks are implemented according to the project description; dashed blocks are proposed or ongoing.

B. Processing Pipeline

The intended processing pipeline is shown in Fig. 2. Steps 1 to 4 and 7 to 8 correspond to the threshold-based prototype; steps 5 and 6 are the proposed machine-learning extension and are shown dashed because they are not yet integrated.



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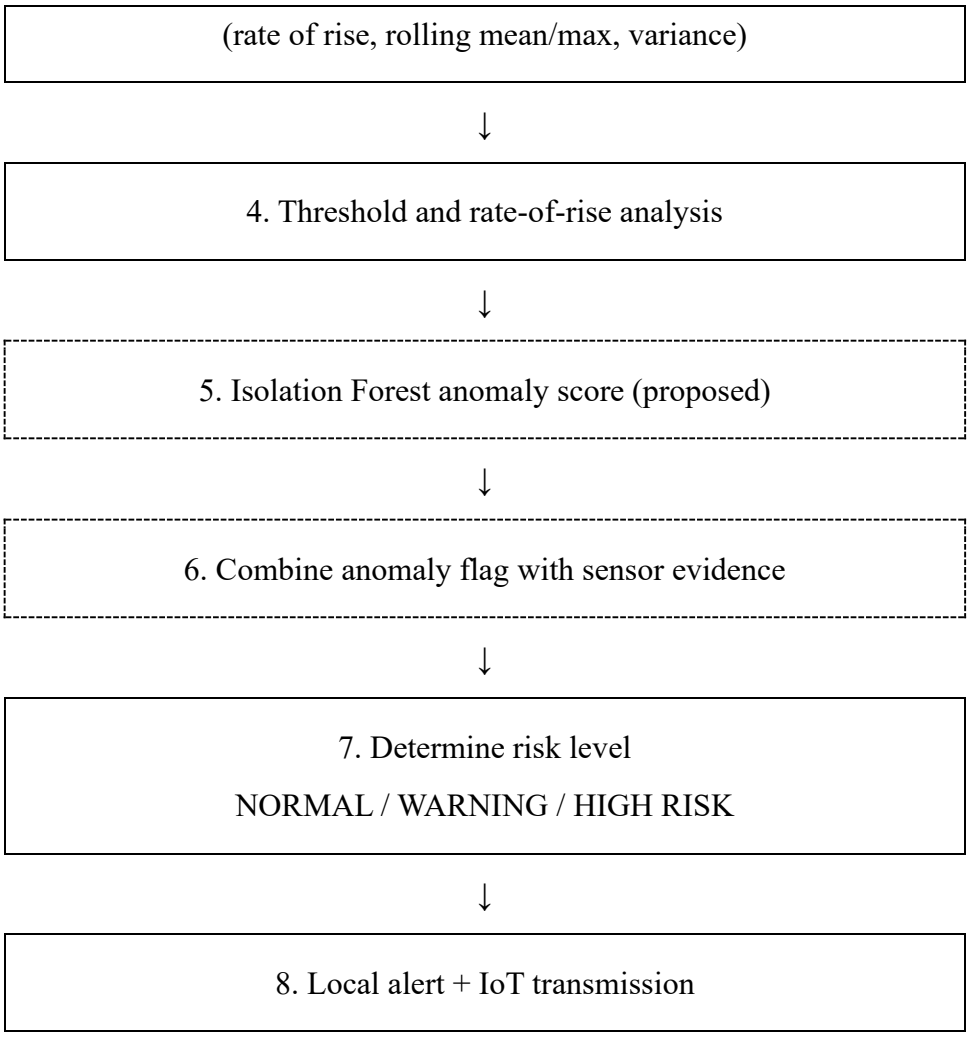


Fig. 2. Sensor data processing pipeline. Dashed steps are proposed and not yet integrated.

V. HARDWARE IMPLEMENTATION

A. Components

The components and their roles are given in Table ??. The ESP32 is responsible for processing, GPIO, analog inputs and Wi-Fi/Bluetooth connectivity [15]. The DHT22 is the temperature and relative humidity sensor that is digital, and has a minimum sampling time of approximately 2 seconds [16]. The MQ-2 is an analog output metal-oxide semiconductor sensor which is sensitive to smoke and multiple combustible gases, and therefore provides an indication of the overall smoke/gas level rather than a specific gas [17]. The infrared flame sensor module is usually digital output and has adjustable sensitivity and reacts to the infrared radiation of flames. A buzzer and LED gives local audible and visual indication.

B. Wiring and Power

The pin mapping used for the reference design on a standard ESP32 dev board is defined in Table ?? and can be varied to match different pin-outs in the final design, but does not affect the logic. The analog

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output of the MQ-2 is connected via a resistive divider (e.g., 10 kΩ and 20 kΩ) to an analog input-only channel of the first analog converter, and its 5 V output is thus reduced to less than 3.3 V. The DHT22 module and the flame-sensor module is powered from the 3.3 V rail, the MQ-2 heater from the 5 V supply and the LED is driven via a series resistor of 220 Ω. The board is powered from a regulated 5 V USB supply.

The calibration and electrical considerations are:

- The MQ-2 must be warmed up and calibrated individually and its output is an indicator of the temperature and humidity [17]. It is typically used with a 5 V power supply, and must not exceed the 3.3 V input range of the ESP32 analog-to-digital converter. The analog channels of the second converter cannot be used when Wi-Fi is running on the ESP32 [15] and the MQ-2 should thus be connected to an analog channel of the first converter.
- The DHT22 must be read at least once in less than its maximum sampling rate (as specified in the manual, cited in the references) and must be placed where it senses the air to be monitored and not the heat from the electronics.
- The sensitivity of the flame sensor should be configured for the location as other infrared sources, like sunlight and incandescent lamps can cause the sensor to go off.
- The buzzer and LED must have current limiting or a driver stage to prevent GPIO current limits from being exceeded.

In this section, software and IoT communication will be presented. In this section, Software and IoT Communication will be presented.

C. Firmware

Arduino IDE is used to write the firmware in C/C++ language. It reads the sensors in each cycle, discards and prints not-a-number readings from the sensors (e.g., a DHT22 read that returns not-a-number), evaluates the decision logic of Section ?? to drive the buzzer and LED, and uploads a record to the server via wi-fi. Upload uses HTTP requests to the ThingSpeak REST interface (or can use MQTT instead).

D. Simulation

Wokwi is an online simulator that facilitates ESP32 projects, and was used to simulate the hardware behaviour. Wokwi is an ESP32 online simulator that was used to simulate the hardware behaviour [18]. Simulated values in the simulation are simulated values and results obtained from them are simulated results and should be reported as such.

E. ThingSpeak Channel

ThingSpeak [9] can store uploaded values in numbered channel fields, and offers time-series plots. The frequency of updates is limited to 15s for free accounts [9] so there is a delay in visibility when it comes to the remote device, compared with the local alert (which doesn't rely on the network). This paper uses the following field mapping, as defined in Table ??.

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F. Python Tooling

For retrieval of channel data, pre-processing, building features and the Isolation Forest model, Python, pandas and scikit-learn [14] are designed. These are all the stages of the work that continues.

VI. ISOLATION FOREST AND FEATURE ENGINEERING

A. Principle

Isolation Forest is a type of unsupervised anomaly detector [10], [11]. To construct each isolation tree, a random subsample is repeatedly sampled, a random feature is selected from the subsample, and a random split value (between the minimum and maximum value of that feature) is chosen from the subsample. To construct each of these trees, a random subsample is repeatedly sampled, a random feature is selected from the subsample, and a random split value (between the minimum and maximum value of that feature) is chosen from the subsample until observations are isolated. Unusual observations occur in the low-density areas and are rare following fewer splits, resulting in a short average path length over the forest. The anomaly score of an observation x is

$$s(x, n) = 2^{-E[h(x)]/c(n)} \quad (1)$$

where h(x) is the path length of x in a tree, E[h(x)] is its average over the forest, n is the subsample size, and

$$c(n) = 2H(n - 1) - 2(n - 1)/n \quad (2)$$

is the average path length of an unsuccessful search in a binary search tree, with $H(i) \approx \ln(i) + 0.5772$ [10]. Scores close to 1 indicate anomalies and scores well below 0.5 indicate normal observations. Because the method needs no fire labels, it suits the limited availability of labelled data. It identifies observations that are unusual; it does not by itself state that a fire is present. Additional decision logic is required to interpret an anomaly as a fire risk (Section ??).

B. Features

A high absolute temperature does not always indicate fire, particularly in industrial settings, whereas changes over time and unusual combinations of readings carry additional evidence. The rate of rise over a window of w seconds is

$$R(t) = [T(t) - T(t - w)] / w \quad (3)$$

where T is temperature. The candidate features are listed in Table ??. Only features that are computed in the final implementation will be reported as used.

C. Preprocessing and Training

If there are any invalid readings, they are discarded, or if there is a short gap, the last valid value is used, and long gaps are used in window features as if they were not there. It is insensitive to linear rescaling of the features, allows to retain the physical units of the features to be interpreted, and selects the split value randomly in each range of the features. The model needs to be trained with data reflecting normal operation of the monitored site, otherwise, the learned baseline is contaminated by unrecognized abnormal episodes present in the training data. The number of trees, the subsample size and the

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contamination setting (which sets the score threshold) are important hyperparameters in scikit-learn [14] which would be chosen based on the held out data. If the normal operating pattern changes, such as with the change of seasons, or a process change, for instance, the model would require retraining. Another alternative is Extended Isolation Forest [12] which could be compared. At this time there is no training or evaluation of these.

There is a need to define risk levels and a threshold level. It's necessary to determine the risk level and threshold level. Anomaly detection can be combined with threshold and trend analysis, using the deterministic conditions that threshold analysis can offer to explain the anomaly. There are three levels: NORMAL, WARNING and HIGH RISK. The decision logic is defined in symbols in Table III.

TABLE III

RISK LEVELS AND DECISION LOGIC

Level	Condition (any)	Action
HIGH RISK	Flame detected; $G \geq G_h$; $R \geq R_h$; $T \geq T_h$	Buzzer, LED, remote record
WARNING	$G \geq G_w$; $R \geq R_w$; $T \geq T_w$; (proposed) anomaly flag	LED, remote record
NORMAL	None of the above	Log only

For discussion, challenges and limitations, refer to the discussion page.

D. Discussion

The configuration of thresholds, temporal features and anomaly detection plus IoT monitoring is designed to address multiple situations and the following statements are anticipated benefits and not what has been seen.

In normal high-temperature environments a site-specific baseline and a rate-of-rise check may minimize reliance on a specific absolute limit. Rapid changes in the rate of rise, not necessarily from a critical cause, but perhaps as a result of rapid heating before the absolute limit, before the cold first reaches it, may also cause it to occur; such changes may be due to a change in a benign source, such as opening the door to an oven and hence for this reason rapid changes in temperature may also cause it to occur. Validity check and window statistics provide robustness and cannot solve a problem with an poorly calibrated or failed sensor.

- Network outages and limited training data: the local alert is not dependent on the network while remote monitoring is; or a small or unrepresentative training set reduces the anomaly detector.
- Simulated versus physical testing: realistic testing using a physical test rig is required, as simulation does not account for sensor noise, drift, airflow or environmental interference.

E. Challenges and Limitations

The proposed and the on-going component is Isolation Forest, which is not integrated into the prototype. Incomplete hardware and software integration where noted in Tables I and ?? and limited real world validation. Low cost sensors require calibration, and the MQ-2 is sensitive to multiple gasses; and the

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flame sensor has limited field of view and range. The remote monitoring relies on Wi-Fi and the update frequency of the cloud platform restricts timeliness remotely. It can be false alarm and missed events. There is no certification of the system and it is not a replacement for commercial fire-alarm equipment.

VII. FUTURE SCOPE

Train and test Isolation Forest with representative normal sensor data. Gather physical sensor responses with controlled sensors and contrast the physical with the simulation. Enhance time-based feature set, update thresholds and risk scoring. Add in strong alert delivery, local buffering and network-recovery. Enhance both cloud monitoring and historical analysis. Compare the proposed method with a threshold-only baseline, and measure the number of false alarms and missed detections. Run longer time tests in relevant settings like bakery, warehouses etc.

VIII. CONCLUSION

This paper introduced the design of an ESP32 based early fire-risk monitoring system with using of temperature, humidity, smoke/gas, flame sensing, threshold analysis, rate of rise analysis, local alarm and monitoring via ThingSpeak with the contributions of unsupervised stage of anomaly detection based on Isolation Forest algorithm. The machine-learning stage, the physical validation and the quantitative evaluation are still to be achieved; the current prototype includes predefined threshold-logic as well as simulation and data transmission. The paper, however, does not guarantee or claim accuracy or early detection or reduced false alarms. A threshold-only baseline will be used to inform the planned evaluation of whether the approach has a practical benefit.

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