

IoT Ground Sensing Systems for Early Wildfire Detection: Technologies, Challenges and Opportunities

Chiu Chun Chan , *Member, IEEE*, Sheeraz A. Alvi , *Member, IEEE*, Xiangyun Zhou , *Fellow, IEEE*, Salman Durrani , *Senior Member, IEEE*, Nicholas Wilson , Marta Yebra 

Abstract—The threat posed by wildfires or bushfires has become a severe global issue due to the increase in human activities in forested areas and the impact of climate change. Consequently, there is a surge in the development of automatic wildfire detection methods. Approaches based on long-distance imagery from satellites or watchtowers encounter limitations, such as restricted visibility, which results in delayed response times. To address and overcome these challenges, research interest has grown in the implementation of ground-based Internet of Things (IoT) sensing systems for early wildfire detection. However, research on energy consumption, detection latency, and detection accuracy of IoT sensing systems, as well as the performance of various anomaly detection algorithms when evaluated using these metrics, is lacking. Therefore, in this article, we present an overview of current IoT ground sensing systems for early wildfire detection. Camera and environmental sensing technologies suitable for early wildfire detection are discussed, as well as vision-based detection algorithms and detection algorithms for environmental sensing. Challenges related to the development and implementation of IoT ground sensing systems for early wildfire detection and the future research directions important for creating a robust detection system to combat the growing threat of wildfires worldwide are discussed.

Index Terms—IoT, sensing, wildfire, bushfire, forest fire, early fire detection.

I. INTRODUCTION

WILDFIRE, also widely known as bushfire in Australia and forest fire in Europe, present a significant risk to people, the environment and assets. In recent decades, the surface air temperature in Australia has risen by 2°C due to climate change, leading to more days with high fire risk [1]. As fire weather worsens, fire occurrence increases [2], [3] and the window of opportunity for successful containment and suppression after ignition narrows [4], [5]. Hence, rapid detection of new ignition will become an increasingly important strategy for fire managers as the climate warms.

This research was funded by the Bushfire Research Centre of Excellence, which was co-sponsored by the Australian National University and Optus. The Australian Capital Territory Emergency Services Agency and the Australian Capital Territory Parks and Conservation Service provided support for the collection and organisation of ignition data. We thank Sam Beaver and Jyotirao Wankhede for organising and assisting with the experimental burns. We also thank Dr. Andrew Sullivan and the CSIRO Bushfire Behaviour and Risks team for their help in initiating the testing of the sensing modules in the Pyrotron Lab. (Corresponding author: Chiu Chun Chan)

Chiu Chun Chan, Sheeraz A. Alvi, Xiangyun Zhou, Salman Durrani and Marta Yebra are with the School of Engineering, The Australian National University, Canberra, ACT 2601, Australia (e-mail: {chiuchun.chan; sheeraz.alvi; xiangyun.zhou; salman.durrani}@anu.edu.au).

Nicholas Wilson and Marta Yebra are with Fenner School of Environment and Society, The Australian National University, Canberra, ACT 2601, Australia (e-mail: {nicholas.wilson; marta.yebra}@anu.edu.au).

All authors are with the Bushfire Research Centre of Excellence, The Australian National University, Canberra, ACT 2601, Australia.

©2023 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

A. Impact of Wildfire Across the Globe

In Australia, this recently reached a catastrophic climax in the 2019-2020 “Black Summer” fires across multiple states where 24 million hectares of land were burnt, causing 33 deaths and approximately 450 more injured by smoke inhalation [6]. The 2019-2020 fires burnt an unprecedented area of land [7] and were likely worsened by climate change [8]. The toll on wildlife was immense. The World Wide Fund for Nature records “143 million mammals, 2.46 billion reptiles, 180 million birds and 51 million frogs” had been harmed, killed, or displaced [9] as a result of the Black Summer. For the already fragile ecosystem of animals in Australia, this is a major hit, as many animals, including koalas, wombats and wallabies, are listed as endangered or vulnerable [10].

Worldwide, wildfires are getting worse, with the European Forest Fire Information System estimating that 837,000 hectares of land have been burnt in countries of the European Union alone in 2022, which is the second worst year for wildfires in its history [11]. The United States also experienced record-setting fires in 2020, with more than 50,000 fires burning nearly 3.64 million hectares of land [12]. Although the number of reported wildfires remains stable in the last 30 years, the area burnt in a year caused by wildfires has increased by 1.62 million hectares compared to the area burnt in the 1990s in the United States [13]. The Brazilian National Institute of Space Research has revealed 3.36 million hectares of land burnt in Brazil annually since 2003 [14]. Notably, in January 2017, the Mediterranean region of Chile experienced hundreds of fires burning more than 500,000 hectares, approximately 14 times the average annual area burnt in the region in the last 40 years [15]. In addition to these observed increases in fire activity, predicted warming and drying of the climate across much of the world are likely to increase fire activity and result in long term declines in forest carbon storage, further warming the climate [16]. In light of the increasing threat posed by wildfires, the imperative to develop precise and reliable detection technologies has taken precedence.

B. Technologies for Early Wildfire Detection

The ability to detect wildfires in their early stages allows effective and efficient fire suppression [17]. Specifically, early detection of initial fire stages, such as smouldering and ground fire, enables the timely deployment of fire suppression tactics

to increase the probability of initial attack success [5]. Therefore, it is vital to develop early wildfire detection methods and technologies. Here, we present a set of requirements to gauge the capability of existing technologies for early wildfire detection. The algorithm should be able to identify fires while they are still small enough to be successfully put out. As the fire grows larger, it becomes eventually too difficult to extinguish [5]. Therefore, early detection that can reduce the time it takes to detect or spot small fires is hugely beneficial. Moreover, a wildfire detection system based on environmental monitoring is highly desirable due to its connection to fire hazards. Finally, the scalability of the wildfire detection system is beneficial so that the system can not only be deployed on a large scale but also be deployed in different terrains.

We hereby briefly introduce the existing technologies for wildfire detection and analyse their suitability for early wildfire detection. For nearly a century, watchtowers and public reporting have been used to detect wildfires. Unfortunately, it requires observers to remain on top of the tower during certain hours of the day and specific periods of the year, constantly looking for smoke that implies fire or the effectiveness of public reporting is significantly influenced by the population density of the region. With the advancement of computer vision technologies [18]–[20], this task can now be accomplished day and night with the help of arrays of high-resolution vision / thermal cameras that record visual information, which is then processed using different detection algorithms to recognise smoke, flame, or heat from fire. However, there are some challenges associated with this technology for early wildfire detection. Firstly, fires can smoulder before reaching a size that is detectable from a distance, which can prolong their detection time. Secondly, monitoring hilly terrain becomes difficult due to line-of-sight blockage. Consequently, it may be difficult to detect small fires in these areas. Thirdly, this technology lacks the ability to convey environmental changes, such as changes in relative humidity and air pressure, which cause diurnal changes in fuel moisture and associated fire activity [21].

As another detection technology, the deployment of crewed fire-spotting aircraft over lightning strike areas or areas of high fire risk is also used, but is often delayed due to resourcing issues or restrictions on night-flying operations. The use of long-endurance drones is on the rise, primarily due to their availability to operate in rough weather conditions, day and night, helping to overcome some of the limitations associated with traditional fire-spotting aircraft [22]–[24]. Unmanned aerial vehicles (UAVs) offer the potential to rapidly confirm suspected ignitions and provide information on the size and behaviour of fires, particularly fires in remote locations. However, this system requires other monitoring technologies to identify suspected ignitions.

For many years, satellite imagery has been a valuable tool for detecting large-scale wildfires [25]. But it also comes with limitations, particularly in terms of temporal or spatial resolutions, making it challenging to detect fires when they are still small. The emerging Low Earth Orbit satellite constellation network offers relatively high spatial resolution capable of detecting small fires [26], however, the temporal frequency (several hours to days) prevents reliable fire detection [27].

Novel algorithms developed specifically for early fire detection using geostationary satellites may offer advances, but have not yet been thoroughly tested [28].

In addition to the technologies mentioned above, a promising complementary approach to detect early wildfires is to use a ground sensing system based on the Internet of Things (IoT). This system provides real-time data from a variety of ground sensors at desired densities for timely and accurate fire detection, due to the proximity of the ground sensors to the fire ignition locations. This IoT-based system can autonomously raise early alarms for wildfire detection, identify its location, and provide situational awareness by reporting the fire movement. The communication delay from data generation at the ground sensors to reception at the central node can be within a few minutes. Moreover, this kind of system can complement other fire detection and extinguishing systems by identifying the area of interest, which then can be investigated for further details and validation of ignitions as well as to initialise responses. The benefits of a ground sensing system would also go beyond wildfire detection and suppression, as they can also be used for environmental monitoring purposes.

Due to its unique benefits, many IoT companies have integrated IoT-based wildfire detection systems into their offerings [29]–[31]. However, it is essential not to rely solely on one detection system for early fire detection, but to recognise the benefits of combining different wildfire detection approaches and take a more comprehensive approach. This requires long-term research and development efforts across academia and industry on a large scale. In Australia, a leading effort on this front is the recent establishment of the Bushfire Research Centre of Excellence at the Australian National University (ANU). The Centre aims to develop an integrated and layered solution to detect and extinguish small fires using multiple technologies, some mentioned above [17], [24].

C. Paper Contributions

There are only a handful of survey papers on this research topic. In [32], [33], the authors provided a summary of recent early fire detection and prevention technologies, while IoT is only a small part of the survey. In [34]–[36], comprehensive studies are presented on IoT-based wildfire detection using Machine Learning (ML) and Deep Learning (DL) approaches. However, the challenges faced in the deployment of IoT sensing systems are only briefly mentioned. Therefore, our objective is to explore the potential benefits of modern sensing technologies and their compatibility with IoT sensing systems to detect early-stage wildfires. Specifically, we investigate the use of vision-based and environmental monitoring technologies, combined with anomaly detection algorithms, to detect wildfires in their early stages. Furthermore, the study highlights critical factors to consider when implementing an IoT-based sensing system for reliable and efficient early wildfire detection, such as sensor placement and network connectivity. The objective of this article is to provide a comprehensive understanding and guidance for the implementation of an IoT ground sensing system for early wildfire detection, together with its challenges and possible research extensions. The

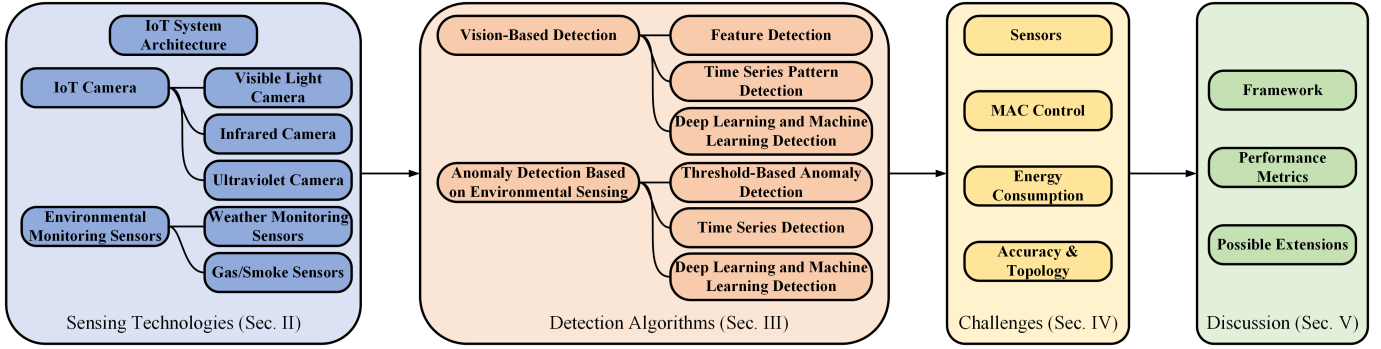


Fig. 1. Overview of this article on IoT ground sensing systems for early wildfire detection.

contributions of this work are summarised as follows:

- In-depth technical overview and performance analysis of existing vision-based and environmental sensing technologies using experimental studies and summarising from the literature.
- Identification of appropriate sensors for early wildfire detection under a resource-constrained requirement in terms of detection time, energy consumption, and cost.
- An overview of existing detection techniques for vision and environmental sensing data. This article aids in data analytics-based algorithm development.
- Identification of operational challenges associated with the deployment of an IoT system in remote areas.
- Presenting a framework for developing an IoT ground sensing system for early wildfire detection. This framework is designed to help decision makers determine the best deployment strategies based on the performance metrics given.

D. Paper Organisation

The structure of this article is outlined in Figure 1. Section II discusses the architecture of IoT systems and IoT camera modules and environmental monitoring sensors that can be used for such an application. It also provides a brief overview of the operating principles of different types of sensors, their characteristics and use case examples. Finally, the performance of the sensors is compared in multiple aspects. In Section III, we provide an overview of the wildfire detection algorithms commonly used in IoT systems. These algorithms can be divided into two categories: vision-based detection and anomaly detection based on environmental sensing data. We further classify these detection methods based on their complexity, such as feature detection, time series pattern detection and ML & DL detection in vision-based and threshold detection, time series detection, ML & DL detection in environmental sensing. Additionally, we discuss energy consumption, detection delay, requirements for deploying detection algorithms and the popularity of different detection algorithms is also provided at the end of the section. Section IV explains the operational challenges associated with the deployment of IoT applications for wildfire detection, including sensor limitations, energy efficiency considerations, network coverage constraints, the

accuracy of detection algorithms and the challenges related to the system deployment. Finally, Section V proposes a framework for the deployment of IoT ground sensing systems in the context of early wildfire detection, offering solutions to most of the challenges identified in Section IV. Recognising the inherent trade-offs among some of these challenges, this section also introduces a performance metric that can guide IoT designers in their decision-making processes. Furthermore, it explores potential extensions for future research within this domain. A list of common acronyms used in this article is presented in Table I.

II. IOT TECHNOLOGIES FOR WILDFIRE SENSING

IoT systems are typically composed of three core elements: (i) end nodes (EDs), (ii) gateways (also referred to as aggregators) and (iii) the central node (also referred to as cloud server). The EDs consist of ground sensors, including low-cost camera modules and / or environmental monitoring sensors, interconnected with microcontrollers (MCUs). These MCUs typically perform data pre-processing tasks using simple algorithms such as moving averages, threshold detection, linear regression, or ML classification. The primary purpose of data pre-processing is to improve data quality, consistency and analysis readiness before sending it to the gateway. After completion of the data processing phase, the data are transmitted to the gateway through suitable Low Power Wide Area Network (LPWAN) communication technologies customised to specific user requirements. This transmission can be optimised based on factors such as data rates, extended ranges, or energy efficiency. An example of a hardware prototype of the IoT ED for early wildfire detection is illustrated in Fig. 2.

The gateway then forwards the vital data received to the central node for post-processing. During the post-processing stage, advanced technologies with high computing capabilities, such as DL algorithms, can be employed at the central node. Unlike EDs, the central node is not constrained by energy consumption or computational capacity. These advanced technologies enable a comprehensive analysis of sensor data, facilitating decision-making processes, such as the detection of fire alarms in a specific scenario [37]. However, the level of accuracy and energy efficiency required for such a wildfire detection system remains largely an open and active research

TABLE I
TABLE OF ACRONYM

Artificial Neural Network	ANN
The Australian National University	ANU
Autoregressive Integrated Moving Average	ARIMA
Backpropagation	BP
Convolution Neural Network	CNN
Carrier-Sense Multiple Access with Collision Avoidance	CSMA/CA
Cumulative Sum Control Chart	CUSUM
Deep Learning	DL
Decision Tree	DT
Discrete Wavelet Transform	DWT
End Node	ED
Gas-Sensitive Fleid Effect Transistor	GasFET
Gaussian Mixture Model	GMM
Histogram of Optical Flow	HOF
Histogram of Orientated Gradient	HOG
Internet of Thing	IoT
Infrared	IR
K-Nearest Neighbours	KNN
Local Outlier Factor	LOF
Line-of-Sight	LoS
Low Power Wide Area Network	LPWAN
Long-Short-Term Memory Network	LSTM
Medium Access Control	MAC
Multi-Criteria Decision Analysis	MCDA
Microcontroller	MCU
Machine Learning	ML
Metal Oxide Semiconductor	MoS
Non-Dispersive Infrared	NDIR
Passive Infrared	PIR
Particulate Matter	PM
Radial Basis Function	RBF
Random Forest	RF
Recurrent Neural Network	RNN
Resistive Temperature Detector	RTD
Seasonal Autoregressive Integrated Moving Average	SARIMA
Scale-Invariant Feature Transform	SIFT
Support Vector Machine	SVM
Total Volatile Organic Compounds	TVOC
Unmanned Aerial Vehicles	UAV
Ultraviolet	UV

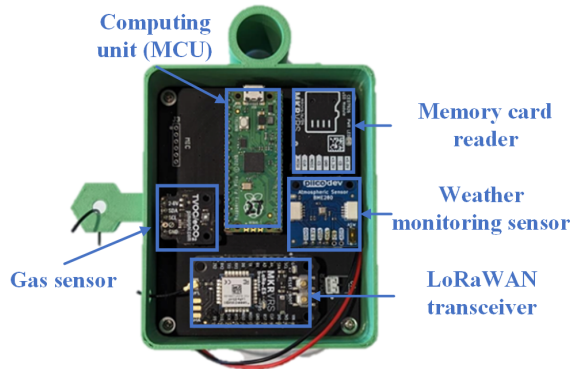


Fig. 2. A hardware prototype of an IoT end device developed by the Bushfire Research Centre of Excellence, which includes a MCU, an memory card reader, a gas sensor, a weather monitoring sensor and a LoRaWAN transceiver.

issue. Developing a robust IoT sensing system for early fire detection requires careful consideration of these performance characteristics and metrics such as overall energy consumption, response time and accuracy detection can be used to evaluate its efficiency.

In this section, we provide a detailed discussion of sensor

technologies crucial for early wildfire detection, focusing on the principles, features and applications of different IoT sensors. The comparison of commercially available sensor modules are provided, highlighting their use in prior wildfire detection projects. We categorise ground sensors used in wildfire detection into two main categories: vision sensors and environmental monitoring sensors. These sensors collect a variety of data types, including visual recordings and meteorological information of forested areas, for local analysis on EDs or for centralised processing. This section also reviews studies on the integration of these sensors with IoT systems, evaluating their effectiveness and practicality for early wildfire detection.

A. Vision-Based Ground Sensing Technologies

Vision-based fire detection has been a longstanding solution in IoT application, employed across both indoor and outdoor settings. Its interpretability by both humans and machines has solidified its status as a reliable detection method. We categorise the vision-based sensors for wildfire detection into three categories spaced across the electromagnetic spectrum.

1) **Visible Light Range Cameras:** Numerous research studies have integrated visible range (RGB) camera systems into ground IoT sensing systems to enable fast and robust wildfire detection. Unlike long-range and high-resolution cameras used on watchtowers or satellites, IoT ground sensing systems require small, cost-effective and energy-efficient cameras for scalable deployment. Recent advances in semiconductor technologies and compact lens systems have made it feasible to miniaturise camera modules. To make it more feasible for IoT applications, these low-performance camera modules have also been modified to operate at smaller viewing angles, lower resolutions and frame rates, to reduce energy consumption and the need for large lens systems. For example, these camera modules only provide video quality at a maximum of 1080p30fps with 102° viewing angle. Such camera modules have been used in various IoT projects, including those involving wildfire detection [38]–[44]. Notable examples of IoT cameras include IMX219 [45] and OV7670 [46]. Using these IoT cameras, microcontrollers can capture 2D video streams or images in pixel-matrix format, enabling vision-based fire detection. However, it is important to recognise that camera images are sensitive to adverse weather conditions and obstructions and are less reliable in dim conditions, particularly for early fire detection. Additionally, the limited viewing angle resulting from camera miniaturisation requires the use of a rotating platform or multiple cameras to achieve a 360° view if the detection system is based solely on cameras.

2) **Infrared Range Cameras:** To improve the night visibility of these ground-sensing devices, the implementation of infrared (IR) cameras has been explored as an alternative solution. This approach of paralleling the utilisation of IR technology with visible light cameras has shown a significant improvement in night visibility in watchtowers and has been adopted by many commercial products in fire detection [31], [47]. IR cameras capture thermal images, where each pixel directly represents the temperature or heat intensity of the corresponding area. This characteristic simplifies the fire detection

process, providing an intuitive indication of the presence of a fire. In an extremely simplified scenario, fire detection can be achieved by analysing the histogram or sum of the pixel intensities. However, the adoption of IR cameras also comes with a drawback, as they tend to be more expensive compared to regular cameras due to their limited market demand. Although IR cameras facilitate fire detection at night, their reliability can be compromised if the detection distance and temperature range of IR sensors are insufficient. For example, certain IoT compatible IR cameras may only detect temperature ranges from 0-80 °C, while forest soil can reach 70 °C during high-hazard weather conditions. Therefore, relying solely on IR cameras in an IoT system may not be the optimal choice. In [48], authors proposed a fire detection system that can be applied to IoT or UAVs, and the experimental results show its feasibility by combining the IR camera and the DL detection algorithm.

3) **Ultraviolet Range Cameras:** In addition to visible-light and IR cameras, ultraviolet (UV) cameras have also shown fire-detecting capability in situations where smoke or other factors may obscure the visible flames. In [49], [50], similar indoor firefighting robot designs have been explored, using low-cost MCUs and multispectral detection methods, including UV, IR and visible light. However, it is important to note that UV cameras are not the primary method of fire detection used in most fire safety systems. They are generally used together with other detection methods because the UV detection range and accuracy are lower due to the high UV absorption by particles and false positive detection caused by other UV-emitting or UV-reflective sources. Furthermore, the requirement for high-quality components, such as lenses, filters and photo sensors, in the construction of UV cameras makes them significantly more expensive than other types of cameras. To address this issue, some researchers have tried to reduce the cost of UV cameras by eliminating colour filters from IoT cameras to allow their UV capture features, and these cost-effective UV cameras have demonstrated their potential in chimney smoke detection [51].

B. Environmental Monitoring Technologies

As mentioned in the previous subsection, vision-based approaches based on visibility from the monitoring location may face potential detection delays. To address this, environmental monitoring sensors offer an alternative by providing information from different perspectives on fire hazards and incidents. These sensors offer advantages such as smaller size, lower cost, reduced energy consumption and increased autonomy compared to the vision-based technology. In addition, they do not require a direct line-of-sight (LoS) between EDs and the monitoring location, enabling faster detection based on changes in the environment. Therefore, environmental monitoring sensing technologies have gained prominence in wildfire detection projects. These projects commonly employ front-line sensors, including thermal, humidity, pressure, gas and smoke sensors.

1) **Weather Monitoring Sensor:** The utilisation of temperature, humidity and air pressure detection technologies

is prevalent in IoT projects, with thermistors and resistive temperature detectors (RTDs) commonly used for temperature sensing [52], [53]. Similarly, humidity and air pressure sensing are employed for resistive humidity sensing, thermal conductivity humidity sensing and piezoresistive pressure sensing, respectively, considering factors such as size and cost in mass production. Weather sensors have the potential to be an important asset in monitoring fire risk, as temperature and relative humidity can be used to calculate the moisture content of fire fuels, which is a major factor in controlling fire activity [54], including ignition probability [55]. Furthermore, it allows the detection of indicators such as increased temperature, humidity reduction and air pressure changes resulting from fire heat, which can be observed by EDs. These indicators are commonly used to determine the spread of wildfires, as well as are widely used in various indoor fire detection schemes [56]–[58].

Thermistors exhibit high sensitivity to temperature changes as a result of the heat conductivity of their sensing materials, resulting in a lower negative temperature coefficient and a nonlinear response. However, thermistors have limited operating temperature ranges and may not be optimal as standalone temperature sensors for IoT fire detection. On the other hand, RTDs offer wider temperature operating ranges but have lower sensitivity compared to thermistors. In humidity detection, both capacitive and resistive humidity sensors are cost-effective. However, capacitive humidity sensors are sensitive to contaminants and temperature variations, while resistive humidity sensors are generally larger in size, which can impact the design considerations of IoT projects. [59], [60] have demonstrated the potential application of these sensing technologies to detect fire hazards in forested areas. A recent study [61] comprehensively analysed the accuracy of several available temperature and humidity sensors on the market. The findings revealed that BME280 exhibited the highest precision, even under extreme weather conditions. However, AM2302E showed higher errors at low temperatures, while AM2302F and SHT71 had a higher error rate within the 30-60% humidity range. Although its successor, AM2321, demonstrated a slight improvement, it remains sensitive to temperature changes. BME280 was considered the most accurate. However, relying solely on weather sensors may prove insufficient for timely wildfire detection due to their slow rate of change.

To assess the responsiveness and effectiveness of weather sensors in detecting fire incidents, our team carried out an experimental burn in a national park. In this experiment, we placed multiple BME280 sensors 10 metres from the source of the fire, evenly spaced in a circle. Fig. 3 presents the average temperature and relative humidity data obtained from the sensors at each time. We ignited two fires using approximately 1.6 kg of *Eucalyptus* leaves (equivalent to 22.535 tonnes per hectare) in a 0.7 square metered fire pit. The fires were lit around 11:00 and 12:00, each lasting ten minutes with an additional five minutes of smouldering, but we can see from Fig. 3 that the weather sensors did not identify any notable irregularities. It suggests that depending only on weather sensors may not be sufficient to identify fires in their initial stages, particularly when the same experiment configuration is

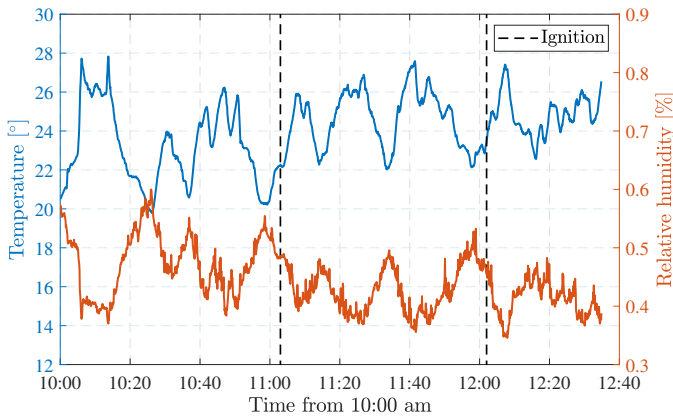


Fig. 3. Average temperature and relative humidity obtained from eight sensors in an outdoor experimental burn. The result show that environmental factors have a substantial influence on temperature and weather data recorded by the sensors, overshadowing the impact of proximity to the fire.

tested for gas sensors at a distance of 30 metres from the fire sources, as demonstrated in Fig. 4. However, the fires used in the example represent the lowest limit of detectable fire size. Fires up to 5 hectares can still be suppressed under mild weather conditions [5], and may alter the local temperature and humidity more than the fire in this example. Besides, as mentioned above in this subsection, fuel moisture, which is important for ignition success, can still be calculated from temperature, relative humidity and air pressure [54], [55]. Therefore, the moisture content of the vegetation can serve as the wildfire risk indicator and provide valuable guidance on the frequency of sensor readings required for early wildfire detection.

2) **Gas / Smoke Sensors:** During the early stages of a wildfire, the smouldering process can result in the release of a significant amount of greenhouse gases and heat. The gases emitted by a small fire may disperse before forming a visible plume [62]. Although heat can be detected by humidity, thermal and pressure sensors, a large amount of gases, such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) [63], together with particulate matter (PM), are also released from wildfires and can be measured using gas/smoke sensors. Previous research has shown that most of the carbon emitted during wildfires is in the form of CO_2 (88%), with smaller amounts of carbon monoxide (6%) and organic compounds without CH_4 (3.8%) [64]. As a result, gas/smoke sensors capable of detecting concentrations of these gases or smoke particles are often used in wildfire detection systems. Various types of sensors, including metal oxide semiconductors, chemical field-effect transistors and electrochemical sensors, are currently used to measure the concentrations of total volatile organic compounds (TVOC) and CO_2 in the atmosphere, while optical or laser scattering sensors are commonly used to detect PM particles. These sensors provide gas concentration readings at a high sampling rate to MCUs or to the cloud server, which can facilitate early fire detection. In particular, sudden changes in gas concentrations are often more detectable than gradual changes in environmental factors such as temperature and humidity,

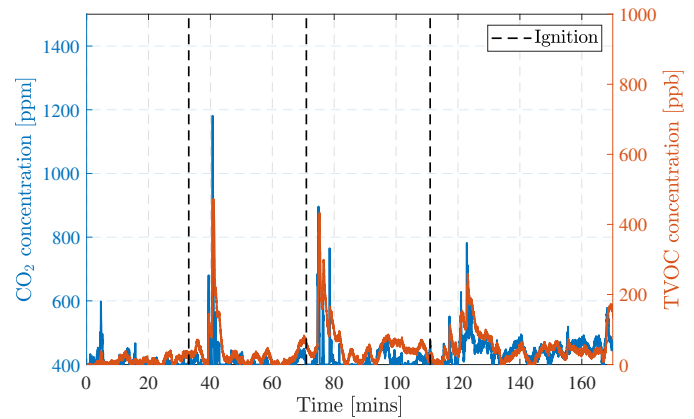


Fig. 4. Measurement of the concentration of CO_2 and TVOC over a period of two hours, with the dash lines indicating the time of ignition. The findings show that both concentration levels are more responsive to wildfires than to other meteorological measurements such as temperature and humidity.

making wildfire detection easier using such gas/smoke concentration data. We conducted another experiment with the same parameters as the one shown in Fig. 3, with sensors placed 30 metres from the fire and with multiple ignitions. Fig. 4 illustrates a strong connection between fires, CO_2 and TVOC levels, while PM concentration is strongly associated with wildfires, as demonstrated in [65].

Despite the availability of these sensors on the market, it is still necessary to compare their characteristics and performance. Therefore, further research efforts are necessary to determine the most suitable sensor type for an IoT-based wildfire detection project. In the following sections, we present a review of various sensor types that exhibit the potential to detect smoke PM, CO_2 and TVOC gases.

(i) **Resistive Metal Oxide Semiconductor Sensor (MoS):**

MoS sensors have gained widespread usage in a variety of IoT projects because of their cost-effectiveness and popularity in IoT development. The operational principle of MoS sensors involves the controlled heating of a metal oxide plate to a specific temperature, typically within the range of 300-400°C. This temperature enables the metal oxide to react with the target gas, leading to a chemical reaction that reduces the electrical resistance of the semiconductor. Therefore, changes in the resistance of the MoS sensor can be used to determine the concentration of the target gas. These sensors are particularly well suited for early stage wildfire detection systems in outdoor environments, because of their affordability and ability to be deployed on a large scale. Metal oxide gas sensors exhibit robustness and stability in outdoor settings, allowing them to withstand various weather conditions, temperature fluctuations and humidity levels. As a result, they offer reliable operation for extended periods in forested areas [66].

Despite the advantages of MoS sensors, they are known for their relatively high energy consumption, as they require energy to heat the metal oxide plates. Additionally, extreme weather conditions, such as high humidity, can adversely affect their performance. Therefore, protective

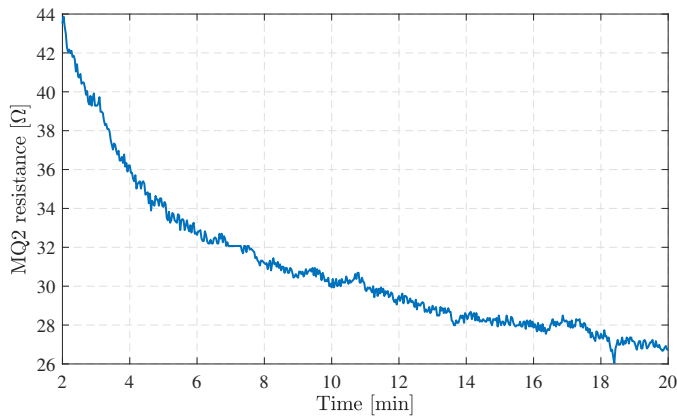


Fig. 5. Measurement of a MoS sensor (MQ2) resistance in a controlled environment over 20 minutes, showing that the sensor reading baseline is drifting over time.

measures, such as placing sensors in weatherproof enclosures, are necessary in such conditions. MoS sensors have a high sensitivity to a wide range of gases, allowing for a quick response to the target gas, but this heightened sensitivity also introduces a high cross-sensitivity to other gases, leading to inaccurate readings, particularly in the presence of smoke. Furthermore, MoS sensors need a period of time to reach the temperature needed for precise measurements. As a result, the baseline reading of the MoS sensors can change over time due to variations in temperature, changes in humidity and exposure to different gases, as illustrated in Fig. 5. Consequently, periodic calibration of the baseline is necessary when operating for extended periods.

Nowadays, advancements in integrated circuit technology have led to the integration of multiple MoS modules into a single sensor using micro-electronic mechanical systems technology. This integration enables the detection of a wider range of gases. In addition, digital control circuits have been incorporated into these sensors to facilitate baseline calibration and power management [67]–[69]. It should be noted that several studies, such as [29], [70], have explored the application of these digital MoS sensors for fire detection. In [70] and [71], it is recommended that metal oxide sensors be placed within a maximum distance of 25 metres from the fire source to ensure a timely fire detection in 15 minutes.

- (ii) Catalytic Bead Sensor: Catalytic bead sensors have been used for gas detection and monitoring for several decades as a result of their ability to respond to different sets of gases, making them highly versatile. However, with the advent of IoT projects that demand tailor-made solutions for specific objectives, the diminishing popularity of these sensors can be attributed to their cross-sensitivity issues. The catalytic bead sensor differs from the MoS sensor in its operating principle. Instead of employing a metal oxide membrane, the catalytic sensor utilises small catalyst-loaded ceramic pellets. As the target gases come into contact with the catalyst, they undergo a reaction that generates heat, which is subsequently detected by

the thermistor within the sensor. The gas concentration can then be determined on the basis of the measured resistance of the thermistor.

In [72], the response time and the recovery time of various metal oxide catalysts were evaluated at a distance of 6 cm from a concentration of 500 ppm of SO_2 and the minimum response time was found to be 80 seconds, while the minimum recovery time was 70 seconds accordingly. Catalytic sensors are more accurate than MoS sensors in detecting combustible gases such as Methane, Ethane, Butane and other VOCs. This is because catalytic sensors have low cross-sensitivity, meaning that they are less likely to respond to other gases. As a result, catalytic sensors require less calibration effort than MoS sensors. Similarly to MoS sensors, the utilisation of catalytic beads requires elevated temperatures to activate the catalytic pellets, resulting in shorter life and higher energy consumption. Furthermore, it should be noted that for IoT systems in wildfire scenarios, where most released gases are composed of CO_2 , catalytic sensors may not be the most suitable choice for detection, as they are designed primarily for combustible gases. Furthermore, catalytic sensors are highly sensitive to temperature fluctuations and tend to be more expensive than MoS sensors. They are also prone to contamination when exposed to high concentrations of combustible gases, which can lead to degradation in sensor performance. Therefore, catalytic beads sensors are used primarily in indoor environments, such as process plants and cargo compartments of aircraft, due to their suitability for these specific applications [73], [74].

- (iii) Electro-Chemical Sensor: Electrochemical sensors have been widely used in indoor fire detection and environmental monitoring projects in the past decade. However, because of its working principle, the miniaturisation of the electrochemical sensor becomes very limited and becomes less popular than the MoS sensor technology for early wildfire detection projects. Typical electrochemical sensors comprise an electrode that interfaces with an electrolyte solution, enabling the detection of target gases. When the gas is exposed, it diffuses through a porous membrane surrounding the electrode, initiating oxidation or reduction reactions, and generating an electric current within the circuit. The gas concentration is then determined through the measured current. Compared to MoS sensors, electrochemical sensors exhibit higher selectivity toward CO_2 and CO due to their use of chemical reactions for gas detection, while MoS sensors are based on the physical properties of the material. Direct measurement of current induced by chemical reactions in electrochemical sensors offers selectivity higher than that of the physical properties exploited by MoS sensors, making the former more effective in detecting specific gases. Furthermore, electrochemical sensors generally have longer lifetimes and lower power consumption because their electrodes do not require heating to allow chemical reaction. However, their operating temperature range can be limited, and their sensing range

may be restricted.

In [75], a comprehensive analysis of two low-cost electrochemical sensors is presented. Although the response time of electrochemical sensors is quite promising, the accuracy of CO concentration was found to be reliable only at environmental concentrations below 12 ppm. Therefore, its application may be restricted to specific industries and air stations where low CO concentrations are expected. In general, electrochemical sensors offer improved accuracy, sensitivity and selectivity compared to MoS sensors. However, their limited operating temperature and humidity make them less suitable for low-cost IoT applications. Some examples of real-life electrochemical sensors can be found in [76], [77].

- (iv) Optical Scattering Sensor & Non-Dispersive Infrared (NDIR) Sensor: Recently, the use of optical or laser scattering sensors in environmental monitoring and other IoT projects has gained increased research interest because they offer higher accuracy in determining PM concentrations and faster response time when compared with MoS sensors. These laser or optical scattering sensors utilise a laser or LED beam as a light source that is directed into a detection chamber. This chamber may contain suspended particles or aerosols within the gas. As the beam traverses the chamber, it interacts with the gas/smoke particles or aerosols, causing the scattered light to disperse in various directions, including backscattering toward the detector. Positioned at an angle to the beam, a photodetector captures the scattered light, and its intensity is measured. Changes in intensity serve as an indication of the presence and concentration of gas/smoke particles or aerosols within the chamber. Through the analysis of the scattered light intensity, the concentration of PM is determined by using established calibration curves or algorithms.

Analysis of the characteristics of PMs emitted during wildfire events has revealed that in the early stages of a wildfire, there is a substantial release of sawdust or dust from trees due to incomplete combustion [78], [79]. Therefore, the utilisation of optical scattering sensors also offers advantages in terms of improved accuracy and detection time, because they do not rely on chemical reactions between metal oxides or catalysts and gases. Furthermore, these sensors exhibit improved reliability compared to MoS-based sensors or other chemical reactions. However, it is important to note that optical scattering sensors can only detect the presence of obstructions in the air and cannot measure the concentration of specific gases. This limitation may impact their suitability for detecting wildfire gases, especially considering the limited travel distance of particle matter. Real-life examples supporting the efficacy of these sensors can be found in the literature, such as the work presented in [65], where they have been used successfully for early-stage wildfire detection. To improve the accuracy of fire detection, the authors of [80] implemented an IoT system that combined optical scattering sensors, NDIR sensors and electrochemical sensors.

Meanwhile, there has also been growing interest among manufacturers in the NDIR sensor, leading to a wide availability of NDIR sensors for integration into IoT systems. NDIR sensors are specifically designed to detect and measure gas concentrations using the principle of infrared absorption. These sensors employ components such as an infrared light source, an optical filter and an infrared detector, similar to the photoelectric detection technique. The functionality of NDIR sensors involves transmitting infrared light through a sample chamber that contains the gas to be analysed. The target gas selectively absorbs specific wavelengths of transmitted infrared light, resulting in a reduction in the intensity of the light at a specific wavelength reaching the detector. The magnitude of light absorption is directly proportional to the concentration of the gas, enabling the NDIR sensor to accurately quantify the gas concentration.

One notable advantage of NDIR sensors is their low energy consumption, making them well suited for IoT applications. Furthermore, compared to optical scattering or other photoelectric sensors, NDIR sensors exhibit lower cross-sensitivity as a result of their reliance on infrared absorption calculations of specific gases. However, it is important to note that both NDIR and optical scattering sensors have limitations in terms of their operating temperature range, which should be taken into account.

- (v) Gas-Sensitive Field Effect Transistor (GasFET):

GasFET sensors are relatively new to IoT projects and have not yet been widely used. However, they might become popular because of several advantages over other types of gas/smoke sensors. GasFET sensors operate on the principle of gas interactions on the sensor surface, resulting in changes in electrical conductivity. These sensors typically consist of a thin film of metal oxide deposited on a silicon substrate. The operational process of gasFET sensors involves key steps such as adsorption, conductivity modulation, gate voltage variation and signal detection [81], [82]. When the metal oxide surface is touched, gas molecules are adsorbed, potentially undergoing chemical reactions or physical interactions that modify the surface properties and affect the conductivity of the metal oxide film. This modulation in conductivity influences the electrical properties of the FET structure, which includes a gate electrode that controls the conductivity of the metal oxide channel. When a voltage is applied to the gate electrode, the conductivity of the metal oxide can be precisely controlled. The resulting changes in conductivity, caused by gas molecule adsorption, are detected as variations in the output current or voltage of the FET sensor, providing information on the concentration of the target gas in the surrounding environment. Different gases produce different responses, allowing the identification and differentiation of specific gases or volatile compounds. It is important to differentiate FET gas sensors from MoS membranes, as their underlying algorithms differ significantly.

In general, gasFET sensors utilise the conductivity

changes of a metal oxide thin film upon exposure to gas molecules, enabling gas detection and quantification. The design and materials of FET sensors can be optimised to provide enhanced selectivity and sensitivity to different target gases. These sensors offer advantages such as an extended operating temperature range, maintenance of performance over time, and provide consistent and accurate gas detection [82]. Furthermore, FET gas sensors exhibit faster response times and greater stability compared to MoS sensors. However, they are sensitive to changes in humidity levels and can exhibit variations in baseline characteristics due to manufacturing variances between individual sensors. Furthermore, FET-type sensors are relatively newer technology compared to other sensor types. Although they offer advantages such as high sensitivity and selectivity, their development and commercialisation have been slower than those of more established sensor technologies. This slower progress may be due to complex fabrication processes and challenges in achieving consistent performance across different gas types.

Although several researchers have dedicated their efforts to advancing these sensor technologies [81], [83], [84], it is challenging to find FET-type sensors readily available on the market for the detection of gases such as CO, CO₂ or TVOCs. Ongoing research and development efforts focus on the advancement of FET-type gas sensors with substantial potential for their application in various fields. The future holds promising prospects for the wide availability and utilisation of FET-type gas sensors in diverse applications.

- (vi) **Other Gas / Smoke Sensing Techniques:** In addition to the sensing technologies mentioned above, the use of photodiode sensors has been observed in various research projects for flame detection. However, the effectiveness of fire detection by photodiode flame detectors is limited due to their maximum detection distance of only one metre. Other technologies exist that could be used for wildfire detection, such as photoionisation, chemiluminescence, photoelectric, chromatography and resonant gas sensors. These have been evaluated to provide precise real-time gas/smoke measurements [85], [86], but their suitability for wildfire detection may be limited due to the substantial operational costs associated with these sensor technologies and the practical challenges involved in the deployment of these technologies in field settings.

The performance of gas/smoke sensors can vary greatly, making it difficult for IoT designers to understand the difference in each sensor performance. To address this, many research efforts have been made to compare the accuracy, response time, selectivity and cross-sensitivity of sensors. A comparative study conducted by [87] examined the sensitivity and accuracy of MoS, GasFET, Electro-Chemical, NDIR and optical scattering detectors. The results showed that the MoS and GasFET sensors had sensitivity comparable to those of the other sensor types. Furthermore, [57] provided an extensive review of recent developments in fire detection sensors,

including an explanation of their operating principles and a comparison of the performance of different types of sensors using different detection elements.

To help IoT designers understand the features of these gas/smoke detectors, we have compiled a comparison of the performance of various types of gas/smoke sensors that are suitable for IoT projects for early wildfire detection in Table II. This analysis is based on commercially available sensors and takes into account factors such as cost, energy usage, reaction time, durability and precision. These aspects are beneficial to the IoT designer and can help them select the right sensor for their project. In addition, the most remarkable characteristics of the sensors are also included in the table. Furthermore, Table III presents an overview of various IoT-based wildfire detection initiatives and the types of ground sensors used in each. It shows that many wildfire detection projects rely mainly on environmental monitoring sensors, including both weather monitoring and gas/smoke sensors, and MoS sensors are the most widely used gas/smoke sensors in these projects. In [80], [88], a comprehensive solution is presented, from hardware design to detection flow and DL detection, while [89] also offers a complete solution with implemented ML detection. [90] provides an experimental hardware prototype, but also includes a fire-carbon spreading model which can help determine the optimal detection distance and deployment height. [91] presents a real project of the deployed wildfire detection system in the United States and also provides information on the sensor topology. [38], [70], [92]–[95] present experimental proof-of-concepts of IoT ground sensing systems and different measurements are taken using their setup, while [93] demonstrates the feasibility of mounting environmental monitoring sensors on UAVs to detect early wildfires. Although [96] is only an example of the real deployment of the PM2.5 IoT sensing system, it also shows the ability of on board ML detection and the robustness of the use of LoRaWAN connectivity. [29], [31], [97] are real commercial IoT projects for early wildfire detection. Lastly, [98] provides an IoT system for early fire detection featuring GasFET sensors.

III. DATA ANALYTIC ALGORITHMS FOR WILDFIRE DETECTION

After collecting these data from EDs, the integration of camera images or sensor data is used to identify any fire or non-fire event. To do this, either the MCUs on the EDs or the computing unit on the central server must use data-analytic algorithms to convert the problem into a mathematical expression. The analytical process of identifying unusual events within IoT applications often aligns with the principles of anomaly detection. In the context of wildfire detection, this is specifically focused on distinguishing the rare occurrences of fires, while non-fire situations happen most of the time. Each anomaly detection technique has its own benefits and drawbacks, which make them more or less suitable for use in IoT projects.

In this section, a summary of early wildfire detection algorithms is provided. These algorithms can be classified

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT TYPES OF GAS/SMOKE SENSORS FOR IOT ENGINEERING APPLICATIONS

Sensor type	Cost [\$]	Energy consumption [mW]	Response time [sec]	Lifespan [yrs]	Accuracy [%]	Remark
MoS (Resistive) [67], [69]	Low (1.5-30)	Moderate (68-90)	Moderate	2-3	Moderate	Cheap, high cross-sensitivity
Catalytic Bead [99]-[101]	Moderate to High (70-350)	High (145-190)	Fast	2-3	High	Accurate, volatile gases only
Electrochemical [76], [77]	Low to Moderate (50+)	Low (10-60)	Fast	2-3	High	Fast response, low power cost
Optical Scattering [102], [103]	Low to Moderate (30-100)	High (300-500)	Fast	8-10	High	limited operating temperatures Fast response, high accuracy, PM particles only
NDIR [104]-[106]	Low (20-50)	Low (40-300)	Moderate (60-90)	5-10	High	Accurate, long-life
GasFET	N/A	Very Low (≤ 1)	Moderate to Fast	2-3	High	slow response Sensitive to humid environment

TABLE III
ILLUSTRATION OF GROUND SENSORS EMPLOYED IN PROJECTS AIMED AT WILDFIRE DETECTION

Sensor Type	[80]	[90]	[91]	[107]	[88]	[70], [92]	[38]	[93]	[94]	[31] [⊕]	[29] [⊕]	[95]	[89]	[96]	[97] [⊕]	[98]
Temperatures	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Humidity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pressure	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wind speed	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Soil moisture	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MoS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Electro-chemical	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Optical scattering	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NDIR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Photodiode (flame) FET	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Camera	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Micro-controller	†	‡	⊖	⊖	†	‡	✓	ESP32	‡	N/A	N/A	‡	‡	ESP32	⊖	⊖

† Cortex - A53

‡ ATmega328

⊖ ATmega128

⊕ Commercial

into two main categories based on the way they obtain their detection criteria: feature detection and pattern detection in time series. The discussion of the use of ML and DL to improve the performance of features or pattern detection for both vision-based and non-vision-based detection is also provided, as the use of ML/DL in IoT projects is gaining more research interests. Although ML/DL are heavily dependent on computers to recognise irregularities through iterative learning of features/patterns, it is essential to remember that these techniques are still based on statistical and mathematical models and can be classified as a part of the features/patterns detection. To make it easier for IoT designers in finding relevant information, we have divided this into an individual item. The following subsections will discuss fire/smoke vision-based detection algorithms for recognising anomalies in features/patterns and how to enhance them using ML/DL, followed by detection algorithms for non-vision-based detection for recognising anomalies in features/patterns and how to improve them using ML/DL.

A. Vision-Based Detection Algorithm

Vision-based fire detection algorithms typically use image processing techniques to identify and extract relevant features from images or videos. These extracted features are then compared to the known characteristics of a fire to determine if a fire is present. Since flames and smoke are the most visible signs of fires [108], most existing algorithms focus on image processing analysis to detect the features of flames and smoke. The physical properties of flames and smoke [109] can be identified using feature detection algorithms, such as colour, motion, spectral and texture. Meanwhile, pattern detection algorithms, such as spatial and temporal wavelet detection, can be used to observe the propagation of fire or smoke over a period of time. Feature detection algorithms are easier to run on IoT EDs, as they require less computing power and memory space than pattern detection algorithms. However, pattern detection algorithms used to be more accurate, as they are based on the analysis of the video stream.

1) **Feature Detection Algorithms:** In the following we discuss various feature detection based image processing algorithms for fire detection.

- (i) **Colour Pixel Analysis:** The use of colour analysis for vision-based fire detection is a widely accepted approach [110]–[118]. It involves recognising the values of R, G and B of the pixels in the image to capture the colour property of flames and smoke. Different colour spaces such as YCbCr [113], CIELAB [114], YUV [115] and HSV [116] are used to model the fire colour and also generate colour masks in the literature. RGB and HSV are the most commonly used models [109]–[112], [119], with the latter providing more useful information on fire illumination. In IoT applications, the IoT camera module takes pictures of its environment and the MCU evaluates the colour values of each pixel to decide if there is a fire present. This enables the colour characteristics of fire and smoke to be recorded. Colour-pixel analysis is relatively straightforward by simply using a threshold for

a variety of colour combinations in the form of adding or subtracting two colour pixel values, which is simpler to implement in IoT EDs [120]. Although colour analysis can be used to distinguish fires from images, it is not accurate enough to do so dependably, particularly when fire-coloured objects are present in the image. This results in a high rate of false alarms. To enhance precision, colour analysis is usually combined with motion analysis for fire detection. In [120], a combination of vision-based detection and gas sensor detection is used to make a fire decision.

- (ii) **Motion Pixel Analysis:** Motion analysis is another technique commonly used in vision-based fire detection [119]. This technique, known as background subtraction, captures the motion of flames and smoke by subtracting the first frame received from the subsequent frames. To achieve thresholding, in various studies, dynamic background subtraction methods based on the Gaussian mixture model (GMM) have been proposed [121]–[125]. GMMs are used to analyse the intensity values of each pixel in the previous frames, forming a Gaussian distribution that displays the information state of each pixel [126]. This image, with the background removed, can be used to identify motions, such as a fire. To detect motion pixels, a comparison between the current frame and the previous frame is necessary, which requires a bit more temporal storage for the pixels. In [122], it is demonstrated that fire detection using the motion pixel approach is not resistant to moving objects such as humans and animals. Therefore, relying on fire motion detection may not be reliable, as there is a chance that wildlife is moving around in the forest.
- (iii) **Local Feature Extraction Analysis:** A range of local feature extractors can be used to improve fire detection in IoT devices, helping to recognise fire or smoke objects. The Histogram of Orientated Gradient (HOG) algorithm computes the magnitude and direction of the gradient for each pixel in a given block and then creates a histogram of the normalised values. The Scale-Invariant Feature Transform (SIFT) method identifies local features by constructing a scale-space pyramid using Gaussian masking and detecting the difference of Gaussians between adjacent pixels. Shi-Tomasi calculated the 2x2 eigenvalues of each section of the image, allowing the corners of the image to be highlighted by sorting the highest minimum of the eigenvalues. All these techniques are particularly useful for recognising the edges of an object. In [41], the performance of various local feature extractors was evaluated using a Sony IMX219 camera and a Raspberry Pi 4 MCU. HOGs were found to be more successful in capturing fire and smoke characteristics. However, they were all sensitive to non-fire objects, such as humans and animals. To enhance accuracy, the MCU performed local feature extraction, and then the features were transmitted to the cloud server and used to identify fire through DL algorithms.
- (iv) **Other Feature Detection Techniques:** In addition to the feature detection methods discussed, there are numerous

other feature extractors, such as the Harris corner detector, the Canny edge detector, binary robust invariant scalable keypoints and orientated rotated brief. These were only mentioned as they are commonly employed for fire detection on IoT devices, such as HOG and Shi-Tomasi, or can be used as a detection benchmark, such as colour and motion pixel detection and SIFT.

2) **Time Series Pattern Detection:** In the following we discuss various pattern detection based image processing algorithms for fire detection.

(i) **Temporal Wavelet Analysis:** In addition to feature detection, more sophisticated image processing techniques can be used to detect patterns in time-series data. Temporal wavelet analysis combines colour and motion analysis to detect fires. Moving objects of fire can sometimes trigger a false alarm, but analysing the flickering property of a fire can help distinguish between real fires and these objects [115], [119], [127]–[130]. The flickering frequency of the fire is around 10 Hz [131], and an oscillating frequency of a pixel intensity value greater than 0.5 Hz indicates the presence of the fire [132]. [133] used the Discrete Wavelet Transform (DWT) to extract information on temporal variation from a pixel by placing its intensity history in a two-stage filter bank. And by comparing the simulated results for fire pixels and non-fire pixels, fire pixels can be distinguished by counting the number of zero crossings within a certain number of frames [134]. Although temporal wavelet analysis combines motion and colour analysis to enhance fire detection accuracy, this comes at the cost of increased computational complexity and the need for more temporary memory capacity, leading to higher energy consumption and longer detection latency. Furthermore, smoke and flames can flicker in various ways, and to accurately capture the characteristics of early wildfires, various studies have suggested multiple approaches by integrating temporal wavelet analysis with other techniques in fire detection [135], [136].

(ii) **Spatial-Temporal Wavelet Analysis:** In addition to temporal wavelet analysis, spatial variations can also be used to differentiate between fire and objects in motion that are coloured with fire. Fire regions in the image show a great deal of spatial variance, while objects in motion with a fire-like colour show no changes in spatial colour variations [127], [133]. Spatial wavelet analysis is used to calculate the spatial variation of the image frame [119]. DWT is applied to decompose the original image into four subimages, which represent the horizontal, vertical and diagonal spatial energy of the image. A decision variable ν_4 is calculated using these subimages, indicating the level of spatial variation of the image frame analysed. Equation ν_4 can be written as [134],

$$\nu_4 = \frac{1}{MN} \sum_{k,l} |x_{lh}[k,l]|^2 + |x_{hl}[k,l]|^2 + |x_{hh}[k,l]|^2, \quad (1)$$

where the number of row and column pixels in the frame is denoted by M and N , respectively, such that particular row and column for the calculation of the pixel value are represented by k and l respectively. x_{lh} , x_{hl} , x_{hh} are low-high, high-low and high-high subimages, respectively. If ν_4 is above a certain threshold, then the probability of the presence of a real fire is higher [134]. In [128], the advantage of spatial wavelet detection over colour and motion pixel detection is shown, as it significantly reduces the false alarm rate. Additionally, spatial wavelet analysis is more efficient in terms of temporal memory and detection time, since it requires only performing DWT of the image. However, the two-dimensional wavelet decomposition used in spatial wavelet analysis has a limited capacity to analyse time-series data.

To improve its ability in time-series detection, many researchers have proposed the use of spatial-temporal wavelet analysis, which combines spatial and temporal wavelet analysis and uses a weighted sum fuzzy logic for both detection methods. In [137], the spatial-temporal variance is used to calculate the spatial-temporal energy to detect any sudden increase in energy, which is indicative of a fire. We had also conducted a comparison of vision-based detection on a 64-bit quad-core ARM Cortex A53 with 1GB RAM, and the results demonstrate that all spatial wavelet, temporal wavelet and spatial-temporal wavelet analyses are suitable for IoT devices. The amount of time that each algorithm took to process 100 consecutive frames was 2.1, 4.1 and 6.3 minutes, respectively, while the colour and motion detection benchmark was completed in 2 minutes.

(iii) **Histogram of Optical Flow:** The Histogram of Optical Flow (HOF) is a popular technique for detecting spatial-temporal patterns, such as fire motion detection. To generate HOF vectors, video frames are first converted to greyscale and then optical flow is calculated using various algorithms, the most well known being the Lucas-Kanade method [138]. HOG and HOF are usually used together, as they are both histogram-based descriptors. This implies that once the gradients and optical flows have been obtained, they can be quickly converted into HOG and HOF through the same process and are also computationally efficient. In addition, HOG is more likely to give details about objects, while HOF is better at recognising temporal motion. By combining HOG and HOF, many studies have shown that the accuracy of fire detection is improved compared to using either method independently [139], [140]. However, all of these measurements have been performed on desktop PCs, and only one study [41] has demonstrated its practicality on an IoT device. The limited computing power of EDs can lead to delayed detection times when using wavelet analyses and HOF. To address this issue, researchers have proposed using location pattern detection in EDs, which transmit data for processing by ML or DL algorithms [41], [141].

(iv) **Other Time Series Pattern Detection Algorithms:** In ad-

dition to the time-series pattern detection methods mentioned, there are other detection algorithms such as auto-regression and spectral analysis, while the most commonly used and widely adopted time-series detection model for capturing fire and smoke in IoT EDs is listed.

3) **Machine Learning and Deep Learning Algorithms:** In the following we discuss various ML and DL based detection algorithms for fire detection.

(i) ML algorithms have been increasingly utilized in fire detection tasks in recent years [142]–[151]. Simple ML methods can be applied directly to enhance feature or texture detection, such as colour and motion pixels. In [152], it shows that the use of a support vector machine (SVM) can improve the accuracy of forest fire detection by colour pixel analysis by 0.5%. In [153], K-means algorithm was used to re-cluster the pre-labelled anchor frame parts in the dataset. Furthermore, the author suggested that using K-means to cluster the fire-like area into local binary patterns for SVM could improve the accuracy by more than 1.75%. In addition to feature detection, ML methods can also help to make decisions from different detection algorithms. In [41], fire detection is achieved by combining classification results using a linear SVM, and the performance of this ML detection outperforms the simple temporal wavelet detection of 5%.

(ii) Another popular method is using Convolution Neural Networks (CNN) in DL to train a classification model to automatically identify fire and non-fire images. Unlike conventional algorithms that require hand-crafted features, DL algorithms can effectively learn the features themselves, resulting in better performance [108]. A typical CNN consists of an input layer, an output layer, multiple common layers and hidden layers, which are usually convolutional layers. Convolution is the main process for CNNs to learn features, completed by multiplication of elements between the convolution matrix and the input image. The convolutional process generates values that represent information about the features of the input image, which are then passed through common layers such as activation, pooling, normalisation and fully connected layers [154]. The most important features are highlighted during the pooling process. The last few layers are always fully connected layers, where all the information on different layers of CNN is combined to obtain a final result. The final result is compared with the input data benchmark to generate a numerical indication of how well the model predicts the input. This indication is passed through each CNN layer from end to end to correct for the weights associated with each layer using backpropagation (BP). CNNs not only represent the types of feature that the model focuses on but also define the CNN itself. Different CNNs perform different tasks with different weights in the layers, even with the same layer structure. AlexNet, ResNet, GoogLeNet and VGG-Net are the most popular CNNs used to solve computer vision

problems [151], [155]–[158].

In DL, fire detection is a binary classification problem that requires a binary classifier to solve the problem. The complexity of the problem can be reduced by focusing on wildfire detection with binary classifiers. An overview of current lightweight CNNs that are built for fire detection and are possible to implement on a resource-constrained device is given below. In [142], the classifier uses a feature learning method that learns basic low-level structures of fire first and high-level semantic features about fire later. Their classifier was compared with other existing fire detection classifiers, including FireNet, InceptionNetV1-OnFire, NasNet-A-OnFire and ShuffleNetV2-OnFire. InceptionNetV1-OnFire achieves the highest accuracy of 95.6% with 12 fps, and NasNet-A-OnFire can achieve the lowest fps of 7 with 95.3% accuracy. In [145], the authors proposed a 14-layer deep CNN model capable of automatic feature extraction and classification in fire smoke, achieving a detection rate of 96.37% and a false alarm rate of 0.60%. In [146], a new lightweight smoke detection CNN is trained using pre-processed images and achieves a detection rate of 99.8%, a false alarm rate of 0.31%, and an overall accuracy of 99.7%. In [147], a fire detection approach was proposed that combines the strengths of conventional and DL algorithms and can detect both flames and smoke in the image, achieving good results. To achieve fire image detection using DL in power-limited devices, a lightweight CNN architecture is proposed in [148]. Fire detection and localisation can be achieved using the proposed CNN architecture, employing techniques such as small kernels, transfer learning, model tuning and a selection algorithm for feature maps. As a result, the size of the architecture is reduced from 238 MB to 3 MB. Additionally, valuable information is provided on the identification of burning objects and the precise location of the fire within the image frame. However, a more efficient alternative approach is demonstrated by the introduction of a scratch-based model design that uses small CNNs. Consequently, this research has led to the development of the well-known CNN model, Firenet, which can be seamlessly integrated into power-limited devices such as the Raspberry Pi [150].

Dataset also plays a crucial role in achieving high performance in DLs. To train a fire classifier, a data set consisting of annotated positive and negative images is required. Videos can also be used as a valid dataset if they are converted to images. In [159], researchers achieved a test accuracy of 90% by training their model in online fire videos, while another study achieved an accuracy of 97% with a diverse database that included self-recorded videos and various online platforms [160]. Public datasets available for fire detection research include the Fire-net dataset with videos and images, the Fire Flame Dataset with 3000 images classified into fire, smoke, neutral and the VisiFire dataset that offers video clips for fire and smoke detection [161], [162]. Recently, there has been a notable trend among global

communities toward collaborative exchange of experimental and prescribed burns footages. This initiative aims to improve fire detection algorithms around the world by providing access to extensive and varied datasets. A notable example of such an effort is documented in [163].

Although the use of vision-based technologies has shown great potential in the analysis of satellite images, real-time camera systems on UAVs, and alleviating the workload previously carried out by watchtower observers responsible for detecting occurrences of wildfires [164], it remains susceptible to interference from various environmental factors, such as weather conditions (e.g., cloud cover, rainfall and reflection of sunlight), as well as physical obstructions such as trees and buildings. As a result, the response time of imaging detection can be significantly delayed when camera modules are used on IoT EDs. Besides, if the number of cameras mounted on an IoT ED is limited, the camera is usually required to rotate and scan every hour to cover a full 360 degrees of view, which will increase the time it takes to detect something. Furthermore, these camera systems can be expensive to deploy and consume significant amounts of energy. Therefore, early wildfire detection using environmental sensing data in IoT systems has been explored as a potential alternative.

B. Detection Algorithm based on Environmental Sensing Data

In addition to vision-based detection methods, early wildfire detection can also be achieved using data from environmental monitoring sensors. MCUs can apply various detection algorithms to detect abnormal readings, which could indicate the presence of smoke or fire. This process is commonly referred to as anomaly detection. It is essential that the data given to the detection algorithm have considerable changes when a fire occurs, so that it can differentiate between normal and abnormal data patterns. And there are multiple ways to detect abnormalities, ranging from simple statistical techniques to advanced DL methods. These techniques exhibit diverse capabilities in processing input, from singular data points to continuous data streams within specific temporal windows. Using ML/DL, anomaly detection methodologies can be further differentiated into unsupervised and supervised frameworks. To reflect the significance of anomaly detection being used in early wildfire detection, we divide these techniques into three categories: threshold-based anomaly detection (point-wise), which focuses on individual data points, anomaly detection in time series (pattern-wise), which examines observations within a specified short-term period, and ML/DL strategies for early wildfire detection due to their increasing use in anomaly detection.

1) **Threshold-Based Anomaly Detection:** In order to detect and respond to abnormal readings, a commonly used approach is the implementation of a threshold limit. This method allows users to define a specific threshold value for recorded readings. If the readings exceed this predetermined threshold, it indicates that the readings have exceeded the normal range and, subsequently, trigger the activation of the fire alarm (λ).

The corresponding equation that represents this relationship is as follows,

$$\lambda(t) = (\bigwedge_{i=1}^n (x_i(t) > X_{ith})) \wedge (\bigvee_{j=1}^m (x_j(t) > X_{jth})), \quad (2)$$

where $\lambda(t)$ is true if all sensors in a certain subset have readings $x_i(t)$ at time t exceeding their respective thresholds $X_{ith} \forall i \in n$ and if any sensor from a different subset has a reading $x_j(t)$ exceeding its threshold $X_{jth} \forall j \in m$. This setup allows for a general expression that accommodates various sensor data configurations, incorporating conditions that must all be met simultaneously and those where meeting any one condition is sufficient. The most common way to determine X_{th} is by using the z-score. This involves finding an appropriate threshold value, which is expressed as $X_{th} = \mu \pm z \frac{\sigma}{\sqrt{n}}$. The sample mean, μ , is calculated from either non-fire state data or fire state data. The confidence level is indicated by the parameter z . The standard deviation of the sample is represented by σ , while n is the sample size. This approach assumes that the distribution of sensor data follows a Gaussian distribution. The z-score can then be applied, which states that approximately 99.73% of all samples will be within $3 \frac{\sigma}{\sqrt{n}}$ of the mean. The desired level of sensitivity can be adjusted considering whether a particular sample falls within the range 95.45% (corresponding to $2 \frac{\sigma}{\sqrt{n}}$) or 68.27% (corresponding to $1 \frac{\sigma}{\sqrt{n}}$) range of all samples [165].

Additionally, the Local Outlier Factor (LOF) is also a prominent algorithm used for anomaly detection, where it assesses the outlying level for each data point within a dataset by comparing its local density with that of its neighbouring data points. In some of the literature, the LOF is classified as an ML algorithm. However, due to its simplicity, we classified it as a threshold-based detection method here. The LOF equation, which is well-established, is expressed as follows,

$$LOF(x) = \frac{\sum_{o \in N_k(x)} \frac{LRD_k(o)}{LRD_k(x)}}{|N_k(x)|} \quad (3)$$

$$LRD_k(x) = \frac{|N_k(x)|}{\sum_{o \in N_k(x)} ||x, o||}, \quad (4)$$

where $||x, o||$ is the reachable distance between point x and its neighbour at point o , $|N_k(x)|$ represents the count of nearest neighbours and LRD denotes the local reachable density, which can be interpreted as the inverse of the average reachable distance to its closest k neighbours. If the LOF is approximately 1 or less, it can be inferred that the data point is within the normal range. In contrast, if the LOF exceeds 1, it indicates the presence of an outlier, thus identifying an anomaly. Furthermore, additional statistical techniques, including moving averages and exponential smoothing, can be integrated into z-score calculation and LOF analysis. This involves comparing the observed value with the moving or exponential average to identify notable deviations and signify potential anomalies [166]. Generally, statistical techniques are the most straightforward methods for early fire detection. By using pre-recorded background readings, it is possible to identify a threshold value without the need for on-board processing. This makes it the most energy-efficient option and commonly used detection model for wildfire detection.

However, its accuracy is limited by threshold values, which makes it less precise than other detection methods. Therefore, many research projects employ statistical thresholds to perform initial filtering before performing ML/DL algorithms that require high computing power [89], [92], [96], [167]–[170].

2) **Time Series Detection:** In addition to the threshold-based point-wise detection, the use of detecting changes in power density over a short period of time and seasonality detection has been extensively studied as an alternative, particularly for anomaly detection in IoT systems.

Various techniques have been explored for the detection of abnormal changes over a period of time, including Bayesian online changepoint detection [171], cumulative sum control chart (CUSUM) [172] and bottom-up segmentation [173]. In general, the primary objective of change-point anomaly detection is to identify significant changes or intervals in a time series that deviate from the underlying behaviour or pattern. This involves segmenting the time series, fitting statistical models to each segment and detecting changes between adjacent segments. The presence of an anomaly is inferred if a significant change is detected. The effectiveness of change point detection depends on segmentation, model selection and assumptions made about the data. These approaches capture various types of anomalies, including sudden changes, gradual changes and recurring patterns. In [174], CUSUM was used to detect unusual body movements on a low-power ARM-Cortex R4F. In addition, the implementation of CUSUM for anomaly detection on fog platforms was demonstrated in multiple projects, as summarised in [175]. A sequential approach for anomaly detection using Bayesian changepoint detection in the IoT is also proposed in [176]. Numerous projects have demonstrated the effectiveness of employing changepoint detection models in anomaly detection, particularly within on-board IoT systems. Although changepoint detection exhibits a higher level of complexity compared to point-wise detection techniques, it remains less complex than advanced seasonality or ML/DL detection methods. Moreover, changepoint detection has been observed to offer superior accuracy in anomaly detection in contrast to point-wise detection approaches.

An alternative approach to analysing time-series data is the seasonality detection method, such as seasonal decomposition methods and seasonal forecasting methods. In seasonality detection, the trend or seasonal component captures the overall direction of the data over a long-term period, providing information on whether the time series is increasing, decreasing, or relatively stable. Seasonal decomposition techniques are used to identify patterns in the data that repeat at fixed intervals by isolating the seasonal component so that any recurring patterns in the data can be retrieved. These fluctuations can be considered anomalies or unexpected behaviour in the data [177]. In contrast, seasonality forecasting techniques, such as Holt-Winters and Fourier analysis, also consider seasonality when predicting. However, to enable anomaly detection, users still need to design their own anomaly-checking mechanism. A straightforward detection algorithm is to calculate the mean square error and feed it into a given threshold and confidence intervals to determine if it is an error. In [178], the author evaluated the effectiveness of various IoT air quality

prediction models using seasonal forecasting methods and seasonality ML/DL prediction models. The results of the study showed that it is possible to predict seasonality in EDs using low computing power Cortex-M0 or high-performance Cortex A53. However, seasonal anomaly detection models are not widely used in anomaly detection due to the fact that the full data set may not be available if the seasonal patterns last longer than one year. For example, in [179], researchers have shown that Holt-Winters requires an additional 40KB of data to correctly predict CO₂ and the temperature level on an ESP32. Besides, these methods assume that the time series has repeated seasonal and stationary patterns. If the data includes irregular or non-recurring seasonal patterns or if the seasonal patterns change over time, these methods may not be able to accurately capture the underlying structure.

3) **Anomaly Detection Using ML and DL:** In addition to the detection methods mentioned, the use of ML or DL for anomaly detection has been increasing due to its ability to capture complex relationships and non-linear patterns in data, as well as its adaptability and scalability in dealing with different input features. These ML/DL approaches make it possible to process large or multi-dimensional datasets quickly and easily for point-wise or time-series detection. Moreover, ML techniques can be applied to various components of a network, from IoT devices to network servers. These advantageous characteristics have led to the growing adoption of ML for anomaly detection. Several basic supervised ML algorithms have been used for anomaly detection, such as SVM, K-nearest neighbours (KNN) and decision tree (DT) [180]. SVM uses hyperplanes to classify data into normal or anomaly groups, while KNN determines anomalies based on the Euclidean distance to their nearest-neighbour group. DT uses reduction of entropy values to identify relevant information for anomaly detection. However, these ML techniques require user-labelled data points, which are usually obtained by manual detection. For instance, when it comes to fire detection, users must label the time stream of sensor readings as either fire or non-fire states. The accuracy of these methods is highly dependent on the accuracy of the labelling process. Therefore, some anomaly detection methods are developed using ML clustering techniques, such as K-means and GMMs, and many IoT projects have implemented these approaches, as shown in [89], [181]. Furthermore, some ML forecasting models, such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA), can also be combined with statistical outlier methods to detect anomalies without supervised learning [182]. If the input dimensions of ML are small, the energy consumption of ML can be comparable to that of statistical methods. However, the greatest advantages of ML are its ability to recognise inter-connections between different inputs and to detect anomalies. Furthermore, its complexity and computing power requirements are lower than those of the DL methods, making it more suitable for deployment on resource-constrained EDs. Recent IoT ground sensing system projects have widely used ML anomaly detection algorithms, as summarised in Table IV.

To improve the precision of anomaly detection and reduce the likelihood of errors caused by human labelling in super-

vised ML methods, DL approaches have gained popularity. DL algorithms are capable of modelling complex nonlinear relationships between input features and output labels, allowing for the detection of anomalies that may be missed by simpler linear models. DL models such as Artificial Neural Networks (ANNs) and CNNs can leverage networks that have been pre-trained on large and diverse datasets from similar domains. This can reduce the need for a large number of labelled data during the initial training phase and can also improve the recognition of complex patterns and features in the data. When using ANNs for anomaly detection, the raw input data are processed through multiple hidden layers, which work to identify and capture representations that are indicative of anomalous behaviour. Subsequently, the output layer produces a prediction or score that indicates whether the data are anomalous or normal. In [183], three ANN models were used, namely BP, radial basis function (RBF) and probabilistic neural network, for indoor fire detection using weather and gas sensors. The results demonstrated the exceptional performance of all three models in the detection of fire incidents. In addition to ANN, recurrent neural networks (RNNs) were developed to process sequential data. These networks have recurrent connections that allow them to store information from previous steps or moments. This allows RNNs to recognise and learn patterns in sequences, making them more effective than other DL approaches, since the input data are likely to be a time series of environmental readings from sensors. In particular, long-short-term memory networks (LSTMs), a specific type of RNN, were developed to address the problem of vanishing gradients faced by traditional RNNs. LSTM networks introduce a specialised memory cell that can retain information over long periods of time. This makes it more effective in capturing long-term dependencies in sequential data [80]. Furthermore, LSTM networks and other DL models, such as autoencoders and multilayer perceptrons, can be used for unsupervised or self-supervised learning to reduce errors. These methods are simpler than other self-supervised DL clustering models, making them easier to implement on the edge with relatively low energy consumption. Additionally, these DL models can be trained online or in real time, making them more adaptive to changing environmental conditions, especially useful for early wildfire detection. Some newly developed DL models for unsupervised time series anomaly detection are also reported in [184], [185]. However, their compatibility with performance-constrained EDs has not been investigated yet. The study conducted by [80] investigates the performance of three RNNs, namely simple RNN, LSTM and GRU-RNN, for early forest fire detection. The results demonstrate that all models achieve an accuracy that exceeds 99.7%. Specifically, the GRU-RNN model exhibits the highest accuracy and demonstrates reduced complexity compared to LSTM. These findings highlight the effectiveness of RNN models in accurately detecting forest fires at an early stage, and the GRU-RNN model shows potential advantages in terms of accuracy and complexity.

Table. IV presents a summary of the anomaly detection algorithms used in recent forest fire detection projects. In general, DL and ML approaches are widely used in these

TABLE IV
ILLUSTRATION OF ALGORITHMS USED BY FOREST FIRE DETECTION PROJECTS

	Statistical	Time Series	ML	DL
[80]				RNN, LSTM, GRU-RNN
[186]			RF, SVM	
[167]	✓			ANN
[92]	✓			
[93]			RBF	
[168]	✓			
[89], [181]	✓		K-means	
[96]	✓		SVM	
[180]			SVM,RF,KNN	
[187]				ANN, CNN
[169], [170]	✓			MLP-ANN
[188], [189]				ANN, Fuzzy logic
[182]		✓	ARIMA	
[190]			K-means	BP-ANN

projects. Most of these initiatives employ a threshold limit, based on the z-score, regression, or LOF, for initial filtering. Upon triggering consecutive alerts, the ED transmits data to the server to perform fire detection or performs specific fire detection algorithms on the ED itself. Note that in this section, we have focused on a few anomaly detection techniques that are suitable for implementation on EDs or the gateway for wildfire detection. The selection of these methods was based on their computing power requirements, complexity, and whether they have been previously implemented.

IV. OPERATIONAL CHALLENGES

In order to establish an IoT ground sensing system aimed at early fire detection, a holistic consideration of various factors is essential. This extends beyond the implementation of sensors, gateways and servers, encompassing aspects such as communication technologies, medium access control (MAC) layer control, energy consumption, detection latency and device sustainability. The purpose of this section is to discuss the challenges and constraints related to the implementation of IoT sensing systems to offer valuable perspectives to individuals considering designing their own early wildfire detection system.

A. Sensors

As mentioned in Sec. II, gas/smoke sensors have different characteristics when it comes to wildfire detection. Some sensors have minimal cross-sensitivity, but their operating temperature and humidity ranges are limited. On the other hand, some sensors are highly accurate, but they take time to precisely measure the concentration of the target gases. Additionally, the cost and availability of these sensors, such as energy consumption, maintenance cost and size, are crucial considerations. It is essential to take into account not only the cost of the sensors, but also the operational costs associated with the equipment and needed for their operation and maintenance. A thorough assessment of these elements is necessary when selecting the right sensors for a particular purpose. Sensors can be delicate and need to be calibrated regularly, which can make them costly to use in a wildfire detection system. They may be exposed to extreme environmental conditions and may need to be replaced often. Besides,

the practical implementation of these sensors in the field also presents several challenges, including the establishment of a secure mounting site and the protection of the sensors against environmental hazards. These challenges pose obstacles in deploying sensors in remote regions, which are often the areas most vulnerable to wildfires.

B. Communication link and Access Layer Control

In addition, the reliability and robustness of communication within sensor systems pose significant challenges. One specific challenge arises from the dependence on a clear line-of-sight between transmitters and receivers to establish optimal communication links. However, in IoT ground sensing systems, especially those used for wildfire detection, non-line-of-sight conditions are common due to obstructions such as forests and smokey environments containing high levels of PM2.5 and PM10 particles. To reduce the adverse impacts of short-wave radio technologies and address the issues caused by blocked communication, it is essential to perform a comprehensive analysis of this phenomenon to understand amplified channel pathloss and slow-fading attenuation so that transmission power can be adjusted to reduce these effects. Pathloss measurements reported in [191] reveal that a 922 MHz signal can experience pathloss of up to 100 dB at a distance of 200 metres, projected to rise to 120 dB at 400 metres and even higher at 2.4 GHz frequencies. Furthermore, in the IoT system for early wildfire detection, which is often deployed in remote areas with limited coverage of the cellular network, it becomes imperative to establish extended-range communication between end devices and gateways to facilitate data transmission to the server. Consequently, the transmit power of the end devices needs to be enhanced, resulting in increased energy consumption. To address these challenges, the adoption of an LPWAN protocol suitable for extended-range communication becomes indispensable.

Typically, IoT systems employ LPWAN protocols for communication between the end nodes and the gateway. These LPWAN communication protocols are characterised by ultra-narrowband or simple modulation/demodulation techniques, enabling low energy consumption during communication. The use of ultra-narrowband signals reduces the chance of packet collision, while wideband signals with distinctive patterns allow for easy differentiation from other signals, facilitating extended-range communication. Key players in the LPWAN domain include LoRaWAN, Sigfox, 6LoWPAN, NB-IoT and LTE-M [192]. Although NB-IoT and LTE-M operate within licenced spectrum bands, the LoRaWAN together with Sigfox and 6LoWPAN utilise ISM-shared bands. A performance analysis comparing various wireless communication technologies, as shown in Fig. 6, demonstrates that LPWAN offers the longest range and the lowest energy consumption. However, it should be noted that LPWAN technologies exhibit the lowest data throughput. As a result, IoT system designers must prioritise the significance of data and determine which data to transmit and discard. Although most LPWAN technologies support packet fragmentation, this feature can exaggerate the likelihood of packet collisions and the overall packet loss rate within the system.

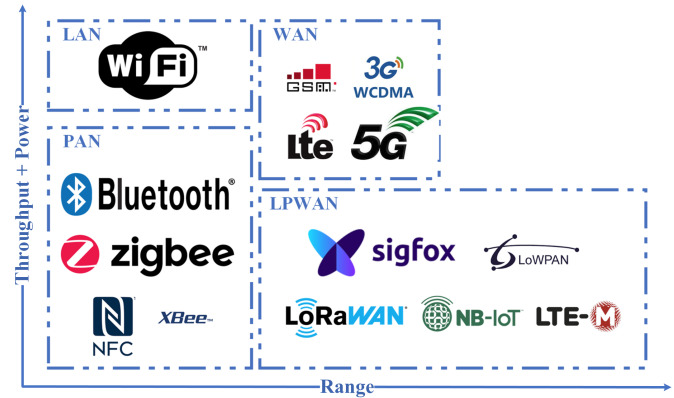


Fig. 6. Illustration of LPWAN performance compared with other wireless technologies.

In wireless communication, packet collision occurs when multiple packets are simultaneously transmitted to a receiver, making it impossible to differentiate between individual packets. To mitigate this issue, a MAC layer is responsible for regulating channel traffic, thereby ensuring successful packet reception. However, the MAC layer in most LPWAN technologies is typically pre-defined, with some employing random access or simple Listen Before Transmit techniques [193], [194]. In contrast, NB-IoT and LTE-M use the same MAC control as cellular networks due to their integration in the cellular communication system. However, optimisation of packet success rates in IoT systems often requires the implementation of a customised MAC control. In [195], a custom Carrier-sense multiple access with collision avoidance (CSMA/CA) MAC layer was implemented in the LoRa communication system to improve the packet success rate. However, the adoption of an in-house MAC layer control can lead to increased energy consumption for end devices due to requirements such as channel listening and synchronisation. An alternative approach is demonstrated in [196], where an in-house CSMA/CA MAC control for LoRa is introduced, resulting in an improvement in energy consumption. Overall, achieving a robust and energy-efficient communication link in IoT systems presents challenges that require thorough consideration of various factors, including gateway coverage influenced by channel loss and modulation schemes, channel interference resulting from traffic load, packet size and packet priorities, as well as quality of service and packet latency. In order to tackle these obstacles, the implementation of a custom MAC layer control emerges as a viable solution for IoT designers.

C. Energy Consumption

Energy consumption poses a significant challenge for IoT EDs, particularly in scenarios where power supply cannot be guaranteed for all devices, such as outdoor remote areas. This issue becomes especially critical for early fire detection systems, as their batteries are expected to last for extended periods without frequent replacement. It is essential to make sure that both the sensors and the microcontroller have low energy consumption and that the detection algorithm, whether based

on DL/ML, does not consume too much power. To mitigate energy consumption, the sampling frequency of sensors may need to be reduced, and devices may require frequent periods of sleep to conserve power. Alternatively, end devices can offload detection tasks by performing initial threshold detection and transmitting the collected data to a central server for DL or other power-intensive detection algorithms. However, this approach may result in increased energy consumption and packet loss in the communication link. Therefore, striking a balance between the packet size sent to the central node for detection and the resulting latency becomes another challenge in the development of the IoT system. A recent study by [197] investigated the energy consumption and execution time characteristics of the YOLOv3-tiny algorithm, which is a vision-based fire detection algorithm. The results of the study indicated that the algorithm itself consumes 6.5W (equivalent to 1300mA at 5V) and takes approximately 121 seconds to complete its execution. These findings imply that if an end node relies on a 3000mAh battery, it would only be able to sustain approximately three hours of continuous operation if the YOLOv3-tiny algorithm is employed throughout. Although the operating cycle of the algorithm can be adjusted, it is important to consider that DL methods such as CNNs and RNNs used in these algorithms also require high storage and computing power. Therefore, the idle energy consumption of microcontrollers should not be overlooked. Consequently, IoT systems designers are advised to carefully select sensors, taking into account the energy requirements of detection algorithms, while also ensuring that the nodes have sufficient battery capacity for transmission purposes.

D. Accuracy and Topology

As mentioned above, to minimise energy consumption in the ED, it is recommended to use energy-efficient detection algorithms. In cases where the decision-making process is based solely on the ED, simpler ML algorithms or statistical threshold detection methods can be employed. However, it is important to note that such an approach can reduce the accuracy of the system, leading to potential issues of excessive sensitivity or the generation of numerous false alarms. To enhance the precision of fire detection systems, a viable solution is to integrate multiple detection aspects, such as combining vision-based detection and detection based on environmental monitoring sensors, to establish a remote sensing system. Nonetheless, this solution may incur additional energy consumption in each individual end device. Consequently, it becomes imperative to investigate the trade-off between accuracy and energy consumption. In addition, it is essential to thoroughly analyse the topology of the sensing system, including deciding the best number of environmental monitoring sensor nodes, the correct number of vision-based detection nodes, and the most suitable spacing and angular arrangement between the sensors. To address these topological issues, extensive measurement and analysis must be performed.

The challenges involved in implementing an IoT sensor system for early wildfire detection in remote areas can be illustrated by the trade-off between energy consumption, detection accuracy and delay. One of the main challenges is

to conserve energy within the system. This can be achieved by using energy-friendly algorithms on the end devices and by sending decisions directly to the main server. However, this approach may not be able to guarantee high accuracy. Furthermore, ensuring detection accuracy requires a comprehensive sensing system that uses multiple aspects for detection and incorporates cross-validation techniques. However, this approach results in increased energy consumption and delay. Alternatively, in the pursuit of avoiding packet collision and achieving rapid response, only the detection results are transmitted to the server, which may lead to compromised accuracy. Overall, there is a complex trade-off between energy consumption, detection accuracy and delay in implementing an IoT sensor system for wildfire detection in remote areas. There is no single solution that is optimal for all situations. The best approach will depend on several factors, including the size of the area to be monitored, the availability of resources and the risk of wildfires.

V. POTENTIAL FRAMEWORK AND POSSIBLE EXTENSION

Despite the challenges encountered, the use of an IoT sensing system can be a valuable tool for early wildfire detection. By integrating detection using environmental data with other imaging detection platforms, such as satellites, UAVs, watch-towers and vision-based IoT, precise early warning systems can be established. In this section, our aim is to present a potential framework for the development of IoT sensing systems addressing issues we discussed in the previous section, with a particular emphasis on reducing energy consumption and dealing with the trade-off when selecting sensors and detection algorithms, through the use of multi-criteria decision analysis (MCDA). The potential for further development and exploration of the IoT ground sensing system for the early detection of wildfires is also discussed.

A. Potential Framework

To reserve energy in the IoT sensing system, it is suggested to use energy harvesting techniques, such as solar energy harvesting, to recharge the battery of EDs. The battery should last for up to the next recharge period. During periods characterised by clear skies, the energy harvested from the solar panel is likely to fully charge the battery. As mentioned in Section II, MoS and pellistor-type sensors require heating, which can lead to a shorter lifespan of EDs and higher maintenance costs. Therefore, alternative sensing technologies, such as NDIR and FET, which consume only a few microwatts per second, should be taken into account. To further reduce energy consumption in IoT EDs, the sensors can be set to sample at different rates according to weather conditions or the calculated moisture content of fire fuel related to the higher risk of fire on a given day. For example, during extreme heat and aridity conditions, it is advisable to increase the sampling rate to collect a larger number of readings from the devices while reducing it under opposite conditions to conserve the battery. This approach has already been implemented in various projects, including [80], [198].

In terms of the deployment height and orientation of IoT EDs, based on our experiments and insights from Dryad study [29] suggest that end devices should be mounted on trees at a height of 2-3 metres to optimise the detection of TVOC and CO₂ in the event of a wildfire. In addition, elevated placement of EDs also improves the LoS between EDs and the gateway. Our experiments have shown that MoS sensors can detect a small fire burning in a 0.7 square metre fire pit within a few minutes from a distance of 50 metres when placed downwind. This implies that the inter-node distances for a grid topology of EDs can be 70.7 metres. The unpredictability of wildfire ignition points in forested areas makes it difficult to determine the best orientation for individual sensors to maximise their detection capabilities. These sensors are similar to directional antennas, capable of sensing only in one direction. Our experiments have shown that when the sensor is not pointed towards the fire source, the detected gas concentration can be reduced to only 10% of its original value when facing the ignition point. To address this issue, [91] proposed a method that involves placing the sensors in a partially enclosed cage, with the opening facing the ground. This design effectively turns a unidirectional sensor into an omnidirectional one. Our tests confirm that this configuration enables the detection of approximately 50% of the gas concentration that would be perceived at maximum reception when the sensor is aligned with the fire source.

To address the challenge of packet collision and the energy consumption that follows from packet loss, it is recommended to reduce the packet size and transmission frequency. Instead of sending all sensor information back to the server for investigation, research has shown that statistical threshold detection and basic ML algorithms such as KNN or linear SVM can be used for preliminary filtering [89], [96], [169], [170], [181]. When EDs detect a series of alerts related to meteorological and gas parameters, they should trigger an alarm and notify fire departments. Then, EDs can send their observational data to a central server, where more advanced DL techniques, such as RNN or LSTM networks, can be used for thorough cross-verification. The central server can apply spatial correlation strategies to accurately identify the possibility of a fire hazard [186]. After confirming a fire incident, camera modules on site can be used to acquire visual evidence for further examination. In addition, direct to satellite communication is viable for remote, network-lacking areas. Although it increases gateway energy consumed, costs can be reduced compared to packet relaying. In order to enhance the dependability of the system and reduce false positives, the generated alert can also be confirmed by cross-validating with watchtowers, UAVs, or satellite entities. In conclusion, the integration and centralisation of IoT technology, UAVs, watchtowers and satellite systems should be coordinated and monitored by fire control centres.

In this section, we have mentioned a range of strategies to enhance the performance of an IoT ground sensing system, focusing on prolonging the lifespan of EDs, optimising detection capabilities and minimising transmission delays. Despite progress in the IoT sensing system, there are still fundamental restrictions due to hardware performance limitations in EDs

and energy consumption. This ongoing challenge requires balancing the trade-off between energy consumption, detection accuracy and detection latency. Therefore, the MCDA framework can be used to balance the specified requirements. In a basic MCDA model, assigning a weight to each evaluation criterion enables the calculation of the overall effectiveness, as the weighted sum of all criteria. In this case, the contribution of each criterion is directly proportional to its assigned weight. Additionally, some criteria, such as the latency in detection or the sensor's recovery time, can be given an exponential weight, thus introducing a combination of linear and exponential weights into the analysis. This modified MCDA cost C can be expressed by the following equation,

$$C = \sum_i^m W_{A_i} x_i + \sum_j^n W_{D_j} e^{y_j}, \quad (5)$$

where the values of the criteria x_i represents the criteria contributing linearly to C and y_j represents the criteria contributing exponentially to the cost. W_{A_i} and W_{D_j} are the corresponding linear weights and exponential weights, respectively. The indices i and j range from 1 to m and 1 to n respectively, with $m + n$ being the total number of evaluation criteria. This MCDA framework can be customised to assist in the selection of a suitable sensor based on factors such as cost, energy consumption, response recovery time and operational environmental ranges. Additionally, it can be used to determine the most effective anomaly detection method, whether point-wise, time-series, or ML/DL detection techniques. Furthermore, unsupervised detection algorithms cannot be evaluated using the F1 scoring system as in supervised learning, so the MCDA can also be used to effectively compare the two methods. This can be done by taking into account criteria such as the delay from the ignition point until detection and the number of false alarms. Last but not least, the framework can be used to evaluate the effectiveness of on-board processing in EDs or processing on the centralised server.

B. Possible Extensions

The effective detection of wildfires is based on the use of multiple sensors, each capable of detecting different fire indicators such as heat, TVOC and CO₂. Integration of data from various sensors allows for a more accurate assessment of the fire situation and facilitates informed decision-making on response strategies. In a study by [199], the authors summarise the correlation analysis between various types of sensor data, revealing that TVOC, CO₂, and PM exhibit limited correlation with fire alarms. Consequently, more research effort is needed to determine the optimal combination of sensor inputs that can effectively enhance the accuracy of ML/DL detection algorithms. Furthermore, a comprehensive examination of the sensor system's topological configuration is also important, particularly in the context of IoT-based wildfire detection algorithms deployed in forested areas where the fire source obstructs NLoS between most sensors. Understanding whether the behaviour of the system differs from that of open outdoor areas is crucial, including aspects such as optimal sensor height and topology. Lastly, performing an analysis of the

energy consumption of the solar battery system and exploring novel techniques to reach the maximum power point of the charging circuitry can significantly enhance the performance of energy charging. These areas of investigation are essential to improve the overall effectiveness and sustainability of the wildfire detection system.

VI. CONCLUSION

An overview of the state-of-the-art of IoT ground sensing wildfire detection systems is presented in this article. The underlying principles of various vision-based detection algorithms, as well as the working principles of multiple environmental sensing units and various detection algorithms employed in ground sensing anomaly detection, are explained. A detailed discussion of the challenges encountered during the development of an IoT ground sensing system for wildfire detection is also provided. Based on the findings of the literature review and our own experimental observations, a potential framework for the development of a robust and reliable detection system is proposed, along with suggestions for future research possibilities.

REFERENCES

- [1] CSIRO and The Bureau of Meteorology, "State of the Climate 2022," *Stat. of the Clim. Rep.*, 2022. [Online]. Available: <http://www.bom.gov.au/state-of-the-climate>
- [2] H. Clarke, R. Gibson, B. Cirulis, R. A. Bradstock, and T. D. Penman, "Developing and Testing Models of the Drivers of Anthropogenic and Lightning-Caused Wildfire Ignitions in South-Eastern Australia," *J. Environ. Manage.*, vol. 235, pp. 34–41, 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0301479719300568>
- [3] N. Wilson and M. Yebra, "The Role of Climate in Ignition Frequency," *Fire*, vol. 6, no. 5, 2023. [Online]. Available: <https://www.mdpi.com/2571-6255/6/5/195>
- [4] M. Rodrigues, F. Alcasena, and C. Vega-García, "Modeling Initial Attack Success of Wildfire Suppression in Catalonia, Spain," *Sci. Total Environ.*, vol. 666, pp. 915–927, 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0048969719308319>
- [5] M. P. Plucinski, "Factors Affecting Containment Area and Time of Australian Forest Fires Featuring Aerial Suppression," *For. Sci.*, vol. 58, no. 4, pp. 390–398, 08 2012. [Online]. Available: <https://doi.org/10.5849/forsci.10-096>
- [6] CSIRO, "Australia's Black Summer of Fire Was Not Normal – and We Can Prove It," 11 2021. [Online]. Available: <https://blog.csiro.au/bushfires-linked-climate-change/>
- [7] M. M. Boer, V. Resco de Dios, and R. A. Bradstock, "Unprecedented Burn Area of Australian Mega Forest Fires," *Nat. Clim. Chang.*, vol. 10, no. 3, pp. 171–172, 2020.
- [8] N. J. Abram, B. J. Henley, A. Sen Gupta, T. J. Lippmann, H. Clarke, A. J. Dowdy, J. J. Sharples, R. H. Nolan, T. Zhang, M. J. Wooster *et al.*, "Connections of Climate Change and Variability to Large and Extreme Forest Fires in Southeast Australia," *Commun. Earth Environ.*, vol. 2, no. 1, p. 8, 2021.
- [9] D. Vernick, "3 Billion Animals Harmed by Australia's Fires," World Wildlife Fund, 07 2020. [Online]. Available: <https://www.worldwildlife.org/stories/3-billion-animals-harmed-by-australia-s-fires>
- [10] Australian Government, "Threatened Species List," environment.gov.au, 2019. [Online]. Available: <https://www.environment.gov.au/cgi-bin/sprat/public/publicthreatenedlist.pl>
- [11] Joint Research Centre (European Commission), "Forest fires in Europe, Middle East and North Africa in 2022," 11 2023. [Online]. Available: <https://op.europa.eu/en/publication-detail/-/publication/c73f55b7-88ec-11ee-99ba-01aa75ed71a1/language-en>
- [12] Center for Disaster Philanthropy, "2020 North American Wildfire Season," 12 2020. [Online]. Available: <https://disasterphilanthropy.org/disasters/2020-california-wildfires/>
- [13] K. Hoover and L. A. Hanson, "Wildfire Statistics - FAS Project on Government Secrecy," *Cong. Res. Serv. Rep.*, 2022. [Online]. Available: <https://sgp.fas.org/crs/misc/IF10244.pdf>
- [14] T. Ye, Y. Guo, G. Chen, X. Yue, R. Xu, M. d. S. Z. S. Coêlho, P. H. N. Saldiva, Q. Zhao, and S. Li, "Risk and Burden of Hospital Admissions Associated with Wildfire-Related PM2.5 in Brazil, 2000–15: a Nationwide Time-Series Study," *Lancet Planet. Health*, vol. 5, no. 9, pp. e599–e607, 2021.
- [15] D. M. Bowman, A. Moreira-Muñoz, C. A. Kolden, R. O. Chávez, A. A. Muñoz, F. Salinas, Á. González-Reyes, R. Rocco, F. De la Barrera, G. J. Williamson *et al.*, "Human–environment drivers and impacts of the globally extreme 2017 Chilean fires," *Ambio*, vol. 48, pp. 350–362, 2019.
- [16] H. Clarke, R. H. Nolan, V. R. De Dios, R. Bradstock, A. Griebel, S. Khanal, and M. M. Boer, "Forest Fire Threatens Global Carbon Sinks and Population Centres under Rising Atmospheric Water Demand," *Nat. Commun.*, vol. 13, no. 1, p. 7161, 2022.
- [17] M. Yebra, N. Barnes, C. Bryant, G. J. Cary, S. Durrani, J.-U. Lee, D. Lindenmayer, R. Mahony, R. Prinsley, P. Ryan, R. Sharp, M. Stocks, A. Tridgell, and X. Zhou, "An Integrated System to Protect Australia from Catastrophic Bushfires," *Aust. J. Emerg. Manag.*, vol. 36, no. 4, p. 20–22, 2021. [Online]. Available: <https://search.informit.org/doi/10.3316/informit.193907664320405>
- [18] S. Yan, J. Zhang, and N. Barnes, "Transmission-Guided Bayesian Generative Model for Smoke Segmentation," in *Proc. of the AAAI Conf. Artif. Intell.*, vol. 36, no. 3, 2022, pp. 3009–3017.
- [19] S. Ma, T. Wu, X. Chen, Y. Wang, J. Ma, H. Chen, A. Riaud, J. Wan, Z. Xu, L. Chen, J. Ren, D. W. Zhang, P. Zhou, Y. Chai, and W. Bao, "A 619-Pixel Machine Vision Enhancement Chip Based on Two-Dimensional Semiconductors," *Sci. Adv.*, vol. 8, no. 31, p. eabn9328, 2022. [Online]. Available: <https://www.science.org/doi/abs/10.1126/sciadv.abn9328>
- [20] P. Dudek, T. Richardson, L. Bose, S. Carey, J. Chen, C. Greatwood, Y. Liu, and W. Mayol-Cuevas, "Sensor-Level Computer Vision with Pixel Processor Arrays for Agile Robots," *Sci. Robot.*, vol. 7, no. 67, p. eabl7755, 2022. [Online]. Available: <https://www.science.org/doi/abs/10.1126/scirobotics.abl7755>
- [21] R. H. Nolan, M. M. Boer, V. Resco de Dios, G. Caccamo, and R. A. Bradstock, "Large-Scale, Dynamic Transformations in Fuel Moisture Drive Wildfire Activity Across South-Eastern Australia," *Geophys. Res. Lett.*, vol. 43, no. 9, pp. 4229–4238, 2016.
- [22] O. M. Bushnaq, A. Chaaban, and T. Y. Al-Naffouri, "The Role of UAV-IoT Networks in Future Wildfire Detection," *IEEE Internet Things J.*, vol. 8, no. 23, pp. 16 984–16 999, 2021.
- [23] F. A. Hossain, Y. M. Zhang, and M. A. Tonima, "Forest Fire Flame and Smoke Detection from UAV-Captured Images Using Fire-Specific Color Features and Multi-Color Space Local Binary Pattern," *J. Unmanned Veh. Syst.*, vol. 8, no. 4, pp. 285–309, 2020. [Online]. Available: <https://doi.org/10.1139/juvs-2020-0009>
- [24] E. Palethorpe, S. Alvi, G. J. Cary, R. Mahony, A. Tridgell, M. Yebra, M. Stocks, R. Stocks, C. Bryant, S. Durrani, N. Barnes, X. Zhou, and N. Wilson, "AFAC Conference: Report: Towards an integrated hi-tech solution to detect small fires," *Aust. J. Emerg. Manag.*, vol. 37, no. 4, p. 44–47, 2022. [Online]. Available: <https://search.informit.org/doi/10.3316/agispt.20221129078811>
- [25] E. Chuvieco, I. Aguado, J. Salas, M. García, M. Yebra, and P. Oliva, "Satellite Remote Sensing Contributions to Wildland Fire Science and Management," *Curr. For. Rep.*, vol. 6, pp. 81–96, 2020.
- [26] F. Schroeder, P. Oliva, L. Giglio, B. Quayle, E. Lorenz, and F. Morelli, "Active Fire Detection Using Landsat-8/OLI Data," *Remote Sens. Environ.*, vol. 185, pp. 210–220, 2016, landsat 8 Science Results. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0034425715301206>
- [27] R. Smith, M. Adams, S. Maier, R. Craig, A. Kristina, and I. Maling, "Estimating the Area of Stubble Burning from the Number of Active Fires Detected by Satellite," *Remote Sens. Environ.*, vol. 109, no. 1, pp. 95–106, 2007. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0034425706005153>
- [28] J. I. Yoojin Kang, Eunna Jang and C. Kwon, "A Deep Learning Model Using Geostationary Satellite Data for Forest Fire Detection with Reduced Detection Latency," *Glsci. Remote Sens.*, vol. 59, no. 1, pp. 2019–2035, 2022. [Online]. Available: <https://doi.org/10.1080/15481603.2022.2143872>
- [29] Dryad, "Dryad Networks: Ultra Early Wildfire Detection," 2020. [Online]. Available: <https://www.dryad.net/>
- [30] Manx Technology Group, "Forest Fire Detection Using IoT (and CO2 Sensors)," 2021. [Online]. Available: <https://www.manxtechgroup.com/forest-fire-detection-using-iot-and-co2-sensors/>
- [31] Attentis, "Attentis: Intelligent Sensors," 2021. [Online]. Available: <https://attentistechnology.com/intelligent-sensors>

- [32] A. Mohapatra and T. Trinh, "Early Wildfire Detection Technologies in Practice and A Review," *Sustainability*, vol. 14, no. 19, 2022. [Online]. Available: <https://www.mdpi.com/2071-1050/14/19/12270>
- [33] A. A. Alkhatib, "A Review on Forest Fire Detection Techniques," *Int. J. Distrib. Sens. Netw.*, vol. 10, no. 3, p. 597368, 2014. [Online]. Available: <https://doi.org/10.1155/2014/597368>
- [34] M. Grari, M. Yandouzi, I. Idrissi, M. Boukabous, O. Moussaoui, M. AZIZI, and M. MOUSSAOUI, "Using IoT and ML for Forest Fire Detection, Monitoring, and Prediction: a Literature Review," *J. Theor. Appl. Inf. Technol.*, vol. 100, no. 19, 2022.
- [35] F. Carta, C. Zidda, M. Putzu, D. Loru, M. Anedda, and D. Giusto, "Advancements in Forest Fire Prevention: A Comprehensive Survey," *Sensors*, vol. 23, no. 14, 2023. [Online]. Available: <https://www.mdpi.com/1424-8220/23/14/6635>
- [36] F. Abid, "A Survey of Machine Learning Algorithms Based Forest Fires Prediction and Detection Systems," *Fire Technol.*, vol. 57, no. 2, pp. 559–590, 2021.
- [37] D. Hanes, G. Salgueiro, P. Grossetete, R. Barton, and J. Henry, *IoT Fundamentals: Networking Technologies, Protocols, and Use Cases for the Internet of Things*. Cisco Press, 2017.
- [38] P. Kanakaraja, P. Syam Sundar, N. Vaishnavi, S. Gopal Krishna Reddy, and G. Sai Manikanta, "IoT Enabled Advanced Forest Fire Detecting and Monitoring on Ubidots Platform," *Materials Today: Proceedings*, vol. 46, pp. 3907–3914, 2021, int. Conf. Mater. Manuf. Mech. Eng. Sustain. Dev. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2214785321014449>
- [39] N. Kalatzis, M. Avgeris, D. Detchouniotis, K. Papadakis-Vlachopapadopoulos, I. Roussaki, and S. Papavassiliou, "Edge Computing in IoT Ecosystems for UAV-Enabled Early Fire Detection," in *IEEE Int. Conf. Smart Comput.*, 2018, pp. 106–114.
- [40] H. Kaur, S. K. Sood, and M. Bhatia, "Cloud-Assisted Green IoT-Enabled Comprehensive Framework for Wildfire Monitoring," *Cluster Comput.*, vol. 23, no. 2, p. 1149–1162, jun 2020. [Online]. Available: <https://doi.org/10.1007/s10586-019-02981-7>
- [41] A. H. Altowaijri, M. S. Alfaifi, T. A. Alshawi, A. B. Ibrahim, and S. A. Alshebeili, "A Privacy-Preserving IoT-Based Fire Detector," *IEEE Access*, vol. 9, pp. 51 393–51 402, 2021.
- [42] S. Surit and W. Chatwiriyaya, "Forest Fire Smoke Detection in Video Based on Digital Image Processing Approach with Static and Dynamic Characteristic Analysis," in *Int. Conf. Comput. Netw. Syst. Ind. Eng.*, 2011, pp. 35–39.
- [43] P. V. A. de Venâncio, A. C. Lisboa, and A. V. Barbosa, "An automatic fire detection system based on deep convolutional neural networks for low-power, resource-constrained devices," *Neural. Comput. Appl.*, vol. 34, no. 18, pp. 15 349–15 368, 2022.
- [44] M. N. A. Khan, T. Tanveer, K. Khurshid, H. Zaki, and S. S. I. Zaidi, "Fire detection system using raspberry pi," in *Int. Conf. Inf. Sci. Commun. Technol.*, 2019, pp. 1–6.
- [45] Sony, "Diagonal 4.60mm (Type 1/4.0) 8M Pixel CMOS Image Sensor with Square Pixel for Color Cameras," 2014. [Online]. Available: <https://www.electronicdatasheets.com/download/5721ed8ce34e24fd697a913a.pdf>
- [46] OmniVision, "OV7670/OV7171 CMOS VGA (640x480) CameraChip with OmniPixel Technology," 2005. [Online]. Available: <https://www.votii.nl/docs/OV7670.pdf>
- [47] Exci, "Smoke Alarm for the Bush," 2023. [Online]. Available: <https://www.exci.ai/>
- [48] S. Goyal, M. Shagill, A. Kaur, H. Vohra, and A. Singh, "A YOLO Based Technique for Early Forest Fire Detection," *Int. J. Innov. Technol. Explor. Eng.*, vol. 9, pp. 1357–1362, 2020.
- [49] M. K. Rangan, S. M. Rakesh, G. S. P. Sandeep, and C. S. Suttur, "A Computer Vision Based Approach for Detection of Fire and Direction Control for Enhanced Operation of Fire Fighting Robot," in *Int. Conf. on Control Autom. Robot. Embed. Syst.*, 2013, pp. 1–6.
- [50] T. AlHaza, A. Alsadoon, Z. Alhusinan, M. Jarwali, and K. Alsaif, "New Concept for Indoor Fire Fighting Robot," *Procedia Soc. Behav. Sci.*, vol. 195, pp. 2343–2352, 2015, world Conf. Technol. Innov. Entrepreneurship. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1877042815036708>
- [51] T. C. Wilkes, A. J. S. McGonigle, T. D. Pering, A. J. Taggart, B. S. White, R. G. Bryant, and J. R. Willmott, "Ultraviolet Imaging with Low Cost Smartphone Sensors: Development and Application of a Raspberry Pi-Based UV Camera," *Sensors*, vol. 16, no. 10, 2016. [Online]. Available: <https://www.mdpi.com/1424-8220/16/10/1649>
- [52] C. Labrado, H. Thapliyal, S. Prowell, and T. Kuruganti, "Use of Thermistor Temperature Sensors for Cyber-Physical System Security," *Sensors*, vol. 19, no. 18, 2019. [Online]. Available: <https://www.mdpi.com/1424-8220/19/18/3905>
- [53] M. S. Mekala and P. Viswanathan, "A Novel Technology for Smart Agriculture Based on IoT with Cloud Computing," in *Int. Conf. IoT Soci. Mobile Anal. Cloud*, 2017, pp. 75–82.
- [54] V. Resco de Dios, A. W. Fellows, R. H. Nolan, M. M. Boer, R. A. Bradstock, F. Domingo, and M. L. Goulden, "A Semi-Mechanistic Model for Predicting the Moisture Content of Fine Litter," *Agric. For. Meteorol.*, vol. 203, pp. 64–73, 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0168192315000039>
- [55] J. Cawson, B. Pickering, A. Filkov, J. Burton, M. Kilinc, and T. Penman, "Predicting Ignitability from Firebrands in Mature Wet Eucalypt Forests," *For. Ecol. Manag.*, vol. 519, p. 120315, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0378112722003097>
- [56] S. Arslan, M. Challenger, and O. Dagdeviren, "Wireless Sensor Network Based Fire Detection System for Libraries," in *Int. Conf. Comput. Sci. Eng.*, 2017, pp. 271–276.
- [57] F. Khan, Z. Xu, J. Sun, F. M. Khan, A. Ahmed, and Y. Zhao, "Recent Advances in Sensors for Fire Detection," *Sensors*, vol. 22, no. 9, 2022. [Online]. Available: <https://www.mdpi.com/1424-8220/22/9/3310>
- [58] T. Islam, H. A. Rahman, and M. A. Syrus, "Fire Detection System with Indoor Localization Using ZigBee Based Wireless Sensor Network," in *IEEE Int. Conf. Inf. Elec. Vis.*, 2015, pp. 1–6.
- [59] S. Abdullah, S. Bertalan, S. Masar, A. Coskun, and I. Kale, "A Wireless Sensor Network or Early Forest Fire Detection and Monitoring as a Decision Factor in the Context of a Complex Integrated Emergency Response System," in *IEEE Workshop on Environ. Energy Struct. Monit. Syst.*, 2017, pp. 1–5.
- [60] T. P. D. Pieris, A. L. Kulasekera, and K. V. D. S. Chathuranga, "Multi-AI Based Wireless Sensor Node for Forest Fire Detection," in *Int. Conf. Inf. Technol. Res.*, 2022, pp. 1–6.
- [61] "Compare DHT22, AM2302, AM2320, AM2321, SHT71, HTU21D, Si7021, BME280," www.kandrsmith.org. [Online]. Available: https://www.kandrsmith.org/RJS/Misc/Hygrometers/calib_many.html
- [62] V. Fateev, M. Agafontsev, S. Volkov, and A. Filkov, "Determination of Smoldering Time and Thermal Characteristics of Firebrands Under Laboratory Conditions," *Fire Saf. J.*, vol. 91, pp. 791–799, 2017, fire Safety Science: Proceedings of the 12th International Symposium. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S037971121730125X>
- [63] California Air Resources Board, "Wildfire Emission Estimates for 2021," *CARB*, 2022. [Online]. Available: <https://ww2.arb.ca.gov/wildfire-emissions>
- [64] S. Urbanski, "Wildland fire emissions, carbon, and climate: Emission factors," *For. Ecol. Manag.*, vol. 317, pp. 51–60, apr 2014. [Online]. Available: <https://doi.org/10.1016/j.foreco.2013.05.045>
- [65] S. Kelleher, C. Quinn, D. Miller-Lionberg, and J. Volckens, "A Low-Cost Particulate Matter (PM_{2.5}) Monitor for Wildland Fire Smoke," *Atmos. Meas. Tech.*, vol. 11, no. 2, pp. 1087–1097, 2018. [Online]. Available: <https://amt.copernicus.org/articles/11/1087/2018/>
- [66] H. Yu, C. Guo, X. Zhang, Y. Xu, X. Cheng, S. Gao, and L. Huo, "Recent Development of Hierarchical Metal Oxides Based Gas Sensors: From Gas Sensing Performance to Applications," *Adv. Sustain. Syst.*, vol. 6, no. 4, p. 2100370, 2022.
- [67] B. Global, "BME688 Digital Low Power Gas, Pressure, Temperature & Humidity Sensor with AI," 2022. [Online]. Available: <https://www.bosch-sensortec.com/products/environmental-sensors/gas-sensors/bme688/>
- [68] AMS AG, "CCS811 Ultra-Low Power Digital Gas Sensor for Monitoring Indoor Air Quality," 2016. [Online]. Available: https://cdn.sparkfun.com/assets/learn_tutorials/1/4/3/CCS811_Datashet-DS000459.pdf
- [69] Sensirion, "SGP30 Multi-gas(VOC and CO₂eq) sensor," 2020. [Online]. Available: <https://sensirion.com/products/catalog/SGP30/>
- [70] G. Roque and V. S. Padilla, "LPWAN Based IoT Surveillance System for Outdoor Fire Detection," *IEEE Access*, vol. 8, pp. 114 900–114 909, 2020.
- [71] K. Nörthemann, J.-E. Biengen, J. Müller, and W. Moritz, "Early Forest Fire Detection Using Low-Energy Hydrogen Sensors," *J. Sens. Sens. Syst.*, vol. 2, no. 2, pp. 171–177, 2013. [Online]. Available: <https://jsss.copernicus.org/articles/2/171/2013/>
- [72] P. Tyagi, A. Sharma, M. Tomar, and V. Gupta, "Efficient Detection of SO₂ Gas Using SnO₂ Based Sensor Loaded with Metal Oxide Catalysts," *Procedia Eng.*, vol. 87, pp. 1075–1078, 2014, euro. Conf. on Solid-State Transducers. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S187705814024643>

- [73] A. Prashanth Kumar Reddy, E. Sathwik Reddy, T. Bhaskar, B. P. Yadav, and A. K. Singh, "Design of Fire and Gas Detection System for a Process Plant: A Review," *Adv. Ind. Saf.*, pp. 271–280, 2020.
- [74] T. Cleary and W. Grosshandler, "Evaluation Of Fire Detection Technology For Suitability In Aircraft Cargo Compartments," in *Int. Aircraft Fire Cabin Saf. Res. Conf.*, 1998, pp. 16–20.
- [75] N. Afshar-Mohajer, C. Zuidema, S. Sousan, L. Hallett, M. Tatum, A. M. Rule, G. Thomas, T. M. Peters, and K. Koehler, "Evaluation of Low-Cost Electro-Chemical Sensors for Environmental Monitoring of Ozone, Nitrogen Dioxide, and Carbon Monoxide," *J. Occup. Environ. Hyg.*, vol. 15, no. 2, pp. 87–98, 2018, pMID: 29083958. [Online]. Available: <https://doi.org/10.1080/15459624.2017.1388918>
- [76] Alphasense, "OX-B431 Oxidising Gas Sensor-Ozone + Nitrogen Dioxide-4-Electrode," 2022. [Online]. Available: https://www.alphasense.com/wp-content/uploads/2022/09/Alphasense_OX-B431_datasheet.pdf
- [77] Honeywell, "Carbon Monoxide Sensor 0-2000 ppm," 2022. [Online]. Available: <https://prod-edam.honeywell.com/content/dam/honeywell-edam/sps/siot/en-us/products/sensors/gas-sensors/s-series/documents/sps-ast-citytech-cle-0023-400-cle-4-co-2000-en.pdf>
- [78] S. Yin, "Effect of Biomass Burning on Premature Mortality Associated with Long-Term Exposure to PM_{2.5} in Equatorial Asia," *J. Environ. Manag.*, vol. 330, p. 117154, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S030147972202727X>
- [79] H. K. Preisler, D. Schweizer, R. Cisneros, T. Procter, M. Ruminski, and L. Tarnay, "A Statistical Model for Determining Impact of Wildland Fires on Particulate Matter (PM_{2.5}) in Central California Aided by Satellite Imagery of Smoke," *Environ. Pollut.*, vol. 205, pp. 340–349, 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0269749115003115>
- [80] W. Benzekri, A. El Moussati, O. Moussaoui, and M. Berrajaa, "Early Forest Fire Detection System Using Wireless Sensor Network and Deep Learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 5, 2020.
- [81] S. Hong, M. Wu, Y. Hong, Y. Jeong, G. Jung, M. Shin, J. Park, D. Kim, D. Jang, and J.-H. Lee, "FET-Type Gas Sensors: A Review," *Sens. Actuators B Chem.*, vol. 330, p. 129240, 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/abs/pii/S092540052031580X>
- [82] S. Dhall, B. Mehta, A. Tyagi, and K. Sood, "A Review on Environmental Gas Sensors: Materials and Technologies," *Sensors Int.*, vol. 2, p. 100116, 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2666351121000371>
- [83] Y. Hong, S. Hong, D. Jang, Y. Jeong, M. Wu, G. Jung, J.-H. Bae, J. S. Kim, K. S. Chang, C. B. Jeong, C. S. Hwang, B.-G. Park, and J.-H. Lee, "A Si FET-type Gas Sensor with Pulse-driven Localized Micro-heater for Low Power Consumption," in *IEEE Int. Electron Devices Meeting*, 2018, pp. 12.6.1–12.6.4.
- [84] G. Jung, Y. Hong, S. Hong, Y. Jeong, W. Shin, J. Park, J. Lee, D. Jang, and J.-H. Lee, "Detection of Low Concentration NO₂ gas Using Si FET-type Gas Sensor with Localized Micro-heater for Low Power Consumption," in *IEEE Sens. J.*, 2019, pp. 1–4.
- [85] A. Zribi, A. Knobloch, W.-C. Tian, and S. Goodwin, "Micro-Machined Resonant Multiple Gas Sensor," *Sens. Actuator A Phys.*, vol. 122, no. 1, pp. 31–38, 2005, sSSAMW 04. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0924424705000701>
- [86] S. Park, I. Yoon, S. Lee, H. Kim, J.-W. Seo, Y. Chung, A. Unger, M. Kupnik, and H. J. Lee, "CMUT-based Resonant Gas Sensor Array for VOC Detection with Low Operating Voltage," *Sens. Actuators B Chem.*, vol. 273, pp. 1556–1563, 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925400518312814>
- [87] D. Gutmacher, C. Foelml, W. Vollenweider, U. Hoefler, and J. Wöllenstein, "Comparison of Gas Sensor Technologies for Fire Gas Detection," *Procedia Eng.*, vol. 25, pp. 1121–1124, 2011, eurosensorsXXV. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S187705811059455>
- [88] V. Dubey, P. Kumar, and N. Chauhan, "Forest Fire Detection System Using IoT and Artificial Neural Network," in *Int. Conf. Innov. Comput. Commun.*, S. Bhattacharyya, A. E. Hassanien, D. Gupta, A. Khanna, and I. Pan, Eds. Springer, 2019, pp. 323–337.
- [89] U. Dampage, L. Bandaranayake, R. Wanasinghe, K. Kottahachchi, and B. Jayasanka, "Forest Fire Detection System Using Wireless Sensor Networks and Machine Learning," *Sci. Rep.*, vol. 12, no. 1, p. 46, 2022.
- [90] E. Abdul Kadir, S. Listia Rosa, A. Syukur, M. Othman, and H. Daud, "Forest fire spreading and carbon concentration identification in tropical region indonesia," *Alex. Eng. J.*, vol. 61, no. 2, pp. 1551–1561, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1110016821004191>
- [91] C. Hartung, R. Han, C. Seielstad, and S. Holbrook, "FireWxNet: A Multi-Tiered Portable Wireless System for Monitoring Weather Conditions in Wildland Fire Environments," in *Int. Conf. Mobile Syst. Appl. Serv.*, ser. MobiSys '06. New York, NY, USA: Association for Computing Machinery, 2006, p. 28–41. [Online]. Available: <https://doi.org/10.1145/1134680.1134685>
- [92] K. Mehta, S. Sharma, and D. Mishra, "Internet-of-Things Enabled Forest Fire Detection System," in *Int. Conf. IoT Soci. Mobile Anal. Cloud*, 2021, pp. 20–23.
- [93] S. Fathima, B. Velammal, K. Shanmugam, and K. Jayareka, "An Integrated IoT Based Approach Enabled in UAV for the Early Prediction of Forest Fires," *Ann. Romanian Soc. Cell Biol.*, vol. 25, no. 6, pp. 11 042–11 054, 2021.
- [94] N. Choudhary, "Design and Implementation of Wildfire Monitoring System," *Int. J. Mod. Trends Sci. Technol.*, vol. 7, no. 5, pp. 139–143, 2021.
- [95] P. Sahatiya, A. Kadu, H. Gupta, P. Thanga Gomathi, and S. Badhulika, "Flexible, Disposable Cellulose-Paper-Based MoS₂/Cu₂S Hybrid for Wireless Environmental Monitoring and Multifunctional Sensing of Chemical Stimuli," *ACS Appl. Mater. Interfaces*, vol. 10, no. 10, pp. 9048–9059, 2018, pMID: 29442495. [Online]. Available: <https://doi.org/10.1021/acsami.8b00245>
- [96] H. Forehead, J. Barthelemy, B. Arshad, N. Verstaevl, O. Price, and P. Perez, "Traffic Exhaust to Wildfires: PM_{2.5} Measurements with Fixed and Portable, Low-Vost LoRaWAN-Connected Sensors," *PLoS One*, vol. 15, no. 4, p. e0231778, 2020.
- [97] Libelium, "Detecting Forest Fires using Wireless Sensor Networks," 2021. [Online]. Available: <https://www.libelium.com/iot-products/waspmote/>
- [98] U. Hoefler and D. Gutmachera, "Fire Gas Detection," *Procedia Eng.*, vol. 47, pp. 1446–1459, 2012. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S187705812044931>
- [99] Dräger, "Dräger Catalytic Ex-Sensors," 2022. [Online]. Available: https://www.draeger.com/en_aunz/Products/Catalytic-Ex-Sensors/
- [100] Alphasense, "CH-D3 Combustible Gas Pellistor," 2013. [Online]. Available: <https://www.alphasense.com/wp-content/uploads/2013/07/CHD3.pdf>
- [101] S. SensorTech, "VQ548MP Datasheet," 2014. [Online]. Available: <https://www.sgxsensortech.com/content/uploads/2014/07/DS-0140-VQ548MP-Datasheet-V6.pdf>
- [102] H. Z. Yong Zhou, "PMS5003 Series Manual Datasheet by Adafruit Industries LLC," 2016. [Online]. Available: <https://www.digkey.jp/htmldatasheets/production/2903006/0/0/1/pms5003-series-manual.html>
- [103] Sensirion, "Datasheet SPS30 - Particulate Matter Sensor for Air Quality Monitoring and Control," 2018. [Online]. Available: https://cdn.sparkfun.com/assets/2/d/2/a/6/Sensirion_SPS30_Part particulate_Matter_Sensor_v0.9_D1_1_1.pdf
- [104] —, "SCD4x: Breaking the Size Barrier in CO₂ Sensing," 2021. [Online]. Available: https://au.mouser.com/datasheet/2/682/Sensirion_CO2_Sensors_SCD4x_Datasheet-2321195.pdf
- [105] L. Zhengzhou Winsen Electronics Technology CO., "Intelligent Infrared Carbon Dioxide Module (Model: MH-Z14A)," 2019. [Online]. Available: <https://www.winsen-sensor.com/d/files/MH-Z14A.pdf>
- [106] Alphasense, "IRC-AT Carbon Dioxide Infrared Sensor – Thermopile Detector," 2022. [Online]. Available: https://www.alphasense.com/wp-content/uploads/2022/09/Alphasense_IRC-AT_datasheet.pdf
- [107] D. M. Doolin and N. Sitar, "Wireless Sensors for Wildfire Monitoring," in *Sensors and Smart Struct. Technol. Civ. Mech. Aerosp. Syst.*, M. Tomizuka, Ed., vol. 5765, International Society for Optics and Photonics. SPIE, 2005, pp. 477 – 484. [Online]. Available: <https://doi.org/10.1117/12.605655>
- [108] S. Geetha, C. Abhishek, and C. Akshayanat, "Machine Vision Based Fire Detection Techniques: A Survey," *Fire Technol.*, vol. 57, pp. 591–623, 2021.
- [109] P. Barmpoutis, P. Papaioannou, K. Dimitropoulos, and N. Grammalidis, "A Review on Early Forest Fire Detection Systems Using Optical Remote Sensing," *Sensors*, vol. 20, no. 22, p. 6442, 2020.
- [110] V. Cappellini, L. Mattii, and A. Mecocci, "An Intelligent System for Automatic Fire Detection in Forests," *IEEE Int. Conf. Image Processing and its Applications*, pp. 351–364, 2005.
- [111] T.-H. Chen, P.-H. Wu, and Y.-C. Chiou, "An Early Fire-Detection Method Based on Image Processing," in *IEEE Int. Conf. Image Processing*, vol. 3. IEEE, 2004, pp. 1707–1710.
- [112] K. Dimitropoulos, O. Gunay, K. Kose, F. Erden, F. Chaabene, F. Tsalakanidou, N. Grammalidis, and E. Çetin, "Flame Detection for Video-Based Early Fire Warning for the Protection of Cultural

- Heritage," in *Progress Cult. Herit. Preserv.* Springer, 2012, pp. 378–387.
- [113] T. Celik and H. Demirel, "Fire Detection in Video Sequences Using a Generic Color Model," *Fire Saf. J.*, vol. 44, no. 2, pp. 147–158, 2009.
- [114] T. Celik, "Fast and Efficient Method for Fire Detection Using Image Processing," *ETRI J.*, vol. 32, no. 6, pp. 881–890, 2010.
- [115] G. Marbach, M. Loepfe, and T. Brupbacher, "An Image Processing Technique for Fire Detection in Video Images," *Fire Saf. J.*, vol. 41, no. 4, pp. 285–289, 2006.
- [116] H. Yamagishi and J. Yamaguchi, "Fire Flame Detection Algorithm Using a Color Camera," in *IEEE Int. Symp. Micro mech. Hum. Sci.* IEEE, 1999, pp. 255–260.
- [117] H. Gati'Dway and A. F. Mutar, "Study Fire Detection Based on Color Spaces," *Al-Mustansiriyah J. Sci.*, vol. 29, no. 4, pp. 93–99, 2018.
- [118] M. S. Vadivu and M. Vijayalakshmi, "Implications of color models in image processing for fire detection," *Int. J. Comput. Appl.*, vol. 975, p. 8887, 4 2018.
- [119] A. E. Çetin, K. Dimitropoulos, B. Gouverneur, N. Grammalidis, O. Günay, Y. H. Habiboğlu, B. U. Töreyn, and S. Verstockt, "Video Fire Detection–Review," *Digit. Signal Process.*, vol. 23, no. 6, pp. 1827–1843, 2013.
- [120] A. Sharma, P. K. Singh, and Y. Kumar, "An Integrated Fire Detection System Using IoT and Image Processing Technique for Smart Cities," *Sustain. Cities Soc.*, vol. 61, p. 102332, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2210670720305539>
- [121] R. T. Collins, A. J. Lipton, T. Kanade, H. Fujiyoshi, D. Duggins, Y. Tsui, D. Tolliver, N. Enomoto, O. Hasegawa, P. Burt *et al.*, "A System for Video Surveillance and Monitoring," *VSAM*, vol. 2000, no. 1-68, p. 1, 2000.
- [122] T. Celik, H. Demirel, H. Ozkaramanli, and M. Uyguuroglu, "Fire Detection Using Statistical Color Model in Video Sequences," *J. Vis. Commun.*, vol. 18, no. 2, pp. 176–185, 2007.
- [123] Z. Xiong, R. Caballero, H. Wang, A. M. Finn, M. A. Lelic, and P.-Y. Peng, "Video-Based Smoke Detection: Possibilities, Techniques, and Challenges," in *Fire Suppression & Detection Res. Appl.*, 2007.
- [124] B. Lee and D. Han, "Real-time Fire Detection Using Camera Sequence Image in Tunnel Environment," in *Adv. Intel. Comput. Theories Appl.* Springer, 2007, pp. 1209–1220.
- [125] S. Calderara, P. Piccinini, and R. Cucchiara, "Smoke Detection in Video Surveillance: a MoG Model in the Wavelet Domain," in *Comput. Vis. Syst.* Springer, 2008, pp. 119–128.
- [126] Y.-m. Song, S. Noh, J. Yu, C.-w. Park, and B.-g. Lee, "Background Subtraction Based on Gaussian Mixture Models Using Color and Depth Information," in *IEEE Int. Conf. on Control Autom. Inf. Sci.* IEEE, 2014, pp. 132–135.
- [127] M. K. Hossen, M. H. Chowdhury, and I. A. Chowdhury, "Fire Detection from Video Based on Temporal Variation, Temporal Periodicity and Spatial Variance Analysis," *Int. J. Eng. Math.*, vol. 7, no. 2, pp. 359–368, 2018.
- [128] B. U. Töreyn, Y. Dedeoğlu, U. Güdükbay, and A. E. Cetin, "Computer Vision Based Method for Real-time Fire and Flame Detection," *Pattern Recognit. Lett.*, vol. 27, no. 1, pp. 49–58, 2006.
- [129] J. Chen, Y. He, and J. Wang, "Multi-feature Fusion Based Fast Video Flame Detection," *Build. Environ.*, vol. 45, no. 5, pp. 1113–1122, 2010.
- [130] O. Günay, K. Taşdemir, B. Uğur Töreyn, and A. E. Çetin, "Fire Detection in Video Using LMS Based Active Learning," *Fire Technol.*, vol. 46, pp. 551–577, 2010.
- [131] B. W. Albers and A. K. Agrawal, "Schlieren Analysis of an Oscillating Gas-jet Diffusion Flame," *Combust.*, vol. 119, no. 1-2, pp. 84–94, 1999.
- [132] W. Straumann, D. Rizzotti, and N. Schibli, "Method and Device for Detecting Fires Based on Image Analysis," *E.U. Patent*, vol. 1, p. 26, 2002.
- [133] B. U. Töreyn, Y. Dedeoğlu, and A. E. Cetin, "Contour Based Smoke Detection in Video Using Wavelets," in *Euro. Signal Processing Conf.*, 2006, pp. 1–5.
- [134] A. E. Cetin and R. Ansari, "Signal Recovery from Wavelet Transform Maxima," *IEEE Trans. Signal Process.*, vol. 42, no. 1, pp. 194–196, 1994.
- [135] B. U. Töreyn, Y. Dedeoğlu, and A. E. Çetin, "Wavelet Based Real-Time Smoke Detection in Video," in *Eur. Signal Process. Conf.*, 2005, pp. 1–4.
- [136] S. Ye, Z. Bai, H. Chen, R. Bohush, and S. Ablameyko, "An Effective Algorithm to Detect Both Smoke and Flame Using Color and Wavelet Analysis," *Pattern Recognit. Image Anal.*, vol. 27, pp. 131–138, 2017.
- [137] D. K. Appana, R. Islam, S. A. Khan, and J.-M. Kim, "A Video-Based Smoke Detection Using Smoke Flow Pattern and Spatial-Temporal Energy Analyses for Alarm Systems," *Inf. Sci.*, vol. 418-419, pp. 91–101, 2017. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0020025516317121>
- [138] J. R. R. Uijlings, I. C. Duta, N. Rostamzadeh, and N. Sebe, "Realtime Video Classification Using Dense HOF/HOG," in *Proc. Int. Conf. on Multimedia Retr.*, ser. ICMR '14. New York, NY, USA: Association for Computing Machinery, 2014, p. 145–152. [Online]. Available: <https://doi.org/10.1145/2578726.2578744>
- [139] P. Barmoutis, K. Dimitropoulos, and N. Grammalidis, "Smoke Detection Using Spatio-Temporal Analysis, Motion Modeling and Dynamic Texture Recognition," in *Euro. Signal Process. Conf.*, 2014, pp. 1078–1082.
- [140] K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, "Smoke Detection Using Temporal HOGHOF Descriptors and Energy Colour Statistics from Video," in *Int. workshop Multi-Sensor Syst. Netw. Fire Detection Manag.*, 2012.
- [141] L. Huang, G. Liu, Y. Wang, H. Yuan, and T. Chen, "Fire Detection in Video Surveillances Using Convolutional Neural Networks and Wavelet Transform," *Eng. Appl. Artif. Intell.*, vol. 110, p. 104737, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0952197622000434>
- [142] A. Akagic and E. Buza, "LW-FIRE: A Lightweight Wildfire Image Classification with a Deep Convolutional Neural Network," *Appl. Sci.*, vol. 12, no. 5, 2022. [Online]. Available: <https://www.mdpi.com/2076-3417/12/5/2646>
- [143] A. J. Dunning and T. P. Breckon, "Experimentally Defined Convolutional Neural Network Architecture Variants for Non-Temporal Real-Time Fire Detection," in *IEEE Int. Conf. Image Process.*, 2018, pp. 1558–1562.
- [144] W. Thomson, N. Bhowmik, and T. P. Breckon, "Efficient and Compact Convolutional Neural Network Architectures for Non-temporal Real-time Fire Detection," in *IEEE Int. Conf. Mach. Learn. and Appl.*, 2020, pp. 136–141.
- [145] Z. Yin, B. Wan, F. Yuan, X. Xia, and J. Shi, "A Deep Normalization and Convolutional Neural Network for Image Smoke Detection," *IEEE Access*, vol. 5, pp. 18 429–18 438, 2017.
- [146] Y. Luo, L. Zhao, P. Liu, and D. Huang, "Fire smoke detection algorithm based on motion characteristic and convolutional neural networks," *Multimed. Tools Appl.*, vol. 77, pp. 15 075–15 092, 2018.
- [147] Z. Xu, W. Wanguo, L. Xinrui, L. Bin, and T. Yuan, "Flame and Smoke Detection in Substation Based on Wavelet Analysis and Convolution Neural Network," New York, NY, USA, p. 248–252, 2019. [Online]. Available: <https://doi.org/10.1145/3319921.3319962>
- [148] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, "Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications," *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 49, no. 7, pp. 1419–1434, 2019.
- [149] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "SqueezeNet: AlexNet-Level Accuracy with 50x Fewer Parameters and < 0.5MB Model Size," *arXiv*, 2016.
- [150] A. Jadon, M. Omama, A. Varshney, M. S. Ansari, and R. Sharma, "FireNet: A Specialized Lightweight Fire & Smoke Detection Model for Real-Time IoT Applications," *arXiv*, 2019.
- [151] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," *arXiv*, 2015.
- [152] R. Chi, Z.-M. Lu, and Q.-G. Ji, "Real-time multi-feature based fire flame detection in video," *IET Image Process.*, vol. 11, no. 1, pp. 31–37, 2017. [Online]. Available: <https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-2016.0193>
- [153] S. Zhang, Q. Yang, Y. Gao, and D. Gao, "Real-Time Fire Detection Method for Electric Vehicle Charging Stations Based on Machine Vision," *World Electr. Veh. J.*, vol. 13, no. 2, 2022. [Online]. Available: <https://www.mdpi.com/2032-6653/13/2/23>
- [154] A. Gaur, A. Singh, A. Kumar, A. Kumar, and K. Kapoor, "Video Flame and Smoke Based Fire Detection Algorithms: A Literature Review," *Fire Technol.*, vol. 56, pp. 1943–1980, 2020.
- [155] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Commun. ACM*, vol. 60, no. 6, p. 84–90, may 2017. [Online]. Available: <https://doi.org/10.1145/3065386>
- [156] K. He, X. Zhang, S. Ren, and J. Sun, "Identity Mappings in Deep Residual Networks," in *Comput. Vis.* Springer, 2016, pp. 630–645.
- [157] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going Deeper with Convolutions," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, June 2015.
- [158] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv*, 2015.

- [159] Q. Zhang, J. Xu, L. Xu, and H. Guo, "Deep Convolutional Neural Networks for Forest Fire Detection," in *Int. Forum Manag. Educ. Inf. Technol. Appl.* Atlantis Press, 2016/01, pp. 568–575. [Online]. Available: <https://doi.org/10.2991/ifmeita-16.2016.105>
- [160] H. Yar, T. Hussain, Z. A. Khan, D. Koundal, M. Y. Lee, S. W. Baik et al., "Vision Sensor-Based Real-Time Fire Detection in Resource-Constrained IoT Environments," *Comput. Intell. Neurosci.*, vol. 2021, 2021.
- [161] O. Moses and O. Abimbola, "Fire-Smoke-Dataset: An Image Dataset for Training Fire and Frame Detection AI." [Online]. Available: <https://github.com/DeepQuestAI/Fire-Smoke-Dataset>
- [162] A. E. Cetin, "Computer Vision Based Fire Detection Software & Dataset." [Online]. Available: <https://http://signal.ee.bilkent.edu.tr/VisiFire/>
- [163] A. Dewangan, Y. Pande, H.-W. Braun, F. Vernon, I. Perez, I. Altintas, G. W. Cottrell, and M. H. Nguyen, "FIGLib & SmokeyNet: Dataset and Deep Learning Model for Real-Time Wildland Fire Smoke Detection," *Remote Sensing*, vol. 14, no. 4, p. 1007, 2022.
- [164] J. Purtill, "Australia's First Satellite that Can Help Detect Bushfires Within One Minute of Ignition Set for Launch," 3 2021. [Online]. Available: <https://www.abc.net.au/news/science/2021-03-14/bushfires-detecting-them-from-space-fireball-satellite-launch/13203470>
- [165] N. Laptev, S. Amizadeh, and I. Flint, "Generic and Scalable Framework for Automated Time-Series Anomaly Detection," in *Int. Conf. Knowl. Discov. Data Min.*, ser. KDD '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 1939–1947. [Online]. Available: <https://doi.org/10.1145/2783258.2788611>
- [166] Z. Cheng, C. Zou, and J. Dong, "Outlier Detection Using Isolation Forest and Local Outlier Factor," in *Conf. Res. Adapt. Convergent Syst.*, ser. RACS '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 161–168. [Online]. Available: <https://doi.org/10.1145/3338840.3355641>
- [167] H. Soliman, K. Sudan, and A. Mishra, "A Smart Forest-Fire Early Detection Sensory System: Another Approach of Utilizing Wireless Sensor and Neural Networks," in *IEEE Sens. J.*, 2010, pp. 1900–1904.
- [168] D. N. Ghuge, A. Chavan, R. Gaikwad, and K. Kale, "Forest Fire Detection Using Arduino Based WSN," in *Int. Conf. Commun. Inf. Process.*, 2021.
- [169] A. Papaioannou, P. Verikios, C. S. Kouzinopoulos, D. Ioannidis, and D. Tzovaras, "A Low-Power Embedded System for Fire Monitoring and Detection Using a Multilayer Perceptron," in *IEEE Sens. Appl. Symp.*, 2021, pp. 1–6.
- [170] S. Choueiri, D. Daoud, S. Harb, and R. Achkar, "Fire and Smoke Detection Using Artificial Neural Networks," in *Int. Conf. Open Source Syst. Technol.*, 2020, pp. 1–6.
- [171] R. P. Adams and D. J. MacKay, "Bayesian Online Change-point Detection," *arXiv*, 2007.
- [172] L. Xie, G. V. Moustakides, and Y. Xie, "Window-Limited CUSUM for Sequential Change Detection," *IEEE Trans. Inf. Theory.*, 2023.
- [173] E.-S. Apostol, C.-O. Truică, F. Pop, and C. Esposito, "Change Point Enhanced Anomaly Detection for IoT Time Series Data," *Water*, vol. 13, no. 12, 2021. [Online]. Available: <https://www.mdpi.com/2073-4441/13/12/1633>
- [174] S. Kianoush, S. Savazzi, V. Rampa, L. Costa, and D. Tolochenko, "A Random Forest Approach to Body Motion Detection: Multisensory Fusion and Edge Processing," *IEEE Sens. J.*, vol. 23, no. 4, pp. 3801–3814, 2023.
- [175] B. M. Alencar, R. A. Rios, C. Santana, and C. Prazeres, "FoT-Stream: A Fog platform for data stream analytics in IoT," *Comput. Commun.*, vol. 164, pp. 77–87, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S014036642031940X>
- [176] R. F. El Khatib, N. Zorba, and H. S. Hassanein, "Rapid Sensing-Based Emergency Detection: A Sequential Approach," *Comput. Commun.*, vol. 159, pp. 222–230, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0140366419318043>
- [177] J. Hoehenbaum, O. S. Vallis, and A. Kejariwal, "Automatic Anomaly Detection in the Cloud Via Statistical Learning," *arXiv*, 2017.
- [178] M. Ansari and M. Alam, "An Intelligent IoT-Cloud-Based Air Pollution Forecasting Model Using Univariate Time-Series Analysis," *Arab. J. Sci. Eng.*, pp. 1–28, 2023.
- [179] P. D. Rosero-Montalvo, P. Tözün, and W. Hernandez, "Time-Series Forecasting to Fill Missing Data in IoT Sensor Data," *IEEE Sens. Lett.*, vol. 7, no. 9, pp. 1–4, 2023.
- [180] S. Chen, J. Ren, Y. Yan, M. Sun, F. Hu, and H. Zhao, "Multi-Sourced Sensing and Support Vector Machine Classification for Effective Detection of Fire Hazard in Early Stage," *Comput. Electr. Eng.*, vol. 101, p. 108046, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S004579062200307X>
- [181] A. Andrade, C. Montez, R. Moraes, A. Pinto, F. Vasques, and G. L. da Silva, "Outlier Detection Using K-Means Clustering and Lightweight Methods for Wireless Sensor Networks," in *Annual Conf. IEEE Ind. Electron. Soc.*, 2016, pp. 4683–4688.
- [182] D. R. Panuju, B. H. Trisasongko, B. Susetyo, M. A. Raimadoya, and B. Lees, "Historical Fire Detection of Tropical Forest from NDVI Time-Series Data: Case Study on Jambi, Indonesia," *ITB J. Sci.*, vol. 42, no. 1, pp. 49–66, 2010.
- [183] X. Wang, S. Lo, and H. Zhang, "Influence of Feature Extraction Duration and Step Size on ANN based Multisensor Fire Detection Performance," *Procedia Eng.*, vol. 52, pp. 413–421, 2013, 2012 International Conference on Performance-based Fire and Fire Protection Engineering. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1877705813002816>
- [184] H. Xu, Y. Wang, S. Jian, Q. Liao, Y. Wang, and G. Pang, "Calibrated One-class Classification for Unsupervised Time Series Anomaly Detection," *arXiv*, 2022.
- [185] P. Wang, Z. Li, X. Zhou, C. Su, and W. Wang, "FlowADGAN: Adversarial Learning for Deep Anomaly Network Intrusion Detection," in *Int. Workshop Secur. Trust Manag.* Springer, 2022, pp. 156–174.
- [186] M. R. Nosouhi, K. Sood, N. Kumar, T. Wevill, and C. Thapa, "Bushfire Risk Detection Using Internet of Things: An Application Scenario," *IEEE Internet Things J.*, vol. 9, no. 7, pp. 5266–5274, 2022.
- [187] A. Khalifeh, A. Nassar, M. M. AlAjlouni, A. AlNabelsi, Z. Alrawashdeh, B. Hejazi, R. Alwardat, and J. Lima, "A Machine Learning-Based Early Forest Fire Detection System Utilizing Vision and Sensors' Fusion Technologies," in *IEEE Middle East North Africa Commun. Conf.*, 2022, pp. 229–234.
- [188] B. Sarwar, I. S. Bajwa, N. Jamil, S. Ramzan, and N. Sarwar, "An Intelligent Fire Warning Application Using IoT and an Adaptive Neuro-Fuzzy Inference System," *Sensors*, vol. 19, no. 14, 2019. [Online]. Available: <https://www.mdpi.com/1424-8220/19/14/3150>
- [189] S. Chen, H. Bao, X. Zeng, and Y. Yang, "A Fire Detecting Method Based on Multi-Sensor Data Fusion," in *IEEE Int. Conf. Syst. Man Cybern.*, vol. 4, 2003, pp. 3775–3780 vol.4.
- [190] T. Fujinaka, M. Yoshioka, S. Omatu, and T. Kosaka, "Intelligent Electronic Nose Systems for Fire Detection Systems Based on Neural Networks," in *IEEE Int. Conf. Adv. Eng. Comput. Appl. Sci.*, 2008, pp. 73–76.
- [191] S. Chandrasekharan, A. Al-Hourani, K. Magowe, L. Reynaud, and S. Kandeepan, "Propagation Measurements for D2D in Rural Areas," in *IEEE Int. Conf. Commun. Workshop*, 2015, pp. 639–645.
- [192] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "Overview of Cellular LPWAN Technologies for IoT Deployment: Sigfox, LoRaWAN, and NB-IoT," in *IEEE Int. Conf. Pervasive Comput. Commun. Workshops*, 2018, pp. 197–202.
- [193] Sigfox®, "Sigfox 0G Technology," 2021. [Online]. Available: <https://www.sigfox.com/>
- [194] L. Alliance®, "RP002-1.0.3 LoRaWAN® Regional Parameters," 2021. [Online]. Available: <https://hz137b.p3cdn1.secureserver.net/wp-content/uploads/2021/05/RP002-1.0.3-FINAL-1.pdf?time=1686548049>
- [195] L. Germani, V. Mecarelli, G. Baruffa, L. Rugini, and F. Frescura, "An IoT Architecture for Continuous Livestock Monitoring Using LoRa LPWAN," *Electronics*, vol. 8, no. 12, 2019. [Online]. Available: <https://www.mdpi.com/2079-9292/8/12/1435>
- [196] C. Pham, "Investigating and Experimenting CSMA Channel Access Mechanisms for LoRa IoT Networks," in *IEEE Wirel. Commun. Netw. Conf. IEEE*, 2018, pp. 1–6.
- [197] H. Feng, G. Mu, S. Zhong, P. Zhang, and T. Yuan, "Benchmark Analysis of YOLO Performance on Edge Intelligence Devices," *Cryptography*, vol. 6, no. 2, 2022. [Online]. Available: <https://www.mdpi.com/2410-387X/6/2/16>
- [198] K. R. Singh, K. Neethu, K. Madhurekaa, A. Harita, and P. Mohan, "Parallel SVM Model for Forest Fire Prediction," *Soft Comput. Lett.*, vol. 3, p. 100014, 2021.
- [199] N. Andelic, S. Baressi Šegota, I. Lorencin, and Z. Car, "The Development of Symbolic Expressions for Fire Detection with Symbolic Classifier Using Sensor Fusion Data," *Sensors*, vol. 23, no. 1, 2023. [Online]. Available: <https://www.mdpi.com/1424-8220/23/1/169>