A Social IoT-Based Solution for Real-Time Forest Fire Detection

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***Abstract*—Conservation of the natural ecosystem is a hot topic that is receiving increasing attention not only from the scientific community, but from the entire world population. Forests and woodlands are major contributors to climate change mitigation, able to absorb significant amounts of carbon dioxide. This paper proposes a novel real-time fire monitoring and detection system based on Digital Mobile Radio (DMR) nodes and a Social Internet of Things (SIoT) platform on which fire detection decision making algorithms have been implemented. The results obtained by employing a K-Nearest Neighbors (KNN) algorithm and a Recurrent Neural Network (RNN) show the ability to detect the slightest variation in the observed parameters, determining the direction and speed of fire propagation with an accuracy of more than 98%.**

***Index Terms*—IoT networks, Ambient intelligence, IoT architectures.**

I. Introduction

Over the past few decades, climate change has become a defining factor, leading to unpredictable shifts between abundant rainfall within a short span and prolonged periods of drought, along with other climatic events deviating from seasonal norms. At the same time, there is a growing emphasis on policies aimed at mitigating pollution through proactive and reactive measures. Within the literature, numerous preventive policies have emerged, leveraging the Internet of Things (IoT) in specific application scenarios, such as industry [1], smart cities [2], and mobility [3]. These IoT-based approaches offer potential solutions to address environmental challenges caused by climate change.

Hurricanes, floods, snowstorms, low temperatures, cyclones, and typhoons are highly destructive weather elements that remain difficult to control, except through intelligent urban development policies aimed at minimizing their impact on the hydrological system. Additionally, extreme weather events, droughts, and climate change contribute significantly to fires, which increasingly threaten regions at high risk of desertification. These interconnected factors form the basis of global desertification processes, affecting a quarter of the world's population. The European Forest Fire Information System (EFFIS) [4] utilizes satellite imagery from the European Copernicus project to analyze and monitor fire incidents. Since the start of 2022, over 600,000 hectares of forests have been consumed by fires in the European Union, with arson fires posing a significant threat to ecosystems, human life, and causing immense economic and social damages. Furthermore, fires disrupt the natural balance, elevating risks of landslides and avalanches. To address these challenges, a reactive approach is required in the short and medium term, involving forest monitoring to enable early intervention. Presently, fire risk prevention and mitigation practices are insufficient, highlighting the crucial role of early fire detection. Currently, "lookout" operators stationed at strategic points observe specific areas, but such human-centric practices have limitations. Information and communication technologies (ICT) offer a promising solution, supplementing or replacing human sensory practices over vast territories, thus enhancing fire management capabilities.

Recent advancements have given rise to monitoring systems employing strategically placed cameras, which are remotely operated from monitoring centers. Although the introduction of cameras has the potential to facilitate human monitoring and control activities, the presence of an operator remains indispensable for correctly interpreting the gathered data [5]. A progressive step in the evolution of firefighting systems involves partially replacing human operators with artificial intelligence (AI) tools. This transformation is made feasible by the development of high-performance digital cameras, coupled with advanced image processing techniques and the utilization of machine learning (ML) algorithms. Consequently, firefighting systems can now rely entirely on image recognition. Through ML techniques, it becomes possible to identify potential risk situations with a certain level of accuracy [6]. However, it is important to consider that ML-based models introduce additional factors that influence the system's accuracy and may lead to false alarms. Moreover, these models demand substantial computational capabilities from the involved devices. Additionally, setting up cameras necessitates a suitable infrastructure for power supply, image transmission, and processing. The objective of this study is to address the aforementioned limitations by proposing an innovative real-time fire detection system using a Social Internet of Things (SIoT) approach. The system processes data from a network of interconnected sensors to achieve this goal. These sensors, spread across various network nodes, continuously monitor and transmit real-time data related to temperature, humidity, atmospheric pressure, CO2, CO, ethanol, ammonia, and other relevant gases. By correlating this data appropriately, the system can effectively identify the presence or occurrence of a forest fire outbreak. To facilitate seamless communication, the wireless sensor network (WSN) nodes and gateways utilize the Digital Mobile Radio (DMR) standard. The acquired information from DMR nodes is relayed to a DMR gateway, which further transmits it to an SIoT platform called Lysis [7]. The system ensures that DMR nodes can directly communicate through multicast/broadcast with civil defense and forest rangers' equipment. This direct communication enables the provision of real-time information, thereby enhancing emergency response time in critical situations.

The rest of the paper is organized as follows: in section II, an overview of state of the art is presented. The system architecture and design of the proposed fire-fighting system are described in section III. The system implementation, scenario and results are discussed in section IV. Finally, conclusions are drown in section V.

II. Related Works

There are a number of works in the literature that have inspired the search for an intelligent and innovative solution that has a low environmental and infrastructural impact and, most importantly, can reduce the response time by response authorities. Specifically, the works analyzed can be divided into two broad categories: those using ML and image processing and those using sensors to analyze environmental parameters. ML and image processing techniques are fundamental tools for information extraction, pattern recognition, classification and recognition of objects/patterns in images, and understanding contextual information. T. Divya et al., [8] process satellite images based on intensity levels to identify fire-affected regions (hot spots). Agglomerative hierarchical clustering algorithms are used to identify these regions and fire propagation directions.Fire identification by image analysis is based on the analysis of RGB pixel values.

E.E. Maeda et al. [9], process multi-temporal satellite images acquired from MODIS sensors and employ artificial neural networks (ANNs) to identify areas of high forest fire risk. In this work, samples of areas where forest fires have been detected were selected to train, validate and test the ANNs, yielding promising results in terms of fire prediction speed and accuracy.

On the analysis of image acquisitions, a system based on devices placed locally in the scenario of interest is proposed by N. Ya'acob et al., [10]. The proposed acquisition system essentially consists of two devices: a raspberry Pi Zero W and a Pi Camera V2 module. The produced images are processed and analyzed using Matlab. R. D. Aachal Ramteke et al., [11] developed an IoT platform based on a Raspberry Pi microcontroller equipped with a smoke sensor and camera is proposed. The detection system relies on color and motion information to minimize false detections. This information is processed together with that of the smoke sensor. When a fire is detected, the device sends an SMS to the monitoring station via GSM. With recent developments in unmanned aerial vehicles (UAVs), real-time monitoring for military and civilian applications employing these devices is gaining in popularity. A forest fire monitoring and detection system has been designed using UAVs equipped with sensors and cameras [12]. Algorithms based on image comparison, infrared detection, and correlation of acquired data (e.g., temperature) are used to monitor forest fires. In [13], an early fire detection system based on the use of drones is presented. The work refers to networks of UAVs through which to acquire thermal images, RGB, and positioning and distance data, useful in the fire mitigation phase. To process data from multiple sources, both traditional and deep learning-based computer vision algorithms have been developed and employed. In general, systems that rely on image processing have advantages in terms of fire detection accuracy, but at the same time they have several disadvantages: hardware system implementation and maintenance costs and high computational capacity requirements. The limitations encountered in the ML-image processing pair were partially overcome by using different approaches based on the use of sensors that analyze environmental parameters. P. R. Reddy et al., [14] propose a method that can improve the accuracy of forest fire detection performance of evergreen and temperate forests by detecting temperature and atmospheric carbon dioxide level. B. Montrucchio et al., [15] deal with dense air quality monitoring networks based on low-cost sensing strategies. These experiments include analysis of vehicular traffic, investigation of pollution using different means of transportation, and analysis of pollution during special events. The automatic fire detection system proposed by U. Dampag et al. in [16] includes two sensors: smoke sensor MQ-2 with very high sensitivity toward propane, methane, LPG, smoke, alcohol, carbon monoxide and hydrogen; fire sensor. Sensors are mounted on the slave nodes which acquire the environmental values of the area where they are located and then send this information to the leader nodes via RF. Once received, the leader node analyzes the data and communicates the presence of fire to the control station via GSM. Despite the many proposals from the scientific world, we are very far from implementing real preventive policies causing immediate repercussions on green areas with particular interest on forest fires. A SIoT-based system for real-time detection of forest fires is proposed. The system is scalable, the sensor network is self-configuring based on the positioning of DMR nodes, and can be deployed without the need for 4G/5G network coverage. To cope with the high influence and uncertainty of some parameters in order to detect limit/cancel false positive fire cases, two decision-making processes were tested within the SIoT Lysis platform: the K-Nearest Neighbors (KNN) algorithm and a Recurrent Neural Network (RNN). The proposed work has the following strengths summarized as follows:

1) the system is easily implemented and installed;
2) the cost of the proposed system is lower than camera-based solutions;
3) the DMR node system is energy self-sufficient;
4) it exploits the DMR network at long range, freeing itself from the limitations of the Wi-Fi network or the 4G LTE network, which does not have 100% coverage especially in mountainous areas;
5) the network is highly scalable and through the implemented multi-hop, the gateway can receive data from

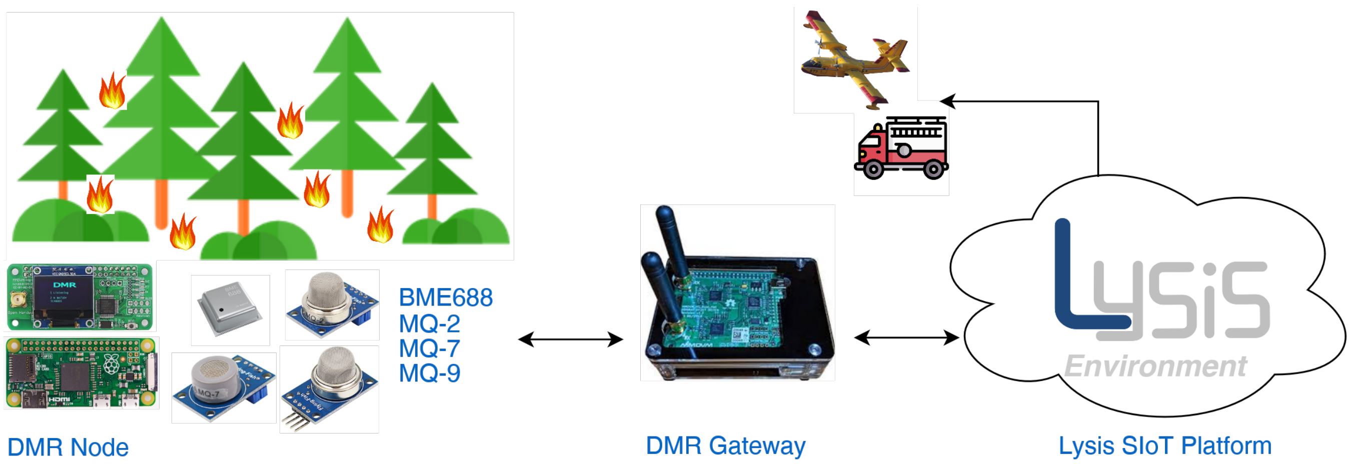

Fig. 1: DMR System

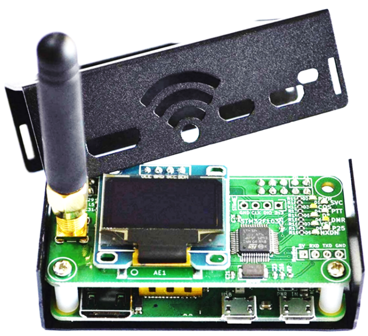

Fig. 2: DMR Node - bidirectional Tx/Rx at 144 MHz

DMR nodes that cannot reach it directly;

6) the network is self-configuring because nodes are geolocated, so the social relationships between nodes implemented in the SIoT Lysis platform take into account the physical distance between DMR nodes;

III. System Architecture and Design

The complete system shown in Fig. 1 consists of a hardware entity, a data transmission system, and a software system based on the SIoT Lysis platform for data storage and real-time fire danger detection. The system shown in Fig. 1 is designed to work completely autonomously without any special human intervention, restarting all processes in case of temporary power source failure.

A. The DMR hardware system

The DMR node consists of a board to which sensors, a charge controller, rechargeable batteries and a small solar panel are connected, making the individual node totally energy autonomous. The transmission standard is DMR operating on 144 MHz and 430 MHz, and is compatible with the standard currently used by civil defense. In detail, the modules used are summarized below:

- the **4FM YSF NXDN DSTAR P25 DMR module** shown in Fig. 2 represents the core of the fire detection node. The node manages the main smoke detection sensors and sends them in VHF/UHF to the DMR gateway. In addition, the node is powered through rechargeable batteries connected to a charge controller and a suitably sized solar panel. This node is based on a Raspberry Pi Zero 2W+ and a transmission module compatible with the DMR standard;
- the **BME688** 4-in-1 Air Quality Breakout (Gas, Temperature, Pressure, Humidity) sensor has updated features as a gas scanner that can react to volatile organic compounds (VOCs), volatile sulfur compounds (VSCs) and the presence of carbon monoxide and hydrogen to give a general measure of indoor or outdoor air quality;
- the **MQ-x sensors family** integrate air parameters collected using the BME688 sensor, with smoke gas sensor (MQ-2), carbon monoxide sensor (MQ-7), and carbon monoxide combustible gas sensor (MQ-9), respectively;
- a **solar panel** (10W 6V 1700mA 260x140x2.5mm) equipped with USB Charge for Outdoor Working support was appropriately sized to support the energy needs of the node throughout the day, charging the 3500mAh - 10A 18650 batteries;
- the **DMR gateway** is based on a Bewinner Hotspot Duplex MMDVM module, 32 Bit High Performance Arm processor MMDVM Hotspot Module Supports DMR, P-25, D-Star and System Fusion for Raspberry Pi with SMA Antenna. This shield houses on a Raspberry Pi 4 connected to the cloud through 4G LTE network.

From an energy standpoint, the system has been designed to achieve complete self-sufficiency and effectively compensate for the most critical days of the year with minimal

TABLE I: DMR node energy conditions.

State	Energy consumption	Operating timeline
State ON	220 mAh	0-150 sec
Data acquisition	246 mAh	151 - 170 sec
Data sending	266 mAh	171 - 180 sec
Deep sleep mode	600 uAh	181 - 720 sec
Daily energy consumption	0.25 Wh	H24
Solar panel	**Energy generation**	**Operating timeline**
Max current = 2 Ah	Average current 40 mAh	H24
	Daily average 19.2 Wh	H24
Power bank	**Energy Storage**	**Operating timeline**
Output (max): 5V 3A	Capacity = 100.000 mAh Capacity = 500 Wh	H24

reliance on the charging contribution from the storage system. The DMR acquisition system underwent analysis in four distinct time phases. The initial 150 seconds following power-up were dedicated to configuring certain sensors requiring calibration to their optimal settings. During this stage, the sensors were not actively acquiring data, and the current draw was measured. Subsequently, a period of 20 seconds was allocated for data acquisition, followed by an additional 10 seconds for data packing and transmission through the DMR standard. After 180 seconds, the system entered deep sleep mode and remained in this state for 9 minutes. This timing was programmed to ensure that the system sampled 5 readings every hour, one every 12 minutes, while keeping power consumption within manageable limits. The measured power consumption during this phase amounted to 0.25 Wh. Concurrently, measurements and calculations were performed on the energy supply of a solar panel measuring 10x20 cm, with a stated power output of 10 W and 5V. These calculations took into account average weather conditions, seasonality, and geographical location. The reference data relied on an average annual solar irradiation of 4.8 kWh/m^2 per day. Based on these data and assuming a panel efficiency of 20%, the average daily energy output was determined to be 19.2 Wh. As evident from the data presented in the table, the solar panel's contribution proved sufficient to offset the entirety of the DMR system's energy consumption. Finally, the storage system demonstrated its capacity to withstand adverse weather conditions, as it possesses sufficient capacity to allow for energy input even when there is minimal or negligible input from the solar panel.

B. *Lysis-compliant modules*

The DMR gateway collects information from all DMR nodes and transmits the data to the SIoT Lysis platform, using the 4G Long Term Evolution (LTE) network. The SIoT Lysis platform is built for distributed IoT applications involving socially connected objects. The objects are able to establish social relationships independently of their owners, with the advantage of improving network scalability and information discovery efficiency. The overall architecture of the SIoT Lysis platform consists of four functional levels:

- the lower level is made up of the *"things"* in the real world;
- the virtualization level, which interfaces directly with the real world and is made up of Social Virtual Objects (SVOs);
- the level of aggregation is responsible for composing different SVOs to set up entities with augmented functionalities called micro engines (MEs);
- the last level is the application level in which user-oriented macro services are deployed.

In order to exploit the Lysis architecture advantages, the virtualization layer elements (SVOs) were designed and implemented, representing DMR nodes. Each DMR node has its own SVO with which it communicates to send and record information relating to GPS position, air quality parameters and smoke levels (DMR-SVO).

The data from the SVOs represent inputs to the fire detection decision making tools. DMR sensors data are essentially raw data that depending on humidity and temperature

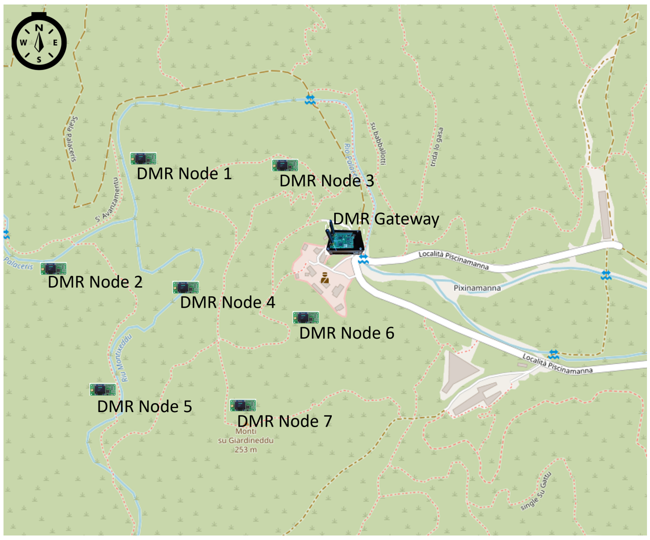

Fig. 3: The scenario employed for preliminary testing with 7 DMR nodes and DMR gateway within an area of 2 kmq.

conditions are subject to variation that can generate false positives. In the top SIoT platform Lysis, a KNN and an RNN were implemented and tested. The KNN is one of the simplest machine learning algorithms based on the supervised learning technique, it assumes the similarity between the new cases/data and the available ones and places the new case in the most similar category to the available ones, and stores all the available data and classifies a new data point based on the similarity. The KNN algorithm has been working on the dataset and when it receives additional new data from the DMR-SVOs, it classifies them into a category very similar to the previous data.

RNNs have the advantage of having neurons that can also admit loops and/or can also be interconnected to neurons of a previous level. DMR-SVOs can provide information that is subject to measurement error or altered by particular weather conditions. The SIoT Lysis platform handles dynamic information over time and thus learns to build and instruct a network with memory (RNN) so that it can observe changes and recognize different actions. Output feedback will enable the network to base its decisions on past history.

IV. System Implementation

A. *Scenario*

The proposed basic system consists of 7 DMR nodes working independently of each other. Each node is equipped with sensors for detecting forest fire smoke, as well as other useful parameters for studying dynamics such as temperature, humidity, atmospheric pressure, and UV index. DMR nodes are equipped with on-board GPS geolocation, are synchronized with each other, and every 5 minutes make a data transmission. The real scenario employed for the tests is depicted in Fig. 3.

The node arrangement allows the detection of fire smoke from any direction and direction. The tests were conducted during several days of "mistral" type wind, typical of the Sardinia region, with west/northwest (WNW) direction. The tests were conducted in compliance with current regulations and according to the authorization of state authorities. The

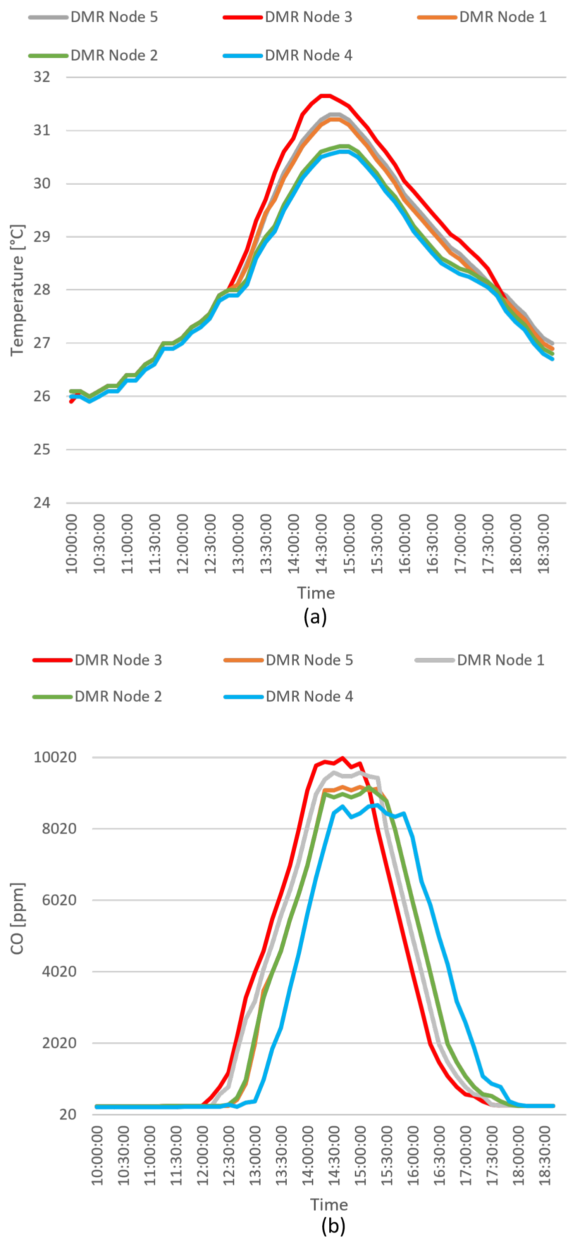

Fig. 4: Trend of temperatures (a), and CO (b) detected by the DMR nodes due to the presence of a fire with WNW origin.

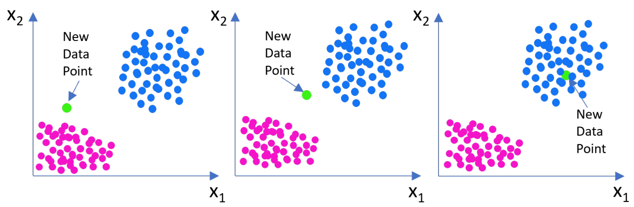

Fig. 5: KNN based on values of DMR-SVOs and the three main cases verified in the decision making process.

smoke source was positioned WNW with respect to the proposed scenario, so that nodes 1 and 2 were the first to respond to smoke stresses. Thereafter, detections were reported by nodes 3, 4 and 5, and finally by nodes 6 and 7. The timing of detection plays a very important role in determining the direction of origin of the fire front. Typically, the first nodes to detect smoke are also the ones closest to the fire, so they are critical in identifying the direction of the fire and implementing appropriate countermeasures. Smoke propagation situations were artificially created from burning of organic material of the brushwood type. The DMR nodes' synchronized transmission is received by the DMR gateway, which forwards the data in real time to be processed by the SIoT Lysis platform. The DMR nodes detected an increase in temperatures and a surge in CO and CO2 values simultaneously with the acquisition of the values.

B. Data acquisition and results

The BME688 and MQ-x sensors were tested in the laboratory in a controlled environment before being placed in an outdoor environment, showing no significant deviations other than those stated by the manufacturer. As can be seen in Fig. 4, the trend of the detections of the 7 DMR nodes shows an overlap in the first part of the graph, in the time interval from about 10:00 to 13:10. At 1:00 p.m., the smoke source positioned WNW relative to the system of the 7 DMR nodes positioned as in Fig. 4(a) was activated. The tests were conducted on a mistral wind day to simulate the same conditions as a high fire risk day. This was critical in assessing the worst-case scenario in which responders would face the emergency. The system promptly responded to the stresses by detecting not only an increase in temperatures due to the presence of hot air caused by the fire, but also differences in the temperatures detected by the various DMR nodes. In fact, the nodes closest to the source (i.e., 1 and 2) were the first to detect the temperature increase. Similarly, the other nodes farthest from the source also "noticed" the presence of an external heat source affecting the normal daily temperature trend. The greater the distance of the nodes, the smaller the temperature increase, as shown for DMR nodes 3, 4, 5 compared to DMR nodes 1 and 2, similarly for DMR nodes 6 and 7 compared to DMR nodes 3, 5 and 4. The second consideration that needs to be discussed concerns the peaks of the individual curves. The shorter the distance between the DMR nodes and the fire front, the shorter the time in which the curve reaches the maximum temperature peak. More distant nodes will arrive at the peak with some delay. Therefore, the greater the distance between the fire front and DMR nodes, the longer the response time and the smaller the modulus of the peak temperature detected by fire. At 2:20 p.m., the source representing the fire was cut off, and the curves dropped and asymptotically overlapped due to natural conditions, and without an additional external source to influence the trends. The trend of CO detected by individual DMR sensors is shown in Fig. 4(b). The characterizing aspects from these curves mainly concern the amplitude modulus and the delay of detection of the change in CO concentration. Regarding the first aspect, the greater the distance between the fire source and the DMR node, the lower the concentration detected by the DMR nodes

TABLE II: RNN confusion matrix

		Predicted Data	
Real Data		***Fire detection***	***Fire absence***
	Fire detection	98.27	2.13
	Fire absence	1.73	97.87
	Sum	100	100

due to the greater dispersion of the smoke being detected. Due to the greater distance from the smoke source, nodes 6 and 7 measure lower concentrations than nodes 1 and 2. Similarly, the DMR nodes furthest from the smoke source detect concentrations with a time delay compared to the nearest nodes. In the figure, the rightward shift of the nodes moving away from the fire source can be seen. Concomitantly with the temperature readings and other parameters, CO data were processed to make a prompt detection of fire criticality by determining its propagation speed, and direction. These aspects allow the SIoT Lysis platform substantial time savings in initiating the rescue machine and all policies necessary to fight and extinguish forest fires in the shortest possible time.

In Fig. 5 there are two categories characterized by the purple and blue dots. The purple category represents the temperature/CO value pairs with which the KNN was used to identify fire-free configurations. Since from the best of our knowledge, no classified datasets exist, 100 tests were done which generated the point cloud shown in Fig. Similarly, the blue category represents the clouds of temperature/CO pairs employed to test KNN, generating smoke from burning organic material such as brushwood and small branches. The three subfigures indicate the evolution as the transition from no fire situation to fire situation occurs, passing through a region of uncertainty. The SIoT Lysis platform can monitor the evolution of the ”new data point” and provide real-time alert as soon as it is associated with the fire category. Finally, Table II summarizes the confusion matrix of the collected data, which highlights the high accuracy (i.e., over 98%) of the RNN in correctly detecting forest fire with very low values of false positives and false negatives. The recursive structure of the RNN jointly with the work done by the DMR-SVOs allow limiting the cases of uncertainty by applying oversampling of the acquired data through queries made by the SIoT Lysis platform to the DMR nodes.

V. Conlcusions

This paper presents a new system based on the SIoT Lysis platform for real-time forest fire detection, based on a network of sensors attested on DMR nodes. The proposed system models environmental data streams by constantly monitoring air quality through dedicated prototype ”electronic noses,” which the authors have fabricated. Acquisition of raw data is typically affected by environmental conditions, requiring refined processing in order to determine whether a fire condition has occurred or not. DMR-SVOs were developed to manage social relationships between nodes, and two fire detection decision making techniques were employed. The KNN was adopted during a preliminary phase of tests conducted to evaluate sensor behavior. However, in some cases the KNN may show uncertainty depending on the values associated with the ”new data point.” The limitations encountered with the KNN were largely overcome using an RNN, with more than 98% correct detection of the presence of forest fire smoke and nearly 98% correct detection of the absence of fire. The design architecture proved to be highly scalable and responsive to the stimuli it was subjected to in a real mountain scenario.

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References

[1] H. Fujii, S. Managi, and S. Kaneko, “Decomposition analysis of air pollution abatement in china: empirical study for ten industrial sectors from 1998 to 2009,” *Journal of Cleaner Production*, vol. 59, pp. 22–31, 2013.

[2] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, “Internet of things for smart cities,” *IEEE Internet of Things journal*, vol. 1, no. 1, pp. 22–32, 2014.

[3] F. Callegati, G. Delnevo, A. Melis, S. Mirri, M. Prandini, and P. Salomoni, “I want to ride my bicycle: A microservice-based use case for a maas architecture,” in *2017 IEEE Symposium on Computers and Communications (ISCC)*. IEEE, 2017, pp. 18–22.

[4] EFFIS, “European Forest Fire Information System (EFFIS).” [Online]. Available: https://effis.jrc.ec.europa.eu/

[5] D. Stipaničev, L. Šerić, M. Braović, D. Krstinić, T. Jakovčević, M. Štula, M. Bugarić, and J. Maras, “Vision based wildfire and natural risk observers,” in *2012 3rd International Conference on Image Processing Theory, Tools and Applications (IPTA)*, 2012, pp. 37–42.

[6] A. Jha, S. Vedak, K. Mundada, R. Walnuskar, U. Chopade, and A. Iyer, “Early fire detection using deep learning,” in *2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)*, 2021, pp. 1–6.

[7] R. Girau, S. Martis, and L. Atzori, “Lysis: A platform for IoT distributed applications over socially connected objects,” vol. 4, no. 1, pp. 40–51.

[8] T. Divya and M. Vijayalakshmi, “Analysis of wild fire behaviour in wild conservation area using image data mining,” in *2015 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2015, pp. 1–3.

[9] E. E. Maeda, A. R. Formaggio, Y. E. Shimabukuro, G. F. B. Arcoverde, and M. C. Hansen, “Predicting forest fire in the brazilian amazon using modis imagery and artificial neural networks,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 11, no. 4, pp. 265–272, 2009. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0303243409000233

[10] N. Ya’acob, M. Najib, N. Tajudin, A. Yusof, and M. Kassim, “Image processing based forest fire detection using infrared camera,” *Journal of Physics: Conference Series*, vol. 1768, p. 012014, 01 2021.

[11] R. D. Aachal Ramteke, Rohini Pochhi, “Iot based forest fire detection system using raspberry pi and gsm,” *International Journal of Advanced Research in Science, Communication and Technology*, 2021.

[12] W. Liu, Y. Yang, and J. Hao, “Design and research of a new energy-saving uav for forest fire detection,” in *2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI)*, 2022, pp. 1303–1316.

[13] S. Li, L. Qiao, Y. Zhang, and J. Yan, “An early forest fire detection system based on dji m300 drone and h20t camera,” in *2022 International Conference on Unmanned Aircraft Systems (ICUAS)*, 2022, pp. 932–937.

[14] P. R. Reddy and P. Kalyanasundaram, “Novel detection of forest fire using temperature and carbon dioxide sensors with improved accuracy in comparison between two different zones,” in *2022 3rd International Conference on Intelligent Engineering and Management (ICIEM)*, 2022, pp. 524–527.

[15] B. Montrucchio, E. Giusto, M. G. Vakili, S. Quer, R. Ferrero, and C. Fornaro, “A densely-deployed, high sampling rate, open-source air pollution monitoring wsn,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 15 786–15 799, 2020.

[16] U. Dampage, B. Lumini, W. Ridma, K. Kinshawa, and J. Bathiya, “Forest fire detection system using wireless sensor networks and machine learning.” *Sci Rep.*, 2022.