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An IoT-based electronic sniffing for forest fire detection

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***Abstract*—The preservation of the natural ecosystem is a topical issue that is receiving increasing attention not only from the scientific community but from the entire world population. Forests and woodlands are the main actors responsible for mitigating climate change, able to absorb significant amounts of carbon dioxide. The preservation of the arboreal areas has been addressed through the adoption of various solutions. This paper proposes a new real-time fire monitoring and detection system based on Digital Mobile Radio (DMR) nodes and a Social Internet of Things (SIoT) platform on which artificial intelligence algorithms have been implemented. The results obtained show the ability to detect the slightest variation in the observed parameters, determining the direction and speed of fire propagation.**

***Index Terms*—Sensors and Actuator Systems, Internet of Things, Internet of Everywhere, and Edge Computing, Machine Learning, Deep Learning and AI in CE**

I. Introduction

Recent decades are characterized by climatic changes with obvious alternations of abundant rainfall concentrated in a few hours and a few days, with periods of prolonged drought. Two approaches can be used to address global pollution issues: a preventive approach and a reactive approach. In the first case, many IoT examples are in literature in many configurations concerning in industry [1], smart cities [2] and mobility [3]. The spread of tree diseases can also cause the canopy to dry out and facilitate the spread of uncontrollable fires. The use of plant disease identification systems could provide crowdsourcing tools for people inexperienced in helping to determine diseases in trees in advance [4]. 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. Therefore, in the short and medium term, it is necessary to work according to a reactive approach by monitoring forests in order to be able to intervene promptly.

The European Forest Fire Information System (EFFIS) [5] collects and analyzes satellite images collected within the European Copernicus project. According to data collected since the beginning of 2022, more than 600,000 hectares of forests have burned across the European Union. Arson is one of the greatest threats to both the ecosystem and human life, as well as a source of enormous economic and social damage. Moreover, as a result of fires, the previous natural balance is undermined with additional risks due to landslides and avalanches.

Generally, fire risk prevention and mitigation practices are marginal and insufficient. Therefore, early detection plays a very important role. Currently, this task is entrusted to "lookout" operators conveniently placed at strategic points to view the area of interest. Obviously, the use of a system based on human sensory practices applied over large areas involves different limitations that can be appropriately supplemented through the use of ICT technologies. More recently, the monitoring system has been integrated through the installation of video cameras placed at strategic locations and remotely controlled within monitoring centers.

Although the introduction of cameras may facilitate human monitoring and control activities, the presence of an operator remains essential for the correct interpretation of the sensed data [6]. The latest evolution of the firefighting system, based on scene observation through cameras, is the partial replacement of the human operator with artificial intelligence (AI) tools. From a technical point of view, the development of high-performance digital cameras together with increasingly complex image processing techniques and the use of machine learning (ML) algorithms have made it possible to create firefighting systems based entirely on image recognition. The basis of this concept is the evaluation of variations in pixel values of different images. Using ML techniques, it is possible to determine the occurrence or non-occurrence of a situation of potential risk [7]. On the other hand, ML-based models require additional considerations that affect the accuracy of the system and the generation of false alarms, as well as requiring high computational capabilities on the part of the devices involved. Finally, there are several works in the literature on air quality monitoring in urban environment [8], [9], and the creation of low-cost prototypes [10] that have inspired the proposed work on air monitoring of large areas in rural environments. To overcome the limitations stated above, a multi-sensor fire monitoring system is proposed in this paper that obtains real-time information from the scenario under control, in terms of temperature, CO2, CO, ethanol, ammonia and other gases that can complement the detection system. In the proposed system, environmental information is forwarded from the nodes to the IoT cloud platform via Digital Mobile Radio (DMR), where it will be analyzed and correlated through a CNN with the purpose of promptly detecting fire outbreaks. In the last years, the smart applications have been deeply studied to support sustainable environments and to improve human living conditions. In this context, a smart solution based on the Social Internet of Things paradigm for real-time monitoring and detection of potential forest fires is presented. 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 drawn in section V.

II. Related Works

In the literature there are several solutions to detect and manage forest fires. In particular, contributions may be divided into two broad categories: those using ML and image processing and those using sensors to analyze environmental parameters.

In the category of ML and image processing, there are several methods of image acquisition used as input by the detection system. In [11], the authors propose a work in which satellite images are processed according to intensity levels to identify fire-affected regions (hot spots). Agglomerative hierarchical clustering algorithms are used to identify these regions and the directions of fire propagation. Fire identification by image analysis is based on the analysis of RGB pixel values. In [12], the authors 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.

With recent developments in unmanned aerial vehicles (UAVs), real-time monitoring for military and civilian applications employing these devices is gaining in popularity. In [13], a forest fire monitoring and detection system has been designed using UAVs equipped with sensors and cameras. Algorithms based on image comparison, infrared detection, and correlation of acquired data (e.g., temperature) are used to monitor forest fires. In [14], an early fire detection system based on the use of drones is presented. The paper 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.

Regarding analysis on image acquisitions, a system based on devices placed locally in the scenario of interest is proposed in [15]. 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. In [16], an IoT platform based on a Raspberry Pi microcontroller equipped with a smoke sensor and camera is proposed. The proposed 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.

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. For these reasons, several works employ approaches based on sensors that analyze environmental parameters. In [17], the authors 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.

The automatic fire detection system proposed in [18] includes two sensors: smoke sensor MQ-2 with very high sensitivity toward propane, methane, LPG, smoke, alcohol, carbon monoxide and hydrogen; fire sensor. These 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. In [19], a monitoring system based on a WSN composed of multi-sensor devices, a solar charging mechanism and a wireless transmission module is proposed. The device acquires environmental information regarding temperature, humidity, smoke, and methane every 15 minutes and then transmits it to the base station where it is stored, processed, and analyzed and then, if necessary, contacts the Civil Defense.

III. System Architecture

A. The DMR hardware system

This section describes in detail the components used to realize DMR nodes and the DMR gateway. The DMR node consists of a board, a charge controller, rechargeable batteries, and a small solar panel, making the individual node totally energy autonomous. The transmission standard is DMR, according to the standard currently used by civil defense.

- the **4FM YSF NXDN DSTAR P25 DMR module** is 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.
- a **solar panel** (10W 6V 1700mA 260x140x2.5mm) 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

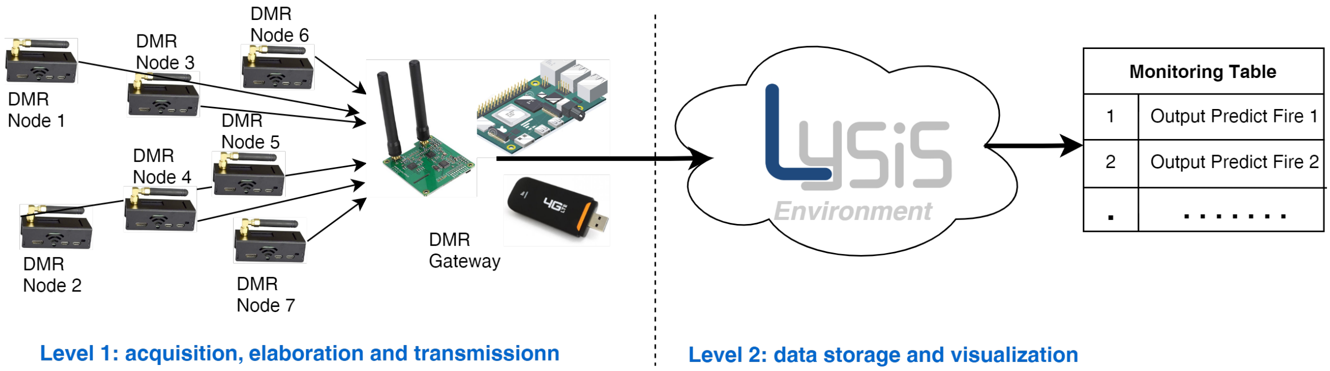

Fig. 1: General view of the DMR system with Lysis platform for real time monitoring and alert.

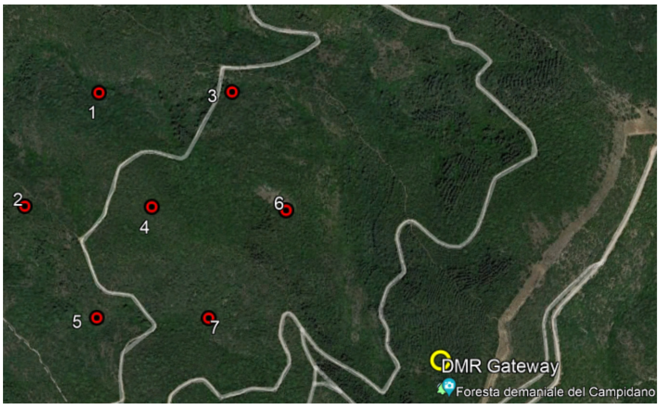

Fig. 2: The scenario employed in a mountain area for preliminary testing using 7 DMR nodes and DMR gateway within an area of 1 km^2.

with SMA Antenna. This shield houses on a Raspberry Pi 4 connected to the cloud through 4G LTE network.

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.

B. The software architecture

The proposed system consists of 7 DMR nodes working independently of each other. Each node is equipped with sensors for detecting forest fire smoke in addition to other useful parameters for studying dynamics such as temperature, humidity, atmospheric pressure, UV index. The nodes are mainly in deep sleep mode to preserve batteries and limit power consumption. A wake-up is triggered every 5 minutes to acquire sensor data, perform a packet processing and, finally perform DMR wireless transmission of the acquired data. The DMR gateway collects information from all DMR nodes and transmits the data to a Social IoT (SIoT) platform called Lysis, using the 4G LTE network. Lysis is a SIoT platform carried out for distributed IoT applications involving socially connected objects [20]. Objects are capable of establishing social relationships in an autonomous way with respect to their owners with the benefits of improving the network scalability and information discovery efficiency [20].

The overall architecture of the Lysis platform through four functional levels:

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

To take advantage of the Lysis architecture, the virtualization layer elements (SVOs) representing DMR nodes were designed and implemented. Each DMR node has its own SVO with which it communicates to send and record information relating to smoke levels and other useful parameters.

A Recurrent neural network (RNN) was developed within Lysis for fire case detection through training performed in the field through simulations of fire and smoke propagation. Lysis collects sensor data and processes it through continuous comparison with previously stored data. The DMR nodes have social relationships to enable greater identification of hazardous situations. Outliers are processed mathematically to avoid false positives and create warning situations. The proposed work has the following strengths:

1) DMR-SVOs have been developed for data management and social relations between nodes, by removing the cases of false positives and false negatives that would generate false alarms;
2) at the software level, nodes that do not receive an ack from the DMR gateway can exploit closer nodes to implement multihop techniques;
3) all transmissions occur according to the DMR long range standard, overcoming the limitations of poor Wi-FI and 4G LTE coverage over rural and mountainous areas.

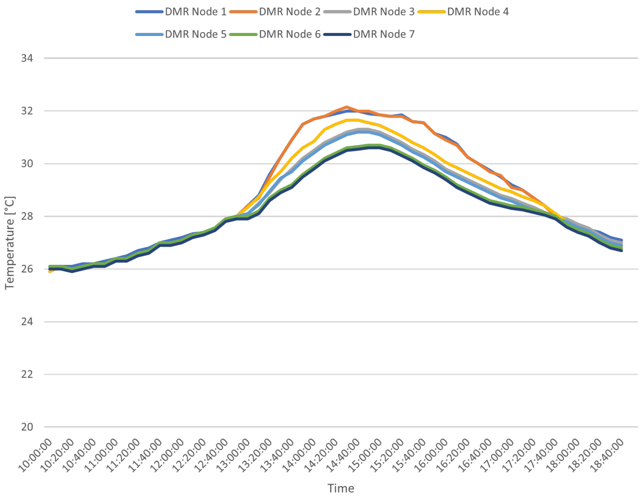

Fig. 3: Trend of temperatures detected by the various DMR nodes due to the presence of a fire with WNW origin.

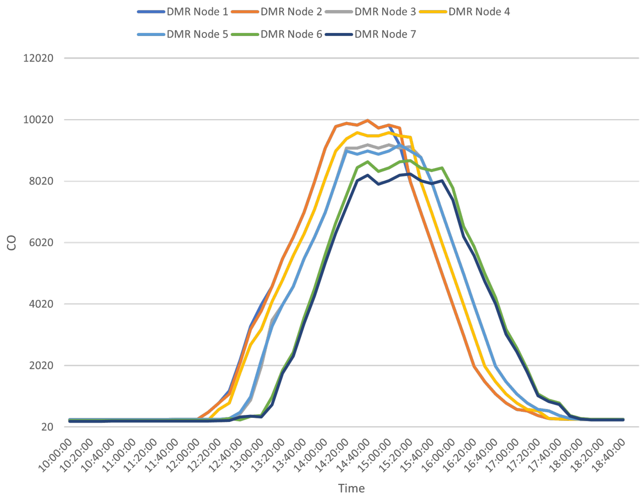

Fig. 4: Trend of CO detected by the various DMR nodes due to the presence of a fire with WNW origin.

IV. System Implementation

A. Scenario

The scenario employed for the preliminary tests has been depicted in Fig. 2. The identified region is located in Sardinia (Italy) in the mountainous area "Campidano State Forest" at 500 meters above sea level. The area has several elevation profiles typical of the region and is characterized by "maquis" type vegetation. The nodes were placed as in the figure, on tree trunks at a height of 5 meters above the ground. The arrangement of the nodes allows the detection of fire smoke from any direction. The tests were conducted on a "mistral" type wind day with west/northwest (WNW) direction. The smoke source was positioned WNW with respect to the proposed scenario so that nodes 1 and 2 were the first to be involved in smoke reception. Then the detections were reported by nodes 3, 4 and 5, and finally by nodes 6 and 7. The detection timeline plays a very important role in determining the direction of origin of the fire front. Typically, the first nodes to notice the smoke are also the ones closest to the fire, so they are critical for identifying the direction of the fire and implementing appropriate countermeasures.

B. Results

The hardware/software system was tested within a real-world scenario where DMR nodes periodically transmitted sensed data to the gateway. The DMR gateway transmitted the data in temporal time to the cloud where it is processed and represented graphically. Smoke propagation situations were artificially created from burning of organic material of the brushwood type. DMR nodes detected an increase in temperatures and a surge in CO and CO2 values at the same time as the values were acquired. As we can appreciate in Fig. 3, the tampering trend of the 7 DMR nodes shows an overlap in the first part of the graph, in the time range from 10:00 a.m. to 1:10 p.m. The BME688 sensors were tested in the laboratory in a controlled environment before being placed in an outdoor environment, without showing deviations other than those stated by the manufacturer. At 1:00 p.m., the fire source positioned WNW relative to the system of the 7 DMR nodes positioned as in Fig. 2 was activated. The tests were conducted on a mistral wind day with the same direction in which the fire source was positioned. This aspect was crucial in assessing the worst-case scenario in which emergency responders would be faced with the emergency. The system readily returned responses by detecting not only a rise in temperatures due to the presence of hot air caused by the fire, but accentuated differences in temperatures detected by DMR nodes. In fact, the nodes closest to the source (i.e., 1 and 2) were the first to detect the temperature rise. Similarly, the remaining nodes farthest from the source also "noticed" that there was an external heat source affecting the normal daily temperature trend. The greater the distance of the nodes, the lower the temperature rise, as shown for DMR nodes 3, 4, 5 compared to nodes 1 and 2. Similarly it is verified for node 7 compared to node 6, and for node 6 compared to nodes 3, 5 and 4. The second consideration concerns the peaks of the individual curves. The shorter the distance between the DMR node 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 node, 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. 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 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, due to low wind intensity, the nodes furthest from the smoke source detect concentrations with a delay compared to the nearest nodes. In the figure,

TABLE I: RNN confusion matrix

Real Data	Predicted Data		
		Fire detection	***Fire absence***
	Fire detection	96.78	1.54
	Fire absence	3.12	98.46
	Sum	100	100

the rightward shift of the nodes moving away from the fire source can be seen. Concomitantly with the temperature readings, CO data were processed to make a prompt detection of fire criticality by determining its propagation speed, and direction. These aspects allow the detection center substantial time savings in initiating the rescue machine and all policies necessary to fight and extinguish forest fires in the shortest possible time. The data of temperature, humidity, CO and other environmental parameters represent the input of the RNN, which is continuously retrained based on the outputs produced. Dynamic environmental conditions make it necessary to continuously adapt the network inputs to limit instances of false positives or false negatives, greatly increasing the success rate of fire detection decision making. As shown in Table I, the RNN returns a correct detection of fire smoke with a percentage of 96.78%, and a correct detection of no fire of 98.46%.

V. CONCLUSIONS

The suitably placed DMR nodes within the forest area of interest, collect parameters such as temperature and CO variation are detected. The values detected by the various nodes are interpreted within the SIoT Lysis platform using a RNN, which returns real-time alerts when appropriate conditions occur. The system is able to calculate the progress of the fire front and its direction through a social analysis of the data detected by the various nodes. The system was tested and trained in a real outdoor scenario demonstrating the effectiveness of the system.

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