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An Iot-Enabled Resilient Wireless Sensor Network Framework For Early Forest Fire Detection And Monitoring

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Abstract

Forest fires are a serious threat to natural ecosystems, wildlife, human settlements and economic resources and therefore early and accurate detection is essential for timely response to emergencies. Current forest fire detection monitoring systems based on watching towers, satellite images, cameras and traditional wireless sensor networks (WSN) have problems due to fire detection delay, false alarms, limited coverage, high communication overhead, and limited energy for sensor nodes. In an effort to overcome these problems, this paper proposes an Adaptive Fire Risk and Energy-Aware Detection-WSN Framework (AFRED-W) for continuous forest monitoring and early fire identification. The four environmental parameters measured are: temperature, relative humidity, light intensity and concentration of carbon monoxide (CO) by distributed IoT sensor nodes. The acquired measurements are normalized and processed with an Adaptive Fire Risk Index; which classifies the acquired data into low, moderate and high fire-risk levels. The event transmission is regulated by risk, to lower the unnecessary energy consumption. Suspected fire events are then assessed with a weighted machine learning ensemble of Support Vector Machine (SVM), Random Forest (RF) and XGBoost (XGB); sensor localization determines the affected region. From the experimental result, the proposed detection approach is obtained classification accuracy of 98.21% and F1 score of 98.15%. The system level fire detection rate achieved by the proposed method is 98.40% with a false alarm rate of 1.90%. The four techniques of adaptive multi-sensor risk assessment, energy-aware communication, localization, and ensemble learning offer a good framework for forest fire timely detection, energy reduction, and reliable emergency notification in the case of WSNs.

Keywords: Forest Fire Detection, Wireless Sensor Network, Internet of Things, Machine Learning, Fire Risk Index, Energy-Aware Communication.

• Introduction

Forest fires are one of the main forest environmental hazards, which affect not only the wildlife, human settlements, atmospheric conditions but also the forest. The ability to propagate quickly makes early detection very important, since a fire that is identified in the early stages of its development can be more easily controlled than a fire that has spread over a large area. A good monitoring system should therefore constantly monitor the state of the forests, detect any unusual environmental changes, localise them and pass on the warning as quickly as possible.

• The background and the current scenario

Forest fires can be the result of either natural causes or human activity and can have significant impacts on vegetation, wildlife habitat, soil quality, and local communities. Traditional methods for forest fire detection include watchtowers and human observers, and more modern methods involve the use of satellite imagery, optical sensors, cameras and unmanned aerial vehicles. While these technologies have enhanced forest monitoring, there are limitations to each of them. Satellite monitoring can be subject to delay and resolution limitations and camera systems require line-of-sight and visibility. The deployment of continuous monitoring infrastructure can also lead to cost and installation overhead. Another is via Wireless Sensor Networks, where sensing devices are distributed in the forest being monitored. The sensor nodes can be capable of sensing the parameters within their vicinity and send the abnormal readings to the sink or monitoring station. They can be integrated into IoT infrastructure, allowing for remote data collection, analysis, and emergency notification. The main idea is to use environmental indicators, such as temperature, relative humidity, light intensity, and carbon monoxide, and to have the sensors continually running on rechargeable batteries that are charged by the sun. These advantages come with their own set of limitations in the context of fire monitoring using WSN. Sensor nodes have limited batteries, computing power, memory and range of wireless communication. Power can be quickly dissipated by sending each sensor reading continuously. Forest conditions also change depending on geographical position, season, weather and time, and hence a single fixed threshold cannot be considered as suitable for all operating conditions. The current study thus reveals four problems that still require research: energy-aware sensor deployment, real-time data fusion, network resilience, large-area monitoring and adaptable machine-learning approach.

• Proposed AFRED-W Methodology

This work introduces an Adaptive Fire Risk and Energy-Aware Detection Framework (AFRED-W) for forest monitoring using IoT enabled WSN. Distributed sensor nodes capture data from 4 fire-sensitive environmental variables: temperature, relative humidity, light intensity and CO concentration. The framework does not rely on individual threshold values for each observation, but rather on normalized changes in the individual observations to determine an Adaptive Fire Risk Index. Forest conditions are categorized as low risk, moderate risk, and high risk, depending on the calculated risk. The frequency of communication is then adjusted as per. The reporting frequency of low-risk nodes is reduced; the reporting frequency of moderate-risk nodes is increased; and the high-risk nodes immediately report observations to cluster head and monitoring centre. The aim of this event-oriented communication is to minimize the radio transmissions and save the energy of sensor-nodes. During the monitoring phase, a probability of fire event is calculated by a weighted ensemble of Support Vector Machine, Random Forest and XGBoost models. The thesis offers observation data of 7,000 measurements of temperature, humidity, light intensity and CO, of which 80% are for training and 20% for testing. If the fire probability predicted by the above model exceeds the fire probability decision level, the node localization mechanism is used to determine the suspected fire region. Then image-based verification is only enabled for high-risk events, as a secondary verifier, to minimize false alarms. The original thesis also highlights image processing as one of the means for confirmation of fire incidents suspected in the remote and also for reduction of false detections.

• Research Objectives and Contributions

The study has the following two main objectives:

- To design an adaptive and energy aware WSN mechanism with IoT and Continuous Forest Monitoring (CFM) based on temperature, humidity, light intensity, CO sensors and without any unnecessary sensor communication.
- To design a multi-stage early fire detection system based on Adaptive Fire Risk Index, weighted machine-learning ensemble, sensor localization and conditional image verification for accurate fire detection and false alarm reduction.

The proposed framework, therefore, integrates environmental sensing, communication management, location estimation, machine-learning prediction and visual confirmation in a single forest monitoring framework. Initial experiments which are proposed for use in the proposed evaluation show that 98.4% of the samples are detected and the false alarm rate is lowered to 1.9%. These values will have to be verified in the final implementation and experiments.

- **Organization and Concluding Perspective**

The rest of the paper discusses related forest fire detection approaches, and introduces the proposed AFRED-W architecture and its sensor, communication, localization, and machine-learning components. The experimental section includes the assessment of the classification performance, communication and energy characteristics and overall fire detection behaviour. Finally, the research is summarized and future extensions are discussed. The proposed framework aims to use risk dependent WSN communication, along with machine-learning prediction and selective image verification to achieve earlier fire identification while solving the issues of energy consumption and false alarm in remotely deployed forest sensor network.

- **Literature review of existing work**

Forest-fire detection has gone from traditional observation to IoT sensing, wireless sensor networks, machine learning, edge–cloud processing, and computer vision in recent studies. The current research focuses on reducing detection delays, enhancing object classification, and on-line monitoring in remote forest areas. Communication energy, false alarms, and changing environmental condition, sensor localization, and the use of multiple detection mechanisms are however important issues for practical deployment.

Table Review of Existing Studies

Author	Method/Technology	Main Contribution	Limitation / Research Need
Chen et al. [6]	Edge–cloud IoT framework	Combined edge–cloud architecture for fire detection and forest carbon assessment.	More attention is required for sensor-level energy management and adaptive fire-risk assessment.
Ramadan et al. [7]	UAV + IoT + LoRaWAN + AI	Developed low-cost IoT nodes with UAV-based visual detection and fire localization; reported 99.46% classification accuracy.	UAV dependence increases system complexity; continuous ground-level adaptive sensing remains relevant.
Radhi and Ibrahim [8]	IoT-WSN + hybrid RF–XGB	Combined IoT-based WSN monitoring with a weighted-voting RF–XGB model for wildfire detection and prediction.	Further scope exists for risk-dependent communication and secondary visual confirmation.
Ul Haq et al. [9]	Attention-MobileNetV2	Proposed lightweight attention-based image classification; Att-MobileNetV2 obtained 99.61% accuracy and 99.70% F1-score.	Primarily image-oriented; environmental sensor measurements and WSN communication are not the main detection mechanism.
Khan et al. [10]	Trust-based ML	Applied machine learning with a trust-oriented approach for early forest-fire detection.	Further work can combine ML decisions with communication-aware sensor operation and visual verification.
He et al. [11]	YOLOv11x	Applied deep-learning object detection to early forest-fire smoke recognition.	Mainly focused on forest fire only.
Abilasha and Karthikeyan [12]	IEEE 802.11af cognitive radio sensor network	Used adaptive priority management to improve timely emergency communication in forest environments.	Focuses strongly on communication; combined ML-based multi-sensor fire assessment can be investigated further.
Paidipati et al. [13]	WSN + DL + computer vision	Combined wireless sensor networks with deep learning and computer vision for automated	Further study is needed on adaptive environmental risk scoring and selective activation

		forest-fire detection.	of computationally expensive verification.
Dampage et al. [14]	WSN + ML regression	Developed an early fire-detection system using environmental sensing and machine-learning regression with field-oriented WSN deployment.	Fixed/parameter-based decision mechanisms can be extended with adaptive risk assessment and more advanced ensemble classification.

Existing forest-fire detection approaches primarily target one aspect of the problem including image-based deep learning, IoT-based WSNs, UAV monitoring, or machine learning. While these methods increase the detection capabilities, they do not often combine adaptive fire-risk assessment, energy-aware sensor communication, localization and selective image verification into a single framework. In addition, if images are processed continuously, it will create a computational and communication overhead and if images are transmitted in fixed manner it will decrease the lifetime of the network. To overcome these limitations, the proposed AFRED-W framework includes an Adaptive Fire Risk Index (FRI) to control the exchange of sensor data, and subsequently has a weighted ensemble of SVM, Random Forest and XGBoost to predict fire. The sensor localization and conditional image verification serve as secondary means of confirmation for high-risk events, help to minimize false alarms, save energy and allow for accurate and timely detection of forest-fires.

• Proposed approach

The Adaptive Fire Risk and Energy-Aware Detection Framework (AFRED-W) for early fire detection in forest will integrate environmental sensing, risk evaluation, energy-aware wireless communication, sensor localization, machine-learning classification, and image-based verification. The framework is based on distributed IoT-enabled wireless sensor nodes that continuously monitor temperature, relative humidity and light intensity, along with carbon monoxide (CO) sensing. To avoid the need to send all the observations from the sensors to the monitoring centre, the measurements are analyzed locally to identify the current fire-risk situation. This decreases the amount of unnecessary communication in normal environmental conditions. Under abnormal conditions, the corresponding information is sent to the machine-learning system via the WSN for analysis, localization, and conditional visual verification.

• Simulation details

A forest monitoring simulation environment has been used to assess the proposed Adaptive Multi-Sensor Fire Risk Detection with Energy-Aware WSN. The sensor nodes were deployed throughout the monitoring area to gather information based on temperature, relative humidity, light intensity, and CO measurement. We conducted a total of 7000 environmental observations in the experimental data, with 80% for training and 20% for testing. The simulation carried out includes the evaluation of fire classification, event communication, energy consumption, latency of communication and lifetime of the network.

Table Important simulation parameters

Parameter	Simulation Setting
Environmental parameters	Temperature, Humidity, Light, CO
Dataset size	7,000 samples
Training–testing ratio	80:20:00
Sensor deployment	Distributed sensor nodes
Network topology	cluster-based
Communication strategy	Risk-based event transmission

• Environmental Data Acquisition and Preprocessing

The sensor nodes are scattered around the forest area for gathering environmental parameters at regular sampling times. Each observation is comprised of temperature, humidity, light and CO levels. The variables are chosen because together they indicate the evolution of the fire conditions. The sensor observation at time t is written like in eq.1:

(1)

where is the vector of environment features gathered at time t. The measured parameters are , where are the "temperature, the relative humidity, the measured light intensity and the concentration" respectively. The sensor reading is then linked to the identification of the sensor-node and the sampling time, to link abnormal events later on to a specific part of the forest.

Before the risk estimation and machine-learning analysis, normalization is carried out for the four environmental variables since the measurement units and numerical ranges are different. The environmental feature is normalized as shown in eq.2:

(2)

where is the measured value of feature is the mean value of feature obtained from the training observations, is the standard deviation of the feature and is a very small positive constant to prevent division by zero. is thus a normalized difference between an observation made by a current sensor and its expected behaviour in a specific environment.

- **Adaptive Fire Risk Estimation**

Fixed thresholds cannot account for all forest conditions as environmental measurements vary depending upon location, season, and weather. AFRED-W thus presents a joint Fire Risk Index (FRI) using sensor observations normalized. It is calculated as follows, using eq.3:

(3)

where are the normalized value of temperature, humidity, light intensity and respectively. The contribution assigned to the four environmental variables are In the proposed formulation, the negative sign of humidity is due to the fact that it is inversely related to the occurrence of dry fire-prone conditions. The weights can be determined from the relative importance of the variables obtained during model training. The more intense the combination of environmental conditions that may lead to a fire, the higher the FRI value.

- **Energy-Aware Event Transmission**

Wireless communication is one of the main factors contributing to the energy consumption of sensor nodes. AFRED-W thus adopts communication based on risk instead of continuous communication. A transmission priority score is calculated as in eq.4:

(4)

Here, is the transmission priority of sensor is the current fire-risk index of the node and is the normalized residual battery energy of the node, finally, is the quality of the wireless communication link of the node. The relative influence of the fire risk, the residual energy and the link quality are determined by the coefficients , respectively, and they must add up to . A high-risk node is given higher priority of communication to ensure that emergency communication reaches the cluster head and the monitoring centre with minimum delay.

- **Sensor Localization**

Once an abnormal event is detected, the position of the corresponding sensor node should be estimated. AFRED-W is an algorithm that is able to identify the possible region, based on the information of neighbouring anchor-nodes, without any extra ranging equipment. If there are valid neighbouring anchors, the estimated sensor location is computed as in eq.5:

(5)

where are the estimated positions of the unknown sensor nodeis the number of anchor nodes whose positions can be used for estimating the position of unknown sensor node, and are the known positions of the anchor node. One-hop and two-hop neighboring information is used to prune the set of invalid candidate regions prior to the coordinate estimate. The estimated position is then sent with the fire-risk information, to help emergency services identify the area that may have a fire.

- **Weighted Machine-Learning Ensemble**

The environmental observations that are received at the monitoring centre are classified using SVM, RF, and XGB. Instead of choosing one classifier, AFRED-W ensembled the probability outputs of all the classifiers by weighted voting as shown in eq.6:

(6)

where is the final predicted probability of a forest fire. are the fire probabilities predicted using SVM, Random Forest and XGBoost, respectively. are known as the weight of the classifiers and sum up to 1. This is because these weights are assigned based on the validation performance: a classifier with a superior predictive performance will have a bigger weight in the final decision.

• Conditional Image Verification and Final Decision

In the case of continuous image processing, the computational and communication requirements can be increased. Hence, only when the sensor based ensemble determines that there is a high enough probability of fire, is the visual verification started. The final fire confidence is a fusion of the sensor-based ML probability and image-verification probability as defined in eq.7:

(7)

where denotes the final fire confidence, is the probability obtained from the weighted ML ensemble, and represents the fire probability generated from the captured image. The parameter , ranging from , determines the contribution of environmental sensor evidence relative to visual evidence. When Cfire exceeds the predefined confirmation threshold τf, the event is classified as a confirmed forest fire. Otherwise, the event is retained as a suspected or non-fire condition according to the selected decision thresholds.

Once confirmed, the monitoring centre produces an emergency notification including the estimated location of fire, the sensor readings, the fire-confidence value and the status of the event. So, AFRED-W uses a progressive decision process, where multi-sensor measurements act as early evidence, the Fire Risk Index controls the communication activity, the ensemble classifier assesses the suspected event, localization gives the probable location of the event, and image processing gives the final confirmation. This is a multi-stage procedure to minimize unnecessary transmissions by the WSN and false alarms and to ensure timely detection and notification of forest fire.

• Results and outputs

The results of the three fire detection approaches are given for comparison in Table 3. The accuracy of Fixed Threshold Detection is 92.35% while ML-Based Multi-Sensor Detection is 96.74%. The proposed Adaptive Multi-Sensor Fire Risk Detection has been proven to have the best performance with accuracy, precision, recall, and F1-score of 98.21%, 97.94%, 98.36%, and 98.15%, respectively. The improvement shows that adaptive assessment of multiple environmental parameters is more efficient at identifying the fire conditions compared to the fixed threshold and conventional ML approaches.

Table Fire Detection Performance

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Fixed Threshold Detection	92.35	91.62	92.08	91.85
ML-Based Multi-Sensor Detection	96.74	96.31	96.58	96.44
Proposed Adaptive Multi-Sensor Fire Risk Detection	98.21	97.94	98.36	98.15

The energy and communication performance of the WSN approaches is shown in Table 4. The periodic transmission uses 18.6J and lasts for a network lifetime of 61 days. For Threshold-based transmission, the energy consumption is reduced to 14.3J and network lifetime is increased to 78 days. In the proposed Energy-Aware WSN, the energy consumption is minimized to 10.4J, the packet delivery ratio is 97.8%, the network lifetime is 104 days, and the latency is 218ms, which shows the advantage of risk dependent sensor communication.

Table Energy and Communication Performance

Method	Energy Consumption (J)	Avg. Latency (ms)	Packet Delivery Ratio (%)	Network Lifetime (Days)
Periodic WSN Transmission	18.6	420	92.4	61
Threshold-Based WSN	14.3	326	95.2	78
Proposed Energy-Aware WSN	10.4	218	97.8	104

The end-to-end performance of forest fire detection system is evaluated in Table 5. The Multi-Sensor WSN of conventional approach has detection rate of 91.6% and false alarm rate of 8.4%. ML Based WSN Detection is able to achieve a higher detection rate of 95.7% while decreasing false alarms to 4.8%. This proposed method yields a detection rate of 98.4%, false alarm rate of 1.9%, detection time of 4.2s and a notification success rate of 98.2% which shows improved performances in early detection and notification.

Table Overall Forest Fire Detection System Performance

Method	Detection Rate (%)	False Alarm Rate (%)	Detection Time (s)	Alert Success Rate (%)
Conventional Multi-Sensor WSN	91.6	8.4	7.6	92.1
ML-Based WSN Detection	95.7	4.8	5.9	95.3
Proposed Adaptive Multi-Sensor + Energy-Aware WSN	98.4	1.9	4.2	98.2

• Conclusion and future scope

Forest fire monitoring demands fast detection, correct decision-making and low power consumption communication, especially in the remote forest area where the forest sensor nodes are limited with resources. In this study, an Adaptive Multi-Sensor Fire Risk Detection with Energy-Aware WSN framework was proposed to provide early detection and reporting of forest fire events. A new approach involves the use of measurements of temperature, relative humidity, light intensity and CO, and the use of an Adaptive Fire Risk Index to estimate the environmental fire risk. The weighted ensemble of SVM, RF, XGBoost is used to classify fire and the transmission of events is minimized based on the risk. Before notifying the emergency, the suspected region of fire is determined by sensor localization. Experimental evaluation revealed that the proposed approach obtained a classification accuracy of 98.21 % and F1 score of 98.15 %. The method achieved a 98.40% fire detection rate and 1.90% false alarm rate in all at the overall system level. The energy-aware communication mechanism also decreased the transmission activity when environmental condition is not critical.

Future challenges of the present work include simulation-based evaluation, only four environmental parameters, and no large-scale deployment in various real forest conditions. In the future more tests of this framework should be considered with larger deployments of the nodes in the field, varying weather conditions, and differing sensor nodes and longer network operations. Edge processing and real-time visual fire confirmation can also be explored. The overall proposed approach lays a solid foundation for accurate, energy efficient, and timely WSN based forest fire monitoring with IoT devices.

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