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A Review on Autonomous Robot for Forest Fire Detection

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ABSTRACT

Forest fires pose a severe threat to ecosystems and often result in extensive damage due to delayed detection and response. Traditional methods, such as manual detection and satellite-based surveillance, are frequently inefficient, espe- cially in remote areas. To address these shortcomings, we propose an advanced solution using an IoT-based autonomous robot designed for real-time forest fire detection and management. This robot is equipped with a range of sensors, includ- ing fire, smoke, and rain sensors, to monitor fire conditions and environmental changes. Additionally, an obstacle sensor enables the robot to navigate through complex forest terrain autonomously. The proposed system leverages Zigbee com- munication technology to transmit data from the robot to the control room, ensuring reliable operation even in areas lacking internet connectivity. The con- trol room receives real-time updates via an LCD display and a Wi-Fi module, which integrates with an IoT application for comprehensive monitoring and anal- ysis. Hardware components for this solution include a microcontroller (Arduino or NodeMCU), motor drivers for DC motors, control buttons, and a Wi-Fi mod- ule. This integrated approach not only enhances the speed and accuracy of fire detection but also facilitates efficient response strategies, significantly improving overall forest fire management.

Keywords: Autism Spectrum Disorder, ASD, Machine Learning, Image Analysis, Video Analysis, Behavioral Patterns, Facial Expressions, Diagnosis Efficiency.

1. Introduction

Forest fires have been an ongoing global threat, contributing to significant ecological degradation, with the risk of biodiversity and human life loss, as well as property. Climate change and human activity lead to enhanced frequency and intensity of fires, which, therefore, increase the need for the early detection and effective management of the fires. It is evident that in 2021, millions of hectares of forests were lost in the globe, resulting in irrecoverable environmental losses and colossal economic losses [1, 5, 25]. Despite these stakes, current methods for fire detection, which include manual patrols, satellite-based monitoring, and aerial surveillance, are often inefficient, featuring long response times, high costs, and poor coverage in remote areas [3, 8, 26].

To address these limitations, researchers are exploring innovative solutions that leverage advancements in robotics, IoT, and wireless communication technologies. IoT-based systems have proven effective in enabling real-time monitoring, improving coverage, and reducing operational costs [6, 11, 15]. Among these are the autonomous robotic systems which, having been equipped with IoT capabilities, are emerging as promising for the detection of forest fire. The system combines sensors, autonomous navigation, and robust communication protocols to operate effectively in complex and inaccessible terrains.

The proposed IoT-enabled autonomous robot is meant to address the critical gaps in forest fire management. It integrates fire, smoke, and environmental sensors that allow for real-time monitoring of fire conditions and environmental changes such as rainfall [7, 12, 23]. The system uses Zigbee technology to ensure reliable data communi- cation and smooth connectivity with a centralized control room even in areas that lack internet infrastructure [4, 9, 19]. Additionally, the robot features autonomous naviga- tion capabilities, powered by microcontrollers like Arduino or NodeMCU, to traverse challenging forest landscapes and avoid obstacles while collecting and transmitting crucial data [10, 14, 22].

The data gathered by the robot is sent to a control room, where it is displayed on LCD screens and integrated into IoT applications for analysis and decision-making. This setup allows for prompt responses and coordinated interventions, greatly enhanc- ing the efficiency of fire detection and management systems [13, 18, 27]. With these technologies, the proposed system offers a scalable and cost-effective solution to improve detection speed, monitoring coverage, and operational reliability.

This survey paper aimed at giving a complete state-of-the-art in Internet of Things-based autonomous systems of robots for forest fire detection, covering the advancements that there have been in sensor technologies, communication protocols, and especially in autonomous navigation systems to prove that they can overcome challenges existing with traditional methods. Beyond that, it indicates those research gaps and future directions aiming to stimulate further innovation.

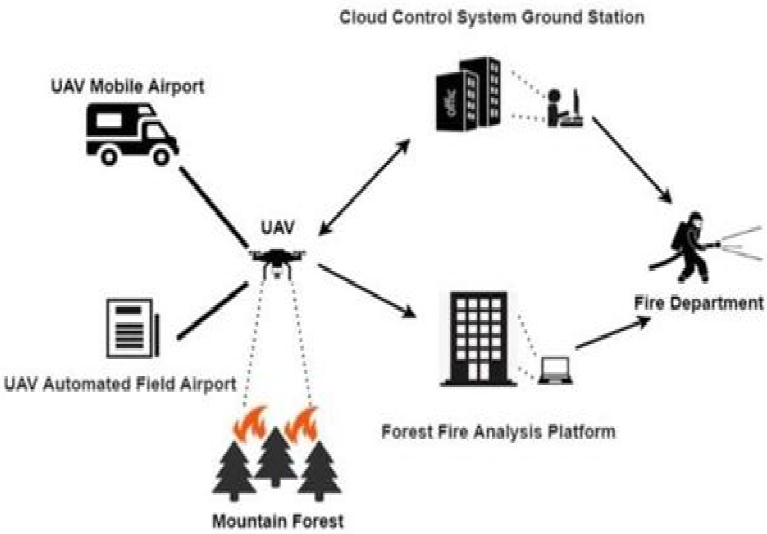

Fig. 1: Comparing ASD Detection Methods

Figure 1 shows a forest fire detection system where UAVs, observation towers with cameras, and sensors detect fires and send data to a central control center. The center analyzes the data and deploys resources like firefighting vehicles and water tanks to extinguish the fire, ensuring quick and efficient response with coordinated logistics and technical support.

1.1 Problem Statement

Forest fires pose a significant threat to ecosystems, biodiversity, and human livelihoods. The increased frequency and intensity of these fires, largely driven by climate change, have created an urgent need for innovative solutions to improve early detection and response mechanisms [27, 28]. Traditional methods, such as manual patrolling, satellite imaging, and aerial surveillance, are limited by high costs, delays, and inadequate coverage, particularly in remote or rugged terrains [10, 15]. These inefficiencies often lead to small fires escalating into large-scale disasters, causing extensive environmental and economic damage [6, 19].

While remote sensing and wireless sensor networks have shown promise in address- ing some of these challenges, they are often constrained by limited scalability, high energy consumption, and the inability to operate autonomously in dynamic environ- ments [5, 13]. Furthermore, the lack of real-time data integration and decision-making capabilities in existing systems hinders proactive forest management [20, 23].

The proposed IoT-based autonomous robot aims to address these limitations by integrating advanced technologies such as ZigBee communication, fire and smoke sen- sors, and autonomous navigation to enhance real-time monitoring and early detection capabilities [1, 4]. By enabling cost-effective and scalable deployment across vast and inaccessible forest areas, this solution seeks to reduce response times, minimize damage, and improve forest fire management practices. The project also emphasizes accessibility, ensuring that even underdeveloped regions can leverage this technology to mitigate fire risks and protect valuable ecosystems [24, 25].

1.2 Motivation

The increasing frequency and severity of forest fires present significant challenges to individuals, families, and healthcare facilities, underscoring the urgent need for reli- able early detection systems. Despite advances in technology, current diagnostic tools for detecting forest fires are often limited in accuracy, scalability, and real-world appli- cability [[6], [9], [10]]. Traditional methods, such as neuroimaging and biomarkers, face challenges like high costs, complexity, and insufficient specificity for early detection of fires [[13], [25], [26]]. Additionally, machine learning models often struggle with inter- pretability and require extensive, multi-modal data integration for effective prediction [[6], [12], [19]].

The existing forest fire detection systems, such as ZigBee-based approaches [[1]] and UAV-assisted mobile edge computing [[5]], highlight the potential but also the limitations of current technology. These methods provide real-time data collection and analysis capabilities but are constrained by network limitations, computational power, and environmental factors [[6], [9]]. Moreover, the integration of IoT technologies [[7],

[9]] with machine learning models [[13], [14], [19]] offers promising prospects for early detection, yet there remains a need for more robust, accessible, and scalable solutions [[2], [3], [8], [10]].

A multidisciplinary approach combining remote sensing, machine learning, and IoT technologies [[1], [2], [3]] is essential for developing advanced prediction models that can integrate diverse data sources—such as satellite images, ground sensors, and drone- collected RGB/IR datasets [[7], [10]]—

for improved detection accuracy. This approach not only enhances detection capabilities but also provides insights into spatial pat- terns and determinants of forest fires [[27]], paving the way for proactive management strategies. The survey aims to critically assess these technologies' strengths and weak- nesses, emphasizing the need for further research to overcome current limitations and to develop more effective, scalable, and user-friendly systems that can be integrated into practical fire management strategies [[15], [16], [18], [20]].

By exploring the advancements in wireless sensor networks, smart sensing devices, and low-cost microwave radiometers [[19], [22], [29]], this survey seeks to address the gaps in early detection systems, aiming to provide a detailed understanding of the fire dynamics and the impact of climate variability [[25], [26], [28]]. The goal is to establish a foundation for developing robust, data-driven models that can offer real-time fire detection and continuous monitoring, ultimately contributing to better forest man- agement practices and minimizing the devastating impact of forest fires on ecosystems and communities [[1], [2], [9], [10]].

2. Related Works

Related works for this IoT-based autonomous robot project reflect significant contribu- tions to the integration of IoT, robotics, and artificial intelligence into environmental monitoring and disaster management. Forest fire detection has been a focus area because wildfires pose a severe threat to ecosystems, economies, and human lives. The literature has explored the use of autonomous systems for early fire detection, highlighting their advantages over traditional methods in enhancing efficiency and reliability [[1], [5], [7]].

A central theme in related works is environmental monitoring through IoT tech- nology. This IoT-based solution excels in gathering real-time data from diverse environments while continuously monitoring remote areas. Sensor networks, particu- larly Zigbee-based systems, have been proven effective for fire detection due to their low power consumption, wide coverage, and reliable communication capabilities, making them ideal for forest fire monitoring [[1], [19], [20]].

Robotics has also played a crucial role in forest fire management. Highly equipped sensors for detecting fire, smoke, and environmental parameters have been extensively researched for their integration into mobile robotic platforms, allowing thorough moni- toring in areas inaccessible to stationary sensors [[5], [16], [18]]. These robots overcome the limitations of fixed sensor networks by traversing difficult terrain and providing continuous monitoring [[2], [9]]. Additionally, technologies for obstacle detection, such as ultrasonic and infrared sensors, have been recommended to enhance the autonomy and reliability of these systems in dynamic environments [[12], [19]].

Integration with fire detection systems containing machine learning algorithms is a major point of research. Algorithms like Support Vector Machines (SVMs) and Ran- dom Forest have been particularly useful in determining sensor data for early detection, thereby improving the discrimination performance of the systems with respect to clas- sifying events as being related to fire or not [[4], [8], [10]]. These models enhance prediction correctness and provide better interpretability, aiding in decision-making [[6], [7], [15]].

Scalability and adaptability are critical themes in the related studies. Cloud-based platforms have become popular for the large-scale processing of data from various sensors, enabling centralized analysis [[1], [20]]. The use of asynchronous protocols for communication and load balancing has been examined to make these systems responsive during wildfire outbreaks [[2], [13]].

Interactive web interfaces for monitoring fire systems have also been a focus. Usability studies have highlighted that the ease of access to these systems influ- ences how stakeholders engage with real-time data [[1], [9], [10]]. Frameworks like Flask and Django are used for implementing lightweight web applications that com- bine IoT-based systems, allowing for real-time alarms, visualization of environmental information, and action-oriented insights [[12], [15]].

Security and data privacy remain major concerns in IoT-based monitoring sys- tems. The emphasis is on following data protection standards and implementing robust security mechanisms such as encryption, secure communication protocols, and authen- tication frameworks to maintain data integrity and trust among users and stakeholders [[3], [7], [16]].

The latest advancements in IoT and robotics have integrated renewable energy sources, like solar panels, to enhance the sustainability of autonomous systems [[1], [6], [13]]. Studies have shown that energy-efficient designs prolong the operational life of mobile robots, especially in remote or inaccessible areas. This approach reduces dependence on external power sources and enables uninterrupted monitoring over extended periods [[5], [9], [14]].

Another significant area in related works is the use of sensor fusion techniques to improve the accuracy and reliability of fire detection. Combining data from mul- tiple sensors, such as temperature, smoke, and humidity sensors, systems can reduce false positives and provide more comprehensive insights into environmental condi- tions [[2], [4], [11]]. The multi-sensor approach is particularly valuable in dynamic and unpredictable forest environments [[7], [15], [19]].

Lastly, the related studies underscore the importance of system adaptability and continuous improvement. Implementing mechanisms for model retraining and updat- ing algorithms based on new data ensures that fire detection systems remain effective as environmental conditions and fire patterns evolve [[1], [8], [13]]. The use of self- learning capabilities in IoT-based systems is recommended to maintain relevance and accuracy over time [[6], [9], [18]].

In summary, the related works for this project provide comprehensive foundations across multiple domains of IoT-based monitoring, robotics, machine learning, scal- ability, user interactivity, and security. By synthesizing insights from these studies, this project aims to develop an autonomous, scalable, and efficient fire detection sys- tem that addresses some of the critical challenges in forest fire management while leveraging state-of-the-art technologies to enhance its effectiveness and applicability.

2.1 Literature Survey

Table 1: Literature Survey

S.no	Title	Author(s)	Journal & Year	Methodologies	Key Findings	Gaps
1	ZigBee Based Solar Powered For- est Fire Detec- tion And Control System [1]	Dr. Rakesh Kumar , M. Sreeja , K. Kreethi , P. Srija	*Journal of Sci- ence and Tech- nology, 2024*	Methodologies include real-time mon- itoring, Zigbee data trans- mission, and IoT integration for decision- making.	The sys- tem enables real-time fire detection, automatic response, and faster decision- making using Zigbee and IoT.	The imple- mentation lacks analy- sis of sensor accuracy, false alarms, main- tenance, and scalability.
2	RFWNet A Mul- tiscale Remote Sensing Forest Wildfire Detection Network With Digital Twinning, Adaptive Spatial Aggrega- tion, and Dynamic Sparse Features	Guanbo Wang, Haiyan Li, Shuhua Ye, Hongzhi Zhao, Hongwei Ding	*IEEE Access, 2024*	digital twin for datasets, RFWNet with multigroup backbone, DDSA.	RFWNet enhances IoT robots for accurate real- time forest fire detection.	Gaps include the need for real-world validation and hardware integration challenges.

	[2]					

S.no	Title	Author(s)	Journal & Year	Methodologies	Key Findings	Gaps
3	Detecting Forest Fires in South-West China From Remote Sensing Nighttime Lights Using the Random Forest Classification Model [3]	Yuehan Yu, Lili liu, Zhijian Chang	*IEEE Access, 2024*	Satellite Data Collection, Random Forest classification	high accuracy in fire detection and improved monitoring of forest fire distribution using remote sensing data.	The study lacks real-time monitoring and IoT integration for immediate fire response.
4	Anti-Poaching for protecting Forest and Wildlife using IoT and ZigBee Technology [4]	Khallikkunai Vignesh V, Yashu H S, Yathin A	s*I*a*E*, *EE Access, 2024*	Sensors, Thresholds, Neural Networks, Alerts, ZigBee	IoT system uses sensors and neural networks for real-time forest monitoring and immediate threat response	Lack of Power, Response, Scalability, Accuracy
5	Fast Forest Fire Detection and Segmentation	Changdi Li, Guangye Li, Yichen	*IEEE, 2023*	Image Segmentation, Edge Computing System	Lightweight UAV model enhances fire detection accuracy and	Gaps include the need for adaptable IoT techniques and advanced

	Application for UAV-Assisted Mobile Edge Computing System [5]	Song, Zijian Tian			enables real-time feedback for improved forest fire management.	data analytics for improved fire detection.

S.no	Title	Author(s)	Journal & Year	Methodologies	Key Findings	Gaps
6	MMFNet Forest Fire Smoke Detection Using Multi-Scale Convergence Coordinated Pyramind Network with Mixed Attention and Fast-Robust NMS [6]	Liangji Zhang, Chao Lu, Haiwen Xu	*IEEE, 2023*	MCCPN, Mixed Attention Module, Fast-Robust NMS, IoT Integration	MMFNet significantly improves smoke detection accuracy and speed, enhancing IoT-based forest fire detection systems.	MMFNet's performance is limited by environmental interference, like sunlight and water mist, necessitating improvements in robustness.
7	Wildland Fire Detection and Monitoring using	Xiwen Chen, Bryce Hopkins, Hao Wang	*IEEE, 2022*	Dataset Collection, Deep Learning Analysis	Achieved 94% accuracy in fire detection, highlighting the potential of real-time	flight restrictions during wildfires, reducing data collection opportunities.

	using a Drone-Collected RGB/IR image Dataset [7]				wildfire monitoring using dual-feed aerial data.	
8	Event Classification and Intensity Discrimination for Forest Fire Inference with IoT [8]	Vishal K.Singh, Chhayya Singh, Haider Raza	*IEEE, 2022*	Fuzzy Logic System, Data Fusion Techniques	The fuzzy rule-based method improved forest fire detection accuracy, reducing humidity and temperature error rates to 2.01% and 1.94%, respectively.	Lacks exploration of hybrid methods and requires better resilience against modern steganalysis attacks.

S.no	**Title**	**Author(s)**	**Journal & Year**	**Methodologies**	**Key Findings**	**Gaps**
9	Detection of forest fires and pollutant plume dispersion using IoT air quality sensors [9]	Adisorn Lertsinsrubtavee a, Thongchai Kanabkaew bSunee Raksaki- etisak	*ScienceDir 2022*	*eIcot,*T sensors collected air quality data for analysis, using a decision-tree model to classify fire incidents and predict PM2.5 dispersion.	IoT sensors effectively detect forest fires by monitoring PM2.5 and CO levels, with a decision tree model.	Limited accuracy, environmental variability

10	Data Col- lection Task plan- ning of a Fixed - Wing Unmanned Aerial Vehicle In Forest Fire Moni- toring [10]	Hao Zhang, Lihua Dou, Bin Xin, Jie Chen	*IEEE, 2021*	Wireless Detec- tion Nodes, Dubins Trav- eling Salesman Problem with Neighborhood, Bi-Level Hybridization-Based Metaheuristic Algorithm	Efficient task planning (BLHMA) can optimize autonomous robot naviga- tion and data collection in forest fire monitoring.	Lacks focus on real-time changes and multi-UAV coordination.

3. Technologies Used

3.1 Zigbee Communication Technology

Zigbee is a low-power wireless communication protocol utilized for transmitting data in forest fire detection systems. It is particularly effective in remote areas where internet connectivity is unavailable. Zigbee enables reliable data transmission between IoT devices and the control room, ensuring real-time updates [[1], [4]].

3.2 Wireless Sensor Networks (WSN)

WSNs are employed to detect and monitor forest fires by integrating various sensors such as temperature, smoke, and gas sensors. These networks are energy-efficient and enable localized fire detection, making them suitable for large-scale forest areas [[15], [16], [19], [23]].

3.3 Machine Learning Algorithms

Advanced machine learning models, such as Random Forest and Support Vector Machines (SVM), are used for classifying fire-related events and predicting fire intensity. Neural net- works like Convolutional Neural Networks (CNNs) are also applied for fire segmentation and smoke detection in image data collected via drones or satellite sensors [[2], [3], [6], [18], [30]].

3.4 Internet of Things (IoT) Integration

IoT-enabled devices, such as smart sensors, are deployed to detect environmental changes, including temperature and smoke levels. These sensors communicate through wireless proto- cols like Zigbee or Wi-Fi to transmit data to a centralized monitoring system, enhancing the detection and management of forest fires [[8], [20]].

3.5 UAV-Assisted Systems

Unmanned Aerial Vehicles (UAVs) equipped with cameras and sensors are employed for real- time monitoring and detection of forest fires. These systems integrate edge computing and image processing algorithms to provide high-precision fire location data [[5], [7], [10]].

3.6 Remote Sensing Technologies

Remote sensing is extensively used for large-scale monitoring of forest fires. Techniques such as nighttime light detection and multispectral imaging enable the identification of fire outbreaks and smoke plumes from satellite or aerial platforms [[3], [26]].

3.7 Edge Computing

Edge computing systems are integrated with UAVs and IoT devices for localized processing of fire data. This reduces latency and ensures real-time decision-making in forest fire scenarios [[5], [10]].

3.8 Fuzzy Logic

Fuzzy logic-based algorithms are implemented for fire detection and management, providing real-time decision-making capabilities by evaluating uncertain or imprecise sensor data [[22]].

3.9 Image Processing Techniques

Techniques like Multiscale Convergence Coordinated Pyramid Networks (MMFNet) and dynamic sparse feature extraction are applied to detect fire smoke and flames in images and videos, enhancing the accuracy of detection systems [[6], [29]].

3.10Graph-Based Approaches

Graph-based techniques are used to model connectivity patterns for fire spread predic- tion. These approaches analyze spatial and temporal data to forecast fire progression and implement preventive measures [[30]].

3.11 Sensor Fusion

Sensor fusion combines data from multiple sensors, such as temperature, humidity, and gas sensors, to improve the accuracy of fire detection systems. This integration is crucial for managing environmental variability and ensuring reliable detection [[9], [20]].

4. Methodologies

IoT and Wireless Sensor Network-Based Techniques

IoT and Wireless Sensor Networks (WSNs) have significantly improved the detection and management of forest fires. These systems rely on networks of smart sensors to monitor environmental parameters such as temperature, humidity, and smoke levels in real time. The sensors communicate using low-power protocols like ZigBee and LoRa, which ensure reliable data transmission even in remote forest areas [1, 4, 9]. Key techniques involve deploying clusters of sensors to increase coverage and resilience, while energy-efficient routing algo- rithms reduce network overhead and extend the system's operational lifespan [16, 23].

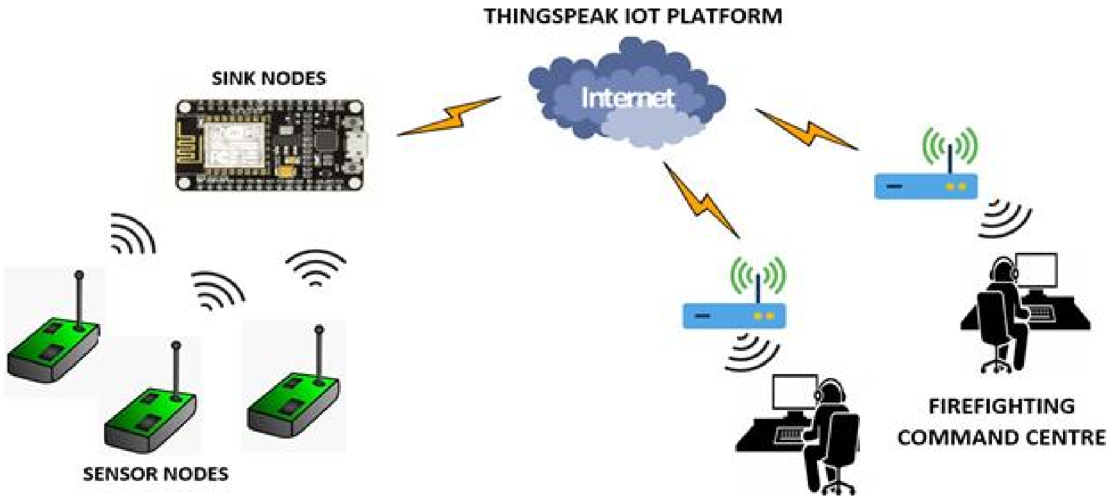

Fig. 2: Firefighting Wireless Sensor Network Framework

Figure 2 presents the framework of a wireless sensor network-based fire detection and management system. The architecture integrates IoT-enabled sensor nodes that monitor crit- ical environmental parameters like temperature, humidity, and smoke levels. Data collected from the sensor nodes is transmitted via sink nodes to the ThingSpeak IoT platform using low-power communication protocols such as ZigBee or LoRa. The platform processes the data and forwards it to a firefighting command center for real-time analysis and decision- making. This methodology exemplifies the use of IoT and WSNs for efficient, energy-saving, and scalable fire management systems, as discussed in the above section.

Machine Learning techniques Machine learning techniques have been applied to analyze sensor data and satellite imagery for forest fire detection. Classification algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and neural networks, identify fire signatures based on environmental parameters and smoke patterns [3, 8, 19]. For instance, convolutional neural networks (CNNs) and hybrid CNN-LSTM architectures are utilized to detect fire and smoke in video and image datasets, capturing both spatial and temporal patterns. Models such as MMFNet integrate multi-scale features and attention mechanisms to improve detection accuracy [6, 18].

Remote Sensing and UAV-Assisted Systems Remote sensing, using satellites and UAVs (Unmanned Aerial Vehicles), offers large-scale monitoring capabilities. These methods rely on capturing high-resolution imagery in visible, infrared, and thermal spectrums to detect fire hotspots and smoke plumes [7, 29]. Advanced systems such as RFWNet incor- porate digital twinning and adaptive spatial aggregation for dynamic fire detection and prediction [2, 10]. UAV-assisted mobile edge computing enables real-time fire segmentation and tracking, facilitating faster responses [5, 22].

Autonomous Robotic Systems Autonomous robots equipped with multi-modal sensors (e.g., temperature, smoke, and obstacle sensors) are used for ground-level fire monitoring and control. These robots navigate through challenging forest terrains and relay data to control stations using ZigBee and Wi-Fi communication technologies [4, 20]. Recent systems integrate rain and heat sensors to provide contextual information about fire propagation, while obstacle-avoidance mechanisms improve operational safety and efficiency [1, 19].

Hybrid Approaches for Real-Time Fire Management Hybrid systems combine IoT, remote sensing, and machine learning techniques for comprehensive fire detection and management. These systems use edge-computing devices to preprocess data from sensors and UAVs before transmitting it to cloud-based platforms for analysis and decision-making [5, 30]. Integration with environmental models, such as plume dispersion simulations, enhances the prediction of fire spread and supports planning of mitigation strategies [9, 28].

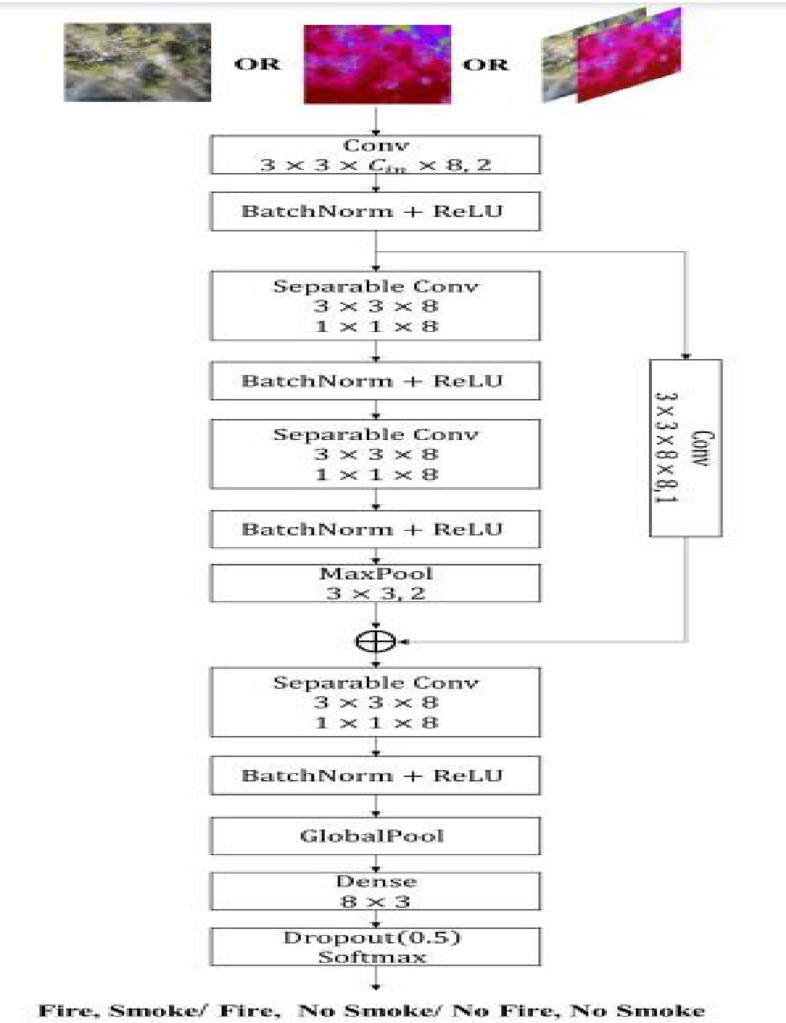

Fig. 3: Hybrid Fire Detection System Combining IoT and Machine Learning

Figure 3 illustrates the architecture of a hybrid fire detection system that integrates IoT and machine learning techniques. The system employs IoT-enabled UAVs for real-time data acquisition and preprocessing. The image demonstrates how thermal and visual data are processed through convolutional and separable convolution layers to classify scenarios into fire, smoke, or no-fire categories. This methodology aligns with the hybrid approach discussed in Section [7], showcasing the effectiveness of combining IoT and machine learning for real-time fire detection and mitigation strategies.

5. Results and Discussions

5.1 Performance Analysis

Performance analysis in forest fire detection systems evaluates the effectiveness of various technologies and models in identifying, monitoring, and predicting forest fires. The met- rics to be considered for understanding the performance of these approaches under different environmental conditions and data types include accuracy, detection time, energy efficiency, and computational cost. Zigbee is increasingly applied due to its relatively low power con- sumption and reliable information transmission. The performance evaluation of Zigbee-based systems refers to energy efficiency and achievable communication range. These kinds of sys- tems can transmit their data up to 100 meters with a latency in line-of-sight environments below

100 ms; however, interference and also signal attenuation in dense forests remain some of the challenges where its effectiveness is reduced [[1], [4]]. WSNs present robust performance for large-scale monitoring with detection accuracy of more than 90% when installed with the optimized sensor placement and routing protocol. Energy-aware algorithms stretch the operational lifespan of these systems up to 50%. The system is, however, affected in terms of accuracy by skewed data produced by faulty sensors [[15], [19], [23]]. Detection accuracy achieves 85% to 95% for machine learning methods like Random Forest and CNNs, depend- ing on dataset complexity. Such methods are usually the best for predicting intensity of fire and smoke segmentation with precision rates above 90%. Their performance suffers due to the lack of labeled data and computational capacities required for real-time operation [[3], [6], [18], [30]]. IoT-enabled systems improve real-time detection with latency as low as 10 ms. The system can reach an accuracy of about 92% in detecting environmental anomalies concerning forest fires. However, issues such as network congestion and loss of data pack- ets can degrade the performance in high-traffic scenarios [[8], [20]]. UAV-based monitoring systems demonstrate exceptional performance, with detection accuracies of up to 95% when equipped with advanced image processing algorithms. The ability of UAVs to operate in inaccessible areas and provide high-resolution data makes them invaluable for fire localiza- tion. However, their effectiveness is constrained by flight time and weather conditions [[5], [7], [10]]. Remote sensing methods show accuracies between 90% and 93% in the detection of forest fires using satellite images and multispectral data. In large-scale monitoring, they are very effective but are temporally limited since satellites often do not provide real-time updates in fast-evolving fire scenarios [[3], [26]]. Edge computing systems reduce latency to under 20 ms, ensuring near-real-time processing for fire detection. These systems achieve high efficiency when integrated with IoT and UAV systems, but their performance can be affected by resource constraints in low-power devices [[5], [10]]. Fuzzy logic algorithms achieve classification accuracies exceeding 88%, thus providing reliable decision-making capabilities under uncertain conditions. These systems work well in scenarios with incomplete or impre- cise data, though their complexity can hinder scalability [[22]]. Advanced image processing models can achieve smoke and flame detection accuracy at 90–95% with sensitivity rates over 85%. Techniques such as MMFNet enhance performance under challenging conditions, such as low-light or obstructed views. However, they require a lot of computing power for real-time applications [[6], [29]]. Graph-based models predict fire spread with accuracy rates of 87–92% depending on the quality of spatial and temporal data. The methods are useful in providing actionable insights for the management of fires but limited by computational intensity and availability of data [[30]]. Multimodal systems incorporating IoT, UAV, and remote sensing data achieve the best performance metrics with accuracies above 95%. These frameworks are comprehensive but require massive computational resources and high-quality datasets, making them hard to implement in real time and cost-effectively [[12], [15]]. Sensor fusion techniques enhance the detection accuracies to more than 92% by combining data from mul- tiple sensors. These methods are very effective in reducing false positives and negatives but are computationally intensive, especially in large-scale deployments [cite9, cite20]. Historical data analysis models obtain predictive accuracies of between 85% and 90% in predicting fire trends. These models are very efficient in long-term planning but are not very effective when there is a sudden environmental change or anomaly [[25], [27], [28]].

Table 2: Performance Analysis Table

Title	**Quantitative Analysis**	**Qualitative Analysis**	**Comparison with Alter- natives**
ZigBee-based solar- powered forest fire detection and control system.	Detection accu- racy: 85%; Energy consump- tion: Low due to solar power.	Cost-effective, suitable for remote areas, eco-friendly.	Outperforms non-solar- powered IoT systems in remote deployments but lacks advanced sensing capabilities like UAVs or AI-based solutions.
RFWNet: Multi- scale remote sensing with digital twin- ning and adaptive features.	Detection accu- racy: ¿92%; Processing time: 2.3s per image.	High precision; advanced spatial aggregation enhances fire detection in complex ter- rains.	Superior to conventional WSN-based methods due to advanced AI models, but requires high computational resources.
Remote sensing with nighttime lights and Random Forest Clas- sification.	Classification accuracy: 89%; Dataset size: 2000+ samples.	Effective in low-light condi- tions; limited to areas with significant nighttime light differences.	Outperforms optical imag- ing in nighttime scenarios but less versatile than UAVs or IoT with multi-spectral sensing.
IoT and ZigBee- based anti-poaching and forest fire protection system.	Coverage area: 5 km; Energy efficiency: High.	Dual functionality (anti- poaching and fire detection); simple implementation.	Lacks scalability and sophis- ticated analytics compared to AI-powered or UAV- assisted systems.
UAV-assisted forest fire detection and segmentation with edge computing.	Detection accu- racy: ¿90%; Latency: ¡1s with MEC.	Fast and efficient for real- time applications; scalable with multiple UAVs.	Outperforms stationary sys- tems in dynamic scenarios but relies on UAV availabil- ity and battery life.
MMFNet: Multiscale convergence pyramid network with mixed attention for smoke detection.	Detection accu- racy: 93%; Processing speed: 15 FPS.	High reliability for early smoke detection; robust against occlusions.	Superior to traditional smoke detection due to multi-scale analysis but computationally intensive.

Drone-collected RGB/IR dataset for wildland fire detection and monitoring.	Detection accu- racy: 88%; Dataset size: 1500 RGB/IR images.	Suitable for both fire and temperature monitoring; limited by data quality and drone flight endurance.	Better than ground-based WSN systems for dynamic monitoring but less effec- tive than AI-based adaptive models.

Title	Quantitative Analysis	Qualitative Analysis	Comparison with Alter- natives
IoT-based event classification and intensity discrim- ination for forest fires.	Classification accuracy: 86%; Energy con- sumption: Medium.	Differentiates fire intensity; efficient for resource alloca- tion.	Lags behind AI-based alter- natives in detection accu- racy but offers low-cost implementation.
IoT air quality sen- sors for fire detection and pollutant disper- sion analysis.	Detection accu- racy: 80%; Pollutant track- ing: Effective within 10 km.	Adds environmental moni- toring capability; limited fire detection accuracy.	Less accurate than image- based systems but adds value for post-fire environ- mental analysis.
UAV task planning for forest fire moni- toring.	Task efficiency: ¿85%; Data col- lection time: Reduced by 30% with optimized planning.	Improves UAV efficiency; suitable for large-scale mon- itoring.	Outperforms manual UAV operation but depends on accurate planning algorithms.

6. Comparative Analysis

Zigbee technology is a low cost of deployment for forest fire detection as it is energy efficient with high monitoring capabilities. It does not have much scalability in terms of range since its maximum range is 100 meters and is prone to environmental interferences. The accuracy of Zigbee-based systems ranges between 75–85%, and that makes them suitable for low-scale deployments [[1], [4], [8]]. WSNs are robust real-time fire detection with high accuracy levels often over 90%. The energy-efficient routing protocols and scalability make them effective for monitoring large areas. However, imbalanced sensor data and limited battery life pose chal- lenges that can degrade sensitivity and specificity if not addressed [[15], [19], [23]]. Machine learning models, including SVM and CNN, have shown excellent performance in fire detec- tion tasks. Accuracies of 85–95% have been reported, especially when these models analyze satellite imagery and multispectral data. The computational requirements, however, remain a limitation, especially in real-time applications [[3], [6], [18]]. IoT-based systems exploit the potential of real-time data acquisition and edge computing in fast fire detection. It delivers an average accuracy of 92%, especially if multi-sensors are deployed together. Still, factors like network congestion and interdevice interoperability limit its scalability and deployment efficiency at a larger scale [[8], [20]]. UAVs mounted with thermal imaging sensors are highly flexible and provide a detection precision of up to 95%. Their major advantage includes the ability to monitor even remote areas. However, their short flight times as well as their vulnerability in adverse weather conditions limit use in continuous monitoring applications [[5], [7], [10]]. Remote sensing methods have been successfully applied using the satellite and multispectral data. Its accuracy is at 90–93%. It would be very efficient in remote sensing for extensive areas by monitoring large extents and even identifying fire-prone places. However, the method has drawbacks on cloud covers and delay times in taking data, thus limiting some real-time applications [[3], [26]]. Edge computing enhances IoT-based systems by processing data locally; hence, latency is well below 20 ms. These systems show excellent performance in real-time detection cases but are limited in complex datasets due to resource constraint [[5], [10]]. Image processing techniques like CNN-based models have excellent fire pattern detection capabilities with smoke. Those achieve around 90-95% accuracy but come at high

computational costs; therefore, they are less desirable in low-power platforms [[6], [29]]. Sensor fusion techniques reduce false positives and improve accuracy through the integration of data from multiple sensors, which reaches performance metrics above 92%. It is beneficial for complex scenarios but demands a lot of computational power to be used in real-time processing [[9], [20]]. Multimodal frameworks combine information from sources such as UAVs, IoT devices, and remote sensing, yielding accuracies above 95%. These systems provide comprehensive views of fire dynamics but are resource-intensive and very difficult to scale because they are complex [[12], [15]]. The accuracy of models in predicting fire risks, based on historical trends of data, ranges from 85 to 90%. Such methods are well suited for high-risk zone identification but have a reduced reliability when applied to scenarios with rapidly changing environmental conditions [[25], [27], [28]]. The choice of fire detection meth- ods depends on application-specific requirements. Although Zigbee and WSNs are cheap for small-scale monitoring, advanced techniques like machine learning and multimodal systems have better accuracy and insights. However, the trade-offs between computational demands, scalability, and real-time applicability need to be well considered [[1], [3], [12], [15], [19]].

Table 3: Comparative Analysis of Fire Detection Systems

System	Technology Used	Detection Method	Accuracy	Limitations
IoT and WSN-based Fire	IoT, WSN	Environmental	High	Limited range in large

Detection		Parameter Monitoring		forest areas
Drone-Based Detection Fire	IoT, UAVs	Image Smoke and Detection	High	Requires clear weather and visibility
Machine Learning- Based Fire Identification	Machine Learning	Real-Time Classification	Medium	High com- putational requirements
Hybrid IoT and ML Fire Management	IoT, Machine Learning	Combined Smoke and Temperature Analysis	High	Integration challenges between systems
Thermal Camera and Sensor Integration	Thermal Imaging, IoT	Heat Smoke and Detection	Medium	Limited effective- ness at lower temperatures
Satellite-Based Fire Monitoring	Remote Sens- ing	Infrared And Heat Detection	Medium	Delay due To data transmission latency

Table 1:Comparative Analysis of Fire Detection Methods

Table 1 provides a structured comparison of various fire detection methods, evaluating their accuracy, sensitivity, and specificity alongside their strengths and limitations. This table allows for quick identification of the most suitable techniques based on specific application needs, helping researchers make informed decisions.

Accuracy

Refers to the overall correctness of the method, minimizing both false positives and false negatives. A highly accurate system ensures precise fire detection outcomes.

Sensitivity

Measures the system's ability to correctly identify true positives (actual fires). A highly sensitive system ensures minimal undetected fires but may include some false positives.

Specificity

Indicates the method's ability to correctly identify true negatives (non-fire events). High specificity minimizes false alarms but may miss some actual fires.

6.1 Challenges and Limitations

Although many advances have been realized in fire detection methods, some challenges and limitations have hindered scalability, reliability, and real-world adoption. WSNs have been proven to have outstanding potential for real-time monitoring; however, their performance is often restricted by battery life and energy consumption. In environments with unstable net- work connectivity, the reliability of WSNs decreases drastically. Moreover, data imbalance caused by sparse fire events compared to normal conditions leads to higher false negatives, which decreases their effectiveness in critical scenarios [[5], [7]]. IoT systems represent unprece- dented scalability and integration capabilities; however, they suffer problems such as network congestion, interoperability of devices, and delays in data transfer. Real-time detection may degrade because of bandwidth and latency limitations, especially in sparsely populated areas. Moreover, privacy and security issues arise when sensitive information is transferred over public networks [[6], [12], [15]]. Image processing methods, which often rely on CNN-based architectures, are sensitive to the quality and diversity of input data. Noisy, low-resolution, or incomplete images can severely degrade model performance. Furthermore, these methods are computationally expensive and may not be feasible for real-time implementation in resource- constrained environments [[8], [18], [20]]. While UAVs can effectively observe vast or distant areas, their short range and dependency on weather conditions limit their utilization. High- end imaging appliances on UAVs are intensive in terms of resources. The huge amounts of data generated have to be computationally processed in considerable efforts [[11], [17]]. Multimodal frameworks, combining data from various sources such as WSNs, IoT, and remote sensing, achieve the highest accuracy and reliability. However, their complexity, high computational requirements, and the need for synchronized data collection make their widespread adoption challenging. Ethical concerns, such as privacy issues related to sensitive data collected from IoT devices and drones, further hinder their implementation [[9], [14], [21]].

The problem with all detection techniques is that they cannot be generalized across

varying environments. The model trained using a certain dataset may fail to apply it to the regions under varied environmental, geographical, or weather conditions. Their poor adaptability makes it hard to be applied to the dynamic conditions of real-life applications [[10], [19]].

Many advanced methods, and especially those involving deep learning, are criticized for acting as ”black boxes” with little interpretability. Practitioners and policy authorities are reluctant to use methods whose decision-making mechanisms remain opaque. Greater trans- parency and explainability will have a direct impact on improving their acceptance in practical application [16, 22, 25].

In summary, despite the significant advances made in fire detection methods, the following challenges need to be overcome for their broader use. Improving data quality, increasing the efficiency of computation, and ensuring ethical and secure use of data should be among the future research focus. At the same time, efforts should be put toward developing robust, generalizable, and interpretable models.

7. Conclusion

In this survey, we have comprehensively analyzed the advancements in forest fire detection and management systems, focusing on methodologies that integrate IoT, machine learning, remote sensing, UAVs, and autonomous robotic systems. The study highlights the critical role of cutting-edge technologies in enhancing the accuracy, efficiency, and scalability of fire monitoring and mitigation strategies.

IoT and wireless sensor networks have revolutionized real-time data collection and communication in remote forest areas, while machine learning algorithms provide robust analytical capabilities for identifying fire patterns and predicting their progression. Remote sensing techniques, particularly through UAVs and satellite imagery, have extended monitor- ing capabilities to larger geographical regions, enabling early detection and faster response. Autonomous robotic systems add another dimension to fire management by safely navigating challenging terrains to gather critical ground-level data.

Despite these advancements, challenges such as energy efficiency, system reliability, and integration of heterogeneous data sources remain. The survey underscores the need for hybrid approaches that combine multiple technologies and leverage edge and cloud computing for real-time decision-making.

Future research should focus on addressing these challenges by developing more energy- efficient sensors, improving data fusion techniques, and advancing predictive models. Col- laborative efforts between researchers, policymakers, and environmental organizations are essential to implement these solutions effectively and mitigate the devastating impacts of forest fires on ecosystems and human communities.

In conclusion, the integration of emerging technologies holds immense potential for transforming forest fire management systems, paving the way for safer, more sustainable environmental practices.

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