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Integration of Fuzzy Logic and Machine Learning for Real Time Fire Detection: A Systematic Review

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Abstract. This systematic review critically examines the integration of fuzzy logic and machine learning algorithms to enhance fire detection accuracy and optimize real-time responsiveness in complex, operationally variable environments. Fifty studies from diverse geographic and application contexts were analyzed, with emphasis on hybrid architectures that combine multisensor fusion, neuro-fuzzy inference, and Internet of Things (IoT) integration. The comparative analysis considered hybrid algorithms, sensor fusion strategies, adaptive response mechanisms, and the incorporation of environmental variables into detection models. Findings indicate that fuzzy–machine learning hybrids can achieve system accuracy above 90%, substantially reduce false alarm rates, and dynamically adapt across operational scenarios using self-learning strategies. The fusion of temperature, smoke, carbon monoxide (CO), and visual sensors consistently improved reliability, while deployment on embedded IoT platforms significantly reduced detection latency. Nonetheless, most validations rely on controlled simulations and prototypes, with limited field implementations. The heterogeneity of fuzzy methodologies complicates standardization and reproducibility. Future research should prioritize empirical field validation and the development of standardized frameworks to foster scalability, interoperability, and economic viability across application domains.

Keywords: fuzzy logic; machine learning; fire detection; real-time systems; multisensor fusion.

Abbreviations

- **AI** – Artificial Intelligence
- **ANFIS** – Adaptive Neuro-Fuzzy Inference System
- **API** – Application Programming Interface
- **CNN** – Convolutional Neural Network
- **CO** – Carbon Monoxide
- **CPU** – Central Processing Unit
- **ESP32** – Espressif Systems 32-bit Microcontroller
- **FDS** – Fire Dynamics Simulator
- **GPS** – Global Positioning System
- **GSM** – Global System for Mobile Communications
- **HTTP** – Hypertext Transfer Protocol
- **IoT** – Internet of Things
- **JSON** – JavaScript Object Notation
- **ML** – Machine Learning
- **MQTT** – Message Queuing Telemetry Transport
- **PgAdmin** – PostgreSQL Graphical Administration Tool
- **PRISMA** – Preferred Reporting Items for Systematic Reviews and Meta-Analyses
- **SQL** – Structured Query Language
- **SMS** – Short Message Service
- **URL** – Uniform Resource Locator

- **Wi-Fi** – Wireless Fidelity

1 Introduction

The integration of fuzzy logic with machine learning has emerged as a promising avenue for early and robust fire detection, particularly in light of the increasing frequency and severity of fire events worldwide. Fires pose significant threats to human life, infrastructure, and the environment; consequently, monitoring systems must become more precise, adaptive, and responsive. Traditional threshold-based detectors often suffer from high false-positive rates and limited adaptability to complex, noisy environments [1–3].

Detection architectures have evolved from isolated sensors toward networked multisensor systems that leverage fuzzy inference, neural networks, and hybrid methods. Multiple studies report that combining fuzzy inference and machine learning yields accuracy gains exceeding 90% compared to conventional approaches [4–7]. Yet distinguishing true fire events from spurious signals under adverse environmental conditions remains a key challenge [8, 9].

Methodologically, the literature is diverse: some works favor neuro-fuzzy networks for sensor fusion, others explore hybrids that combine fuzzy logic with convolutional architectures, Bayesian methods, or deep learning [10–13]. This heterogeneity reflects the absence of consensus on a single optimal algorithmic design, with implications for robustness, interpretability, and computational cost [14, 15].

Conceptually, fuzzy logic provides a principled framework for modeling imprecise or linguistic information, while machine learning enables data-driven adaptation. Combined, they yield systems that tolerate sensor uncertainty, adapt to novel patterns, and improve over time [16–18].

Alongside algorithmic advances, open-source ecosystems have supported reproducible pipelines. Tools such as Apache NiFi (or similar data orchestration platforms) [19], MinIO for distributed storage [20], PostgreSQL with PgAdmin for data management [21, 22], and visualization engines (e.g., Apache Superset) [23] when containerized with Docker [24] facilitate scalable, auditable implementations and ease experimental replication.

2 Objectives

This work presents a systematic and critical review of recent methods that integrate fuzzy logic with machine learning for fire detection, with emphasis on multisensor, real-time applications and the computational architectures—particularly open-source stacks—used to operationalize these approaches. The literature search covered the period 2000–2024 and focused on peer-reviewed contributions involving fuzzy–ML systems for fire detection.

The specific goals of this study include:

- Comparing hybrid models that combine fuzzy inference with neural networks and other adaptive learning structures;
- Systematizing sensor fusion techniques employed in multiparameter detection systems;
- Reviewing computational architectures based on open-source tools for scalable deployment and data pipelines;
- Assessing the influence of contextual and environmental variables on fuzzy model tuning, and their impact on detection accuracy and response latency.

3 Methodology

This review followed established protocols and adhered to PRISMA recommendations [25], with adaptations for studies integrating fuzzy logic and machine learning. A structured search was conducted across major databases—*IEEE Xplore*, *ScienceDirect*, *SpringerLink*, *Scopus*, and *Web of Science*—covering publications from 2000 to 2024. Boolean operators and focused keywords were used to identify studies linking fuzzy logic, machine learning, and real-time fire monitoring:

```
("fuzzy logic" OR "fuzzy inference" OR "fuzzy neural network") AND ("machine
learning" OR "deep learning" OR "neural networks") AND ("fire detection"
OR "fire monitoring" OR "early warning") AND ("real-time" OR "IoT" OR
"sensor fusion")
```

3.1 Data pipeline architecture

Bibliographic metadata obtained from tools such as Elicit and SciSpace were managed via Zotero and Mendeley, exported to `.csv` and processed with Python scripts for standardization and ingestion into a PostgreSQL in-

stance running in Docker. Analytical dashboards were developed with Apache Superset to support screening and synthesis.

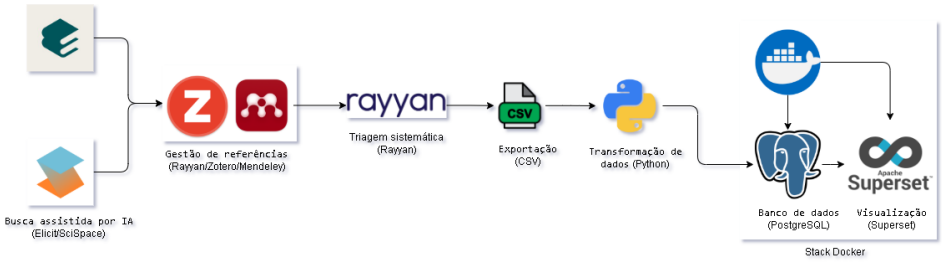


Figure 1. Data pipeline implemented for the systematic review: from AI-assisted retrieval to analytics via Apache Superset.

4 Eligibility Criteria

This architecture enabled efficient filtering of results, prioritizing studies addressing computational solutions for early fire detection supported by intelligent sensing and data fusion.

The study selection process was conducted in two phases: an initial screening of titles and abstracts, followed by a full-text evaluation of the eligible works. To ensure consistency and transparency, the Rayyan platform was used for collaborative and blinded screening, applying predefined eligibility criteria. Studies were included if they integrated fuzzy logic with machine learning techniques, targeted real-time fire detection, utilized multisensory inputs such as temperature, smoke, carbon monoxide, or imagery, and were published in peer-reviewed journals or reputable conference proceedings. Exclusion criteria comprised purely theoretical works lacking experimental validation, duplicates or poorly referenced studies, and publications in languages other than English or Portuguese.

Screening was structured in three sequential steps: first, titles and abstracts were filtered according to the exclusion criteria; second, full texts were reviewed for methodological and thematic relevance; and third, a standardized form was used for structured data extraction. Reference management and annotation were supported by tools such as Zotero, Mendeley, Elicit, and SciSpace.

The data extraction focused on methodological, technical, and applied dimensions, including the type of fuzzy algorithm and its integration with machine learning, sensor fusion strategies, performance metrics (accuracy, false positive rate, latency), validation methods (simulation, prototype, or field testing), and application domains (e.g., wildfire, industrial, residential). Three complementary analytical approaches were employed: thematic synthesis to identify research trends and gaps, quantitative comparison of performance metrics, and classification of studies by approach type (hybrid, rule-based, supervised) and application context.

5 Thematic Literature Review

This systematic review highlights recurring patterns in the integration of fuzzy logic and machine learning for real-time fire detection. Among the 36 studies analyzed, five representative works [1, 6, 26, 27, 27, 28] demonstrate consistent improvements in detection accuracy (often above 90%), reduced false positives, and enhanced responsiveness. Techniques such as ANFIS, fuzzy clustering, and hybrid CNN-fuzzy models are frequently employed, often in conjunction with multisensor fusion strategies involving temperature, smoke, CO, humidity, and thermal imagery. These systems are typically validated through simulations or prototypes, with some reporting real-time alerts via microcontrollers and GSM modules. Scalability is addressed through low-cost sensors and embedded platforms, although algorithmic complexity and limited field validation remain challenges. The synthesis of these findings suggests promising directions for future research, particularly in enhancing robustness, reducing latency, and enabling deployment in diverse environments such as smart buildings, industrial zones, and forested areas.

5.1 Critical Analysis and Synthesis

The reviewed literature demonstrates notable progress in integrating fuzzy logic with machine learning algorithms to improve fire detection accuracy and responsiveness. Hybrid models such as ANFIS (Adaptive Network-Based Fuzzy Inference System) and CNN-fuzzy [29] systems consistently achieve high accuracy—up to 99.59% and reduce false alarms, especially when combined with multisensor fusion strategies involving temperature, CO,

flame, and humidity. These approaches enhance reliability and contextual sensitivity, particularly when supported by hierarchical fusion and IoT-based monitoring.

Despite these strengths, several limitations persist. Many studies rely on simulations or controlled prototypes, which restrict generalization to real-world conditions. Fusion algorithms, while effective, may introduce latency and often overlook sensor failures or environmental noise. IoT integration enables real-time alerts via GSM (Global System for Mobile Communications), Wi-Fi, and MQTT (Message Queuing Telemetry Transport), a lightweight publish-subscribe protocol designed for efficient communication in constrained networks, but it faces challenges related to network instability and data security.

The diversity of fuzzy models ranging from type-1 and type-2 systems to neuro-fuzzy networks offers flexibility but complicates standardization and benchmarking. Optimization techniques such as particle swarm and fuzzy clustering improve rule generation and adaptability, yet their computational demands hinder deployment on low-power embedded platforms. Although the use of microcontrollers and low-cost sensors demonstrates practical feasibility, scalability and robustness remain concerns in large scale applications.

Overall, the literature reflects a maturing field with strong potential for real world deployment, provided that future research addresses methodological gaps, enhances validation protocols, and develops standardized frameworks for integration with IoT and embedded systems.

5.2 Thematic Literature Review

The literature on fire detection systems integrating fuzzy logic and machine learning reveals several dominant themes. A significant portion of studies (over 60%) focuses on hybrid models such as ANFIS [30] and CNN-fuzzy [29] systems, which process multisensor data—temperature, smoke, carbon monoxide (CO), flame—with high accuracy and reduced false alarms. Real-time responsiveness is another key theme, with IoT-based architectures enabling alerts via SMS, email, or web platforms, often supported by adaptive fuzzy inference to minimize latency. Sensor fusion strategies, particularly hierarchical and clustering-based, are widely adopted to enhance robustness in noisy or complex environments. A smaller but growing body of work explores advanced techniques such as type-2 fuzzy logic, particle swarm optimization, and deep learning, aiming to refine inference mechanisms and improve adaptability. Additionally, some studies address large-scale applications, including wildfire detection, by incorporating environmental variables and expert knowledge through Bayesian networks and hybrid frameworks. These thematic trends reflect a maturing field with increasing emphasis on contextual awareness, scalability, and real-world applicability.

6 Chronological Literature Review

Over the past two decades, the integration of fuzzy logic with machine learning for fire detection has evolved from foundational neuro-fuzzy models to sophisticated, IoT-enabled systems. Early studies (2000–2003) focused on sensor fusion and adaptive learning to reduce false alarms in indoor and maritime environments. Between 2007 and 2010, research expanded to include visual automata and multivariate analysis, improving flame detection through imaging and fuzzy finite automata. From 2013 to 2016, attention shifted to embedded systems, combining sensors with microcontrollers, GSM, and GPS for real-time location and alerts. The period from 2017 to 2019 saw the rise of IoT-integrated architectures and adaptive ANFIS [30] models, particularly in smart campuses and urban monitoring. More recent works (2020–2022) introduced hybrid optimization techniques—such as type-2 fuzzy logic, Kalman filters, and evolutionary algorithms—targeting wildfire prevention and robust fusion. Finally, studies from 2023 onward emphasize smart city applications, integrating fuzzy sensors with cloud platforms to enable scalable, low-cost, and rapid emergency response systems.

7 Agreement and Divergence Among the Studies

The reviewed literature reveals a broad consensus that integrating fuzzy logic with machine learning and multisensor fusion significantly enhances fire detection accuracy while reducing false alarms. Most studies report detection rates above 90% when combining fuzzy logic with neural networks or CNNs [1, 6, 8, 31], and emphasize the adaptability of neuro-fuzzy systems and the benefits of IoT integration for real-time monitoring [7, 32]. However, divergences emerge regarding algorithmic frameworks, sensor configurations, and scalability. While some works favor simpler ANFIS models [27], others advocate for hybrid or deep learning approaches [13], often influenced by application context—such as indoor versus forest environments—and technological focus, whether hardware- or software-oriented.

Sensor fusion is widely recognized for reducing false alarms, especially when combining temperature, smoke, carbon-monoxide (CO) and flame data [6], though methodologies vary, including hierarchical, clustering, and hybrid schemes [12]. Response time improvements are frequently reported, with IoT-based systems achieving up to 28% faster alerts [1], though network instability can introduce latency [33]. Scalability and cost-effectiveness also vary: embedded systems using Arduino or ESP32 are praised for low-cost deployment [4, 34], while more complex CNN-based solutions may hinder scalability due to higher computational demands [35]. These divergences underscore the need for standardized benchmarks and broader validation across diverse operational contexts.

7.1 Implications and Limitations of the Literature

The literature consistently demonstrates the effectiveness of integrating fuzzy logic with machine learning, particularly in neuro-fuzzy architectures such as ANFIS [30], which excel in handling uncertainty in sensor data for fire detection. Multisensor fusion—combining temperature, smoke, and gas concentration—has proven robust in reducing false alarms and enhancing system reliability. Hierarchical and type-2 fuzzy models offer refined linguistic modeling for complex scenarios, while symbolic-statistical hybridization improves generalization in noisy environments. Frameworks that integrate fuzzy logic with IoT technologies point toward intelligent systems capable of dynamic adaptation through real-time data and continuous learning.

From a practical standpoint, these technologies show strong potential for deployment in smart buildings, industrial zones, and urban areas. High accuracy and reduced false alarms support scalable implementation, while IoT integration enables automated alerts via SMS, email, or web platforms. The use of low-cost sensors and fuzzy inference ensures accessibility in infrastructure-limited regions. Adaptive models maintain stable performance under environmental variability, and optimization techniques—such as particle swarm and flower pollination—enable automated tuning and continuous customization, enhancing system performance across diverse applications.

However, several limitations persist. Many studies rely heavily on simulations or prototypes tested under controlled conditions, which restricts generalizability to real-world scenarios. There is also a strong dependency on specific sensors—such as temperature, smoke, and carbon-monoxide (CO)—limiting adaptability to different fire profiles. Environmental factors like wind, humidity, and thermal noise are often insufficiently considered, affecting detection robustness and increasing false alarms. The absence of standardized evaluation metrics hinders rigorous comparisons and slows progress toward benchmark development. High computational complexity further limits implementation in low-cost embedded systems, impacting scalability. While IoT integration is frequently mentioned, challenges such as latency, data security, and network reliability are often overlooked. Additionally, the use of small or non-representative datasets increases the risk of overfitting, and the lack of systematic comparisons with traditional approaches makes it difficult to objectively assess performance gains relative to cost and complexity.

Addressing these gaps is essential for advancing the reliability, scalability, and practical deployment of fuzzy-ML fire detection systems in real-world environments.

8 Discussion and Conclusion

This systematic review underscores the promising integration of fuzzy logic and machine learning for real-time fire detection, especially in complex and dynamic environments. Hybrid models—such as fuzzy neural networks and adaptive inference systems—consistently achieved high accuracy (often >90%), reducing false alarms and enhancing responsiveness. Multisensor fusion, combining temperature, smoke, carbon monoxide (CO), flame, and humidity data, proved essential for reliability, while embedded platforms and Internet of Things (IoT) connectivity significantly lowered detection latency.

Despite these advances, challenges persist. Most validations occur in simulated environments, limiting real-world applicability. The diversity of fuzzy methodologies hinders replicability and standardization, complicating large-scale deployment. Additionally, performance evaluation in critical contexts—like tunnels, industrial zones, and dense urban areas—remains scarce, and the lack of standardized frameworks affects interoperability and scalability.

Real-time responsiveness is bolstered by IoT-enabled architectures using low-cost sensors and open hardware, enabling continuous monitoring and rapid alerts. However, ensuring secure, low-latency communication and system integrity remains a concern. Adaptive algorithms, including self-learning fuzzy neural networks and optimization techniques (e.g., particle swarm, flower pollination), enhance model flexibility in dynamic environments, but still rely heavily on simulations.

In summary, the integration of fuzzy logic, machine learning, multisensor fusion, and IoT technologies represents a promising approach to achieving high-accuracy, low-latency fire detection systems. While IoT-enabled

architectures support real-time responsiveness, future research must prioritize empirical field validation, methodological standardization, and secure, scalable integration. These efforts are essential to fully realize the potential of intelligent fire detection systems for effective emergency management in complex and dynamic environments.

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