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| RESEARCH ARTICLE

Artificial Intelligence and Data Analytics in Fire Science: Detection, Modeling, and Suppression

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| ABSTRACT
Fire science has advanced rapidly in recent decades, yet fire events continue to cause significant loss of life, infrastructure, and natural ecosystems. Traditional approaches to fire detection, dynamics modeling, and suppression strategies often face limitations in speed, accuracy, and scalability. The emergence of artificial intelligence (AI), machine learning (ML), and data analytics is transforming fire science by enabling early detection, predictive modeling, and optimization of suppression strategies. This review highlights state-of-the-art applications of AI-driven methods in fire detection, modeling fire growth and smoke propagation, and improving suppression techniques. Key challenges, opportunities, and future research directions are discussed, focusing on how data-driven fire science can improve public safety and resilience against wildfires and structural fires. Fire remains one of the most destructive hazards worldwide, causing extensive human, economic, and ecological losses. Despite advances in fire science, traditional approaches to fire detection, dynamics modeling, and suppression are often constrained by slow response times, computational intensity, and limited adaptability to complex environments. The rapid development of AI, ML, and data analytics offers new opportunities to overcome these challenges by enabling early warning systems, predictive modeling, and data-driven suppression strategies. This review synthesizes recent research on AI-enhanced fire science, focusing on three key areas: detection, modeling, and suppression. In detection, computer vision methods, IoT sensor networks, and predictive analytics improve early identification of ignitions while reducing false alarms. In modeling, surrogate AI frameworks and physics-informed neural networks accelerate simulations of fire dynamics, heat transfer, and smoke propagation, supporting real-time decision-making. In suppression, intelligent resource allocation, autonomous firefighting robots, and smart suppression systems highlight the role of AI in optimizing operations and reducing risks to human responders. Overall, AI-driven fire science has the potential to reduce casualties, mitigate economic losses, and build fire-resilient societies by complementing traditional methods with adaptive, data-driven intelligence.

| KEYWORDS

Fire Detection, Fire Modeling, Fire Suppression, AI, ML, Data Analytics

| ARTICLE INFORMATION

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1. Introduction
Fire remains one of the most devastating hazards to human society and ecosystems. Each year, both wildland and structural fires cause extensive destruction of property, loss of life, displacement of communities, and environmental degradation. The National Fire Protection Association (NFPA) reports that in the United States alone, there were over 470,000 structure fires in 2023, leading to more than 3,000 civilian deaths and billions of dollars in property losses (NFPA, 2024). On a global scale, wildfires are accelerating in frequency and intensity. According to the World Resources Institute, 2024 marked one of the most destructive years, with over 13.5 million hectares of tree cover lost to fire an area equivalent to the size of Greece (WRI, 2024). These trends are amplified by climate change, which has increased the prevalence of droughts, elevated surface temperatures, and extended fire seasons worldwide (Abatzoglou et al., 2021). Beyond immediate destruction, fire events disrupt regional air quality and global carbon budgets. Wildfires are estimated to release 1.8 gigatonnes of CO_2 annually, contributing significantly to greenhouse gas emissions

and accelerating climate change (van der Werf et al., 2017). The cyclical relationship between climate change and wildfires underscores the urgent need for more sophisticated, adaptive approaches to fire science.

Historically, fire safety has relied on a combination of physical models, heat transfer equations, fluid dynamics simulations, and sensor networks. Classic models such as Computational Fluid Dynamics (CFD) and the Fire Dynamics Simulator (FDS) simulate flame propagation, heat transfer, and smoke dispersion with reasonable fidelity (McGrattan et al., 2013). These tools have advanced knowledge of fire dynamics, enabling engineers to design safer structures and improve evacuation planning. CFD and FDS simulations are computationally intensive, requiring hours to days to run, making them impractical for real-time predictions in rapidly evolving fire situations (Hostikka & McGrattan, 2020). Simplifying Assumptions: Many models assume homogeneous fuel beds, steady wind patterns, or uniform material properties, which rarely reflect real-world complexity. Reactive Detection: Sensor-based fire alarms (temperature, smoke, CO sensors) are often triggered after ignition, limiting their utility for early warning. Consequently, traditional fire science approaches, while valuable for post-event analysis and engineering design, lack the adaptability and predictive power required for dynamic, real-time fire management. Early detection is the most crucial factor in preventing small ignitions from escalating into large, uncontrollable fires. AI-driven detection methods include: Computer Vision: Convolutional Neural Networks (CNNs), YOLO, and Transformer-based models have been deployed to detect smoke and flames from surveillance cameras, drones, and satellites (Vasconcelos et al., 2024). These outperform traditional threshold-based image processing by reducing false alarms from confounding sources like fog, dust, or sunlight reflections. IoT and Sensor Fusion: Machine learning algorithms process heterogeneous data from temperature, gas, and infrared sensors, improving detection accuracy even in low-visibility conditions (Ashik et al., 2023; Khan et al., 2024; Islam et al., 2023; Liu et al., 2025). Edge AI enables local computation, delivering real-time alerts without relying solely on cloud systems. Predictive Early Warning: Historical fire data and meteorological inputs are fed into ML models (Random Forest, Gradient Boosting, Deep Learning) to forecast high-risk ignition zones. This is especially valuable for wildfire-prone regions such as California and Australia (Jain et al., 2020; Hossain et al., 2023).

Deep Neural Networks (DNNs) and Physics-Informed Neural Networks (PINNs) can approximate CFD outputs, reducing computational time while retaining predictive accuracy. Zhu et al. (2022) demonstrated a surrogate model achieving R^2 values above 0.93 for global wildfire spread predictions. Predictive analytics allocate firefighting units more effectively, prioritizing high-risk zones based on real-time fire spread models. Autonomous robots and UAVs equipped with AI can navigate hazardous zones, reducing risks to human firefighters (Nguyen et al., 2022). Data-driven sprinklers and adaptive fire suppression systems adjust water, foam, or gas release based on fire dynamics, reducing resource waste while enhancing control. This review aims to synthesize recent advancements in AI-enhanced fire science by exploring its applications in detection, modeling, and suppression. It highlights how computer vision, IoT-based sensing, predictive analytics, surrogate AI frameworks, and autonomous suppression systems collectively advance early fire identification, accelerate real-time modeling, and optimize firefighting operations. The overarching goal is to demonstrate how AI-driven innovations can reduce casualties, minimize economic losses, and strengthen fire-resilient societies through adaptive, data-driven intelligence.

2. Fire Detection Using AI and Data Analytics

Early and accurate fire detection is the cornerstone of effective fire management. Detecting an ignition at the earliest stage drastically reduces the likelihood that it will escalate into a catastrophic event. Traditional fire detection systems, such as smoke and heat detectors, have been invaluable in protecting structures. However, these conventional methods often trigger alarms only after flames or significant combustion products are present, leading to delays that can be critical in both wildfire and urban settings. Artificial Intelligence (AI), Machine Learning (ML), and Data Analytics have introduced new pathways for real-time detection, leveraging computer vision, sensor fusion, and predictive models (Arrieta et al., 2020; Hossain et al., 2023; Saha et al., 2024; Siddiki et al., 2025; Tanvir et al., 2020).

2.1 Image and Video-Based Detection

One of the most active areas of AI-driven fire detection is computer vision. Closed-circuit television (CCTV) cameras, drone-mounted sensors, and satellites generate massive amounts of visual data. Traditional image-processing techniques rely on color thresholds, motion detection, or pixel intensity analysis. While simple, these methods often suffer from high false-alarm rates due to confounding environmental conditions such as fog, sunlight reflections, or dust (Ko et al., 2009). Deep learning has significantly improved accuracy and speed. Convolutional Neural Networks (CNNs) can learn hierarchical image features such as flame contours, smoke textures, and color variations that are less sensitive to noise. Models like YOLO (You Only Look Once) and its recent versions YOLOv5 and YOLOv8 can perform near-real-time detection of fire in surveillance footage, with reported inference times of <0.5 seconds per frame (Boonyuen et al., 2022). These models outperform older hand-crafted feature methods in both detection precision and recall.

2.2 Sensor and IoT-Based Detection

Sensor fusion combines multiple modalities temperature, carbon monoxide (CO), carbon dioxide (CO_2), humidity, and infrared (IR) signals to enhance detection reliability. For instance, Liu et al. (2018) showed that combining temperature and CO sensor data with a Support Vector Machine (SVM) classifier reduced false alarms by distinguishing between actual smoke and benign aerosols like steam. Edge AI has further improved IoT-based fire detection. By embedding ML models directly onto sensor nodes or gateway devices, detection can occur locally without requiring constant connectivity to cloud servers. This reduces latency, power consumption, and reliance on high-bandwidth communication, which is especially important in remote wildfire-prone areas (Rahman et al., 2022). Edge-based detection systems have demonstrated the ability to trigger alarms within seconds of ignition, offering a practical and scalable alternative to centralized architectures.

2.3 Predictive Early-Warning Systems

Beyond direct detection, predictive analytics aims to identify where and when fires are likely to occur. These systems combine historical fire records, satellite observations, weather data, and vegetation indices to forecast ignition hotspots. For example, MODIS and VIIRS datasets provide long-term global fire activity records. By integrating these with meteorological inputs such as wind speed, temperature, and relative humidity, ML models can forecast wildfire risk zones. Random Forest and Gradient Boosting algorithms have been applied to generate fire risk maps, achieving high predictive accuracy across diverse landscapes (Jain et al., 2020). Neural networks, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, are also employed for temporal prediction. These architectures excel at learning sequential dependencies, such as fire ignition probability over time based on evolving climatic conditions. In California, LSTM models trained on historical wildfire and weather datasets have achieved >80% accuracy in forecasting daily fire occurrence probabilities (Zhang et al., 2022).

3. Fire Modeling with AI and Machine Learning

While fire detection focuses on identifying ignition events, fire modeling aims to predict the behavior of flames, heat transfer, smoke propagation, and fire spread under diverse conditions. Accurate modeling is critical for designing safer buildings, forecasting wildfire progression, planning evacuations, and guiding suppression strategies. Traditional fire modeling relies heavily on physics-based simulations such as Computational Fluid Dynamics (CFD) and the Fire Dynamics Simulator (FDS), both of which use conservation equations for mass, momentum, and energy to simulate fire behavior (McGrattan et al., 2013). While robust, these methods are computationally expensive and often impractical for real-time applications. AI and machine learning provide complementary or alternative approaches. By learning patterns directly from data, ML can reduce computational costs, capture nonlinear relationships, and provide faster predictions. Below, we review three key areas where AI is reshaping fire modeling: fire dynamics and heat transfer, smoke propagation and toxicity, and wildfire spread prediction.

3.1 Fire Dynamics and Heat Transfer

Traditional physics-based fire dynamics models involve complex governing equations. CFD approaches simulate combustion, radiation, and turbulent flows to provide detailed flame spread and temperature distributions (Hostikka & McGrattan, 2020). Although accurate, simulations can require hours or days, limiting their applicability in real-time decision support. Surrogate models, powered by ML, are emerging as efficient alternatives. These models are trained on large datasets generated by CFD/FDS simulations and experimental data, learning to approximate outputs with a fraction of the computational cost. For example, deep neural networks (DNNs) have been used as surrogates to predict temperature fields and heat flux in compartment fires with near real-time efficiency (Zhu et al., 2022). Such approaches achieved $R^2 > 0.9$, dramatically reducing simulation times while retaining high fidelity. Physics-Informed Neural Networks (PINNs) are particularly promising. Unlike black-box models, PINNs incorporate physical laws (e.g., conservation of energy, Navier-Stokes equations) into the training process, improving both interpretability and generalization (Yarmohammadian et al., 2025).

3.2 Smoke Propagation and Toxicity Modeling

Smoke is often more dangerous than flames, as inhalation of toxic gases accounts for the majority of fire-related fatalities (Purser, 2019). Accurately predicting smoke spread, density, and toxicity levels is essential for both safety engineering and evacuation planning. ML approaches are filling this gap. For example, Random Forest and XGBoost algorithms trained on environmental parameters (wind speed, temperature, building geometry) can predict smoke travel patterns with high accuracy in indoor and tunnel environments (Shen et al., 2021). Deep learning models, particularly Convolutional LSTMs, have also been applied to time-series data for forecasting smoke concentrations, offering predictive capabilities several minutes ahead of observed measurements. AI-driven indoor smoke detection is another rapidly developing application. Deep learning image recognition systems can distinguish between different smoke densities in CCTV footage, improving detection accuracy during early smoldering phases (Wang et al., 2020). Combined with building evacuation models, AI can dynamically update safe egress routes in response to evolving smoke conditions.

3.3 Predictive Analytics in Wildfire Spread

Wildfires present unique challenges due to their scale, complexity, and interaction with dynamic environmental conditions. Predicting wildfire spread is crucial for planning evacuations, allocating suppression resources, and estimating ecological and economic impacts. Traditional wildfire models include the Rothermel fire spread equation and the FARSITE simulation system (Finney, 1998). While widely used, these models often rely on simplified assumptions about fuel homogeneity and weather inputs.

AI and ML enable data-driven wildfire forecasting that can incorporate heterogeneous datasets: satellite imagery, GIS layers (topography, vegetation cover), meteorological data, and historical fire records.

• Random Forest (RF) and Gradient Boosting (GBM): These algorithms excel at handling structured environmental datasets. Studies in Mediterranean ecosystems and U.S. wildlands have shown that RF can predict ignition probability and spread direction with accuracies exceeding 80% (Jain et al., 2020).
• Deep Learning (DL): Convolutional Neural Networks (CNNs) applied to satellite imagery can identify fire boundaries and predict spread under evolving wind and fuel conditions (Cheng et al., 2020).
• Recurrent Neural Networks (RNNs) and LSTMs: These models capture temporal dependencies in fire spread by learning from sequences of weather and fire activity data. Zhang et al. (2022) reported >85% accuracy in predicting wildfire spread direction in California using LSTMs.

4. AI-Driven Fire Suppression

While early detection and accurate modeling are essential for fire safety, the ultimate challenge lies in effective suppression. Fire suppression encompasses the deployment of resources, tactical decision-making, use of technology, and activation of automated systems to contain or extinguish fires (Figure 1). Traditional suppression relies on human expertise, physical suppression systems (sprinklers, hydrants, foam, and chemical retardants), and large-scale firefighting operations in wildlands. However, as fire events increase in scale and complexity, conventional approaches struggle with limitations of speed, resource allocation, and firefighter safety. Artificial Intelligence (AI), Machine Learning (ML), and data analytics are increasingly used to support suppression activities (Kamruzzaman et al., 2024; Islam et al., 2024; Bhuiyan et al., 2025; Juie et al., 2021; Rahman et al., 2022). These tools optimize how resources are deployed, enable robotic and autonomous firefighting systems, and make suppression systems more adaptive. The following subsections examine how AI is reshaping suppression strategies in three domains: intelligent resource allocation, robotics and autonomous systems, and smart suppression systems.

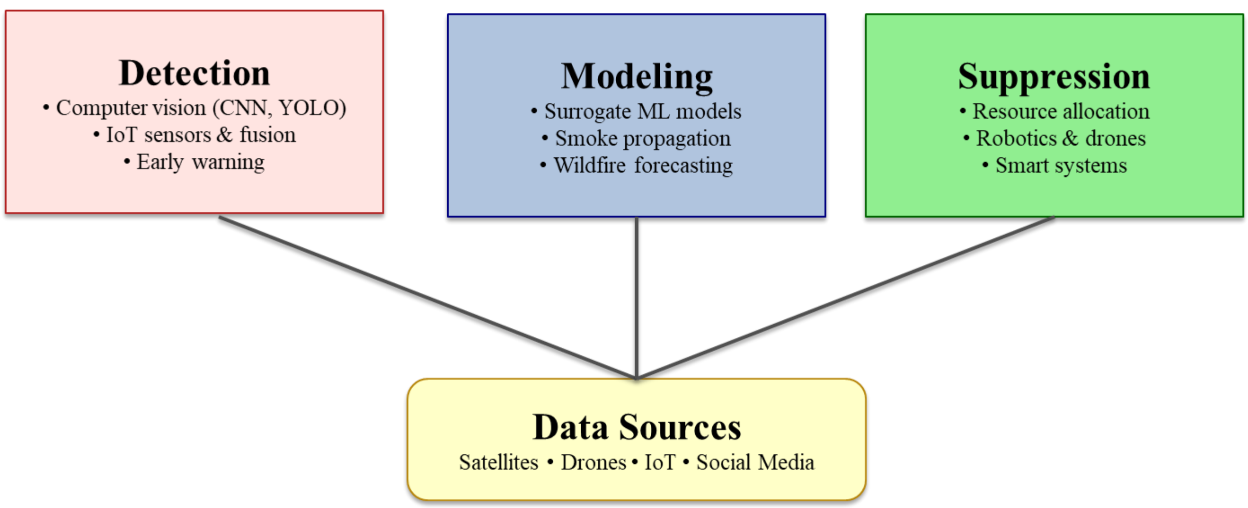

Figure 1. AI and Data Analytics in Fire Science

4.1 Intelligent Resource Allocation

One of the most critical tasks in large-scale fire suppression is deciding where and when to allocate firefighting resources. In wildfires, the speed of spread and the vast geographic area mean that misallocated resources can lead to catastrophic escalation. AI-driven predictive analytics assist in dynamic resource allocation (Bhuiyan and Mondal, 2023; Hossain et al., 2024). By combining fire growth models, weather forecasts, fuel maps, and infrastructure vulnerability assessments, ML algorithms can prioritize high-risk zones. For instance, ensemble models such as Random Forest and Gradient Boosting have been used to rank fire-prone regions and predict fireline intensity, guiding authorities on where to pre-position firefighting units (Jain et al., 2020). Geographic Information Systems (GIS) integrated with AI provide real-time fire risk maps that help commanders visualize active fires and determine deployment strategies. Reinforcement learning has also been proposed for adaptive decision-making, even in human disease like mental health, disease where AI agents simulate multiple suppression strategies and recommend those with the highest probability of containment (Liu et al., 2019; Bulbul et al., 2018; Tanvir et al., 2024; Bhuiyan et al, 2025). In urban and industrial contexts, predictive analytics can determine the optimal routing of fire trucks. Traffic data, building occupancy, and real-time hazard assessments are incorporated to minimize response times. Recent studies demonstrate that AI-based routing systems can reduce urban fire department response times by up to 15–20% compared to traditional GPS routing (He et al., 2021).

4.2 Robotics and Autonomous Systems

Ground Robots: Robots such as tracked firefighting vehicles can enter hazardous areas that are unsafe for humans. Equipped with thermal cameras, LiDAR, and AI navigation systems, they can identify fire hotspots and direct water or foam with precision (Yoon et al., 2020). Machine learning algorithms enhance navigation in low-visibility conditions, ensuring mobility in environments filled with smoke or debris. Aerial Drones: UAVs equipped with AI-driven detection systems provide situational awareness, map fire perimeters, and in some cases, deploy fire suppressants. Swarms of drones coordinated through AI algorithms can cover large areas quickly, relaying live data to commanders. In forest fires, drones carrying small fire-retardant payloads have been deployed for targeted suppression of spot fires before they spread and there are some forest regions even can be vulnerable do their region-specific condition and threat on diversity due to lack of proper use of technology (Restas, 2021; Aminuzzaman & Das, 2017; Das et al., 2016, 2017; Marzana et al., 2018). Swarm Robotics: Recent research explores swarm intelligence for coordinated suppression. Inspired by the behavior of ants or bees, swarm algorithms allow multiple small robots to collaborate in extinguishing fires in tunnels, forests, or industrial plants. Distributed AI enables each unit to make local decisions while contributing to global fire suppression strategies (Gao et al., 2022).

4.3 Smart Suppression Systems

Data-driven sprinklers integrate AI with sensor networks to optimize suppression. Using real-time fire growth predictions and localized temperature/smoke data, these systems adjust water or foam discharge rates dynamically, ensuring efficient use of resources (Wang et al., 2020). Such systems can isolate fire hotspots within buildings, minimizing water damage in unaffected areas. AI also assists in incident command decision-making. During active fires, commanders must choose among suppression strategies under uncertainty. Decision-support systems powered by ML analyze factors such as fire growth projections, available resources, and weather conditions to recommend optimal suppression tactics. For instance, Bayesian decision models have been applied to evaluate trade-offs between offensive and defensive suppression in structural fires (Mell et al., 2020). In industrial contexts, smart gas suppression systems use AI to regulate discharges of CO_2, inert gases, or clean agents (like FM-200). By dynamically adjusting flow rates, AI can balance effectiveness with minimization of toxic exposure to occupants. Another frontier is the use of digital twins—virtual replicas of physical buildings or industrial sites integrated with AI fire models. These twins simulate fire progression in real time and test multiple suppression strategies before implementation. By comparing outcomes, commanders can deploy the most effective response without guesswork (Kapogiannis & Sherratt, 2018).

5. Challenges and Limitations

While the integration of Artificial Intelligence (AI), Machine Learning (ML), and Data Analytics into fire science offers transformative opportunities for detection, modeling, and suppression, these technologies face significant challenges and limitations. Addressing these issues is crucial to ensuring their safe, reliable, and scalable application in real-world fire management (Kamruzzaman et al., 2025; Mondal et al., 2025; Das et al., 2025). The main challenges fall into four categories: data scarcity and quality, computational demand, model overfitting and generalization, and ethical and operational concerns.

5.1 Data Scarcity and Quality Issues

A fundamental challenge in applying AI to fire science is the limited availability and quality of datasets. High-performing ML models require large, diverse, and well-annotated datasets. However, in fire research:

• Fire event data are rare and heterogeneous. Unlike domains such as image recognition, where datasets contain millions of labeled examples, fire events are infrequent and vary widely in scale, duration, and environmental context. For instance, a dataset of urban building fires may not transfer well to wildland fires due to differences in fuel, atmospheric conditions, and fire dynamics (Jain et al., 2020).
• Sensor noise and false positives. IoT sensors deployed in harsh environments often produce noisy or incomplete data. False positives caused by fog, dust, or steam can bias models during training and undermine operational trust (Liu et al., 2018).
• Geographic and ecological biases. Most publicly available wildfire datasets are concentrated in regions such as North America, Australia, and Southern Europe. This creates bias and undermines model generalization to other ecosystems (e.g., boreal forests in Canada or tropical savannas in Africa) (Cheng et al., 2020).
• Privacy and accessibility. High-resolution surveillance data (e.g., CCTV, drones) are often restricted due to privacy regulations, while satellite data may be costly or subject to latency, limiting real-time applications.

To overcome these issues, researchers are exploring data augmentation techniques, synthetic datasets generated from simulations (e.g., Fire Dynamics Simulator outputs), and transfer learning, where models trained in one domain are adapted to another with limited new data (Nguyen et al., 2022).

5.2 High Computational Demand

Another major limitation is the computational intensity of AI-driven fire science applications.

• Real-time constraints. Fire detection and modeling require near-instantaneous processing. For example, UAV-based detection systems must process high-resolution video streams in real time to identify ignitions. Deep learning models like YOLOv8 achieve high accuracy but demand significant GPU resources, which may not be available on edge devices deployed in the field (Boonyuen et al., 2022).
• Scalability challenges. Modeling wildfire spread at regional or global scales requires processing massive amounts of satellite and meteorological data. Training ML models on such datasets can take days to weeks, with high computational and energy costs (Zhu et al., 2022).
• Edge AI limitations. While edge computing reduces latency, it requires model compression or quantization to run on low-power devices. This often leads to reduced accuracy compared to cloud-based systems (Rahman et al., 2022).

Recent research has begun integrating physics-informed machine learning (PIML) to reduce computational demand while maintaining accuracy. By embedding physical laws into neural networks, PIML reduces the need for large datasets and computationally intensive training, while ensuring physically consistent outputs (Yarmohammadian et al., 2025).

5.3 Overfitting and Generalization

AI models in fire science often face the risk of overfitting—performing well on training datasets but failing in unseen real-world conditions.

• Overfitting small datasets. Because fire datasets are limited, deep learning models with millions of parameters can easily overfit, learning spurious correlations that do not generalize. For example, a CNN trained on fire images under clear skies may misclassify similar-looking objects (e.g., red lights or sunsets) as fire in real deployments (Ko et al., 2009).
• Environmental variability. Fire behavior is influenced by multiple interacting factors fuel type, moisture, wind speed, terrain, and humidity. Capturing this complexity in a single model is challenging, and models trained in one region may not transfer effectively to another (Zhang et al., 2022).
• Dynamic conditions. Fires evolve rapidly. A model trained on early ignition data may not generalize to later stages of fully developed fires, where smoke density and flame dynamics change drastically.
Solutions include ensemble modeling (combining multiple algorithms), domain adaptation, and incremental learning, where models are continuously updated with new data. In addition, explainable AI (XAI) approaches can improve trust by helping operators understand why a model produced a certain prediction, reducing blind reliance on potentially flawed outputs.

5.4 Ethical and Operational Concerns

The use of AI in life-critical domains like firefighting raises profound ethical and operational questions.

• Reliance on automated systems. Overreliance on AI for fire detection or suppression could lead to catastrophic outcomes if models fail. For example, a false negative in early detection might delay response and allow a fire to escalate. Conversely, false positives may waste resources and reduce trust in AI systems.
• Human-AI collaboration. Fire management requires coordination among firefighters, incident commanders, and AI systems. If AI outputs are opaque, commanders may struggle to integrate recommendations into operational strategies (Mell et al., 2020).
• Bias and fairness. AI systems trained on biased datasets may prioritize protection in some regions over others, potentially reinforcing inequities in resource allocation. This is particularly concerning in wildfires that affect vulnerable rural or Indigenous communities (Abatzoglou et al., 2021).
• Legal accountability. If an autonomous firefighting robot fails or causes unintended harm, it is unclear who bears responsibility the manufacturer, the deploying agency, or the algorithm developers. This lack of clarity poses legal challenges for deployment.
• Data privacy. Using AI for fire detection in urban areas often involves video surveillance, raising privacy concerns if footage is stored or analyzed without consent.

Mitigating these issues requires establishing transparent AI systems, robust fail-safes, ethical guidelines, and human oversight frameworks. Hybrid human-AI decision-making systems where AI provides recommendations but final control rests with trained professionals appear to be the most acceptable path forward (Kapogiannis & Sherratt, 2018).

6. Future Directions

Artificial Intelligence (AI) and Data Analytics have already begun transforming fire detection, modeling, and suppression. However, the pace of climate change, urbanization, and technological advancement demands more innovative, scalable, and trustworthy solutions. Future fire science research must address existing limitations while embracing new computational paradigms, interdisciplinary collaboration, and real-world deployment. Several key directions stand out: integration of multi-modal data, explainable AI (XAI), quantum-enhanced simulations, and collaborative, interdisciplinary approaches.

6.1 Integration of Multi-Modal Data

Current AI applications in fire science often rely on a single type of data input such as images from cameras, temperature readings from sensors, or satellite-derived hotspots. While effective, single-source approaches are vulnerable to noise, false alarms, and incomplete situational awareness. Future systems will increasingly leverage multi-modal data integration, combining heterogeneous data streams for a more holistic view.

• Remote Sensing and Satellites: Instruments such as MODIS, VIIRS, and Sentinel provide near-global coverage of thermal anomalies, fuel moisture, and burned areas. When combined with local data sources, satellite imagery offers macro-level insights into fire-prone regions (Cheng et al., 2020).
• Unmanned Aerial Vehicles (UAVs): Drone-based systems equipped with thermal, optical, and hyperspectral sensors provide high-resolution, real-time information about fire fronts and smoke plumes (Restas, 2021).
• IoT Sensor Networks: Distributed temperature, gas, humidity, and particulate sensors embedded in forests, tunnels, or industrial facilities can detect micro-level changes leading to fire ignition (Rahman et al., 2022).
• Social Media and Crowdsourcing: Increasingly, eyewitness reports, photos, and social media posts provide rapid situational intelligence during fire events. NLP (Natural Language Processing) and geotagging can turn these into actionable data streams (Fazelpour & Yu, 2021).

Integrating these sources through data fusion frameworks and multi-modal deep learning architectures will reduce uncertainty, improve robustness, and allow predictive systems to update dynamically. For example, a multi-modal AI system could simultaneously use satellite data for macro-level risk forecasting, UAV feeds for tactical monitoring, and IoT sensors for real-time micro-detection.

6.2 Explainable AI (XAI) for Transparent Decision-Making

Despite their success, many AI models in fire science function as black boxes, providing predictions without transparency. This creates challenges in life-critical contexts, where emergency responders must understand why a system makes a certain recommendation. The growing field of Explainable AI (XAI) seeks to address this gap by producing interpretable, trustworthy outputs.

• Post-hoc interpretability: Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) can highlight which features (e.g., wind speed, fuel load, smoke density) influenced a fire spread prediction.
• Inherently interpretable models: Decision trees, rule-based systems, and physics-informed ML frameworks can be designed to balance accuracy with human comprehensibility.
• Operational trust: Incident commanders are more likely to adopt AI tools if they understand the rationale behind predictions. For instance, knowing that a fire spread forecast is driven by dry fuel moisture and high winds makes the output actionable and trustworthy (Arrieta et al., 2020).

6.3 Quantum Computing and AI for Ultra-Fast Fire Simulations

Traditional fire simulations using CFD and FDS are computationally demanding, often taking hours or days to model complex fire dynamics (Hostikka & McGrattan, 2020). Even surrogate ML models require substantial training resources. Looking ahead, quantum computing offers a paradigm shift.

Quantum algorithms excel at solving optimization and differential equation problems that underlie fire modeling. By coupling quantum computing with AI, researchers envision:

• Ultra-fast simulations of fire growth and smoke propagation that can update in near real-time.
• Optimization of suppression strategies, such as routing resources or coordinating robotic swarms, using quantum-enhanced reinforcement learning.
• High-dimensional modeling of fuel moisture, atmospheric conditions, and combustion chemistry at scales unfeasible for classical computing.

Although still experimental, early research in quantum machine learning (QML) suggests potential for reducing computation times by orders of magnitude. For fire science, this could translate into predictive modeling systems capable of operating on-the-fly, supporting decision-making in rapidly evolving fire events.

6.4 Interdisciplinary Collaboration

Fire science sits at the intersection of engineering, environmental science, public safety, and computer science. Future advancements will depend on interdisciplinary collaboration among:

• Fire Scientists and Engineers: To provide domain knowledge on combustion, smoke toxicity, fire dynamics, and safety standards.
• AI/ML Researchers: To design scalable, interpretable, and physics-informed algorithms.
• Emergency Responders: To translate AI outputs into operational tactics and ensure systems align with real-world constraints.
• Policy Makers and Ethicists: To establish guidelines, legal frameworks, and accountability mechanisms for AI in firefighting.

Collaborative platforms such as digital twins of urban environments, where fire scientists, AI experts, and responders can simulate scenarios together, are likely to become central. These shared systems allow testing of fire detection, modeling, and suppression strategies in virtual environments before real-world deployment (Kapogiannis & Sherratt, 2018).

6.5 Toward Resilient, AI-Enhanced Fire Management

Taken together, these future directions highlight a shift toward resilient, adaptive fire management systems:

1. Multi-modal sensing and fusion will provide richer, more reliable data streams.
2. Explainable AI will build trust, ensuring responders understand and validate model outputs.
3. Quantum-enhanced AI will reduce computational bottlenecks, enabling real-time predictions at unprecedented scales.
4. Collaborative ecosystems will bridge the gap between research and practice, ensuring AI systems meet the operational needs of emergency services.

Ultimately, the integration of AI into fire science should aim not to replace human expertise but to augment it providing faster insights, reducing risks to firefighters, and enhancing society's resilience to increasingly severe fire hazards.

7. Conclusion

Artificial Intelligence and Data Analytics are reshaping the field of fire science, offering solutions that were previously unattainable with traditional methods. By leveraging advanced algorithms, real-time data streams, and predictive modeling techniques, AI is making fire detection faster, fire growth modeling more accurate, and suppression strategies smarter and more adaptive. Collectively, these innovations hold the promise of reducing the devastating impacts of fires on human lives, infrastructure, and ecosystems. In detection, AI-driven computer vision systems, IoT sensor networks, and predictive analytics are moving beyond reactive alarm mechanisms to proactive early-warning platforms. These technologies not only reduce false alarms but also provide situational awareness at scales ranging from individual buildings to entire wildfire-prone regions. The integration of multimodal data from satellites, drones, and social media further strengthens the reliability and timeliness of detection systems. In modeling, ML has enabled the development of surrogate models that dramatically reduce the computational burden of traditional physics-based simulations such as CFD and FDS. These AI models capture nonlinear interactions among fuel, weather, and terrain, providing faster and more scalable predictions of fire dynamics, smoke propagation, and wildfire spread. As computational techniques evolve, quantum-enhanced AI and physics-informed neural networks are likely to make real-time fire simulations a practical reality. Suppression strategies are also undergoing transformation through AI. Intelligent resource allocation ensures that firefighting crews and assets are deployed where they are most needed, maximizing efficiency under constrained conditions. Robotics, drones, and swarm-based systems reduce risks to human firefighters while extending capabilities into environments that are too dangerous or inaccessible. Meanwhile, smart suppression systems, enhanced by AI decision-support tools, enable adaptive responses that conserve resources and improve effectiveness. Despite these advances, significant challenges remain. Data scarcity, computational demands, model overfitting, and the ethical implications of relying on AI in life-critical contexts all require careful attention. Ensuring that AI systems are explainable, reliable, and equitable is essential for their widespread adoption. Furthermore, successful implementation will depend on interdisciplinary collaboration among fire scientists, computer scientists, emergency responders, policymakers, and ethicists.

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References

[1] Abatzoglou, J. T., Williams, A. P., & Barbero, R. (2021). Global emergence of anthropogenic climate change in fire weather indices. Nature Climate Change, 11(7), 627–631. https://doi.org/10.1038/s41558-021-01001-9
[2] Abatzoglou, J. T., Williams, A. P., & Barbero, R. (2021). Global emergence of anthropogenic climate change in fire weather indices. Nature Climate Change, 11(7), 627–631. https://doi.org/10.1038/s41558-021-01001-9
[3] Aminuzzaman FM, Das K (2017). Morphological Characterization of Polypore Macro Fungi Associated with Dalbergia Sissoo Collected from Bogra District Under Social Forest Region of Bangladesh. Journal of Biology and Nature. 6(4):199–212.

[4] Arrieta, A. B., Díaz-Rodríguez, N., Ser, J. D., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

[5] Ashik, A. A. M., Rahman, M. M., Hossain, E., Rahman, M. S., Islam, S., & Khan, S. I. (2023). Transforming U.S. Healthcare Profitability through Data-Driven Decision Making: Applications, Challenges, and Future Directions. European Journal of Medical and Health Research, 1(3), 116-125. https://doi.org/10.59324/ejmhr.2023.1(3).21

[6] Bhuiyan, M. N. A., & Mondal, R. S. (2023). AI-driven predictive analytics in healthcare: Evaluating impact on cost and efficiency. Journal of Computational Analysis and Applications, 31(4), 1355–1371.10.48047/jocaaa.2023.31.04.26

[7] Bhuiyan, M. N. A., Kamruzzaman, M., Saha, S., Siddiki, M. S., & Mondal, R. S. (2025). Role of data analysis and integration of artificial intelligence. Journal of Business and Management Studies, 7(4), 379–388. 10.32996/jbms.2025.7.4.20.26

[8] Bhuiyan, M. M. R., Hossain, M. R. B., Kabir, J. U. Z., Rahman, M. M., & Sarker, B. K. (2025). Mental health status in home quarantine: A cross-sectional study on the adolescents of the southern part of Bangladesh. International Journal of Advanced Multidisciplinary Research and Studies, 5(3), 71–78. https://doi.org/10.62225/2583049X.2025.5.3.4203

[9] Boonyuen, K., Khan, M., & Kachitvichyanukul, V. (2022). Real-time fire detection using YOLO-based deep learning models. Applied Intelligence, 52(10), 11650–11667. https://doi.org/10.1007/s10489-021-02768-9

[10] Bulbul IJ, Zahir Z, Tanvir A, et al. Comparative study of the antimicrobial, minimum inhibitory concentrations (MIC), cytotoxic and antioxidant activity of methanolic extract of different parts of Phyllanthus acidus (l.) Skeels (family: Euphorbiaceae). World Journal of Pharmacy and Pharmaceutical Sciences, 2018, 8(1): 12-57. https://doi.org/10.20959/wjpps20191-10735.

[11] Das K, Aminuzzaman FM, Nasim A (2016). Diversity of Fleshy Macro Fungi in Mangrove Forest Regions of Bangladesh. Journal of Biology and Nature. 6(4):218–241.

[12] Das K,Aminuzzaman FM (2017). Morphological and Ecological Characterization of Xylotrophic Fungi in Mangrove Forest Regions of Bangladesh. Journal of Advances in Biology & Biotechnology. 11(4):1–15.

[13] Das, K., Tanvir, A., Rani, S. and Aminuzzaman, F. M. (2025) Revolutionizing Agro-Food Waste Management: Real-Time Solutions through IoT and Big Data Integration. Voice of the Publisher, 11, 17-36. https://doi.org/10.4236/vp.2025.111003.

[14] Fazelpour, S., & Yu, E. (2021). Social media data for disaster response: Review and research directions. Information Systems Frontiers, 23, 1443–1462. https://doi.org/10.1007/s10796-020-10085-8

[15] Finney, M. A. (1998). FARSITE: Fire Area Simulator – Model Development and Evaluation. USDA Forest Service Research Paper RMRS-RP-4.

[16] Gao, J., Li, Z., & Xu, H. (2022). Swarm robotics for fire suppression: A multi-agent reinforcement learning approach. Robotics and Autonomous Systems, 156, 104168. https://doi.org/10.1016/j.robot.2022.104168

[17] He, J., Chen, L., & Wang, F. (2021). AI-based emergency vehicle routing for urban firefighting. Transportation Research Part C: Emerging Technologies, 127, 103161. https://doi.org/10.1016/j.trc.2021.103161

[18] Hossain, E., Ashik, A. A. M., Rahman, M. M., Khan, S. I., Rahman, M. S., & Islam, S. (2023). Big data and migration forecasting: Predictive insights into displacement patterns triggered by climate change and armed conflict. Journal of Computer Science and Technology Studies, 5(4): 265–274. https://doi.org/10.32996/jcsts.2023.5.4.27

[19] Hossain, E., Shital, K. P., Rahman, M. S., Islam, S., Khan, S. I., & Ashik, A. A. M. (2024). Machine learning-driven governance: Predicting the effectiveness of international trade policies through policy and governance analytics. Journal of Trends in Financial and Economics, 1(3), 50–62. https://doi.org/10.61784/jtfe3053

[20] Hostikka, S., & McGrattan, K. (2020). Numerical simulations of fire dynamics using FDS. Fire Safety Journal, 113, 102977. https://doi.org/10.1016/j.firesaf.2020.102977

[21] Islam, S., Hossain, E., Rahman, M. S., Rahman, M. M., Khan, S. I., & Ashik, A. A. M. (2023). Digital Transformation in SMEs: Unlocking Competitive Advantage through Business Intelligence and Data Analytics Adoption. 5 (6):177-186. https://doi.org/10.32996/jbms.2023.5.6.14

[22] Islam, S., Khan, S. I., Ashik, A. A. M., Hossain, E., Rahman, M. M., & Rahman, M. S. (2024). Big data in economic recovery: A policy-oriented study on data analytics for crisis management and growth planning. Journal of Computational Analysis and Applications (JoCAAA), 33(7), 2349–2367. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/3338

[23] Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. Environmental Reviews, 28(4), 478–505. https://doi.org/10.1139/er-2020-0019

[24] Juie, B. J. A., Kabir, J. U. Z., Ahmed, R. A., & Rahman, M. M. (2021). Evaluating the impact of telemedicine through analytics: Lessons learned from the COVID-19 era. Journal of Medical and Health Studies, 2(2), 161–174.https://doi.org/10.32996/jmhs.2021.2.2.19

[25] Kamruzzaman, M., Mondal, R. S., Islam, M. K., Rahaman, M. A., & Saha, S. (2024). AI-driven predictive modelling of US economic growth using big data and explainable machine learning. International Journal of Computational and Experimental Science and Engineering, 10(4), 1927-1938. https://doi.org/10.22399/ijcesen.3612

[26] Kamruzzaman, M., Saha, S., Siddiki, M. S., Mondal, R. S., & Bhuiyan, M. N. A. (2025). Applications of artificial intelligence in small and medium scale business. Journal of Business and Management Studies, 7(4), 314–325. https://doi.org/10.32996/jbms.2025.7.4.20.21

[27] Kapogiannis, G., & Sherratt, F. (2018). Digital twin technology in construction fire safety management. Automation in Construction, 94, 102–110. https://doi.org/10.1016/j.autcon.2018.06.018

[28] Khan, S. I., Rahman, M. S., Ashik, A. A. M., Islam, S., Rahman, M. M., & Hossain, E. (2024). Big Data and Business Intelligence for Supply Chain Sustainability: Risk Mitigation and Green Optimization in the Digital Era. European Journal of Management, Economics and Business, 1(3): 262-276. https://doi.org/10.59324/ejmeb.2024.1(3).23

[29] Ko, B. C., Cheong, K. H., & Nam, J. Y. (2009). Fire detection based on vision sensor and support vector machines. Fire Safety Journal, 44(3), 322–329. https://doi.org/10.1016/j.firesaf.2008.07.005

[30] Liu, Q., Chen, H., & Lin, D. (2025). Research and optimization of a multilevel fire detection framework based on deep learning and classical pattern recognition techniques. Scientific Reports, 15, 20364. https://doi.org/10.1038/s41598-025-06721-3

[31] Liu, Y., Zhang, X., & Sun, H. (2019). Reinforcement learning for firefighting resource allocation under dynamic fire spread. Safety Science, 120, 179–188. https://doi.org/10.1016/j.ssci.2019.07.009
[32] Liu, Z., Cao, Z., & Luo, Y. (2018). A sensor fusion fire detection method using SVM. Sensors, 18(11), 3760. https://doi.org/10.3390/s18113760
[33] Marzana A, Aminuzzaman FM, Chowdhury MSM, Mohsin SM, Das K (2018). Diversity and Ecology of Macrofungi in Rangamati of Chittagong Hill Tracts Under Tropical Evergreen and Semi-Evergreen Forest of Bangladesh. Advances in Research. 13(5):1–17.
[34] McGrattan, K., Hostikka, S., McDermott, R., Floyd, J., & Vanella, M. (2013). Fire Dynamics Simulator Technical Reference Guide. NIST Special Publication 1018.
[35] Mell, W., Manzello, S. L., & Maranghides, A. (2020). Bayesian decision support models for fire suppression strategy evaluation. Fire Technology, 56(6), 2205–2224. https://doi.org/10.1007/s10694-019-00940-4
[36] Mondal, R. S., Kamruzzaman, M., Saha, S., & Bhuiyan, M. N. A. (2025). Quantum machine learning approaches for high-dimensional cancer genomics data analysis. Computer Integrated Manufacturing Systems, 31(1), 13-32. DOI: 10.24297/j.cims.2025.1.21.
[37] NFPA (2024). Fire Loss in the United States 2023. National Fire Protection Association. Retrieved from https://www.nfpa.org
[38] Nguyen, H. T., Zhang, G., & Nguyen, K. T. Q. (2022). Machine learning-based surrogate model for calibrating fire source properties in FDS models of façade fire tests. Fire Safety Journal, 130, 103591. https://doi.org/10.1016/j.firesaf.2022.103591
[39] Purser, D. A. (2019). Toxicity assessment of combustion products. SFPE Handbook of Fire Protection Engineering, 2300–2350.
[40] Rahman, M. M., Ahmed, F., & Islam, M. R. (2022). Edge AI for real-time fire detection in IoT networks. IEEE Internet of Things Journal, 9(5), 3712–3724. https://doi.org/10.1109/JIOT.2021.3098623
[41] Rahman, M. M., Juie, B. J. A., Tisha, N. T., & Tanvir, A. (2022). Harnessing predictive analytics and machine learning in drug discovery, disease surveillance, and fungal research. Eurasia Journal of Science and Technology, 4(2), 28-35. https://doi.org/10.61784/ejst3099
[42] Restas, A. (2021). Drone applications in fire suppression: A review of emerging technologies. Drones, 5(3), 73. https://doi.org/10.3390/drones5030073
[43] Saha, S., Islam, M. K., Rahaman, M. A., Mondal, R. S., & Kamruzzaman, M. (2024). Machine learning driven analytics for national security operations: A wavelet–stochastic signal detection framework. Journal of Computational Analysis and Applications, 33(8), 210. https://doi.org/10.48047/jocaaa.2024.33.08.210
[44] Shen, W., Yang, H., & Li, J. (2021). Smoke propagation modeling using machine learning techniques. Safety Science, 141, 105338. https://doi.org/10.1016/j.ssci.2021.105338
[45] Siddiki, M. S., Mondal, R. S., Bhuiyan, M. N. A., Kamruzzaman, M., & Saha, S. (2025). Assessment the knowledge, attitudes, education, knowledge, attitude and practices toward artificial intelligence. Journal of Business and Management Studies, 7(5), 106–116. https://doi.org/10.32996/jbms.2025.7.5.9
[46] Tanvir, A., Juie, B. J. A., Tisha, N. T., & Rahman, M. M. (2020). Synergizing big data and biotechnology for innovation in healthcare, pharmaceutical development, and fungal research. International Journal of Biological, Physical and Chemical Studies, 2(2), 23–32. https://doi.org/10.32996/ijbpcs.2020.2.2.4.
[47] Tanvir, A.; Jo, J.; Park, S.M. (2024). Targeting Glucose Metabolism: A Novel Therapeutic Approach for Parkinson's Disease. Cells. 13, 1876. https://doi.org/10.3390/cells13221876
[48] van der Werf, G. R., Randerson, J. T., Giglio, L., et al. (2017). Global fire emissions estimates during 1997–2016. Earth System Science Data, 9, 697–720. https://doi.org/10.5194/essd-9-697-2017
[49] Vasconcelos, R. N., Rocha, W. J. S. F., Costa, D. P., Duverger, S. G., Santana, M. M. M. D., Cambui, E. C. B., et al. (2024). Fire detection with deep learning: A comprehensive review. Land, 13(10), 1696. https://doi.org/10.3390/land13101696]
[50] Wang, X., Li, C., & Wu, J. (2020). Indoor smoke detection using deep convolutional networks. Sensors, 20(12), 3489. https://doi.org/10.3390/s20123489
[51] WRI (2024). Global Trends in Forest Fires 2024. World Resources Institute. Retrieved from [https://www.wri.org
[52] Yarmohammadian, R., et al. (2025). Physics-informed surrogate modelling in fire safety engineering: A systematic review. Applied Sciences, 15(15), 8740. https://doi.org/10.3390/app15158740
[53] Yoon, J., Park, C., & Kim, J. (2020). Autonomous firefighting robots with deep learning-based navigation and suppression control. IEEE Access, 8, 112056–112069. https://doi.org/10.1109/ACCESS.2020.3002892
[54] Zhang, Y., Wang, Y., & Li, Z. (2022). Wildfire occurrence prediction using LSTM networks and meteorological data. International Journal of Wildland Fire, 31(9), 789–801. https://doi.org/10.1071/WF21095
[55] Zhu, Q., Li, F., Riley, W. J., Xu, L., Zhao, L., Yuan, K., Wu, H., Gong, J., & Randerson, J. (2022). Building a machine learning surrogate model for wildfire activities within a global Earth system model. Geoscientific Model Development, 15, 1899–1911. https://doi.org/10.5194/gmd-15-1899-2022