Comprehensive Prevention and Control of Coal Fires: A Survey

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Abstract

This survey paper presents a comprehensive examination of coal fire management strategies, emphasizing the integration of machine learning (ML), artificial intelligence (AI), and informatization to enhance monitoring, early warning systems, and fire prevention protocols. The paper is structured to cover key aspects including the mechanisms of spontaneous combustion, technological advances in monitoring systems, and the role of AI in optimizing fire control strategies and emergency response protocols. Real-world case studies highlight the effectiveness of AI-driven systems and autonomous drones in improving situational awareness and operational efficiency. The survey also addresses the limitations of current technologies, such as the dependency on high-quality datasets and the opacity of AI models, while proposing future directions involving interdisciplinary collaboration and ethical considerations. Emerging technologies, such as hybrid intelligence and causality analysis, are identified as pivotal for advancing coal fire management. The paper concludes by advocating for the validation of digital solutions in real-world settings and the integration of strategic resource placement to optimize safety and operational outcomes. By leveraging these insights, coal fire management can achieve significant improvements in safety and sustainability, ensuring more effective mitigation of fire hazards in mining operations.

1 Introduction

1.1 Structure of the Survey

This survey is structured into several key sections that address critical aspects of coal fire management. The introduction underscores the importance of a comprehensive approach to preventing and controlling spontaneous combustion, emphasizing the contributions of machine learning, artificial intelligence, and informatization in enhancing monitoring and early warning systems. The second section provides a background and overview of coal fire management strategies, highlighting the significance of emerging technologies.

The third section examines the mechanisms and stages of spontaneous combustion, detailing the scientific processes and challenges in detection and control. The fourth section focuses on technological advancements in monitoring and early warning systems, particularly the integration of machine learning and AI in developing sophisticated monitoring technologies.

Fire prevention and control strategies are discussed in the fifth section, which covers risk assessment, thermal analysis, and the optimization of fire control strategies through machine learning models. The sixth section addresses emergency rescue and response protocols, emphasizing AI-driven decision support systems and optimization of resource allocation.

In the seventh section, real-world case studies and practical applications illustrate the effectiveness of the discussed technologies and strategies. The survey concludes by examining challenges and future directions in coal fire management, including the limitations of current technologies, emerging

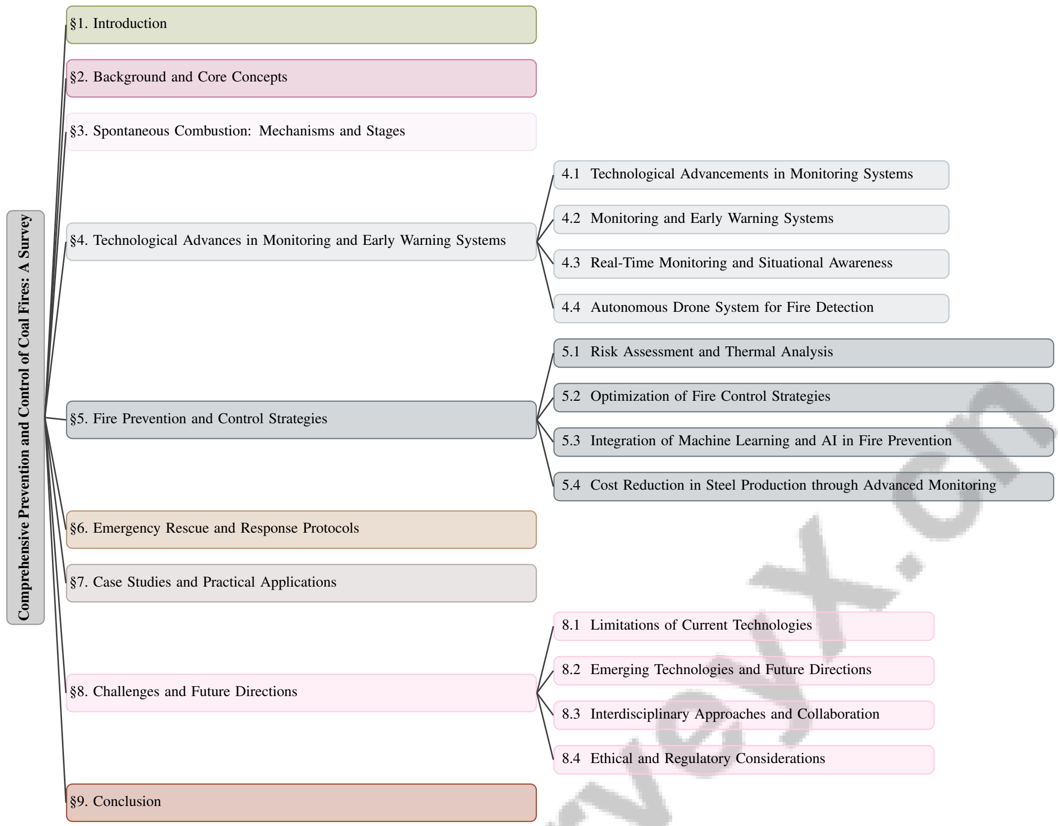

Figure 1: chapter structure

innovations, interdisciplinary collaboration, and relevant ethical and regulatory considerations.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Overview of Coal Fire Management

Coal fire management integrates traditional fire prevention with cutting-edge technologies to address the complexities of spontaneous combustion in coal mines, driven by intricate combustion mechanisms and multiphysics interactions [1]. Machine learning (ML) and artificial intelligence (AI) are pivotal in enhancing monitoring and early warning systems, developing predictive models to analyze extensive datasets for timely fire incident forecasts [2]. These technologies refine fire control strategies by processing multidimensional inputs, improving decision-making [3]. Real-time data analysis enhances situational awareness, supporting data-driven decisions essential for managing coal fires [4]. The evolution of ML and AI in this field has progressed from initial exploration to advanced development, underscoring their growing sophistication [5].

ML and AI applications extend to software engineering, enhancing project management, risk mitigation, and cost estimation, relevant to coal fire management [6]. Advanced technologies have improved risk assessment models, particularly in addressing workday losses from underground fires [7]. Thus, a comprehensive approach to coal fire management integrates these technologies to enhance monitoring, prediction, and control mechanisms, reducing risks and improving mining safety.

2.2 Role of Machine Learning and Artificial Intelligence

Machine learning (ML) and artificial intelligence (AI) revolutionize coal fire management through enhanced predictive analytics and optimized decision-making. Utilizing advanced methods like reinforcement learning and Bayesian Neural Networks, these technologies improve fire risk assessments

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and timely interventions. Hybrid modeling frameworks with Bayesian Neural Networks adjust first principles models, offering parameter distribution estimation and prediction uncertainty quantification [8]. AI surpasses traditional methods by incorporating dynamic simulators and reinforcement learning, functioning as soft sensors for unmeasured variables, crucial for managing data from IoT sensors and monitoring systems [9]. Infusing domain knowledge into AI models enhances interpretability, addressing AI systems' explainability challenges [10].

Collaborative AI Systems (CAIS) adopt risk-driven approaches to uphold safety and compliance within coal fire management frameworks [11]. These systems integrate AI technologies across domains, improving operational efficiency and decision-making. AI's role in risk management strategies strengthens resilience and safety outcomes, reinforcing coal fire management practices [12]. The evolution of AI technologies, including categorization and intelligent system responses, underscores their significance in advancing coal fire management. Diverse applications of ML and AI contribute to predictive model development, enhance decision-making, and promote responsible AI use, improving safety and operational efficiency. Robust governance practices and ethical principles in AI systems are vital, emphasizing their importance in fire management strategies [11]. Integrating causality into AI enhances capabilities in managing complex fire scenarios [13]. The YingLong model exemplifies integrating meteorological features for improved prediction accuracy, crucial for anticipating conditions that may heighten fire risks [14]. Developing comprehensive real-time systems for multi-indoor hazard management, incorporating IoT, BIM, AI, and other digital technologies, signifies AI's potential to transform hazard management in coal fire situations [15].

2.3 Informatization and Real-Time Data Analysis

Informatization enhances coal fire management through improved monitoring and data-driven decision-making. Integrating AI, IoT, and advanced analytics enables efficient data collection and analysis, critical for accurate fire detection and management [16]. Real-time data analysis enhances situational awareness and facilitates rapid decision-making, mitigating coal fire risks. However, AI system opacity poses challenges, potentially undermining trust and decision-making [12]. Establishing robust governance frameworks is essential to manage AI system risks and societal impacts [17]. Developing frameworks for evaluating AI model capabilities clarifies their strengths and limitations [18].

Utilizing big data in AI models faces challenges in data management, energy consumption, and computational inefficiencies, necessitating scalable approaches leveraging deep learning for enhanced accuracy [16]. Integrating domain-specific knowledge into AI models improves interpretability, making predictions more actionable [13]. Continuous evaluation and adjustment of AI models, evidenced by training on diverse datasets, underscore ongoing improvements to minimize biases and enhance performance. Establishing benchmarks for assessing explainable AI (XAI) methods against known ground truth sensitivities provides insights into the robustness and reliability of AI-driven decisions [18].

Informatization through real-time data analysis is crucial for refining coal fire management strategies, enabling prompt identification and quantification of fire incidents via technologies like computer vision and ML. These technologies facilitate collecting critical fire-related data, including localization, flame characteristics, and heat release rates, vital for decision-making and public safety. Leveraging real-time data allows systems to better predict and respond to fire outbreaks, reducing risks to life, property, and the environment [19, 20, 21]. Addressing challenges and harnessing advanced technologies significantly enhance monitoring, prediction, and control mechanisms, improving safety and efficiency in coal fire management.

In examining the complexities of spontaneous combustion in coal, it is essential to understand the multifaceted nature of this phenomenon. The hierarchical structure of spontaneous combustion encompasses various elements, including its introduction, mechanisms, stages, contributing factors, and the challenges associated with detection and control. Figure 2 illustrates this intricate relationship by categorizing the primary concepts into four key areas: influencing factors, physicochemical processes, intrinsic coal properties, and monitoring challenges. This comprehensive overview not only enhances our understanding of spontaneous combustion but also highlights the critical areas that require further research and attention in the field.

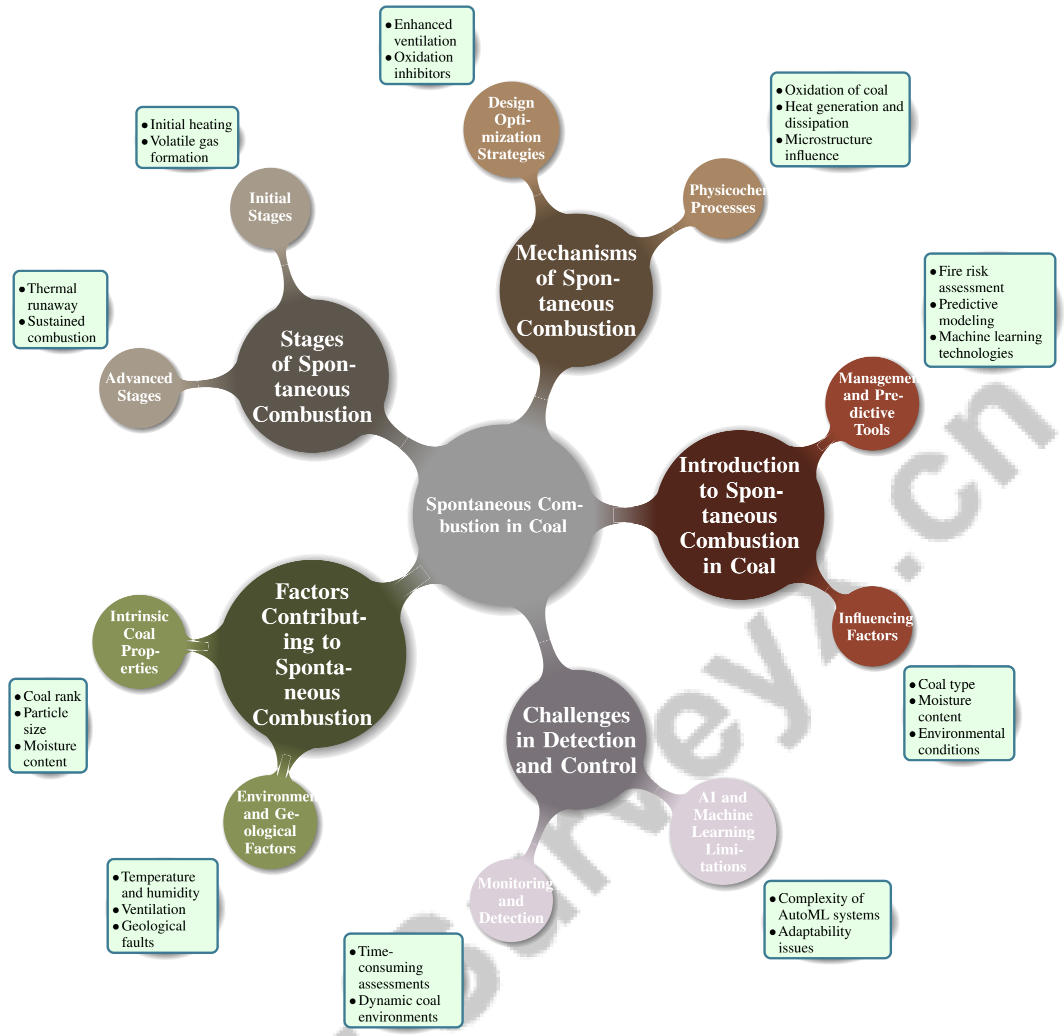

Figure 2: This figure illustrates the hierarchical structure of spontaneous combustion in coal, detailing the introduction, mechanisms, stages, contributing factors, and challenges in detection and control. It categorizes the primary concepts into influencing factors, physicochemical processes, intrinsic coal properties, and monitoring challenges, providing a comprehensive overview of the topic.

3 Spontaneous Combustion: Mechanisms and Stages

3.1 Introduction to Spontaneous Combustion in Coal

Spontaneous combustion in coal poses significant challenges for fire management, characterized by self-heating due to chemical reactions with oxygen, leading to ignition without an external flame. Influencing factors include coal type, moisture content, and environmental conditions during storage or mining. Effective management is crucial to prevent catastrophic fires that cause environmental degradation and economic losses. Recent studies highlight the importance of fire risk assessment and predictive modeling, with machine learning technologies emerging as essential tools for anticipating fire occurrence and spread under changing climate conditions [5, 22]. The challenges in predicting spontaneous combustion parallel those in forest fire management, necessitating precise forecasting of fire behavior [22]. Advanced predictive models are essential for understanding spontaneous combustion dynamics, particularly under varying environmental conditions [23]. Additionally, managing coal fire risks shares similarities with corporate carbon reduction efforts, where advanced analytics are required to handle unstructured data effectively [24]. A foundational understanding of spontaneous combustion is pivotal for developing resilient strategies that mitigate associated risks.

Figure 3 illustrates the key aspects of spontaneous combustion in coal, encompassing the influencing factors, management strategies, and similar challenges encountered in related fields. This visual representation serves to enhance the discussion by providing a comprehensive overview of the interconnected elements that contribute to the phenomenon of spontaneous combustion.

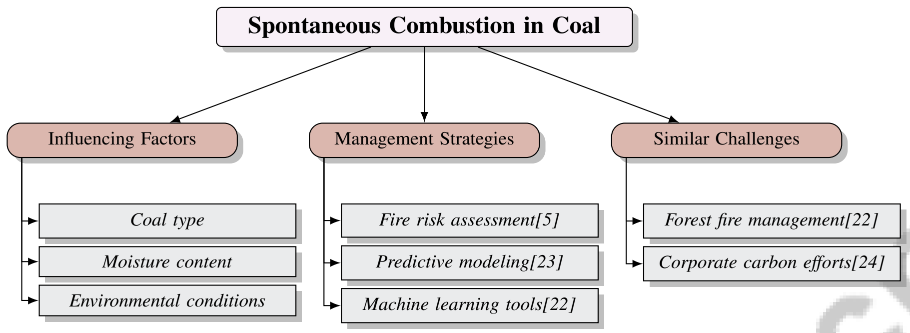

Figure 3: This figure illustrates the key aspects of spontaneous combustion in coal, including influencing factors, management strategies, and similar challenges in related fields.

3.2 Mechanisms of Spontaneous Combustion

Spontaneous combustion in coal involves complex physicochemical processes, primarily the oxidation of coal, which generates heat. If this heat is not dissipated, temperatures rise, potentially reaching ignition points. Liang et al. introduced a multiphysics coupling framework that elucidates the interactions between temperature, gas concentration, and seepage fields, critical for understanding underground coal fire dynamics [1]. At the microstructural level, coal's porosity and surface area significantly influence oxygen absorption and oxidation rates. Choi et al. categorize research into stages, highlighting the importance of microstructure representation in understanding coal's susceptibility to spontaneous combustion [25]. As oxidation progresses, exothermic reactions produce heat, necessitating effective management to prevent escalation into combustion. The structure-property-performance linkage is vital for predicting how changes in coal properties, such as moisture content and particle size, affect thermal behavior and ignition susceptibility. Design optimization strategies, including enhanced ventilation and oxidation inhibitors, are essential for mitigating risks. A comprehensive framework integrating combustion mechanisms, risk assessment, and monitoring technologies can improve predictions and responses to spontaneous combustion in coal operations, addressing significant economic and environmental challenges [5, 1, 26].

3.3 Stages of Spontaneous Combustion

Spontaneous combustion in coal unfolds in distinct stages, including initial heating, volatile gas formation, and eventual ignition, leading to full-scale fires. Understanding these stages is crucial for effective prevention and control strategies, given the economic and environmental challenges posed by underground coal fires [1, 26]. During the pre-heating phase, ambient conditions and coal properties, such as moisture content and particle size, facilitate oxygen absorption, gradually raising the coal's temperature due to surface oxidation reactions. In the self-heating stage, heat generation surpasses dissipation, accelerating temperature increases and fostering further oxidation. The coal's microstructure, particularly porosity and surface area, influences this self-heating rate [1]. Following this, the thermal runaway stage occurs, marked by rapid temperature escalation and exponential reaction rates due to enhanced oxygen availability. The interplay of temperature, gas concentration, and seepage fields becomes critical at this juncture, as described in multiphysics coupling frameworks [1]. The final stage involves sustained combustion, transitioning from smoldering to flaming combustion, characterized by significant heat and gaseous byproduct release, exacerbating fire spread and intensity. Understanding these stages is essential for developing monitoring and intervention strategies to prevent underground coal fires from escalating. Implementing advanced technologies such as machine learning and real-time video analysis can enhance early detection and response efforts, mitigating risks to safety and the environment in coal operations, while contributing to energy conservation and emission reduction [1, 20, 27, 26, 21].

3.4 Factors Contributing to Spontaneous Combustion

The likelihood of spontaneous combustion in coal is influenced by various interrelated factors affecting chemical and physical conditions within seams or stockpiles. Key contributors include intrinsic coal properties such as rank, particle size, and moisture content. Low-rank coals like lignite and sub-bituminous coal are particularly susceptible due to their higher porosity and surface area, facilitating oxygen absorption and oxidation [1]. Smaller particle sizes enhance oxidation rates due to increased surface area. Environmental conditions, including temperature, humidity, and ventilation, also significantly impact spontaneous combustion risk. Elevated temperatures can accelerate oxidation, while high humidity affects moisture content and thermal conductivity. Adequate ventilation dissipates heat but excessive airflow may introduce more oxygen, worsening self-heating [1]. Geological and mining conditions, such as geological faults and mining methods, further contribute to combustion risk. Faults allow oxygen ingress and gas migration, while certain mining techniques may leave behind oxidizable coal residues. Exposure to air during storage and transport increases susceptibility [1]. Chemical factors, including pyrite and other sulfide minerals, can catalyze oxidation, producing heat and destabilizing coal [1]. Understanding these factors is essential for implementing targeted interventions to mitigate risks, such as optimizing storage conditions, controlling ventilation, and using chemical inhibitors to slow oxidation.

3.5 Challenges in Detection and Control

Detecting and controlling spontaneous combustion in coal is challenging due to the interplay of chemical, physical, and environmental factors. Monitoring conditions conducive to combustion is time-consuming, akin to performance-based assessments requiring precision [2]. The dynamic nature of coal environments complicates the development of reliable detection systems that must adapt to fluctuating conditions and varying coal properties. The complexity of AutoML systems intended to automate machine learning processes reflects the challenges in engaging users for effective detection and control of spontaneous combustion [28]. These systems require sophisticated algorithms to process large datasets for early signs of self-heating and ignition, yet their intricacy can hinder user interaction and timely interventions. Furthermore, limitations in current AI algorithms impact their effectiveness in dynamic environments, as they often struggle to adapt to rapidly changing conditions typical of coal storage and mining sites [29]. This lack of adaptability can result in delayed responses, increasing combustion risks. Addressing these challenges necessitates advanced monitoring systems that integrate real-time data analysis with robust AI algorithms. Enhancing adaptability and user engagement through technologies like AI and machine learning can improve spontaneous combustion detection and control, mitigating risks associated with underground coal fires, promoting safer coal management practices, and optimizing fire prevention strategies for better resource management and sustainability [1, 30, 20, 21].

4 Technological Advances in Monitoring and Early Warning Systems

4.1 Technological Advancements in Monitoring Systems

Recent advancements in coal fire monitoring have been significantly enhanced through machine learning (ML) and artificial intelligence (AI), improving detection systems' efficiency and reliability. The AI-Driven Fire Quantification (AIFQ) method exemplifies deep learning algorithms for analyzing smoke and flame imagery, enabling real-time fire parameter quantification [19]. This method is pivotal for developing sophisticated monitoring frameworks that facilitate prompt detection and response to fire hazards. AI's integration with edge computing automates large dataset processing and anomaly detection, crucial in coal fire monitoring where vast IoT data must be efficiently analyzed [15]. Risk-driven assurance frameworks, such as Risk-driven Assurance for Collaborative AI Systems (RA-CAIS), enhance AI systems' effectiveness by incorporating risk analysis to ensure compliance and safety [31].

Furthermore, the synergy between simulations and ML in data-centric engineering frameworks improves predictive accuracy and interpretability [18]. The ConvLSTM model, combining convolutional neural networks with long short-term memory networks, effectively handles spatio-temporal data for predicting environmental impacts, showcasing advanced predictive capabilities [32]. Reinforcement learning with dynamic simulations enhances soft sensors' predictive capabilities, allowing accurate internal state estimation in complex environments [9].

The establishment of adaptive infrastructures and robust risk assurance frameworks alongside advanced AI and ML methodologies has markedly improved coal fire detection systems. These systems utilize sophisticated algorithms for real-time analysis and prediction, enabling timely identification of fire hazards. They leverage image-based frameworks and remote sensing technologies for critical fire-related data gathering, enhancing response mechanisms and public safety. The deployment of IoT devices and 5G technology facilitates proactive monitoring and rapid communication, optimizing coal fire detection and management while mitigating environmental and economic impacts [19, 30, 20, 21]. Collectively, these technological advancements contribute to more accurate, efficient, and reliable monitoring, ultimately improving safety outcomes in coal mining operations.

4.2 Monitoring and Early Warning Systems

Advanced monitoring and early warning systems in coal fire management significantly enhance fire risk prediction and mitigation capabilities. These systems leverage AI to improve detection and prediction models' precision and responsiveness. AI-driven methodologies, including supervised, unsupervised, and reinforcement learning, analyze diverse datasets and scenarios, allowing systems to adapt to changing conditions and refine predictive accuracy over time [33]. The deployment of Digital Twin architectures combined with Active Learning frameworks refines predictive capabilities by incorporating real-time feedback, enhancing the ability to anticipate and address fire risks effectively [34].

A critical challenge in implementing these systems is the high rate of false alarms, which can lead to significant economic and operational repercussions. Addressing this issue is essential for effective fire safety measures [35]. The IoT-FAS method exemplifies the integration of real-time monitoring and rapid response capabilities, utilizing wireless communication and sensor networks to enhance situational awareness and response efficiency [36]. This underscores the importance of robust communication networks for timely interventions to mitigate catastrophic fire events.

The effectiveness of monitoring and early warning systems is further augmented by incorporating ethical guidelines into AI development processes. The ECCOLA method provides a structured approach to integrating ethical considerations, ensuring the trustworthiness of AI-driven systems [37]. This integration is crucial for maintaining stakeholder confidence and compliance with regulatory standards, enhancing coal fire management strategies.

Moreover, the development of conditional analysis of model abilities (CAMA) offers insights into model performance under specific conditions, informing the design of more effective monitoring systems [38]. This approach aligns with the need to consider spatial and temporal variations in model design, as emphasized in power grid behavioral pattern analyses [39]. By addressing these variations, coal fire monitoring systems can achieve greater accuracy and reliability in detecting potential fire hazards.

4.3 Real-Time Monitoring and Situational Awareness

Real-time monitoring is integral to enhancing situational awareness and decision-making in coal fire management, providing continuous information on environmental conditions and potential fire hazards. The integration of advanced technologies such as AI and IoT enables real-time data collection and analysis, facilitating immediate detection and response to fire outbreaks. Sun (2020) effectively adapts methods to filter noise and predict vital signs, allowing timely interventions based on real-time data [40]. Chatterjee (2024) emphasizes the importance of processing vast data volumes quickly to reduce wildfire-induced damage to power systems [41].

Cao (2022) focuses on real-time monitoring and early detection of forest fires through advanced sensor technologies and data integration [27]. This approach highlights the necessity of integrating sophisticated sensor systems with AI to enhance fire hazard detection. However, Wisnios (2024) identifies a need for improved detection technologies and strategies to reduce false alarm rates, emphasizing further research into advanced sensors and AI integration in fire detection [35].

Lopez (2018) explores the challenge of real-time processing of visual data from monitoring systems in emergencies, highlighting the need for effective situational awareness to mitigate impacts [42].

The integration of machine learning techniques with information theory, as shown by Kraevskiy (2024), allows for real-time monitoring of market dynamics, showcasing these technologies' potential in fire management [43].

Wang (2023) demonstrates improved accuracy in fire quantification and real-time analysis capabilities, enhancing situational awareness for responders [19]. This improvement is crucial for maintaining operational safety in coal fire management. Additionally, Jimenez (2025) emphasizes the need for real-time data processing and analysis to adapt to changing conditions and ensure timely interventions [44].

The YingLong model by Xu (2025) captures local and global meteorological features, enhanced by a boundary smoothing strategy to mitigate error accumulation, illustrating the importance of precise meteorological data in fire risk assessment [14]. By overcoming challenges such as the need for labeled datasets and the complexity of integrating AI solutions into real-world applications, real-time monitoring systems can significantly enhance situational awareness and decision-making, ultimately improving coal fire management strategies.

4.4 Autonomous Drone System for Fire Detection

The use of autonomous drone systems for detecting and monitoring coal fires represents a significant advancement in fire management technologies. These systems leverage specialized sensors and AI algorithms to enhance real-time fire detection capabilities, offering a dynamic approach to monitoring challenging environments [45]. The integration of AI into unmanned aerial vehicles (UAVs) facilitates applications such as navigation, object detection, and environmental monitoring, which are critical for effective fire management [29].

Autonomous drones, equipped with AI-driven algorithms and specialized sensors, efficiently navigate complex terrains to conduct comprehensive surveillance and data collection over extensive areas. These UAVs can monitor wildlife, facilitate rescue operations, and detect environmental threats like forest fires in real-time, significantly improving response times and operational effectiveness. By utilizing machine learning and computer vision techniques, these drones enhance data processing and decision-making while ensuring compliance with regulatory frameworks, making them vital for industries ranging from agriculture to disaster management [45, 29]. This capability is particularly beneficial in coal mining regions, where traditional monitoring methods may be limited by accessibility and safety concerns. The drones' ability to process and analyze data in real-time enables early detection of fire hazards, allowing prompt intervention and mitigation measures.

Moreover, the deployment of drones enhances situational awareness by providing high-resolution imagery and thermal data, crucial for assessing the extent and intensity of fires. The integration of AI algorithms, particularly those leveraging machine learning techniques, significantly improves the detection and quantification of fire patterns and hotspots through advanced image analysis and data-driven insights. This capability supports predictive analytics that inform proactive fire management strategies, ultimately improving public safety and environmental protection by facilitating timely interventions and optimizing resource allocation in response to wildfire risks [19, 22, 30, 20]. These systems can operate autonomously, reducing the need for human intervention and minimizing risks associated with manual monitoring in hazardous environments.

The continuous evolution of AI technologies and sensor integration in UAVs promises to further improve the efficiency and reliability of autonomous drone systems in coal fire detection. By harnessing recent advancements in fire management technologies, particularly in combustion mechanisms and machine learning algorithms, coal fire management can enhance precision and responsiveness. This strategic integration not only improves safety outcomes by effectively mitigating the risks associated with underground coal fires but also boosts operational efficiency within mining operations. Furthermore, the adoption of innovative detection and monitoring techniques, such as AI and 5G technology, facilitates real-time assessments and proactive responses, significantly reducing the economic and environmental impacts of coal fires [5, 1, 22, 30].

5 Fire Prevention and Control Strategies

Understanding foundational methodologies, particularly risk assessment and thermal analysis, is crucial for effective coal fire management. These methodologies are essential for hazard identification

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Category	Feature	Method
Risk Assessment and Thermal Analysis	Real-Time Analysis	GGES[7], LCAWS[46], RM-EWS[40], SoftNER[47], MAS-RP[48]
Optimization of Fire Control Strategies	Technological Integration Data-Driven Strategies Model Interpretability	IFFP-EC[27], U-Net[16] DaC[49] ConvLSTM[32]
Integration of Machine Learning and AI in Fire Prevention	AI-Driven Strategies	FCF-FNN[50], ECCOLA[37], SU-LML[51], ML-MWD[52]
Cost Reduction in Steel Production through Advanced Monitoring	Cluster-Based Techniques	KMCMLC[53]

Table 1: This table presents a comprehensive summary of methodologies employed in various domains related to fire prevention and control strategies, including risk assessment, thermal analysis, optimization of fire control strategies, integration of machine learning and AI, and cost reduction in steel production through advanced monitoring. Each category outlines specific features and the corresponding methods utilized, highlighting the integration of advanced technologies and data-driven approaches to enhance efficiency and safety in coal fire management and related applications.

and response strategy formulation. By evaluating risks and analyzing thermal dynamics, a robust framework for mitigating fire incidents and enhancing safety protocols can be developed. Table 1 provides a detailed overview of the methodologies and approaches utilized across different categories in fire prevention and control strategies, emphasizing the integration of advanced technologies and data-driven techniques. Table 2 provides a detailed overview of the methodologies and approaches utilized across different categories in fire prevention and control strategies, emphasizing the integration of advanced technologies and data-driven techniques. The following subsection explores risk assessment and thermal analysis processes.

5.1 Risk Assessment and Thermal Analysis

Risk assessment and thermal analysis are vital for coal fire management. Risk assessment examines factors influencing coal fire likelihood and impact, including potential workday losses from job-related injuries [7]. This involves developing methodologies to accurately evaluate risk factors and predict fire incident outcomes. Thermal analysis aids in understanding coal's heat dynamics and combustion characteristics, informing effective fire prevention and control measures. Studies highlight the need for multifaceted approaches integrating various techniques tailored to coal and environmental conditions [1].

Advanced technologies like multi-agent models enhance modeling complex interactions in non-deterministic environments, using historical data for improvement [48]. Low-cost automatic weather stations improve thermal analysis by providing real-time environmental data affecting fire behavior [46]. Innovations in these solutions address barriers to effective large-scale weather monitoring, enhancing natural disaster prediction and management, including coal fires.

Real-time monitoring capabilities offer high prediction accuracy and actionable insights for timely interventions and driver safety in fire prevention [40]. These capabilities are enhanced by the SoftNER approach, which uses semantic features for improved risk factor understanding and decision-making [47].

5.2 Optimization of Fire Control Strategies

The optimization of fire control strategies in coal fire management has advanced through machine learning (ML) models and data-centric engineering. These methodologies leverage real-time operational data to enhance anomaly detection and improve fire management strategy adaptability [49]. The integration of IoT, infrared light sensing, and GIS exemplifies diverse technology convergence for accurate fire detection and management [27].

Machine learning algorithms refine fire control strategies by optimizing prediction accuracy and resource allocation. The ConvLSTM model, for instance, improves predictions of environmental responses to extreme events, crucial for anticipating fire dynamics [32]. This is complemented by U-Net model variations, enhancing burned-area mapping accuracy [16].

Hybrid modeling approaches integrating AI with traditional models enhance mechanistic model adaptability to real-time conditions. Bayesian Neural Networks fine-tune model parameters, improving prediction accuracy and quantifying uncertainties. This method facilitates better operational decision-making, addressing challenges posed by changing conditions, leading to more reliable systems [18, 54, 55, 8, 2]. Explainable AI (XAI) methods enhance ML model interpretability, improving transparency in fire control strategies [56].

5.3 Integration of Machine Learning and AI in Fire Prevention

The integration of ML and AI into fire prevention strategies marks a significant advancement in coal fire management, enhancing operational efficiency and decision-making. AI-enabled UAVs improve surveillance and monitoring capabilities, facilitating real-time data collection and analysis in challenging environments [29]. AI-driven systems refine fire prevention and control strategies through precise input parameter analysis [50].

AI and ML technologies automate and enhance the accuracy of material type logging and chemical assaying, essential for fire prevention strategies [52]. These technologies support adaptive AI systems that efficiently manage resource-constrained environments while ensuring safety and privacy [57]. This adaptability is vital for processing large data volumes in real-time, improving system responsiveness.

Semi-unsupervised lifelong learning models (SU-LML) achieve high accuracy with minimal labeled data, enhancing fire prevention systems' predictive accuracy [51]. Interpretable ML approaches optimize resource consumption and improve decision-making based on historical sensor data [53]. These methodologies are essential for refining fire prevention strategies, ensuring efficient resource allocation and maintaining operational safety.

A systematic approach to defining and evaluating model capabilities enhances inter-model comparisons and guides AI integration in fire prevention strategies [38]. The ECCOLA method emphasizes accountability and transparency, enhancing fire prevention strategies through AI [37]. Hybrid intelligence systems incorporating human insights into AI processes achieve superior results through collaboration and continuous learning [58].

5.4 Cost Reduction in Steel Production through Advanced Monitoring

Advanced monitoring technologies reduce costs in steel production by optimizing resource consumption and enhancing operational efficiency. ML and AI integration into monitoring systems enables precise production process analysis, resulting in significant cost savings. For example, Knyazev et al. demonstrate a 5

These technologies use real-time data analysis to monitor and adjust production parameters dynamically, ensuring optimal resource utilization. Interpretable ML approaches identify patterns and anomalies in production data, facilitating informed decision-making [53]. This capability is essential for maintaining competitiveness in the steel industry, where cost efficiency is critical.

AI-driven monitoring systems in predictive maintenance strategies enable early equipment failure detection, reducing downtime and enhancing machinery lifespan. Advanced technologies, including self-driven sensors and deep learning algorithms, analyze equipment-generated data, allowing timely interventions and improved reliability [59, 60]. By incorporating advanced sensors and IoT devices, these systems provide continuous oversight of production operations, ensuring potential issues are addressed before escalation.

The synergy between advanced monitoring technologies and steel production processes contributes to cost reduction and enhances industry sustainability. Leveraging AI and ML innovations improves resource efficiency and significantly reduces environmental footprints, supporting economic viability and ecological sustainability. This alignment is crucial as sectors transition toward carbon neutrality, necessitating automated data collection and validation processes that streamline corporate sustainability metrics and improve decision-making [24, 33, 61].

Feature	Risk Assessment and Thermal Analysis	Optimization of Fire Control Strategies	Integration of Machine Learning and AI in Fire Prevention
Technological Integration	Multi-agent Models	Iot And Gis	Ai-enabled Uavs
Predictive Accuracy	High Prediction Accuracy	Improved Prediction Accuracy	High Predictive Accuracy
Operational Efficiency	Enhanced Decision-making	Resource Allocation Optimization	Efficient Resource Management

Table 2: This table presents a comparative analysis of three key methodologies in fire prevention and control strategies, focusing on their technological integration, predictive accuracy, and operational efficiency. The methodologies include risk assessment and thermal analysis, optimization of fire control strategies, and the integration of machine learning and AI in fire prevention, highlighting their respective advantages in enhancing fire management processes.

6 Emergency Rescue and Response Protocols

6.1 Emergency Rescue Protocols

Efficient emergency rescue protocols are crucial for managing coal fire incidents, safeguarding personnel, and minimizing damage. These protocols address challenges such as miscommunication between victims and responders, lack of standardized help requests, and insufficient information in rescue calls [62]. They follow a multi-tiered strategy, beginning with the prompt notification of emergency services and mobilization of on-site teams. Strategic resource placement is guided by spatial-temporal analyses, community vulnerabilities, and the specific disaster context, as evidenced in studies on Hurricane Harvey and resource allocation optimization [62, 63]. Teams trained for coal fire scenarios utilize protective equipment and firefighting apparatus designed for underground environments, focusing on situation assessment, area security, and communication with trapped personnel.

Communication is pivotal in emergency operations, facilitated by next-generation wireless networks and real-time data sharing platforms. These systems leverage IoT and machine learning to process extensive data from diverse sensors, enabling real-time analytics and decision-making with reduced latency and increased reliability [64, 65, 66, 57]. Standardized formats for information dissemination address miscommunication challenges.

Real-time monitoring technologies enhance situational awareness, allowing rapid, informed decision-making. IoT devices and sensor networks continuously monitor critical environmental parameters, such as temperature and gas concentrations, vital for risk assessment and strategic evacuation planning. Advanced technologies like Building Information Modeling (BIM) and AI detect hazards, track occupant locations, and facilitate timely responses, improving safety and emergency preparedness [64, 15, 36, 57].

A centralized command and control center is essential for efficient rescue coordination, facilitating rapid information sharing and decision-making among organizations. This center uses geospatial data integration and real-time visual information to improve response strategies by addressing communication and resource allocation challenges [67, 62, 68, 42, 69]. It oversees all response aspects and liaises with external agencies to streamline efforts.

Comprehensive emergency rescue protocols enhance coal mining operations' resilience by integrating advanced technologies, such as knowledge graphs and large language models, to improve situational awareness and response strategies. Social media analytics provide real-time insights into community needs, enabling targeted and efficient responses. This multifaceted approach ensures robust and adaptable protocols for coal mining emergencies, safeguarding lives and property [62, 70, 69].

6.2 AI-Driven Decision Support Systems

AI-driven decision support systems are vital for enhancing emergency management by offering timely, accurate, and actionable insights during crises. These systems utilize advanced machine learning algorithms to process vast data, enabling rapid, informed decisions. Integrating human oversight with machine predictions optimizes emergency disposal tasks, as emphasized by Guo et al., highlighting the synergy between human judgment and AI capabilities [71].

Multi-objective models, such as those by Yuan et al., enhance decision-making by considering cost, fairness, efficiency, and uncertainty in resource allocation [63]. These models ensure effective deployment to maximize impact during emergencies.

Integrating knowledge graphs with large language models (LLMs), as explored in the E-KELL system by Chen et al., provides evidence-based decision support across various emergency stages [69]. This integration synthesizes complex information, allowing access to comprehensive insights that inform strategies.

Zou et al. propose a framework for analyzing social media's role in emergency rescue operations, highlighting its potential to enhance situational awareness and coordination [62]. Similarly, the Text Mining-based Earthquake Impact Analysis (TMEIA) method illustrates text mining techniques' utility in extracting valuable insights from social media data for decision-making during earthquakes [70].

The Multi-Objective Shuffled Gray-Wolf Frog Leaping Model (MSGW-FLM) by Xu et al. exemplifies advanced optimization algorithms for dynamic emergency resource allocation, ensuring efficient distribution in crisis conditions [72].

AI-driven decision support systems are essential in contemporary emergency management, leveraging technologies like knowledge graphs and LLMs for evidence-based decision-making throughout emergencies. These systems enhance community resilience and response outcomes by delivering accurate, timely information and facilitating effective coordination among organizations. Tools integrating geospatial data and machine learning algorithms enable rapid analysis of critical information, leading to more effective crisis responses like Hurricane Florence [68, 69]. By integrating advanced algorithms, real-time data analysis, and human oversight, these systems offer a comprehensive approach to effective emergency management.

6.3 Optimization of Resource Allocation

AI significantly enhances resource allocation during emergency responses, improving efficiency and effectiveness. AI-driven models, such as the Multi-Objective Shuffled Gray-Wolf Frog Leaping Model (MSGW-FLM), excel in complex multi-objective tasks, offering flexibility and adaptability [72]. These models optimize resource distribution by considering objectives like cost minimization, coverage maximization, and response time reduction while ensuring fairness [63].

Integrating structured emergency knowledge graphs with large language models (LLMs), as demonstrated in the E-KELL system, enhances decision-making by guiding LLMs in generating accurate responses to emergency queries [69]. This approach uses structured data to inform AI-driven decision support systems, ensuring resource allocation decisions are based on comprehensive and reliable information.

Human-machine collaboration is crucial in optimizing resource allocation, as decision-making methods reduce human decision-makers' workload while increasing system trust through interpretable machine suggestions [71]. This collaboration enhances emergency management by combining human expertise with AI capabilities, resulting in more informed and efficient decisions.

AI-driven tools, such as those described by Ortiz, optimize resource allocation by integrating multiple data sources and employing visualization techniques to enhance situational awareness and decision-making [68]. These tools provide a comprehensive view of emergencies, enabling strategic and effective resource allocation.

AI systems' rapid analysis of large datasets, exemplified by the RHMS, delivers actionable insights crucial in time-sensitive situations [73]. This capability ensures swift resource deployment, minimizing emergencies' impact and enhancing community resilience.

AI transforms resource allocation in emergency responses by employing advanced algorithms, structured data, and fostering human-machine collaboration. This integration enhances decision-making processes, as demonstrated by systems like E-KELL, which utilize knowledge graphs and LLMs for evidence-based support across emergency stages. Additionally, AI-driven tools incorporating geospatial data improve coordination among organizations by delivering timely, accurate information, enabling rapid analysis and action on critical data, optimizing strategies like evacuation route planning and resource allocation for effective emergency management [68, 69].

7 Case Studies and Practical Applications

7.1 Case Studies and Practical Applications

Real-world case studies demonstrate the efficacy of advanced technologies in coal fire management. Autonomous drones, equipped with AI algorithms, have shown success in fire detection and monitoring, accurately identifying fires and facilitating timely interventions [45]. These field trials highlight the integration of AI and UAV technologies, which enhance situational awareness and response efficiency.

The evolution of fire management practices is marked by the incorporation of AI, Machine Learning (ML), and 5G technologies, enabling proactive detection, real-time monitoring, and rapid response to mitigate fire risks [20, 22, 30, 21, 5]. Autonomous drones improve the precision and responsiveness of detection systems, allowing for proactive measures to prevent fire escalation. These trials underscore the critical role of AI and UAV integration in improving safety outcomes and operational efficiency.

These case studies emphasize leveraging advanced technologies like AI, ML, and 5G to address coal fire management's multifaceted challenges. Fire management agencies can enhance detection capabilities, refine response strategies, and mitigate environmental and economic impacts by utilizing these tools [45, 20, 30, 5, 19]. Integrating AI-driven systems with traditional strategies offers a comprehensive approach to fire risk mitigation, enhancing safety and operational effectiveness in mining operations. Continuous innovation in these technologies promises to revolutionize coal fire management, contributing to safer and more sustainable mining environments.

7.2 Human-Machine Collaboration

Human-machine collaboration in coal fire management represents a significant advancement, combining human expertise with machine intelligence to enhance decision-making and operational efficiency. Integrating AI with human insights fosters a comprehensive approach, where AI's predictive capabilities complement human operators' contextual understanding [58].

AI-driven systems utilize neural networks and machine learning algorithms to process vast data volumes, identifying patterns indicative of fire risks. These insights empower human decision-makers to undertake informed and timely interventions [50]. This collaboration enhances the accuracy and efficiency of fire detection and response strategies, addressing potential hazards before escalation.

The deployment of AI-enabled unmanned aerial vehicles (UAVs) exemplifies practical human-machine collaboration. Equipped with advanced sensors and AI algorithms, UAVs facilitate real-time data collection and analysis, offering a dynamic approach to monitoring challenging environments. Their autonomous operation in complex terrains complements human efforts, reducing risks associated with manual monitoring in hazardous conditions [29].

Human-machine collaboration enhances resource allocation and emergency response protocols by integrating human oversight with advanced decision-making algorithms. This synergy employs AI technologies, such as knowledge graphs and large language models, to support evidence-based decision-making while allowing human operators to interpret and adjust machine-generated recommendations in real-time. By combining human expertise with machine learning capabilities, organizations can effectively navigate unplanned events and optimize operational efficiency, leading to reliable and timely responses in critical situations [74, 28, 58, 71, 69]. AI-driven decision support systems aid human operators in evaluating scenarios and determining optimal actions, ultimately enhancing the resilience and effectiveness of coal fire management strategies. This integration ensures timely and well-coordinated emergency responses, improving safety outcomes in coal mining operations.

8 Challenges and Future Directions

8.1 Limitations of Current Technologies

Current technologies in coal fire management are constrained by several factors that limit their effectiveness, especially in dynamic environments. A significant hurdle is the dependency on high-quality labeled datasets for accurate model training; the scarcity of such datasets can result in misidentifications, as models may struggle to generalize to new conditions [16]. The reliance on real-time imagery and data, as highlighted by Ortiz, can impede responsiveness during emergencies when such data is unavailable [68].

The complexity and opacity of AI systems pose challenges for their assessment and compliance with ethical standards, complicating stakeholder evaluation of their reliability [75]. This lack of interpretability can erode trust in critical applications like coal fire management, where incorrect predictions can have severe consequences [76]. Data-centric approaches introduce spatial complexity due to numerous invariants, complicating management efforts [49].

Scalability and accessibility are often restricted by the lack of user-friendly software implementations, limiting widespread adoption [18]. Many studies lack comprehensive validation methods for complex systems with latent confounding variables, leading to inaccuracies in predictive models [13]. Additionally, reliance on traditional Numerical Weather Prediction (NWP) outputs for boundary conditions in models like YingLong may hinder performance, especially when NWP forecasts are inaccurate [14]. The absence of comprehensive metrics for evaluating the long-term effectiveness of training methods and diverse user needs further complicates the landscape. Addressing these limitations requires enhancing data quality, improving model interpretability, and incorporating broader socioeconomic considerations to develop more reliable coal fire management systems.

8.2 Emerging Technologies and Future Directions

The future of coal fire management will be shaped by emerging technologies and innovative research directions aimed at enhancing predictive capabilities, operational efficiency, and safety. A critical focus is the development of transparent, ethical, and inclusive AI technologies while addressing the environmental impacts of large language models (LLMs) [77]. Enhanced model performance can be achieved through data sharing initiatives and the integration of sophisticated machine learning techniques [78]. Establishing standardized interfaces for interoperability, expansive datasets for AI training, and hybrid approaches that blend symbolic and non-symbolic AI techniques are pivotal areas for future exploration [79].

Proactive measures and dedicated funding for AI safety are crucial to prevent catastrophic outcomes, emphasizing the management of extreme AI risks [17]. The integration of real-time spatio-temporal data will enhance model adaptability and effectiveness in emergency scenarios [72]. Additionally, refining causal inference methods and enhancing the integration of causality in AI will bolster predictive capabilities [13].

Future research should refine the validation process for invariants and explore methods to mitigate the spatial complexity of large invariant sets [49]. Validating AI models with real-world fire data and improving their robustness against varying conditions is essential for broader applicability [19]. Dynamic certification criteria that evolve with advancing AI technologies are necessary to ensure consistent adherence to ethical standards [75].

Moreover, expanding datasets and enhancing the accuracy of models like the TN-ML could broaden their application in various clinical settings, improving diagnostic capabilities [76]. Research should also focus on including larger, more diverse populations and integrating additional health indicators for comprehensive clinical validation, highlighting the need for emerging technologies in respiratory monitoring [80]. In predictive modeling, exploring advanced architectures, such as attention-based models, could further enhance forecasting abilities [32].

By leveraging these emerging technologies and research directions, coal fire management strategies can become more resilient and adaptive, ultimately improving safety, efficiency, and sustainability in mining operations. This approach will equip the industry with the necessary tools to effectively address coal fire challenges through advancements in AI, ML, and 5G connectivity, facilitating proactive detection, real-time monitoring, and enhanced response strategies, thereby safeguarding human lives and the environment from coal fire impacts [5, 30, 20].

8.3 Interdisciplinary Approaches and Collaboration

Interdisciplinary collaboration is crucial for advancing coal fire management, integrating diverse expertise to tackle complex challenges. The integration of AI in coal fire management underscores the need for collaboration between technical and organizational domains, as evidenced by frameworks

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that explore the sociotechnical interplay between technical systems and organizational dynamics [81]. This approach is critical for developing comprehensive strategies in coal fire management.

The energy digitization era highlights the importance of collaboration between AI and energy sectors, as noted by Xie et al., to enhance predictive capabilities and operational efficiency in fire management [33]. Such collaboration fosters innovative solutions that leverage AI technologies for improved monitoring and early warning systems.

Moreover, interdisciplinary collaboration is vital for AI safety and governance, drawing from lessons learned in other safety-critical technologies [17]. This collaboration is crucial for managing extreme AI risks and ensuring responsible AI deployment in coal fire management.

Salvador et al. established a framework for regulating AI safety, inspired by successful models in aviation and pharmaceuticals, underscoring the importance of interdisciplinary approaches in creating robust regulatory frameworks [82]. These frameworks are essential for ensuring the safety and reliability of AI-driven systems in coal fire management.

Additionally, Chun et al. introduce a novel framework for categorizing compound hydrological events based on autocorrelated, multivariate, and spatiotemporal patterns, emphasizing the need for interdisciplinary collaboration to address complex environmental challenges [83]. This approach is applicable to coal fire management, where various environmental and technical factors must be considered.

The significance of partnerships between established firms and startups in driving innovation is also highlighted, as these collaborations can foster the development of new technologies and strategies for effective coal fire management [84]. By promoting interdisciplinary collaboration, coal fire management can benefit from a holistic approach that integrates technical, organizational, and regulatory perspectives, ultimately enhancing safety and operational effectiveness.

8.4 Ethical and Regulatory Considerations

The integration of AI in coal fire management necessitates a robust ethical and regulatory framework to address concerns such as data privacy, algorithmic fairness, and explainability of AI systems. Ethical frameworks are vital for guiding AI deployment, ensuring that data privacy and user consent are prioritized, as highlighted in studies on the Internet of Behaviors (IoB) framework [85]. Adherence to ethical data use principles is crucial for maintaining trust and compliance with legal standards.

The necessity for explainability in AI systems is underscored by regulations like the General Data Protection Regulation (GDPR), which mandates that users receive meaningful information about the logic behind algorithmic decisions. This requirement is particularly relevant in coal fire management, where transparency in AI-driven decision-making processes is essential for stakeholder trust and accountability [37]. The potential risks associated with misinformation and automation, as explored in the context of GPT-4's capabilities, further emphasize the need for robust ethical frameworks to mitigate these challenges [86].

Proactive governance is critical in adapting to the evolving landscape of AI technologies and their associated risks. Regular updates to computational thresholds and governance frameworks are necessary to ensure AI systems remain compliant with ethical standards and effectively manage potential risks [75]. Recognizing that frameworks are not value-neutral and involve normative decisions about risk prioritization is vital for ethical considerations in coal fire management [11].

Regulatory frameworks must also address the specific challenges associated with deploying AI technologies in unmanned aerial vehicle (UAV) systems, increasingly used in coal fire detection and monitoring. The ethical and regulatory challenges related to UAV deployment emphasize the need for comprehensive legal guidelines to ensure safe and responsible use of these technologies. Furthermore, integrating drones in coal fire management necessitates adherence to aviation and environmental laws to ensure operations are conducted within legal boundaries [75].

The potential for regulatory capture or insufficient consumer protection poses additional risks in the AI regulatory landscape. This concern highlights the importance of developing balanced regulatory responses that protect consumer interests while fostering innovation [44]. Additionally, potential violations of antitrust laws necessitate careful consideration by policymakers to ensure AI development is conducted within legal requirements, with appropriate evaluations and pauses in development.

9 Conclusion

This survey underscores the transformative role of integrating cutting-edge technologies in coal fire management, offering pathways to significantly bolster safety and operational effectiveness. The deployment of machine learning and artificial intelligence in monitoring and early warning systems emerges as a pivotal advancement, enhancing predictive precision and informing decision-making processes. These technologies, while presenting new challenges, hold the potential to revolutionize fire management strategies, as evidenced by their application in solving complex problems like firebreak placement.

Moreover, the survey highlights the importance of augmenting traditional regulatory frameworks with advanced AI methodologies to achieve superior risk management. The incorporation of the Internet of Behaviors and explainable AI demonstrates substantial potential in influencing user behavior and optimizing energy consumption, thereby driving improvements in fire management practices. Ensuring the integration of domain expertise is paramount for maintaining the transparency and reliability of AI systems, enhancing their explainability without compromising performance.

The survey also identifies the necessity for continued research to overcome current limitations in large language models and multimodal applications, which are crucial for advancing safety and healthcare management initiatives. Hybrid Intelligence approaches, which blend quantitative and qualitative evaluations, present promising prospects for developing sophisticated coal fire management strategies. Additionally, the application of causality analysis to improve AI model interpretability and forecast complex climate phenomena underscores the expansive potential of these technologies in environmental management.

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