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# Transforming fire protection: AI's evolving role in proactive and reactive applications

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**Abstract.** This paper comprehensively reviews the applications of artificial intelligence (AI) in the field of fire protection. It traces the historical development of AI, from its origins in the 1930s and 1940s to its current state, focusing on major milestones and algorithms that have shaped the field. The paper discusses the evolution of AI, particularly in terms of machine learning, deep learning, and the emergence of various models such as deep neural networks (DNNs), transformer models, and graph neural networks (GNNs). The application of AI in fire protection is explored in two primary categories: proactive and reactive applications. Proactive applications encompass AI's role in decision-making, construction, and operation, including the use of machine learning for environmental analysis, building information modelling (BIM) for design optimization, 3D printing and intelligent robots in construction, and intelligent fire facility management. Reactive applications focus on early fire detection and monitoring, especially in forests, utilizing terrestrial, aerial, and satellite systems equipped with advanced sensors and deep learning techniques. This paper highlights the significant contributions of AI in mitigating fire risks, improving fire detection and response, and enhancing the safety and efficiency of fire protection systems.

**Keywords:** artificial intelligence, fire protection, construction, forest.

## 1. Introduction

In recent years, the development of artificial intelligence (AI) has revolutionized various industries, including the field of fire protection. AI's origins can be traced back to the early works of Alan Turing and Claude Shannon, with subsequent advancements in algorithms, machine learning, and neural networks paving the way for its widespread adoption. Over the decades, AI has undergone several waves of development, each marked by significant technological breakthroughs and applications.

As the construction industry continues to grow, with an increasing number of large and complex public buildings being completed, fire prevention measures have become increasingly important. Fire hazards not only pose threats to human lives and property but also necessitate innovative solutions to manage the complexity of modern buildings. Similarly, forest fires represent a significant risk to natural resources and ecosystems, highlighting the need for efficient early detection and monitoring systems.

In this context, AI has emerged as a powerful tool in fire protection, offering proactive and reactive approaches to managing fire risks. Proactive applications of AI in fire protection include the use of machine learning for intelligent decision-making, design optimization, and construction efficiency. BIM

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(Building Information Modelling) technology, 3D printing, and intelligent robots are some of the key AI-driven technologies that have significantly enhanced the fire safety of construction projects. Reactive applications, on the other hand, focus on early fire detection and accurate monitoring, particularly in forests where wildfires can cause devastating consequences. Recent advancements in computer vision, machine learning, and remote sensing technologies have led to the development of sophisticated systems for detecting and monitoring forest fires in real or near-real-time.

This paper aims to provide a comprehensive overview of the applications of AI in the field of fire protection. It delves into both proactive and reactive approaches, discussing the latest advancements, challenges, and future trends in this rapidly evolving domain. By reviewing the current state-of-the-art and emerging technologies, this paper seeks to contribute to the further development and adoption of AI in fire protection, ultimately enhancing the safety and resilience of our built and natural environments.

## 2. Literature review

### *2.1. Artificial intelligence*

The origins of AI can be traced back to Alan Turing's 1936 paper "On Computable Numbers and Their Application to Determination Problems." Later, in 1950, Claude Shannon introduced computer games, and in 1954, Alan Turing introduced the Turing Test, which began to popularize the idea of making machines intelligent. In 1956, a symposium at Dartmouth College, attended by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, formally introduced the concept of "artificial intelligence."

In terms of algorithms, Frank Rosenblatt proposed the Perceptron algorithm in 1957, which initiated the wave of machine learning and laid the foundation for neural networks. However, neural network research can be traced back to the neuronal model proposed by neurophysiologists W. S. McCulloch and W. Pitts in 1943.

By the 1960s, AI experienced its first surge with the development of symbolic logic, general-purpose problem-solving, and the initial emergence of natural language processing and human-computer dialogue techniques. Notable events include Daniel Bobrow's 1964 publication of "Natural Language Input for a Computer Problem Solving System" and Joseph Weizenbaum's 1966 publication of "ELIZA-A Computer Program for the Study of Natural Language Communication between Man and Machine."

Early AI focused on descriptive logic and general-purpose problem-solving. By the end of the 1960s, Edward Feigenbaum presented the first expert system, DENDRAL, and provided a preliminary definition of a knowledge base, leading to the second wave of AI. However, enthusiasm for AI gradually faded, and the field entered a "winter" that lasted nearly a decade.

In the late 1970s and early 1980s, AI entered its second wave, marked by the construction of large-scale knowledge bases by Randall Davis in 1976, the proposal of non-monotonic logics by Drew McDermott and Jon Doyle in 1980, and the emergence of robotic systems. In 1980, a computer built by Hans Berliner defeated the backgammon world champion, a landmark event. Subsequently, behavior-based robotics, driven by Rodney Brooks and R. Sutton, developed rapidly and became an important branch of AI. Self-learning backgammon programs built by Gerry Tesauro and others laid the foundation for augmented learning.

During this period, machine learning algorithms flourished, with Geoffrey Hinton and others proposing the multilayer perceptron to solve the problem of nonlinear classification. Judea Pearl advocated probabilistic methods and Bayesian networks, laying the foundation for causal inference. Machine learning methods also rapidly developed in areas such as machine vision.

The second important development was the theory of statistical machine learning, including support vector machines by Vapnik Vladimir et al., conditional random fields by John Lafferty et al., and the topic model LDA by David Blei and Michael Jordan et al. Overall, AI-related fields made great strides during this period.

The third wave of AI was marked by the advent of deep learning in 2006 by Geoffrey Hinton and others. This wave was led by companies: Sebastian Thrun led the self-driving car project at Google;

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IBM's Watson won Jeopardy in 2011; Apple launched Siri in 2011; and DeepMind's AlphaGo defeated Go world champion Lee Sedol in 2016. The impact of this AI wave was unprecedented.

Currently, AI has entered a new era with many excellent models used in various fields. Trendy models include deep neural networks (DNNs), transformer models, and graph neural networks (GNNs). DNNs are artificial neural networks with multiple hidden layers interconnected by numerous nodes, each with an activation function to model the non-linear properties of neurons. DNNs enable the modeling and recognition of complex patterns by passing input data layer by layer and performing feature extraction and transformation at each layer. The Transformer model is based on the Self-Attention Mechanism, allowing the model to consider global information when processing sequential data. In Transformers, the output of each position is a function of all other positions, enabling the capture of long-range dependencies. GNNs process graph-structured data by applying convolutional operations on the nodes in the graph. GNNs progressively update the feature representation of each node until the information of the whole graph is aggregated, typically through message passing and node feature updating [1].

### *2.2. Fire protection*

In recent years, the construction sector has significantly bolstered its contribution to the national GDP, showcasing its strong foothold in the economy. As a result, there has been a noticeable uptick in the demand for public buildings that adhere to higher performance and environmental standards. This surge has driven the completion of more intricate and substantial public structures. Despite this growth, employment within the construction industry has seen a decline, particularly in low-skilled labor engagement.

The evolving landscape of public buildings has also led to a shift in demand towards highly skilled and innovative facility management personnel. The increased complexity of facility systems, coupled with the management challenges they present, emphasizes the necessity for efficient and forward-thinking facility management. This further underscores the critical importance of implementing robust fire prevention measures in large and intricate public buildings. This is crucial in mitigating potential threats to life and property, especially given the rising likelihood of fire incidents and the growing complexity involved in fire prevention and control.

Forests, too, are susceptible to high fire risks, as wildfires can emerge rapidly and cause significant devastation to ecosystems, human life, and infrastructure. Implementing automated detection systems and early warning mechanisms plays a crucial role in safeguarding forest resources and mitigating the adverse impacts of such catastrophic events [2].

In the field of fire protection, AI is commonly used in two ways: proactive and reactive.

### *2.3. Proactive application*

This way is used AI before a real fire has really happened. The application of AI in the field of fire protection of construction engineering mainly includes three aspects: decision-making, construction, and operation.

#### *2.3.1. Decision-making*

Machine learning represents an innovative approach to learning that leverages historical data and past experiences to enhance algorithms. Artificial intelligence, a key component of machine learning, can assess a range of factors such as surrounding environment, geological conditions, traffic patterns, and human requirements in the vicinity of a construction endeavor. Integration of this analysis with virtual reality technology has the potential to revolutionize the process of planning and designing projects. Through this pioneering planning and design approach, it is possible to effectively minimize fire hazards that conventional methods may overlook, foster a more sustainable and healthier building environment, and achieve comprehensive intelligent planning for construction projects [3][4].

### *2.3.2. Design*

Building Information Modelling (BIM) [5] is an innovative technology that plays a crucial role in the initial design phase of construction projects. It utilizes accurate data to streamline the design process, expedite construction, and provide visual oversight of engineering projects. Originally developed by Professor Eastman of the Georgia Institute of Technology in the 1970s, BIM technology greatly improves the efficiency of engineering construction and enables the optimization of structures to mitigate fire hazards. Notable landmarks that have benefited from BIM technology adoption include the impressive Shanghai Centre, the remarkable Wuhan Centre, and the iconic China Zun. During the construction of the Shanghai Centre, the introduction of BIM technology resulted in significant reductions in drawing design errors, engineering rework, and construction time, demonstrating its effectiveness. By leveraging visual 3D modeling, cloud computing, VR, and other technologies, BIM can effectively prevent design issues such as errors, omissions, clashes, and conflicts across various disciplines. This leads to reduced and optimized design costs, significantly improved fire protection coefficients of the building structure, and enhanced 3D visualization of the project’s design outcomes.

### *2.3.3. Construction*

Advancements in AI technology have revolutionized construction engineering, especially with the introduction of advanced tools like 3D printing and intelligent robots. 3D printing, a state-of-the-art prototyping process based on customized digital designs, is considered a groundbreaking innovation in the industrial sector. In the field of construction engineering, researchers such as Wang et al. have extensively studied the impact of 3D printing technology on construction practices, both nationally and internationally. They have categorized their findings based on printing materials and processes. The use of 3D printing in construction has the potential to significantly improve construction speed, reduce labor costs, minimize material usage, shorten construction timelines, and promote environmentally-friendly, secure, and efficient construction practices [6].

Furthermore, with the widespread research and deployment of intelligent robots, combined with the rapid advancement of 5G technology, there has been a surge in multifunctional intelligent robots. These robots are gradually taking over manual tasks in the construction process, leading to significant improvements in construction quality and reducing the likelihood of errors that could lead to hazardous situations such as fires.

AI is making its mark in the management of construction sites. Sowah et al. have utilized deep learning algorithms for target detection in computer vision. By analyzing on-site video footage from construction site cameras, these algorithms can quickly and automatically assess whether construction workers are following safety protocols and identify potential fire hazards, triggering alarms when necessary. Integration of China's BeiDou satellite navigation system, along with intelligent sensors, enables real-time monitoring of construction site activities [7][8]. This allows for the continuous and accurate supervision of construction processes and prompt resolution of unexpected challenges on-site.

### *2.3.4. Intelligent Fire Facility Management*

Su et al. have developed an innovative fire facility management system using advanced web technology, Ajax, and other state-of-the-art information technologies. This system takes into consideration real-life building conditions, making it practical and highly effective. It has significantly contributed to the digitization and standardization of fire safety management, leading to improved efficiency in fire safety procedures.

Furthermore, Zhang et al. have incorporated data mining, data analysis, and accident analysis theories, utilizing Microsoft SQL Server's business intelligence component for data mining [9]. They have applied four widely used algorithms—cluster analysis, association rules, time series, and decision tree—to comprehensively examine fire accident cases and data. Their main objective is to provide valuable insights for the application methods in accident analysis, thus enhancing both academic and practical value in processing and analyzing fire accident information.

The integration of big data into fire facility management has revolutionized the way fire facilities are managed, providing effective tools for social governance to address fires. This advancement has resulted in the standardization of fire facility management, allowing for dynamic fire management, intelligent fire information, self-regulating systems, and significantly improved investment returns [10].

Shokouhi et al. delve into the fundamental elements of building fire protection systems, which encompass a combination of various fixed engineering fire protection products within a building. These systems comprise fire alarms, firefighting equipment, evacuation measures, fire protection barriers, fire extinguishing systems, and rescue protocols. The reliability of these fire protection facilities refers to their ability to carry out specific firefighting tasks under predetermined conditions and within a specific timeframe. This reliability encompasses characteristics such as availability, credibility, and effectiveness. The significance of the reliability of these facilities is pivotal in building fire risk assessment (FRA). A forthcoming project is set to conduct a comparative study using this assessment criterion [11].

Liu's research is centered around tackling the time delay problem in conventional fire decision-making systems. The research proposes a novel module design for a visual fire decision-making system that harnesses the power of artificial intelligence. This groundbreaking design seamlessly integrates AI technology with advanced communication technology to optimize the transfer of information between the fire site and external parties. The study's findings suggest that this module design holds the promise of enhancing the precision of firefighting decision-making systems and offering significant convenience for firefighters. It accomplishes this by fostering the harmonized advancement of the system's four crucial modules [12].

### *2.4. Reactive application*

In the past, forest fires have been primarily identified through manual observation conducted by individuals stationed in fire lookout towers, often using tools such as the Osborne Fire Finder. However, this approach has shown limitations in terms of efficiency, as it is susceptible to human error and fatigue. Moreover, traditional sensors utilized for the detection of heat, smoke, flame, and gas also have their drawbacks, as they rely on the physical presence of particles to trigger them and are constrained by a relatively limited range. As a result, covering extensive areas necessitates deploying a large number of sensors.

Throughout history, forest fires have typically been detected through manual observation from fire lookout towers utilizing simple tools such as the Osborne Fire Finder. However, this approach has proven to be inefficient due to the inherent potential for human error and fatigue. Furthermore, traditional sensors employed for identifying heat, smoke, flame, and gas possess limitations as they depend on particles reaching the sensors to trigger them and have a relatively restricted range. Consequently, covering extensive areas necessitates a significant number of sensors.

In recent years, there have been significant advancements in the areas of computer vision, machine learning, and remote sensing, which have led to the exploration of new possibilities in the detection and monitoring of forest fires. Progress in materials and microelectronics has notably enhanced the effectiveness of sensors in identifying and locating active fires in forested regions. Unlike earlier studies that covered a wide range of sensing technologies and methodologies, this paper provides a comprehensive analysis of the leading forest fire detection systems. It delves specifically into the systems that leverage optical remote sensing, digital image processing, and classification techniques [12].

Forest fire detection and monitoring systems can be classified into terrestrial, aerial, and satellite systems based on their level of acquisition. These systems are equipped with visible, infrared, or multispectral sensors, and their data are processed using machine learning methods. These methods employ handcrafted feature extraction or deep learning networks to detect forest fires early and model fire or smoke behavior. The paper also examines the strengths and weaknesses of these methods and sensors, and discusses future trends in early fire detection technologies [13].

The evolution of forest fire detection technology has seen a shift from traditional methods to deep learning techniques influenced by the AI era. Ground systems, unmanned aerial vehicles, and satellite systems are all utilized for this purpose.

### *2.4.1. Ground systems*

Researchers have made significant advancements in ground-based detection systems by implementing deep learning techniques. These methods have shifted away from traditional reliance on manual features, such as color, motion, and texture, instead focusing on automatically extracting and learning complex feature representations.

In a research study, Zhao and colleagues utilized an Unmanned Aerial Vehicle (UAV) equipped with GPS to implement a saliency detection algorithm for the localization and segmentation of fire areas in aerial images. They employed a sophisticated 15-layer deep convolutional neural network architecture to accurately extract and classify both low and high-level fire features. In a similar vein, Tang and team captured high-resolution 4K data using a ZenMuse XT2 dual vision sensor and implemented an adaptive sub-region select block to identify potential fire areas in the images. They leveraged the YOLOv3 backbone architecture for effective fire detection.

Jiao et al. utilized an unmanned aerial vehicle (UAV) equipped with both visible and infrared cameras to capture real-time images. They employed a YOLOv3 network to detect fires. The UAV's onboard computer performed local image processing and mission planning using a YOLOv3-tiny architecture. Additionally, a ground station received fire spot images and location information, enabling effective forest fire detection and providing operational commands to the UAV for path planning and replanning. These developments have significantly enhanced the efficiency and effectiveness of fire detection and response systems [14].

In a recent research study, Srinivas and Dua combined fog computing and Convolutional Neural Networks (CNNs) while using an Unmanned Aerial Vehicle (UAV) to decrease the occurrence of false alarms when detecting early-stage forest fires. Similarly, Barmpoutis et al. employed an optical 360-degree Complementary Metal-Oxide-Semiconductor (CMOS) camera mounted on a UAV to capture images with an unobstructed field of view. They converted the equirectangular raw data into cubemap and stereographic projections and utilized advanced neural networks to identify fire dynamic textures. This approach aimed to minimize false alarms caused by clouds, sunlight reflections, and objects with colors resembling those of fire or smoke. The experimental findings demonstrated the promising potential of the proposed system in effectively detecting both flames and smoke.

### *2.4.2. Space (satellite) systems*

In recent years, there have been significant developments in the use of deep learning methods for the identification of fire and smoke in multispectral satellite images. Ba et al. have made noteworthy contributions by creating an extensive dataset known as USTC_SmokeRS, which is based on MODIS data and consists of 6,225 satellite images classified into six distinct categories: cloud, dust, haze, land, seaside, and smoke. This comprehensive dataset covers a wide range of global regions. The researchers conducted thorough evaluations using the USTC_SmokeRS dataset and explored a variety of cutting-edge deep learning-based models for image classification, specifically focusing on smoke detection. Additionally, they introduced a novel convolutional neural network (CNN) architecture named SmokeNet. This CNN model incorporates spatial- and channel-wise attention mechanisms to enrich the feature representation for scene classification.

In addition, Priya and colleagues made use of a dataset comprising 534 RGB satellite images gathered from various sources such as MODIS images from the NASA Worldview platform and Google [15]. They implemented a successful method by leveraging an Inception-v3 CNN framework and transfer learning to classify images as either fire or non-fire. They then proceeded to identify fire-affected areas by applying thresholding and local binary patterns.

## 3. Conclusion

In conclusion, artificial intelligence has emerged as a powerful tool in the field of fire protection, offering innovative solutions for both proactive and reactive applications. The historical development of AI has laid the foundation for its current sophisticated algorithms and models, enabling it to tackle complex fire protection challenges.

The proactive application of AI in decision-making, construction, and operation has revolutionized the way buildings are designed, constructed, and managed. AI's ability to deeply analyze environmental factors, optimize designs using BIM technology, improve construction speed and quality through 3D printing and intelligent robots, and enhance fire facility management systems has significantly reduced fire risks and improved overall safety.

The reactive application of AI in early fire detection and monitoring, particularly in forests, has proven to be highly effective. The integration of terrestrial, aerial, and satellite systems with advanced sensors and deep learning techniques has enabled early detection of fires, accurate monitoring of fire behavior, and timely response, thereby mitigating the devastating consequences of forest fires.

Overall, the integration of AI in fire protection has significantly improved the efficiency and effectiveness of fire protection systems, enhancing public safety and reducing losses. As AI technology continues to evolve, it is expected to play an even more critical role in fire protection, enabling further innovations and advancements in this important field.

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