

Review

# Applications of Artificial Intelligence in Fire Safety of Agricultural Structures

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**Abstract:** Artificial intelligence applications in fire safety of agricultural structures have practical economic and technological benefits on commercial agriculture. The FAO estimates that wildfires result in at least USD 1 billion in agriculture-related losses due to the destruction of livestock pasture, destruction of agricultural buildings, premature death of farm animals, and general disruption of agricultural activities. Even though artificial neural networks (ANNs), genetic algorithms (GAs), probabilistic neural networks (PNNs), and adaptive neurofuzzy inference systems (ANFISs), among others, have proven useful in fire prevention, their application is limited in real farm environments. Most farms rely on traditional/non-technology-based methods of fire prevention. The case for AI in agricultural fire prevention is grounded on the accuracy and reliability of computer simulations in smoke movement analysis, risk assessment, and postfire analysis. In addition, such technologies can be coupled with next-generation fire-retardant materials such as intumescent coatings with a polymer binder, blowing agent, carbon donor, and acid donor. Future prospects for AI in agriculture transcend basic fire safety to encompass Society 5.0, energy systems in smart cities, UAV monitoring, Agriculture 4.0, and decentralized energy. However, critical challenges must be overcome, including the health and safety aspects, cost, and reliability. In brief, AI offers unlimited potential in the prevention of fire hazards in farms, but the existing body of knowledge is inadequate.

**Keywords:** artificial intelligence; agricultural structures; fire safety; neurofuzzy inference system; fire-retardant materials



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## 1. Introduction

This review article appraises scholarly research on the application of artificial intelligence in smart buildings, emphasizing fire safety (real and potential) and fire safety of agricultural structures vulnerable to fire damage linked to fossil fuel storage. Other issues that were considered in this inquiry include prospects of AI and machine learning algorithms in mediating the next Agriculture 4.0 revolution and smart city systems (beyond 5G, decentralized energy systems in smart grids, and Internet of Things smart grid (IoT-SG), intelligent management and utilization of excess CO<sub>2</sub> generated from animal biomass, and compliance with sustainable development goals. The multidimensional view of AI was necessary, considering that the utility of AI and machine learning transcends fire safety in farms and agricultural buildings.

Fire damage has been proven to result in material weakening and softening microstructural transformations and changes in geometric features [1]. The case for AI and IoT systems in fire detection systems is further supported by a wealth of research data and anecdotal evidence. Research on the use of AI in fire mitigation and monitoring was initiated in the 1980s [2]. However, at the time, the primary concern was related to the computation of large sets of analog data [2]. This issue was resolved with recent advances in technology, including probabilistic neural networks (PNNs) and adaptive neurofuzzy

inference systems (ANFISs) [3], and the deployment of backpropagation methods. Recently, a three-layer backpropagation neural network was proven useful by Xu et al. [4] in determining the limiting temperature of steel planar tubular truss exposed to fire.

Currently, the accuracy and ability of sensors to detect fires accurately depend on the proximity between the fire and the sensors [5–10]. If the threshold distance is exceeded, a false result might be generated [11]. This challenge has been partly resolved by AI techniques, which facilitate the detection of fires over wide ranges. Alternatively, vision-based sensors might be integrated to provide better warning [12]. This review builds upon existing findings on evacuation modeling for agricultural structures [13], progress made in AI-based fire evacuation of timber structures [14], and the utilization of genetic algorithms (GAs), an adaptive neurofuzzy inference system (ANFIS), and an artificial neural network (ANN) to model the fire regardless of wall coatings [13–15]. Other researchers have demonstrated the practical usefulness of recurrent LSTM neural networks (R-LSTM-NNs) and deep belief networks (DBNs) in real-life case studies of fire hazard prevention using IoT in smart cities [16–19]. The case for smart cities was supported by Molinara et al. [20], who noted that smart sensors combined with AI networks were indispensable in environmental monitoring [20]. The unique benefits and drawbacks associated with DBNs, ANNs, and other AI networks are critiqued from the perspective of user function/management, information management, basic operation, emergency evacuation, and intelligent fire protection [21]. A greater emphasis was placed on the unique benefits afforded by AI systems in terms of autonomous system function, queries, and path planning (see Figure 1). The information presented in Figure 1 is connected to the main body of the review given AI systems facilitate basic operations, information management, emergency evacuation, intelligent fire protection, and user management. The specific applications of the AI system functions in the prevention of fire in agricultural structures are reviewed in Section 2.

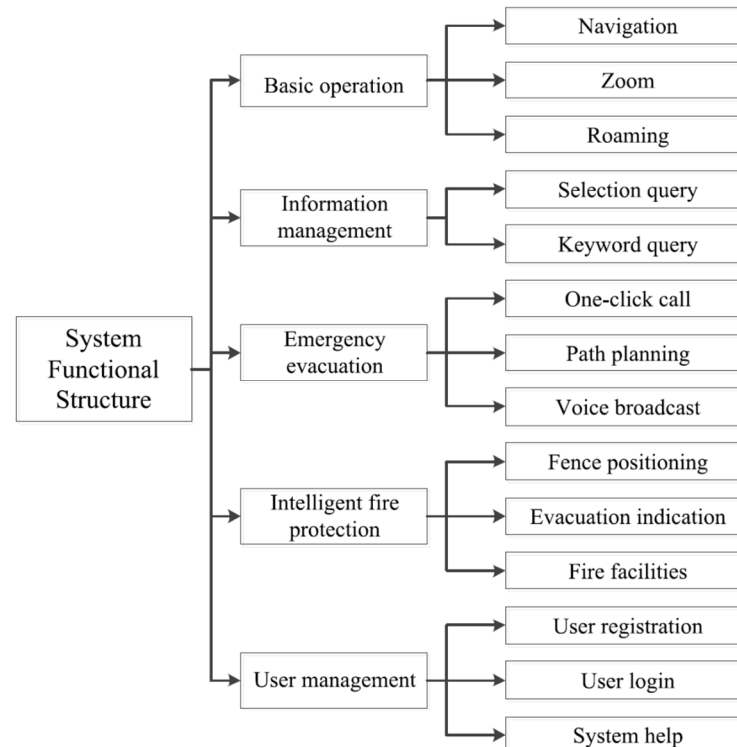


Figure 1. AI system functional structure for fire safety [21].

The discussion is centered on Type B fuel fires caused by liquid fuels (oils, solvents, gasoline, and flammable liquids) [22]. Such fires are much more difficult to extinguish compared to Type A and Type C fires attributed to the burning of crop residues, dry grass and wood, and electrical faults, respectively [23]. Other rare types of fires are attributed

to natural phenomena such as lightning [24]. The severity of fuel fires is evident from the scale of damage in tunnel fires, fires in fuel storage plants in China, the US, and Norway, among other countries [25,26]. The Ministry of Agriculture in Canada estimates that barn fires caused damage worth USD 24 million in farms in 2014 [27]. Similar claims were made by the Animal Welfare Institute [28]. The cost of fires in the US was estimated to be about USD 11 billion [29]. The actual economic losses could be higher, taking into account the time for recovery and long-term environmental and social costs.

The practical benefits and constraints associated with temperature, ionization, photoelectric, and CO sensor fusion in wireless sensor networks are discussed to affirm or reject the use of the naïve Bayes classifier [30], Haar cascade classifier [11], PCA and SVM classifiers [31], WSNs [32], and probabilistic neural network classifiers [33], embedded into genetic algorithms (GAs), adaptive neurofuzzy inference systems (ANFISs), artificial neural networks (ANNs) [34], probabilistic neural networks (PNNs), recurrent LSTM neural networks (R-LSTM-NNs), and deep belief networks (DBNs).

## 2. Fire Safety in Agricultural Structures/Farms

The need to focus on technology-based solutions for fire safety in farm environments is reinforced by the enormous costs of fire damage [35,36] and the inability of fire codes to prevent fire hazards. The codes and guidelines emphasized automated sensors [37]. Investments in AI algorithms remain low [37]. Naser et al. [14] argue that most fire codes fail because they are incompatible with traditional loading practices and vary significantly across countries. Beyond broad variation, the fire codes are incomplete. For example, Section 303.3 of the International Fire Code stipulates that fuel containers should be placed at a safe distance from the burners. The distance should be at least 10 feet. Other provisions under Section 603.3.2.6 of the code provide clear guidelines on spill containment. “Tanks exceeding 55-gallon capacity or an aggregate capacity of 1000 gallons that are not provided with integral secondary containment shall be provided with spill containment sized to contain a release from the largest tank” [38]. However, there are clear exceptions for property-insulated containers, which can be positioned close to burners. The IFC’s [38] case for fire codes is supported by Margentino et al. [22], who note that farmers are required to obtain approvals and permits prior to initiating construction projects in farms. This means there is a form of a regulatory requirement that aims to improve compliance. However, fire statistics in farm and nonfarm environments suggest otherwise [14,30,38]. The high risk of fire indicates that local municipal and national guidelines on the prevention of fire hazards are often disregarded.

Farms and agricultural structures are rarely equipped with spill containment materials, while in other cases, there is no sufficient space to ensure there is adequate spacing of combustible fuels and other flammable materials. In other cases, the violation of the requirements is unintentional—for example, errors are committed in controlled burning of land for bush clearing, controlled processing of crops, and poor handling of agricultural chemicals [23]. The disconnect between policy and practice helps to explain why there have been numerous agriculture-related fires. Based on recent events and traditional patterns in the agricultural sector, there are no incentives for farmers or agricultural investors to allocate resources toward hazard prevention [23]. Even though this is paradoxical considering the immense drawbacks associated with fires, the distinct patterns can be explained from the context of Field’s research, which noted that most agricultural activities are initiated and planned from a subsistence point of view, and there is considerable underemphasis on fire safety and other nonproductive activities compared to commercial industries [23]. The lesser emphasis on nonproductive activities is not unique to farms. For example, the successful integration of AI-based decision support systems in farms and nonfarm environments might be compromised by undue emphasis on quantitative information, such as output vis-à-vis the costs [39]. This has so far been the case for energy-based DSS systems. The phenomenon has practical constraints on energy modeling, considering that “technical features of technology expansion tend to prevail in the models

and decision makers' minds rather than other valid priorities, such as social wellbeing". A fundamental concern is that such worldviews are premised on misconceptions and poor conceptions of the long-term benefits and economies of scale associated with collective action. On a positive note, successful AI-based energy modeling would have practical benefits on energy efficiency in buildings [40] and electric system automation [41]. The claims made by Mehmood et al. [40] are in line with Merabet et al.'s [42] research on intelligent systems for thermal comfort and energy efficiency. This might be achieved using heating, ventilation, and air conditioning (HVAC) with climatic, user, and grid response capabilities [43]. A key issue that should be addressed moving forward is whether it is feasible for AI networks to detect the irregular installation of electrical equipment, which is a risk factor for fires in buildings [44]. The risk of such fires is exacerbated by the spontaneous combustion of hygroscopic materials.

Despite the evidence to the contrary, the significant costs associated with fires do not provide sufficient incentives for farmers to invest in fire-prevention systems, considering that such events are isolated [31,36], and there are no binding legal requirements. Nearly all farms across the developed world are not bound by national or regional fire-prevention codes [23]. Despite the challenges, the case for fire prevention is validated by the intrinsic benefits of preventing loss of life and loss from a business perspective considering the cost of fires is enormous. The cost of fire damage should incentivize stakeholders to engage in voluntary preventative action.

The growing demand for fire-retardant materials has practical implications on the design of finishing materials with customized performance profiles for better flame retardance (coating formulations and architectural appearance). The case for fire-retardant materials has been made by different experts, including Margentino et al. [22]. This is despite the fact that such systems do not offset the potential risk associated with highly flammable substances such as fertilizers, hay and straw, pesticides, and paint. Nonetheless, some progress has been made through research and development (R&D).

Recent R&D has led to the development of intumescent coatings, which satisfy the new criteria for fire retardance [15]. The superiority of the new class of coating materials is interlinked with the structural and chemical features of the coatings. The coating features three components, namely polymer binder, blowing agent, carbon donor, and acid donor. Each component serves a unique function. The primary function of the polymer binder is to hold the acid donor, carbon donor, and blowing agent in position. The acid donor guides the decomposition of mineral acid for the subsequent development of carbonaceous char, while the form expansion process is augmented by the macromolecular binder [15]. However, this class of coatings does not satisfy the diverse market demands, especially from a cost and technology perspective. In theory, the application of intumescent coatings and their ability to form insulation barriers on substrates exposed to fires is impacted by the response timelines [2] and the incompatibility of molecular simulations in making a distinction between nongenuine fire phenomenon and the real fire in its incipient stage.

Non-AI-based materials have long response timelines, which, in turn, impact the reliability of such materials. This informs the need to integrate computer simulations and AI for better risk assessment, smoke movement analysis, and failure analysis [45]. The claims made by Koo et al. about the suitability of AI-based materials in fire prevention are consistent with Aspragathos et al.'s investigation of the suitability of AI in forest fire protection systems [31]. In the latter case, AI systems were grouped into four broad classifications, including optical and thermal cameras for fire prevention, wireless sensor networks [46], satellite-based systems, and human-based observational systems. The support for AI-based system by Koo et al. and Aspragathos et al. [31,45] negates the fact that fire safety engineering and evacuation modeling is a multidisciplinary undertaking that integrates elements of behavioral science (sociology and psychology), data analytics (incorporating aspects of physics, mathematics, and computer science), and other technical domains. The inclusion of various experts in evacuation modeling has translated to the development of multiple submodels providing accurate representations of behavioral and physical components of

evacuation [13]. On the downside, this does not automatically translate to better responsiveness to fire hazards. The practical benefits afforded by each system are reviewed to advance the current body of knowledge on fire safety in agricultural structures.

### 2.1. Artificial-Intelligence-Based Networks for Fire Prevention/Monitoring/Simulation

The development of artificial-intelligence-based human-based observation systems for fire prevention/monitoring is supported by the complex nature of fires from a natural perspective. Fire is a destructive force, but whose impact on building materials is not fully conceptualized despite advances in fluid dynamics, materials science, civil engineering, and computer science [13]. The findings documented by Arabasadi et al. [15] concerning the usefulness of AI-based genetic algorithms (GAs), adaptive neurofuzzy inference systems (ANFISs), and artificial neural networks (ANNs) underscores the suitability of the latter in the design of materials and fire retardants that achieve satisfactory fire performance. However, it is of note that different networks offer distinct capabilities. This worldview is validated by Xu and Peng [47], who argued that fuzzy-based network systems were superior to ANN. The unique benefits associated with fuzzy logic were linked to the unique inferences, including the ability to “infer the fuzzy output variables from the fuzzy input variables” [47] (p. 269). This makes it practical to convert the real-world knowledge into mathematical language that can be utilized by the models. The practical utility of the fuzzy system was also demonstrated by Jiang [21], whose simulations utilized fuzzy and selection queries to identify partial location information and consequently establish the location of an individual in buildings at risk of fire.

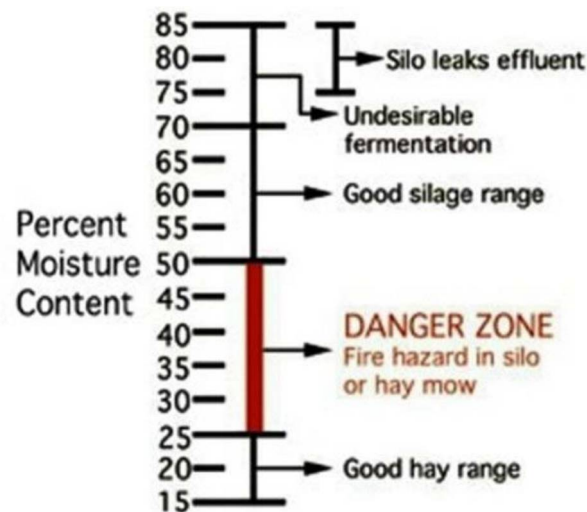
The attainment of satisfactory fire performance could be realized through the customization of the load level, thermal stability and other material features, and geometric parameters. It is impractical to tailor each of these parameters without the integration of AI systems [2,13–15,31]. Even though there is a strong case for AI systems in fire prevention, past computer models and simulations have yielded distinct outcomes, a phenomenon that is attributed to the unique response of different structures and materials, different stimulation parameters and environments, and technical expertise. The key parameters that predict the outcomes of the simulation models include wall thickness, diameter ratio, outer diameter, load ratios and temperature, and diameter–thickness ratio (see Table 1). For example, simulation experiments conducted by Koo et al. [45] confirmed that K-CRISP prediction provides an accurate representation, but the accuracy was impacted by time.

**Table 1.** Link between load ratios, critical temperature, and fire susceptibility [45].

Trusses	$F_u$ (kN)	Critical Temperature (1C)						
		$0.2F_u$	$0.3F_u$	$0.4F_u$	$0.5F_u$	$0.6F_u$	$0.7F_u$	$0.8F_u$
SP1	838	699	646	598	559	521	464	379
SP2	840	701	649	601	564	527	474	408
SP3	848	705	654	606	569	533	485	423
SP4	857	704	653	605	569	532	483	421
SP5	866	705	655	607	571	535	489	429
SP6	848	705	654	606	569	533	485	423
SP7	978	701	649	602	564	526	473	406
SP8	1077	703	652	604	565	530	479	416
SP9	1155	707	657	609	573	537	495	434
SP10	1257	712	663	615	579	543	506	448
SP11	1053	702	649	601	562	525	470	400
SP12	1242	702	650	601	563	525	471	398
SP13	1424	706	654	605	567	530	480	417
SP14	1610	708	657	608	571	534	488	426

Other fundamental concerns relate to the specificity of the technology. The K-CRISP system works best using the Monte Carlo fire simulation model and FireGrid systems [45,48]. There is no guarantee that it would function as intended using alternative mechanisms due

to concerns about the accuracy of AI-based networks in modeling the potential sources of heat that can cause fires in farms. Field [23] noted that fires in agricultural settings could be triggered by heat generated by stored grains. Such heat is generated via anaerobic fermentation and aerobic respiration, which are natural postharvest biological processes that occur as grains lose excess moisture to attain equilibrium in the moisture content. If the storage structures lack appropriate vents for heat to escape through, there is an imminent risk of pyrolysis even in the absence of oxygen [23]. Similar fire risks were documented during the storage of grains stored in biomass fuels in large storage units [49]. In the latter case, the risk of self-ignition was attributed to self-heating. The correlation between fire hazards and the moisture content in silos is depicted in Figure 2. Beyond grain-moisture-specific fire hazards, there are varied concerns about the impact of a different confounding factor. The severity of the fire hazard is predicted by the effect of wind on the fire target and doorway pressure, velocity, and temperature [50]. In other cases [51], the maximum concentration of oxygen (MOC) has been proven to predict the risk of a fire hazard in grain silos.



**Figure 2.** Relationship between the moisture content in silos and fire hazards [23].

The drawbacks and context-specific benefits associated with specific AI networks informed the development of alternative models, including the radial basis function neural network (RBFNN) and the fuzzy logic inference system [47], to complement the traditional backpropagation neural network (BPNN). BPNN systems suffer from a myriad of challenges, including poor convergence and learning speed [47] and the inability to integrate prior knowledge/experience. Xu and Peng [47] utilized the technique and established that RBFNN systems provide a reliable and intelligent assessment system for fire safety. Even though the outcomes were applicable to high-rise buildings [47], they were relevant to multistorey silo structures, prone to fires associated with postharvest anaerobic fermentation and aerobic respiration of grains [23].

The practical utility of the systems was linked to the adaptive fuzzy-RBFNN's high efficiency, accuracy, and reliability. However, there are practical constraints to broad commercial application, including limited application in fire safety assessment [47] and the fact that the simulated findings are specific to high-rise structures. The case for a fuzzy logic system made by Xu and Peng is further supported by Bahrepour et al. [30]. In the latter study, the DFLER-fuzzy-based system was proven useful in wireless sensor networks integrated with temperature and smoke sensors. The network's ability to detect fires accurately was grounded on the following considerations. First, the integration of additional sensors (fusion of temperature, ionization, photoelectric, and CO sensors) translates to better detection capabilities. The benefits attributed to the fusion of different sensors by Bahrepour et al. [30] were collaborated by Sharma et al. [52], who employed

deep-learning-based detectors coupled with IoT sensors for active fire location and real-time monitoring. Second, the fuzzy systems that incorporated the AI approach featured intelligent detection algorithms that facilitate autonomy, where each sensor node is capable of detecting fire on its own. Such capabilities are necessary, considering that fires follow a distinct pattern. The multisensor approach introduces new constraints for farm-related applications, where investments in nonproductive activities such as fire prevention are not a priority.

From a theoretical point of view, it might be challenging for farms to invest in fuzzy systems and sensor fusion due to cost considerations. Alternatively, cost should not be regarded as impediments to investments in AI-based systems, considering advances in technology led to the development of cheap and precise networks. For example, a naïve Bayes classifier-feedforward neural network (FFNN) tool was considered useful in monitoring fire risks by Bahrepour et al. [30]. The basic architecture of the FFNN system is depicted in Figure 3. It is clear that the system comprises interconnected nodes, and the back layers/input layers feed the hidden and output layers. On the downside, the potential application of the naïve Bayes classifier-feedforward neural network (FFNN) tool would involve a tradeoff with other metrics of performance, including the accurate determination of weights or learning. Considering that learning is integral in AI-based systems for fire detection, the activity of naïve Bayes classifier-feedforward neural network (FFNN) systems has to be augmented by gradient descent (GD) learning algorithms [30], which might introduce new challenges, especially in cases when it is impractical to integrate GD systems.

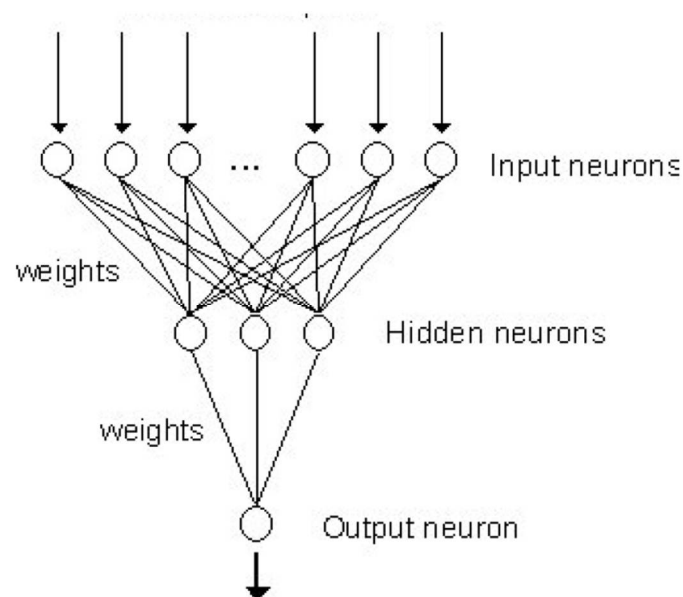


Figure 3. FFNN architecture [30].

After considering the cost benefits of naïve Bayes classifier-feedforward neural network (FFNN) systems, with embedded gradient descent (GD), it is clear that the AI network is appropriate in wireless-sensor-based systems for fire detection. The main advantage is cost and accuracy and unique architectures. In theory, FFNNs can be deployed across multiple locations, especially in settings with distinct requirements and sensor capabilities. The capabilities are reinforced by the fact that wireless sensor networks act as isolated events, where each node can make an independent decision. The outcomes documented by Bahrepour et al. [30] concerning WSNs were collaborated by Wahyono et al. [32]. In the latter case, the computing challenges attributed to the integration of AI into WSNs were resolved using the nearest neighbor (k-NN) algorithm, capable of surmounting attributes that are inappropriate based on the proximity of the attributes with small computational

values [32]. However, it remains unclear whether K-NN algorithms could offset the demanding maintenance and installation and limited energy capacity.

Considering that existing AI networks have practical constraints in real-life settings, Jiang [21] proposed the development of an ant colony algorithm for fire safety simulations. Similar to other networks, the system integrated aspects of IoT and AI in the dynamic modeling, monitoring, and control of fire-fighting infrastructures such as fire hydrants, water sprinklers, fire extinguishers, safety evacuation signs, smoke and temperature sensors. In contrast to the previous model, the probability for success in the ant colony algorithm is reinforced by intelligent optimization. The model focuses on intelligent optimization and the establishment of the shortest possible route for dynamic evacuation. Even though the simulation findings suggest that the model would be useful in finding the best possible evacuation routes in line with the ant colony algorithm, the practical utility of the model can be challenged in farm environments, especially in livestock holding areas. Farm animal's response to fire hazards is dissimilar to humans. In addition, the architectures of barns are unique compared to buildings that house humans.

### *2.2. AI Networks for Fire Prevention, Insurance Claims, and Future Manufacturing/Value Addition of Agricultural Commodities*

The fire risks in silos are relevant to agricultural warehouses used to process or value-add agricultural commodities. Grant and Drysdale [53] state that the settlement for fire claims is a lengthy process, and in the meantime, normal operations would be impacted or even halted in worst-case scenarios [53]. The settlement of multiple fire claims might also translate to higher insurance premiums. This means that farm fires have a broader impact on the insurance industry. The need for reliable and intelligent fire safety systems for agricultural structures, silos, and warehouses is augmented by the immense prospects of intelligent technologies. For example, the smart city model envisioned by Foresti et al. [54] and Dakheel et al. [43] features a new generation of intelligent manufacturing (NGIM) in warehouses and technologies of cyberphysical systems (CPSs) to bridge the gaps between humans and machines and bypass non-digital-native HR. The distinct capabilities cannot be optimized without addressing the risk of regular fire hazards.

### *2.3. Standards, Material-Specific Limits, and Scenario Constraints to Accurate Simulations*

The long-term utility of AI simulations in preventing fires in agricultural structures depends on material properties, standards, and accurate simulations. For example, the fire-retarding ability of reinforced concrete could be impaired by corrosion, which is common in farms [55]. Existing models are unable to accurately predict the temperature-dependent material properties of structural steel. This is a pertinent concern given that most modern agricultural structures are constructed using steel [56]. Moreover, the international building code recommends that pressure tanks, piping systems, valves, and fittings should be made of steel [38]. The broad application of steel predicts its influence on fire safety in various farm and nonfarm environments.

The development of advanced systems is capable of reconciling the discrepancies between ASCE and Eurocode 3 model estimates [56] and seamless interaction and interaction with the existing agricultural sensors for agricultural structures, including electrochemical, ultrasonic, fiber-optic, piezoelectric, wireless, fiber Bragg grating sensors, and self-sensing concrete [57]. From a materials perspective, both Eurocode 3 and ASCE are grounded on erroneous assumptions about steel, including the fact that the fabrication, composition of steel is independent of its origins [56]. Published data on steel vary significantly across different models, a factor that limits the reliability and the utilization of the simulations in fire safety decision making.

The criticism of existing Eurocode 3 and ASCE data relating to temperature-dependent material properties of structural steel is informed by the following facts. First, according to Eurocode 3, the temperature reduction factor of steel at 450 °C is 0.88 [56]. In contrast, the ASCE estimates the value to be 0.63 [56]. Even though such differences are perceived to be marginal, they have significant implications on accurate fire modeling. Recent studies



have attempted to address the problem through the standardization of material properties using AI and machine learning techniques in an ANSYS environment. The accuracy of the model was further predicted by the incorporation of data drawn from various building codes and standards and experimental data in the public domain. The observations made by Naser [56] about the limits of existing building codes and systems relating to steel are in agreement with Field [23], who noted that existing codes were less relevant for agricultural structures and environments. The observations made by Field do not apply to BS5502: Part 23: 2004 [58] and CFP-A Guideline No. 17:2015 F [59], which have specific provisions for agricultural structures.

In contrast to steel, the use of concrete in agricultural construction diminishes the need for fire safety and adherence to fire codes. This is because concrete is a natural fireproofing material that can withstand fire exposure for at least 2 h. The fireproofing abilities of concrete have been acknowledged by the European Committee for Standardization and BSI. A major challenge is that even though concrete structures satisfy most of the codal provisions related to fire safety and have consistently proven useful over time, there is a probability that the fire resistance potential of concrete is overestimated [1]. This has been confirmed in postfire analysis investigations. The resolution of concrete fireproofing challenges using AI networks is underexplored and does not reflect the existing realities in the agricultural construction materials. Old concrete structures in farms were made using concrete materials that bear little semblance to modern concrete. Advances in materials science and engineering have resulted in the creation of concrete materials with advanced properties [1], which, in turn, impact their fireproofing abilities. Recent studies have confirmed significant variations in the composition of old and new concrete structures in terms of volcanic ash, lime, silicates, aluminum tobermorite, calcium, fly ash content [60], and fiber reinforcements [1]. The performance of AI networks for fire safety in old and new concrete structures is a subject that warrants further research attention. The preliminary observations made by Seitllari and Naser [1] using ANN, GA, and ANFIS systems suggested that AI had the potential to accurately determine the risk of fire spalling in reinforced concrete structures. However, the precision of the AI systems in concrete structures could be impacted by the variations in the chemical composition of fiber-reinforced high-performance and high-strength concrete, self-healing concrete [61], shape memory polymer concrete [62], and concrete with piezoelectric sensors [63]. The composition-specific effects are premised on the algorithm's training and testing phases. The input parameters in these phases include concrete strength, RC column width, applied to load, and magnitude of eccentricity. Any changes in the material properties could impact the precision and error rates of AI and IoT systems.

Beyond material-specific limitations, the decision criteria for AI networks introduce additional practical constraints, an observation that is supported by Jain and Liam's research on intelligent systems' behaviors and decision making. On most occasions, the merits are evaluated based on technical and environmental benefits rather than environmental and social aspects [39]. This has been especially the case for AI-based Long-Range Energy Alternatives Planning (LEAP) and HOMER, an application developed by the US National Renewable Energy Laboratory. The scenario-based autonomous decision-making approach introduces practical constraints, given there might not be a strong case for fire prevention due to the intermittent nature of fire hazards.

#### *2.4. Future Prospects of AI in Agricultural Structures and Beyond*

Despite the limitations, it is anticipated that the future prospects of AI technologies in the prevention of fires in agricultural structures would be augmented by the global system for mobile (GSM), smart message service (SMS) [64], emerging networks such as 5G and beyond 5G, and unmanned aerial monitoring vehicles [65] for wide-area coverage, especially in smart cities [66]. In addition, AI and other technologies could mediate compliance with sustainable development goals in smart ecosystems/cities [67], megaprojects [68], distributed energy systems in the Internet of Things smart grid (IoT-SG) [69],

Agriculture 4.0 [70], society 5.0 [54], and optimization of underground spaces [71] and fuel load design [72]. The accuracy of the fused sensors would be enhanced by the progress made in materials science and engineering. For example, Mtz-Enriquez et al. reported the successful development of precise and ultralow energy consumption graphene-based smoke sensors coated with ceramic microparticles [73]. The graphene-based sensors could prove useful in areas prone to fires, given the high thermal stability of carbon.

Beyond AI and related technologies, the risk of fires could be offset by CO<sub>2</sub> sequestration using microalgae from agricultural biomass [70] to generate recycled water and biomass extracts to be used in industries. The recycled wastewater could be used in automatic fire extinguishers. Alternatively, such processes would help mitigate the adverse greenhouse effects associated with agricultural activities and mitigate global warming. The need to safely manage/recycle excess CO<sub>2</sub> generated from farms is critical because high CO<sub>2</sub> concentration elevates the risk of fire. In particular, consistent flow of CO<sub>2</sub> has been proven to generate significant static energy, which can cause a fire in the presence of pyrolysis gases [74]. This claim is supported by the fire hazard associated with animal manure [75]. From an agricultural point of view, Rai et al. [76] note that intelligent technologies might prove useful in the development of realistic strategies for rearing and improvement of poultry and livestock. This is critical considering that advanced economies had resorted to the destruction of natural ecosystems, including the Amazon and the Mediterranean mountains [77], for livestock production [78]. The destruction of natural forests elevated the prevalence of forest fires [66,78]. The intelligent information drawn from the farm-based system could complement sensors for fire safety.

The need to develop and deploy AI solutions to mitigate the destruction of natural forests to create space for agriculture is supported by data models, which showed that activities impacted the mental and psychological wellbeing of communities living close to the forests. This translated to poor academic performance in China and human capital development in the future [79]. In contrast to Graff Zivin [79], Grossmann and Mladeoff [80] claimed that the burning of natural ecosystems to support agriculture impacts the chemical profile of the soils. For example, chemical analyses noted there was reduced calcium, nitrogen, and organic matter content and high phosphorous content. The soil analysis findings are in agreement with Pereira et al.'s [81] research on the effects of wildfires on ecosystems. Even though there are promising future prospects across different sectors, Anastasi et al. [82] caution on the risks associated with embodied artificial intelligence on health and safety. There is a need to balance between automation benefits and the unforeseen hazards associated with intelligent technologies. Moreover, there will be a need to develop standards for Building Intelligence Quotient (BIQ) KPIs based on temperature control, security systems, HVAC systems, and lighting control [83]. In brief, investments in AI systems would be capital intensive in the short term, but future benefits outweigh the costs because agriculture would become more cost effective for farmers [84] and less strenuous on the environment.

### **3. The Cost Benefits of Genetic Algorithms (GAs), Adaptive Neurofuzzy Inference System (ANFISs), and Artificial Neural Network (ANNs), Probabilistic Neural Network (PNNs), Recurrent LSTM Neural Networks (R-LSTM-NNs), and Deep Belief Networks (DBNs)**

The case for AI- and IoT-based networks for fire prevention is supported by the complexity of fire and evacuation procedures and the failure of traditional mechanisms. Traditional guidelines indicate that the risk of fire hazards in livestock barns could be mitigated by the installation of approved fire doors, the incorporation of fire-resistant materials and coatings such as latex, reducing the number of stalls between the points of entry and exit, the integration of autonomous functioning sprinkler systems, fire, and smoke detection systems [85], and an ample supply of water [21,22]. This is in line with the silo fire decision tree [85]. On the downside, there is no guarantee that compliance will help prevent fires. Jiang [21] notes that evacuation is hampered in most cases due to the peculiarities of human behavior, which increases the difficulty of regulating the

spread of fires. Human cognition in isolation cannot accurately predict when it is most appropriate to deploy fire-fighting equipment in buildings while preserving the integrity of function and minimizing potential damage to the equipment and materials preserved in the building. Given the limits of human cognition and traditional planning methods, artificial intelligence technologies have proven useful in simulating fire spread, relocation complexities in high-rise buildings, and best-case scenarios for relocation. The accuracy of intelligent technologies is reinforced by the assimilation of complementary technologies, such as GIS [86], satellite lightning imaging sensor (LIS)/optical transient detector (OTD), statistical machine learning [87], and CFD. Presently, machine learning has accurately predicted fire ignition caused by lightning [24]. This was facilitated by LIS/OTDs.

Model data and experimental evidence have demonstrated that recurrent LSTM neural networks (R-LSTM-NNs), deep belief network (DBNs), genetic algorithms (GA), adaptive neurofuzzy inference systems (ANFISs), and artificial neural networks (ANNs) offer unique benefits in the generalization of real-world objects [16,47,50,56,88]. However, the networks offer localized benefits in error rates, recall, accuracy, and precision. Certain challenges apply to most ANN-based systems, including the ability to quantify the prior knowledge and experience of the engineers/experts into data inputs to mitigate subjectivity [47]. This problem has been partly resolved by incorporating fuzzy logic [12] and the development of combined networks. For example, according to Zhang et al. [16], R-LSTM-NN and DBN networks were better compared to ANN and other networks based on the superior F-1 score scores, marginal error rate (~0.14%), recall, accuracy (>98%), and precision. Beyond combined networks, Seitlari and Naser [1] argued that expert thinking could be conveyed through fuzzy set levels, which are defined by “if-then” rules. The intelligent systems’ ability to quantify expert knowledge is critical in driving uncertainties in different control mechanisms for precise outcomes. The proposals for rule-based algorithms were supported by Park et al. [89].

The accuracy rates of DBNs and R-LSTM-NNs are similar to the naïve Bayes classifier-FFNN system, whose accuracy was estimated to be 98.67% [30]. Considering that different neural networks might possess comparable levels of accuracy, the choice of AI techniques for agricultural fire detection in wireless sensor networks [46] should be guided by other considerations, including cost, learning capabilities, compatibility with support networks, and precision. The case for compatibility with the existing system is validated by the failure of existing systems. Traditional evidence drawn from fires shows that existing systems of sensors for fire detection often fail to detect fires early on [33], while false alarms have been reported due to defective smoke detectors and human noise. This is a critical concern given that late detection of fires complicates evacuation efforts and fire fighting. In other cases, defects in fire sensors are linked to tailored performance. Certain sensors function best with specific materials. Such challenges underscore the need to incorporate AI networks to achieve high classification rates.

Cost- and poor-precision-related issues are nonexistent in probabilistic neural network (PNN)-based fire hazard simulations [33]. The simulation results show that the system had satisfactory mean classification accuracy (83–94%) in RLSSV-8 and hybrid datasets [33] (see Figure 4). The accuracy of PNN-RLSSV-8 is comparable to AI-WSN systems, which achieved a 94% accuracy following the integration of the K-nearest neighbor (k-NN) algorithm to offset the computing limitations [32]. On the downside, the accuracy of PNN systems is lower compared to combined DBN and R-LSTM-NN, which attained an accuracy of >98%, as noted by Zhang et al. [16]. From another dimension, errors should not be a limiting factor to the installation of AI networks in farms, given the challenge can be resolved through pretraining and transfer learning. The low probability of accurate fire detection (35.96–65.02%) of the Haar cascade classifier machine learning algorithm was counteracted by the YOLOv3 model [11], which improved the accuracy of the machine learning algorithm through training. In other studies [90], the YOLO models proved useful in construction engineering management/structural health monitoring in combination

with PCN/GAN/CNN networks. The latter evidence reaffirms the multidimensional benefits of AI networks. The utility is not confined to fire safety.

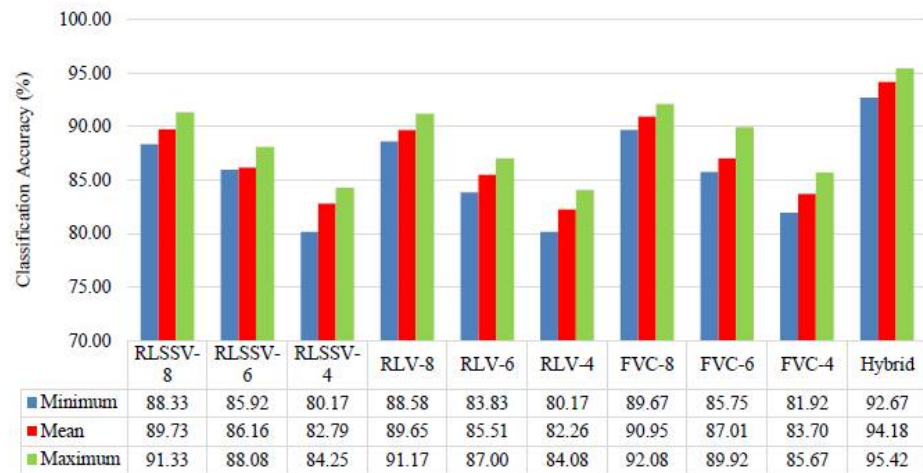


Figure 4. Classification accuracy of PNN networks with IAQ datasets [33].

Zhang et al. [16] observed that there were practical limits with R-LSTM-NN systems in isolation, and the synergistic benefits afforded by DBN-R-LSTM-NN systems improved the reliability of the system. The researcher is conscious of the fact that large error (nearly 100%) rates are acceptable in certain cases depending on the desired application of the model results. Ryder et al. [50] noted that high error rates had negligible effects in nonwind simulations involving Fire Dynamics Simulator (FDS) and computational fluid dynamics. In reality, such errors are nonacceptable in real-life settings, given they are a microcosm of the limits of the material simulations. In addition to errors, large dependence on the grid resolution of the model results and poor soot production models impact the reliability of DBN-R-LSTM-NN systems. A cost–benefit analysis of the merits and drawbacks of the technologies suggests that the practical benefits outweigh the drawbacks due to the close similarities between the simulated/theoretical and experimental values (see Table 2).

Table 2. Comparison of the FDS model predictions and the actual fire data in the wind and nonwind scenarios [50].

Comparison between Pool Fire Data and FDS Model Predictions—Case 1, Wind			Comparison between Pool Fire Data and FDS Model Predictions—Case 2, No Wind		
Distance to target	Experimental approximations (kW/m <sup>2</sup> )	Model prediction (kW/m <sup>2</sup> )	Distance to target	Experimental approximations (kW/m <sup>2</sup> )	Model prediction (kW/m <sup>2</sup> )
50	32	31.13	50	8	4.54
75	17	13.06	75	4	2.87

On the downside, the practical use of DBN and R-LSTM-NN was confined to smart cities. There was minimal evidence of its utility in non-smart-city environments. The unique drawbacks of ANN, GA, ANFIS [16], R-LSTM-NN, and DBN networks [13–15] could be offset by pattern recognition and machine learning capabilities of AI-based systems, as noted by Naser [14]. The case for machine learning systems is supported by Ryder et al.’s simulation of fire scenarios using large eddy simulation codes and computational fluid dynamics. CFD was proven effective in simulating the plume characteristics and large-scale effects of fires [50]. Beyond Ryder et al.’s research, Kochkov et al. noted that advances in machine learning coupled with the availability of affordable computing devices with higher computing power accelerated CFD [88]. Despite the latter progress, non-CFD-based models based on computational models are highly preferred due to the complex geometries (associated with accounting for convective and conductive heat transfer, bluff-body aerodynamics, multiphase flow, turbulent mixing and combustion,

radiative transport), turbulence, assumptions, and context-specific benefits of different CFD programs [50]. Anecdotal evidence suggests traditional farm structures might not have ample resources to invest in CFD systems for fire prevention, given that the allocation of resources to nonproductive activities is often de-emphasized [23]. Additionally, there are no commercial on-demand service providers. The inability to invest in AI-based systems amplifies the risk of catastrophic fire hazards.

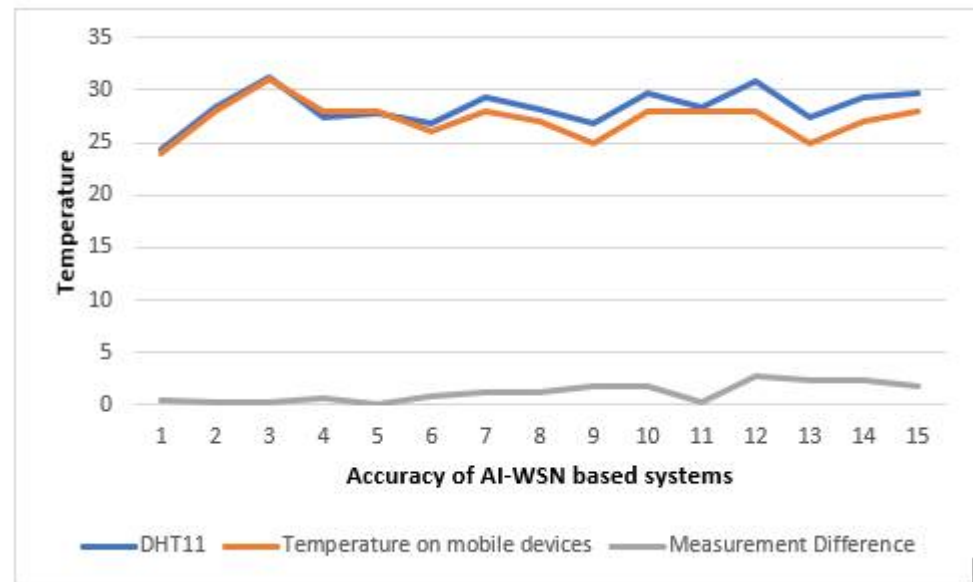
The current discussion has practical implications on the safety of farm/agricultural structures, given it provides compelling insights on the suitability of various fire-retardant materials such as liquid hydrocarbon resin, thermoplastic acrylic resin, melamine, pentaerythritol, and ammonium polyphosphate, which are susceptible to char cracking and form detachment. Beyond the technological aspects of fire-retardant materials, the application of artificial intelligence in smart buildings has economic benefits over the long term. Wildfires in the state of Texas cost about USD 21 million (this includes damage to animal feeds/pasture, death of livestock). This is according to the Texas A&M AgriLife Extension Service [35]. The phenomenon is not unique to the US. The Food and Agriculture Organization (FAO) estimates that commercial and small-holder agriculture is vulnerable to natural disasters, including wildfires. Recent fires have burned vast tracts of land, including farms across Europe, and Greece remains one of the most vulnerable states [31]. Between 1997 and 2007, wildfires in Greece and Indonesia burned 670,000 acres and 8 million hectares, respectively, and resulted in more than 300 deaths [91]. Recently, at least USD 10 billion was lost through fire damage across the US [87] and the UK [51]. The cost of human lives could be offset by investment in intelligent systems for fire safety.

From an economic perspective, wild and human-induced fires are unsustainable given they accounted for 1% of the total production losses on global agriculture, particularly in Asia, Latin America and the Caribbean, and Asia between 2005 and 2015. This is equivalent to more than USD 3 billion in direct economic losses [36], which, in turn, have a long-term impact on the global food safety systems. The significant economic losses provide sufficient incentive for engineers, scientists, and owners of commercial farms to invest in the next generation of AI-based fire-prevention materials, especially in Europe and Asia. The need for AI networks and WSN is supported by global fire statistics. No major fire has been documented in the US since 1871 and 1894 Peshtigo and Great Hinckley Fires in Wisconsin and Minnesota, which claimed nearly 3000 lives [91]. The contrary is true in Asia, Southern Europe, Latin America, and Africa.

### *3.1. Artificial-Intelligence-Based Wireless Sensor Network (WSN)-Based Systems for Fire Prevention/Monitoring*

WSN coupled with IoT has so far proven useful in continuous monitoring of fire risk in forests [31] through real-time animal tracking and autonomous fire detection. The risk of errors in such systems is often offset by the integration of fuzzy-logic-based models to counteract false alarms, while the costs of integrating the sensor systems are addressed through the model for optimal distribution of sensors over large tracts of land and energy efficiency [31]. Despite the strong case for integrating AI into WSNs made by Aspragathos et al. [31] and Bahrepour et al. [30] and other researchers, certain drawbacks must be taken into account. Wahyono et al. [32] claimed that AI networks contributed to the overheating of WSNs in the transmission of computing data. The WSNs are also burdened by fuzzy logic and decision trees, a factor that might impact accurate and valid decision making in cases involving large datasets with multiple components. The drawbacks listed above show that the computational and memory requirements associated with AI are magnified by the potential impairment of WSNs due to overheating and related effects. The potential installation of WSN-supported AI networks in farms/agricultural settings is further complicated by the demanding maintenance and installation process [31], unsatisfactory communication speeds, temperature-dependent accuracy (see Figure 5) [32], and limited energy capacity, which, in turn, translate to higher costs of maintenance and reduced performance. The latter issues can be seen as a characteristic case of the tradeoffs implied by the increase in complexity while implementing modern agricultural applications

and require meticulous studying and possibly the adoption of a scalable WSN architecture, in terms of computational load, communication quality, cloud-edge workload balance, and energy efficiency, for efficiently addressing the critical sensing and acting functions [92]. It is encouraging that new modules are appearing either assisting existing systems in performing AI-related operations (i.e., the Intel NCS2 unit [93]) or acting as standalone units compatible with comparatively easy-to-use platforms for AI model training [94].



**Figure 5.** Impact of temperature on the accuracy of AI-WSN-based systems for fire prevention/monitoring [32].

As noted by Field, farmers and agricultural investors often place lesser emphasis on fire safety and other nonproductive activities [23]. This means the AI networks should be affordable and functional to appeal to budget-conscious farmers/agricultural companies. Because existing technologies have not resulted in the development of energy-efficient and self-sustaining WSN-supported AI networks suitable for farms/agricultural settings, it is anticipated that the widespread use of artificial intelligence-based wireless sensor network (WSN)-based systems for fire prevention/monitoring would be limited at least in the short term. Even if the energy issues are addressed, users have to contend with system errors. Two false alarms were documented by Wahyono et al. [32] out of 11 real-time measurements taken between 13 and 23 March 2020 [32]. The error rates are unacceptable in commercial agricultural settings where fire damage could pose unquantifiable damage to livestock, farm equipment, agricultural structures, and farm produce/stored grains and where the risk of network errors is amplified by extended use. Alternatively, users might opt to integrate K-NN algorithms to enhance the processing/computing capabilities of WSNs in farms.

### 3.2. Artificial-Intelligence-Based Optical and Thermal Cameras Based Systems for Fire Prevention/Monitoring

The AI-based optical and thermal cameras offer practical benefits compared to WSN systems for fire prevention, which are impaired by the greater risk of false alarms, computing limitations, unsatisfactory energy efficiency, demanding installation, and scenario-specific applications [11,32,39]. The practical benefits associated with optical and thermal cameras include globally established platforms for fire monitoring, including UraFire, FireVu, FireHawk, ForestWatch, and EYEfi in Europe, North America, and Africa, that integrate light detection and ranging (LIDAR) systems, IR spectrometers, infrared (IR) thermal imaging cameras, and video cameras for heat flux, smoke gases, flame, and smoke particle detection [31]. Even though large farms might benefit from thermal and optical

imaging provided by independent service providers, the systems are not immune to errors associated with human activities near the target locations and atmospheric turbulence (dust particles, shadows, and clouds, light reflection). This is exacerbated by the detection limits (1.0–10.0  $\mu\text{m}$ ) [95]. Despite the potential limiting factors, the case for optical and thermal sensors is reinforced by the fact that optical detectors have proven more useful compared to ionization chamber smoke detectors in real-life settings due to their higher sensitivity to smoldering fires and tolerance to ambient conditions [95]. The utility of optical and thermal cameras for fire detection could be augmented by AI networks such as DBN, R-LSTM, PNN, GA, and ANFIS, embedded with naïve Bayes classifier [30], Haar cascade classifier [11], PCA and SVM classifiers [31], WSNs [32], and probabilistic neural network classifiers [33]. However, this potential requires further investigation. It must be noted that apart from the high accuracy and resolution (but quite expensive) cameras, reduced capabilities modules, such as the thermal arrays described in [96], pose quite a challenging option, as they can be exploited by several AI algorithms and thus seem to widen the current application and cost options.

#### 4. Conclusions

Following the appraisal of various artificial intelligence-based satellite-based wireless sensors and optical and thermal camera systems for fire prevention/monitoring, each system has practical benefits and constraints. For example, the FSD system exhibited optimal performance in the modeling of gas dispersions through space. This means the technique could be deployed in ascertaining the explosivity limits and flammability of substances in closed environments. Such information could help guide explosion model boundary conditions to ascertain the temperature and pressure waves and changes that are linked to the explosions, among other parameters that are often disregarded in traditional models. Based on the unique benefits, it is clear that FSD offers a practical opportunity to improve fire model simulations, especially in fluid flows. However, future experiments must address current drawbacks, including higher reliance on the accuracy of the grid and grid resolution and the inability to accurately predict limited ventilation fires. The limits of FSD- and CFD-based techniques at large informed the investigation of alternative methods for AI-based fire simulation and prevention, such as the DBN-R-LSTM-NN. According to the researchers, the DBN-R-LSTM-NN method was proven useful, particularly in the prediction of the probability of fire occurrence, using data collected from various IoT devices.

A key constraint was the practical feasibility of IoT data collection in non-smart-city environments such as country farms with limited integration of computing devices. The risk of fire outbreak was classified on a scale of zero to one depending on the simulated smoke, flame, temperature, FPMC, and RH values. Despite the technical challenges, the researcher noted that there were practical benefits associated with the combined DBN and R-LSTM-NN, especially in terms of the higher F-1 score scores, precision, accuracy (>98%), and marginal error rate (about 0.14%). However, the high accuracy rates in isolation cannot predict the choice of neural networks for fire safety in farm environments considering the accuracy of DBNs and R-LSTM-NNs, which is comparable to the naïve Bayes classifier-FFNN system.

Apart from DBNs and R-LSTM-NNs, there are other effective networks for enhancing fire safety in farms. For example, the adaptive fuzzy-RBFNN model was proven useful compared to the traditional BPNN in terms of the simulation accuracy, learning speeds, and ability to mimic human reasoning and infer prior knowledge and the experience of experts. From a long-term point of view, the cost effects, fire code limits, and lack of regulatory incentives for compliance must be addressed to improve the extent of AI system applications in farms. In theory, the cost-related barriers have been partly offset by recent advances in technology, including the development of the naïve Bayes classifier-FFNN system—an efficient and cheap algorithm that has so far proven useful in the real-time detection of forest fires.

Even though context-specific benefits validate the choice of DBN, R-LSTM, PNN, ANN, ANFIS, or GA, certain operational constraints are ubiquitous. For example, the theoretical assumption might not be valid in real life. Additionally, the agent might not be cognizant of the transition statistics and state space and is required to initiate action using information drawn from sensor nodes [92]. Such memoryless and reactive policy challenges are often bound to occur if the actual environment is underexplored or sophisticated and there is a limited conception of the memory dynamics.

The future prospects of AI and related technologies provide a clear justification for farmers/agricultural companies to invest in advanced technologies for fire safety, despite the prevailing disregard for noncore activities. This is because smart message service, 5G networks, UAVS, IoT-SG, and decentralized energy systems in microgrids could catalyze the Agriculture 4.0 revolution and support smart cities, which are integral to agricultural efficiency. This multidimensional view is valid considering the impact of the recent pandemic on agricultural supply chains and production. Based on available evidence, AI systems can be effectively employed when human and animal life risk is at high risk and for indoor livestock confinement. This is because it might not be economical to install AI systems across multiple agricultural structures.

### Limitations

Current research and literature concerning AI networks, including the application of genetic algorithms (GAs), adaptive neurofuzzy inference systems (ANFISs), artificial neural networks (ANNs) [34], probabilistic neural networks (PNNs), recurrent LSTM neural networks (R-LSTM-NNs), and deep belief networks (DBNs) in agricultural fire safety are not well developed. In general, there are limited real-life applications of AI systems in commercial farms for fire safety. Despite the paucity of data, AI is critical to farm sustainability, which, in turn, influences production efficiency [97]. Efficiency is critical, especially in a global pandemic, which has disrupted global economies, supply chains, and human resources [98–102]. However, further research is necessary to determine the usefulness of AI systems in improving agricultural efficiency and resolving other emergencies and crises, apart from fire hazards.

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