Applications of artificial intelligence in indoor fire prevention and fighting

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ABSTRACT

In this study, we design and analysis of artificial intelligence (AI) in indoor fire prevention and fighting. The application of image recognition processing technology has progressed from the early stages using color recognition and feature extraction methods, a newer approach is optical flow using image sequence data to identify motion regions. Image recognition processing technology, a subset of computer vision and AI, has numerous applications across different industries. It allows machines to interpret and make decisions based on visual data, such as photos, videos, or live camera feeds. Recently, AI has many applications in the field of indoor fire prevention and firefighting, leveraging real-time data analysis, predictive modeling, and automation to enhance safety and efficiency. With the application of a neural network, the simulated flame features in the laboratory are used as the input; The image containing the flame from the animation and the features of the image are fed into the artificial neural network obtained from the image from the charge-coupled device camera.

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1. INTRODUCTION

Artificial intelligence, sometimes called AI, is intelligence demonstrated by machines, as opposed to natural human intelligence. Usually, the term AI is often used to describe computers capable of capturing the "cognitive" functions that humans normally associate with the mind, such as "learning" and "problem solving". As machines become increasingly capable, tasks deemed necessary for "intelligence" are often dropped from the definition of AI, a phenomenon known as the AI effect. A maxim in Tesler's Theorem states that "AI is anything that has not been done". For example, optical character recognition, often excluded from what is considered AI, has become a conventional technology. Modern machine capabilities commonly classified as AI include successfully understanding human speech, competing at the highest level in a strategy game (such as chess), autonomous vehicles, routing information intelligence in content delivery networks, and military simulations [1]–[6].

The internet of things (IoT) offers several applications in indoor fire prevention and firefighting, enhancing the safety, speed, and effectiveness of responses to fire incidents, IoT systems significantly improve indoor fire prevention and firefighting by providing real-time data, automating responses, and enabling remote control and analysis. These technologies create safer buildings, faster response times, and

better protection for people and property [7]–[11]. Combining IoT systems with AI greatly enhances their capabilities, providing more intelligent, adaptive, and efficient solutions for a wide range of applications, including fire prevention and firefighting. AI enables IoT systems to analyze data, recognize patterns, and make decisions autonomously, which can transform how indoor fire safety is managed.

AI can be classified into three different types of systems: analytic, human-inspired and AI. Analytical AI has only characteristics that match cognitive intelligence; create a cognitive representation of the world and use learning based on past experiences to inform future decisions. Human-inspired AI has elements from cognitive and emotional intelligence; understand human emotions, beyond cognitive factors, and consider them in decision making. Personified AI shows characteristics of all kinds of competencies, capable of self-awareness and self-awareness in interactions [12]–[17].

Although scientists need to incorporate large amounts of data into AI machines for authentic and accurate results, the main purpose of designing AI machines for firefighting is to predict fire outbreaks using how to apply all calculations on available data. AI powered software is being deployed by scientists in the space and ground to accurately map wildfire hazards to the surroundings when wildfires break out. Even so, the technology is in its early stages and it takes time to understand the complexity of the fire [18]–[22]. Furthermore, it has been analyzed that machine learning methods such as spectral clustering and manifold learning are being used to distinguish smoke types helping managers gain important information to reduce indoor fire caused by fires. Recently, a development plan for intelligent fire extinguishing systems has been launched to prevent fire spread, protection and services occurring in an emergency situation [23]–[27].

In this study, we theoretically analyze the applications of AI in indoor fire prevention and fighting, the study is organized as follows. AI in fire protection is present in section 2. Section 3 presents the system analysis and design. The numerical results and discussions are presents in section 4. The study is included in section 5.

2. ARTIFICIAL INTELLIGENCE IN FIRE PROTECTION

2.1. Convolutional neural network

The convolutional neural networks (CNN) are show in Figure 1, CNN are a class of deep learning models primarily used for image processing, computer vision, and pattern recognition tasks. They are inspired by the visual cortex of the human brain and are particularly effective in handling spatial data [2]. CNNs are revolutionizing industries by providing efficient visual recognition capabilities. From healthcare to self-driving cars, their impact is vast and continuously growing. It is a neural network architecture that is well suited for problems where the data is images or video.

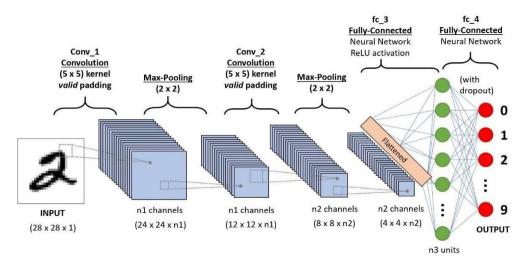


Figure 1. Convolutional neural network

The convolution layer is the core building block of a CNN. It is responsible for detecting features such as edges, textures, shapes, and patterns in images. A convolution operation is performed by sliding a small filter (kernel) over an input image or feature map. At each position, the dot product of the filter and the corresponding region of the input is computed and summed to produce a single output value. In this layer there are 4 main objects: input matrix, receptive field, filters, and feature map, that is shown in Figure 2.

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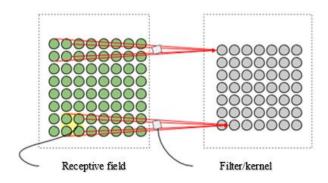


Figure 2. Feature map

Filters help extract specific features from images, the receptive field determines how much context a neuron captures. Deep networks with larger receptive fields improve object detection and classification. Input matrix; the image or feature map being processed, filter (kernel); a small matrix used to extract features, receptive field; the local region of the input that the filter interacts with, feature map; the output matrix containing extracted features.

3. SYSTEM ANALYSIS AND DESIGN

3.1. System design

The built system consists of two main parts: hardware device pairing and system deployment software. First about the hardware system, the hardware is divided into two main parts, the first is the sensors that collect information about the environment and the second is the server that handles tasks such as detecting fire, giving warnings, and notification. The connection model of the system is shown in Figure 3.

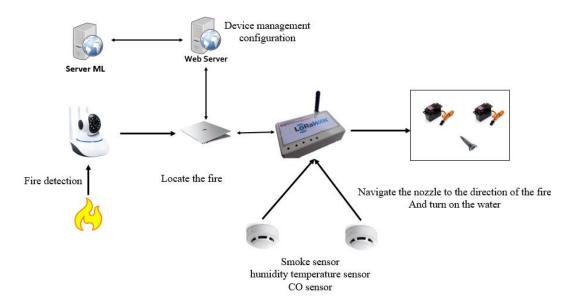


Figure 3. Overview model

Data is collected through sensor nodes sent to the gateway by lora waves, the data is aggregated and sent to the web server. Here the data is processed to give the probability of a fire occurring. The sensor nodes are equipped with temperature and humidity sensors, along with the ATmega328 central microcontroller running on the Arduino Bootloader platform. Here data is collected and sent to the gateway by lora waves. GatewayLora is a place to aggregate data from sensor nodes. Send to server with http protocol. Raw data collected from sensors is stored in the cloud, where the data will be labeled for AI calculations. Relevant function and scenario information in our analysis is provided in Table 1.

Table 1. System operation scenario							
Function	ction Scenario Information						
Fire forecasting function	The function works based on the temperature changes of the environment: humidity, and temperature to give prediction results.						
Message sending function	When there is a prediction result, if the prediction result is >60%, the system will send a message to the processing center and the accounts have been set up before there is a sign of fire.						
Alarm function	When a fire occurs within the operating range of the device, the system will send an alarm signal to the processing center and to sound an alarm with a horn or speaker.						
Fire fighting function	When the alarm is within 30 seconds without any human command, the system will automatically extinguish the fire with the nozzle.						

Figure 4 shows an overview of the operating process of the system. The fire alarm rating server software includes the following main modules. Video analysis: the module is responsible for extracting events from video streams sent to the processing center. This is an important process flow of the system because it has to deal with a large amount of information, with high reliability. Proper semantic analysis will reduce false alarms. Environmental sensor: the module has the role of storing and displaying information from traditional fire alarm sensor nodes. This flow of information not only helps us to decide on fire warnings, but also helps in forecasting areas of high fire risk.

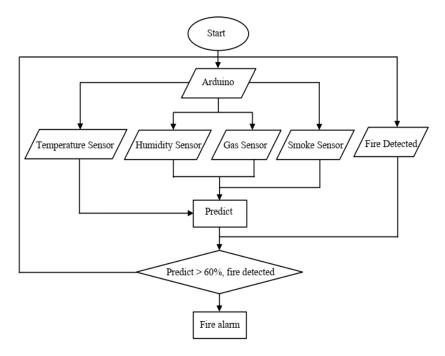


Figure 4. Flowchart of building the fire identification system

Analysis and decision: this is where the analysis evaluates the warning information for the whole building. From anomalies on sensor nodes and cameras in the building, combined with the experience of machine learning algorithms to give appropriate warning levels. Warning system: the task of the warning system is that after receiving the results of environmental analysis from the collected data, it will issue an alarm depending on the results received. The alert system can send messages to zalo accounts in the installed list.

3.2. Training model

After training the dataset, we proceed to use the cross-validation technique to estimate the accuracy or error of the algorithm, the purpose of the technique is to divide the initial data set into the training data used to train the model and an independent dataset is used for evaluation. The most common method is K-fold, where the initial data set is divided into equally sized subsets, called "folds". The K value is the number of data sets to be split.

This method is repeated many times until there are K number of different models, one of the k sets is used as the test set and the other sets are reassembled into the training set. The estimate of accuracy or

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error is averaged over k-tests to evaluate the effectiveness of the model. The training model on Tensorflow is shown in Figure 5.

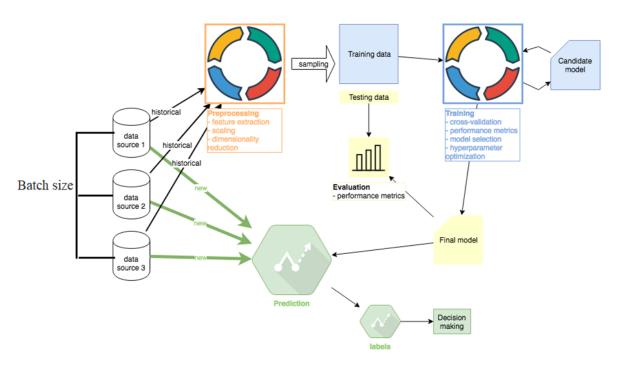


Figure 5. Training model on Tensorflow

The training flowchart of the you only look once (YOLO)-based fire recognition model is shown in the Figure 6. First, we convert the dataset labels into a usable label file for YOLO. YOLO requires a .txt file for each. Furthermore, YOLO requires several files to start training. The value of the filters in the YOLO configuration file (.cfg file) for the second final layer is not arbitrary and depends on the total number of layers. The number of filters can be provided by: filters =5*(2+ number_of_classes).

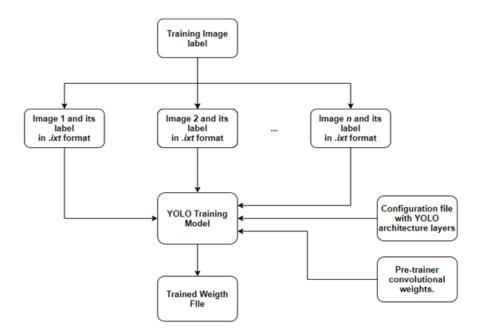


Figure 6. Flowchart of training model algorithm

4. RESULTS AND DISCUSSION

Based on the indicators of the confusion matrix for the classification model to be evaluated and adjusted effectively. First, increase the rate of true positive (TP), true negative (TN), and decrease false positive (FP), false negative (FN) to increase accuracy rate and reduce error rate [14]. The confusion matrix indicator is shown in Figure 7.

Accuracy=
$$\frac{TP+TN}{TP+TN+FP+FN}$$

Precision= $\frac{TP}{TP+FP}$
Recall= $\frac{TP}{TP+FN}$

Where: TP: number of correct predictions, TN: indirectly correctly predicted salary, FP (type 1 error): number of false predictions, and FN (type 2 error): number of indirectly false predictions.

TP	TN	
		Correctly Classified
FP	FN	Misclassified
Classified positive	Classified negative	

Figure 7. Confusion matrix indicator

Figure 8, we can see here that precision returns a fairly high result >0.9 and recall is also relatively >0.9, we can see that the model here will not fall into two cases: high recall low precision or low precision recall. High, but at high precision threshold and high recall return relative results but return results accuracy relative to labeling is high. It shows that precision returns a fairly high result, greater than 0.9 and recall is also relatively, greater than 0.9, we can see that the model here will not fall into two cases: high recall low precision or low precision recall. high, but at high precision threshold and high recall return relative results but return results accuracy relative to labeling is high.

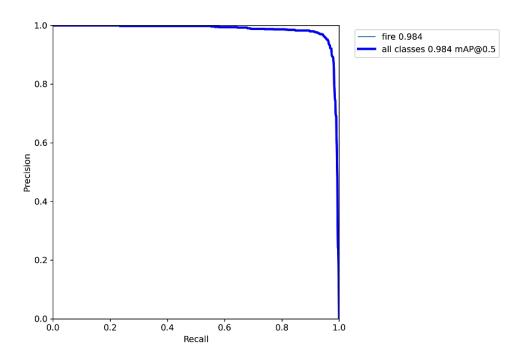


Figure 8. Precision recall curve model

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5. CONCLUSION

In this study, we have described the fire identification and early warning system through smoke and fire detection using machine learning technology. The system was built from actual needs, taking advantage of common hardware systems such as surveillance cameras, temperature and humidity sensors. Machine learning technology is applied to increase the ability and accuracy of the system. Up-to-date technologies and techniques of machine learning in the problem of image recognition and classification have been tested and evaluated. For further research, combining AI expertise with fire safety engineering, robotics, and material sciences. Real-world testing & deployment, implementing AI systems in real indoor environments to validate their effectiveness.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Duong Huu Ai	\checkmark	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
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Khanh Ty Luong	\checkmark						✓			\checkmark	✓	\checkmark		
Viet Truong Le		\checkmark	✓	\checkmark		✓	✓			✓	✓			

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The following sources contain the data that support the findings of this study:

- Relevant data are openly accessible in [MDPI] at doi: 10.3390/app11167716, reference [5].
- Supporting datasets can be found in [IEEE] at doi: 10.1109/NMITCON58196.2023.10276198, reference [12].
- Additional data related to this study are openly available in [IEEE] at doi: 10.1109/TPAMI.2016.2577031, reference number [17].

REFERENCES

- L. Tan, T. Huangfu, L. Wu, and W. Chen, "Comparison of RetinaNet, SSD, and YOLO v3 for real-time pill identification," BMC Medical Informatics and Decision Making, vol. 21, no. 1, 2021, doi: 10.1186/s12911-021-01691-8.
- [2] S. Shinde, A. Kothari, and V. Gupta, "YOLO based human action recognition and localization," *Procedia Computer Science*, vol. 133, pp. 831–838, 2018, doi: 10.1016/j.procs.2018.07.112.
- [3] A. G. Howard et al., "Mobilenets: efficient convolutional neural networks for mobile vision applications," arXiv-Computer Science, pp. 1-9, 2017.
- [4] S. O. Abioye *et al.*, "Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges," *Journal of Building Engineering*, vol. 44, 2021, doi: 10.1016/j.jobe.2021.103299.
- [5] C. Maraveas, D. Loukatos, T. Bartzanas, and K. G. Arvanitis, "Applications of artificial intelligence in fire safety of agricultural structures," *Applied Sciences*, vol. 11, no. 16, 2021, doi: 10.3390/app11167716.
- [6] M. C. Ode, "A brief history of fire alarm equipment: the invention of smoke detectors, heat detectors and related equipment," Electrical Contractor Magazine, 2023. [Online]. Available: https://www.ecmag.com/magazine/articles/article-detail/a-brief-history-of-fire-alarm-equipment-the-invention-of-smoke-detectors-heat-detectors-and-related-equipment

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- [8] D. H. Ai, H. D. Trung, and D. T. Tuan, "On the ASER performance of amplify-and-forward relaying MIMO/FSO systems using SC-QAM signals over log-normal and gamma-gamma atmospheric turbulence channels and pointing error impairments," *Journal of Information and Telecommunication*, vol. 4, no. 3, pp. 267–281, Jul. 2020, doi: 10.1080/24751839.2020.1732734.
- [9] N. Kumar, K. Kumar, and A. Kumar, "Application of internet of things in image processing," 2022 IEEE Delhi Section Conference, DELCON 2022, 2022, doi: 10.1109/DELCON54057.2022.9753308.
- [10] D. H. Ai, D. T. Dang, Q. H. Dang, and T. Le Kim, "Analysis on the performance of pointing error effects for RIS-aided FSO link over gamma-gamma channels," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 21, no. 4, pp. 718–724, 2023, doi: 10.12928/TELKOMNIKA.v21i4.24537.
- [11] D. H. Ai, V. L. Nguyen, H. H. Duc, and K. T. Luong, "On the performance of reconfigurable intelligent surface-assisted UAV-to-ground communication systems," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 21, no. 4, pp. 736–741, 2023, doi: 10.12928/TELKOMNIKA.v21i4.24720.
- [12] H. Prasad, A. Singh, J. Thakur, C. Choudhary, and N. Vyas, "Artificial intelligence-based fire and smoke detection and security control system," in 2023 International Conference on Network, Multimedia and Information Technology (NMITCON), Sep. 2023, pp. 01–06, doi: 10.1109/NMITCON58196.2023.10276198.
- [13] R. Hassan, A. Tamim, and J. Singh, "Fire resilience and sustainability in buildings: initiatives and future directions," *International Fire Protection Magazine*, vol. 96, no. 38, 2023. [Online]. Available: https://ifpmag.com/fire-resilience-and-sustainability-in-buildings-initiatives-and-future-directions/
- [14] M. H. Mozaffari, Y. Li, and Y. Ko, "Generative AI for fire safety," in Applications of Generative AI, Cham, Switzerland: Springer, 2024, pp. 577–600, doi: 10.1007/978-3-031-46238-2_29.
- [15] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," *Neurocomputing*, vol. 288, pp. 30–42, 2018, doi: 10.1016/j.neucom.2017.04.083.
- [16] Y. Ko, M. H. Mozaffari, and Y. Li, "Fire and smoke image recognition," Intelligent Building Fire Safety and Smart Firefighting, Cham, Switzerland: Springer, 2024, doi: 10.1007/978-3-031-48161-1_13.
- [17] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017, doi: 10.1109/TPAMI.2016.2577031.
- [18] M. S. Mahmud, M. S. Islam, and M. A. Rahman, "Smart fire detection system with early notifications using machine learning," International Journal of Computational Intelligence and Applications, vol. 16, no. 2, pp. 1-17, 2017, doi: 10.1142/S1469026817500092.
- [19] D. Gragnaniello, A. Greco, C. Sansone, and B. Vento, "Fire and smoke detection from videos: a literature review under a novel taxonomy," *Expert Systems with Applications*, vol. 255, 2024, doi: 10.1016/j.eswa.2024.124783.
- [20] Z. Q. Zhao, P. Zheng, S. T. Xu, and X. Wu, "Object detection with deep learning: a review," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 11, pp. 3212–3232, 2019, doi: 10.1109/TNNLS.2018.2876865.
- [21] X. Shi et al., "VideoFlow: exploiting temporal cues for multi-frame optical flow estimation," in 2023 IEEE/CVF International Conference on Computer Vision (ICCV), Paris, France, 2023, pp. 12435-12446, doi: 10.1109/ICCV51070.2023.01146.
- [22] N. Raveendran, "Future of smart firefighting with artificial intelligence," Research Gate, pp. 1-4, 2020, doi: 10.13140/RG.2.2.18551.44963.
- [23] J. Hu, L. Xie, X. Gu, W. Xu, M. Chang, and B. Xu, "Information-interaction feature pyramid networks for object detection," 2022 IEEE 34th International Conference on Tools with Artificial Intelligence (ICTAI), Macao, China, 2022, pp. 1301-1306, doi: 10.1109/ICTAI56018.2022.00197.
- [24] N. Poornima, G. S. Gunasagari, A. S. Bangar, P. S. S. Prasad, P. Pai, and T. Mehta, "Patronus: fire detection and extinguisher system using image processing," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 1300-1306, doi: 10.1109/ICICCS56967.2023.10142665.
- [25] S. Kaur, A. L. Yadav, and A. Joshi, "Real time object detection," 2022 International Conference on Cyber Resilience (ICCR), Dubai, United Arab Emirates, 2022, doi: 10.1109/ICCR56254.2022.9995738.
- [26] A. Q. Nguyen, H. T. Nguyen, V. C. Tran, H. X. Pham, and J. Pestana, "A visual real-time fire detection using single shot multibox detector for UAV-based fire surveillance," in 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE), Phu Quoc Island, Vietnam, 2021, pp. 338-343, doi: 10.1109/ICCE48956.2021.9352080.
- [27] S. S. Saini and P. Rawat, "Deep residual network for image recognition," 2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballari, India, 2022, pp. 1-4, doi: 10.1109/ICDCECE53908.2022.9792645.

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