International Journal of Computational Science and Information Technology (IJCSITY) Vol. 12, No. 1/2/3/4, November 2024

REVOLUTIONIZING FIREFIGHTING TRAINING WITH DIGITAL TWINS: REAL-TIME FIRE SPREAD SIMULATION AND ESCAPE ROUTE OPTIMIZATION

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ABSTRACT

The advancement of digital twin (DT) systems had revolutionized various industrial and safety applications, offering virtual replicas of physical processes for improved monitoring and training. Fire scenarios are highly dynamic, with conditions changing rapidly due to factors like wind direction, material flammability, and structural integrity. This study explored the application of a smart fire scene DT system (SFSDTS) for firefighting training and safety management. The novelty and contributions of this study was the proposed SFSDTS integrated machine learning models to predict fire spreading paths and estimate escape routes in real-time, providing an immersive and interactive training environment for firefighters. Various ML models, including random forest (RF), XGBoost, decision tree (DR), logistic regression (LR), and K-nearest neighbors (KNN), were utilized for predicting fire spreading. The performance of these models was evaluated using metrics such as accuracy, precision, recall, and F1 score, with XGBoost and RF models demonstrating superior performance. The proposed SFSDTS also employed the A algorithm for optimized escape route estimation based on dynamic fire conditions. User experience was assessed through a standardized questionnaire, user experience questionnaire (UEQ), revealing positive ratings for the proposed SFSDTS's efficiency, stimulation, and perspicuity. Compared to commercial products, the proposed SFSDTS offered improved accessibility and real-time simulation functionalities. The study highlighted the potential of proposed SFSDTS in transforming firefighting training and safety management.*

KEYWORDS

Digital Twin, Firefighting, Machine Learning, Training Simulation

1. INTRODUCTION

With the advancement of computational simulations integrated with real-world scenarios, the concept of digital twin (DT) systems became a significant research topic, providing virtual replicas for physical processes. A DT served as a virtual duplicate of a physical object, continually simulating real-world conditions. It was frequently employed for monitoring, design, optimization, maintenance, and remote access in industrial production [1]. While initial research on the integration of Industry 4.0 and DT technologies concentrated on the connection of manufacturing machines and systems [2], DTs were also applied to enhance the safety management of workers in various fields [3]. This was particularly crucial in hazardous environments such as chemical plants, manufacturing industries, and fire scenes. In firefighting, which involved different environmental factors and harsh conditions, the DT concept was further

DOI : 10.5121/ijcsity.2024.12401

expanded, which included interconnected networks of complex environmental situations and human conditions [5].

The application of DT technology held significance in the digital transformation of firefighting. DT technology provided firefighters with an immersive and interactive training environment, eliminating the risks associated with traditional real fire training exercises [5]. By simulating realistic building and fire scenarios, DTs were used to train firefighters, helping them familiarize themselves with various fire scenarios and learn optimal response strategies and operational techniques [6]. Diverse fire scenarios could be simulated, and conditions of the fire scenes could be remodeled in different ways to challenge trainees and enhance their problem-solving skills. The advantages of DTs in fire training included three key aspects [7]. Firstly, they provided a safe platform for trainees to experience and respond to high-risk scenarios without the dangers of burns, smoke inhalation, and structural collapse. Additionally, the training could be personalized, allowing instructors to tailor scenarios to address specific learning objectives and trainees' weaknesses. Furthermore, the integration of real-time scene data and analytics allowed for immediate feedback, enabling trainees to review their actions and learn the best strategies to respond to similar situations in actual fire scenarios.

In terms of building safety and security, DTs played a crucial role in advanced obstacles detection, precise localization, fire condition analysis, and real-time fire spreading modeling [8]. Additionally, DT facilitated safety management through building information modeling and machine learning algorithms. These technologies enabled real-time data collection and analysis of dynamic safety information and building data, thereby enhancing firefighter safety during emergencies [9]. Historical fire scene data could also be integrated into the DT, allowing it to utilize artificial intelligence (AI) models to analyze this data in real-time which enabled instant predictions and improved firefighter training [10].

The existing fire scenario simulation and prediction models required significant computational time, ranging from days to weeks, to simulate fire scenarios [11]. Various methods had been proposed by existing studies to overcome this limitation through the use of AI models [12]. For instance, Verlekar et al. [13] utilized a Convolutional Long Short-Term Memory neural network (Conv-LSTM) to link spatio-temporal temperature distributions with the number, size, and location of fire sources. Similarly, Wang et al. [14] demonstrated the effectiveness of using Conv-LSTM in a DT during a full-scale fire test chamber experiment. Additionally, Lei et al. [15] improved the fire prediction effectiveness at the China Palace Museum by utilizing the XGBoost model to categorize buildings into different risk levels based on the information of building materials and environmental factors (temperature, humidity, etc.). Zhang et al. [17] proposed a Transformer network to predict fires in tunnels, which also provided a 3D visual representation of the fire scene, aiding in firefighting operations, evacuation, and training exercises.

On the other hand, numerical fire modeling was implemented through a computational fluid dynamics approach [11]. Crucial steps included mesh generation, capturing combustion physics, turbulence modeling, and heat transmission between solid obstacles. The model addressed ignition, fuel combustion, and conservation of mass, focusing on accurate fire dynamics simulation. To ensure accuracy, the model was validated against experimental data and continuously modified to improve predictive capability. However, numerical modeling required a long duration to simulate sample scenes and lacked real-time fire predictions in firefighting practice. SmokeView [17] served as the visualization companion for the fire dynamics simulator (FDS), displaying simulation results where the virtual smoke, fire, and heat spread were presented in a 3D visual representation, enabling researchers and firefighters to visually analyze and interpret the data generated by FDS.

Meanwhile, fire prediction models utilizing datasets from sensors have gained increasing significance since the 2010s. For instance, Han et al. [18] proposed the FireGrid system, which quickly and accurately forecasted fire spread using real-time sensor data. Optimization methods were employed to enhance FireGrid's computational efficiency, enabling better adaptation to changing fire scenarios. Additionally, various optimization strategies, such as inverse computational fluid dynamics predictions and regional modeling approaches, were utilized to decrease the computational response time to sudden changes in fire scenes and simplify fire models [19].

One of the research gaps in the field of firefighting DT technology was the lack of creation of interior layout information [20]. This project aimed to design a customizable scenario that considered various building layouts, fire intensity, obstacles in different locations, and different building floors. Designing and implementing such scenario allowed firefighters to gain training and experience in different fire scenarios. The contributions of this study included designing and implementing a machine learning (ML)-based fire and smoke prediction model that were customizable in real-time to simulate dynamic fire changes in a DT model. Additionally, the study proposed an AI-based fire escape route recommended model, predicting escape routes based on current fire and smoke conditions.

2. METHODS

2.1. System Overview

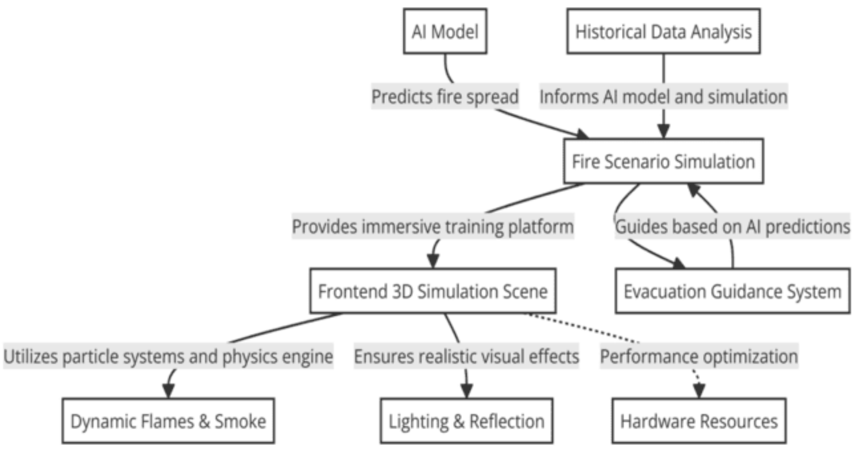


Figure 1. Overview design of the proposed SFSDTS

Figure 1 depicted the overview design of the proposed a smart fire scene DT system (SFSDTS) which consisted of several elements. For demonstration purpose, the SFSDTS started in a building without fire. The fire was started after 5 minutes. Then, the spreading of fire was initially simulated through a machine learning (ML) model, analyzed based on the environmental condition. Then, the evacuation guidance module is triggered, utilizing different AI model to provide an estimated escape route. The estimated escape route was constantly updated, depending on the fire spreading condition. Here, three data values, including temperate, wind level, and fire spread index (see Figure 2), can be adjusted manually in real-time by the users to simulate unexpected events, e.g., rising of temperature in short period due to explosion. Lastly, the realistic 3D fire scene was visualized with the predicted escape route, along with virtual flames and smokes. Similarly, the scene was updated dynamically.

The fire scene had been modeled on a three-floor building in an urban area, as illustrated in Figure 3a. The interior layouts of each floor were depicted in Figures 3b and 3c. Note that the modeled building had no elevators, but with staircases connected each floor, situated on both the left and right sides, as shown in Figure 3d. To simulate realistic fire scenes, fire and smoke particle effects were employed. Three distinct fire effects, representing large, medium, and small fire intensities, were designed, as depicted in Figure 4. These variations in fire effects enabled users to identify and assess the current risks associated with the fire situations.

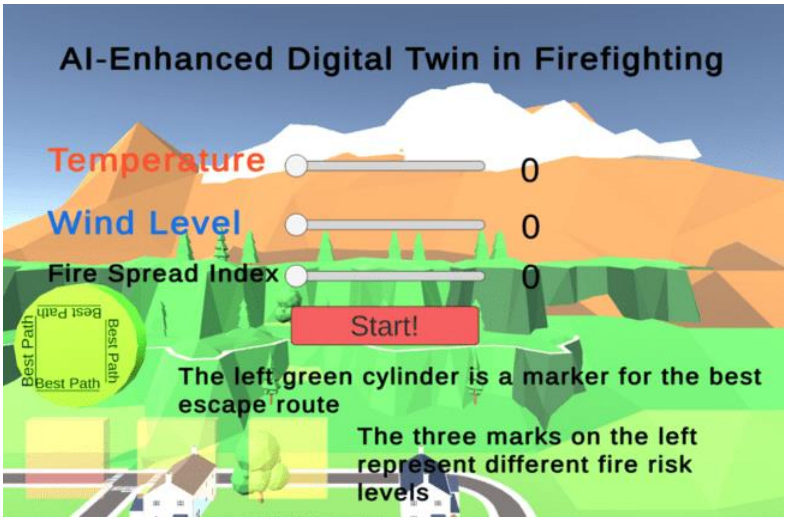
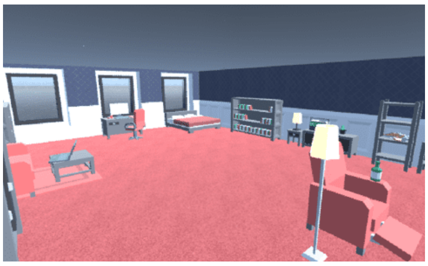
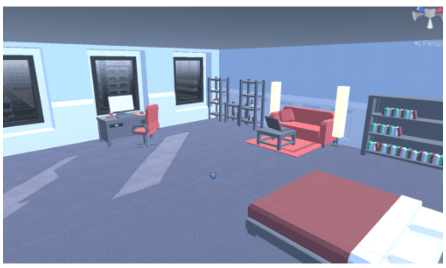
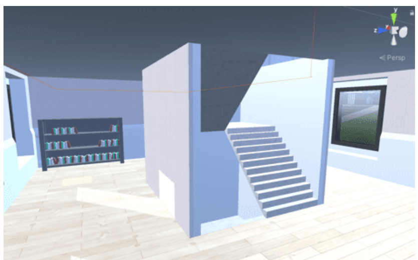


Figure 2. Illustration of a user interface that allows users to manually adjust the data for stimulating changes in environment, including temperature, wind level and fire spread index

(a) (b)

(c) (d)

Figure 3. Views of the modeled building from the (a) outside, (b) first floor, (c) second floor, and (d) staircase

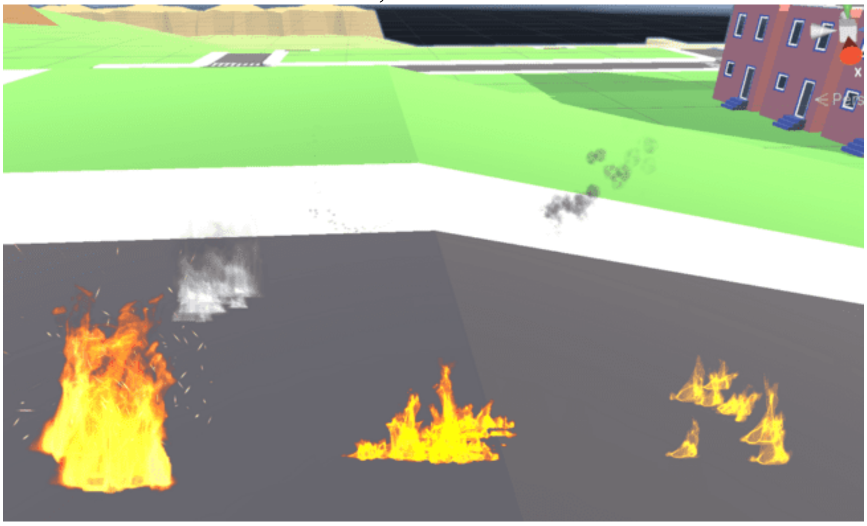


Figure 4. Three different types of fire effects, ranging from large to small fire intensities

2.2. Fire Spreading Prediction And Escape Route Estimation Models

This study adopted ML models to predict fire spreading paths and estimate escape routes. Initially, the paths were modeled in grid-based regions, represented as rectangles, as illustrated in Figure 5a. Each region displayed three different fire risk levels: yellow for low or no risk, orange for medium risk, and red for high risk. These risks were simulated using the associated fire effect types and smoke particles (see Figure 4). Various ML models, including random forest (RF), XGBoost, decision tree (DR), logistic regression (LR), and K-nearest neighbors (KNN), predicted the occurrence of fire in a specific region, $r(x, y)$. This prediction was based on data from neighboring regions, if present, such as top-left ($r(x\text{-}1, y\text{-}1)$), top-middle ($r(x, y\text{-}1)$), top-right ($r(x+1, y\text{-}1)$), center-left ($r(x\text{-}1, y)$), center-right ($r(x+1, y)$), bottom-left ($r(x\text{-}1, y+1)$), bottom-middle ($r(x, y+1)$) and bottom-right ($r(x+1, y+1)$) regions.

This study utilized the Algerian forest fires dataset [21] to train the ML models for fire spreading prediction. This dataset contained 11 attributes and 244 instances, with 138 instances labeled as fire and 106 as non-fire. Key attributes used for model training included temperature (°C), relative humidity (%), wind speed (km/h), rain (mm), Fine Fuel Moisture Code (FFMC), and Duff Moisture Code (DMC).

For escape route estimation, the study employed the A* algorithm [22] to compute optimized escape routes (pathfinding) based on the predicted fire spreading index. The escape routes were modeled as continuous green 3D circles, as shown in Figure 5b. Referring to Figure 5b, it is important to note that the user was in a room with only one exit route (upper left), which the green circles were displayed despite two regions along the route having high fire risk levels.

To assess the feasibility and usability of the proposed SFSDTS, participants were recruited to interact with the system. Prior to the experiment, participants were introduced to the SFSDTS and briefed on their role and the study's purpose. Consent forms were signed by those who agreed to participate. After the experiment, participants completed a questionnaire to evaluate their experiences with the SFSDTS. The study received approval from the university's research ethics committee, following the ethical review process outlined in the university's code of research conduct and ethics.

(a) (b)

Figure 5. Illustration of the modeling for fire spreading, including the (a) paths divided into grid-based regions and (b) color indicators showing different risk levels for each region

The SFSDTS's fire scene 3D modeling was implemented using the Unity3D tool (version 2021.2.7f1). Flask (version 2.0.1) was utilized as the server to connect the front-end (viewer) and back-end (fire spreading prediction and escape route estimation models), implemented in Python (version 3.8) programming language.

2.3. Questionnaire

A user experience questionnaire (UEQ) [23] was utilized as a standardized framework to assess the UX of participants interacting with the proposed SFSDTS. The UEQ comprised three main aspects: valence (VL), pragmatic quality (PQ), and hedonic quality (HQ) [24]. Specifically, VL included attractiveness (AT); PQ included efficiency (EF), perspicuity (PP), and dependability (DP); while HQ included stimulation (ST) and novelty (NV). Thus, the UEQ evaluated a total of six scales. These scales measured overall impressions, ease of use, efficiency of the models, control over interaction, innovation and creativity. Table 1 provided descriptions of each scale associated with the respective aspect.

Table 1. Descriptions of each scale associated with the respective aspect in the UEQ.

Aspect	Scale	Description	Total Items
VT	AT	Overall impression of the game. Do participant like or dislike the proposed SFSDTS?	6
PQ	PP	Is it easy to get familiar with the game? Is it easy to learn how to use the proposed SFSDTS?	4
	EF	Can participants understand the shown escape route without unnecessary effort?	4
	DP	Does the participant feel in control of the interaction?	4
HQ	ST	Is it exciting and motivating to use the proposed SFSDTS?	4
	NV	Is the proposed SFSDTS innovative and creative? Does the proposed SFSDTS capture the interest of participants?	4

3. Results and Discussion

The performance of the fire spreading prediction models was assessed using five different evaluation metrics: accuracy (*AC*, see Equation (1)), precision (*PR*, see Equation (2)), recall (*RC*, see Equation (3)), and *F1* score (see Equation (4)). The respective equations for the evaluation metrics were as follows:

$$AC = (TP + TN) / (TP + TN + FP + FN) \tag{1}$$
$$PR = TP / (TP + FP) \tag{2}$$
$$RC = TP / (TP + FN) \tag{3}$$
$$F1 = (2 \times PR \times RC) / (PR + RC) \tag{4}$$

where *TP*, *TN*, *FP*, *FN* referred to true positive, true negative, false positive and false negative, respectively.

Table 2 summarized the performance of each ML model in predicting fire spreading. The results showed that the XGBoost model ($\mu = 0.972$) performed the best across all metrics. The RF model ($\mu = 0.97$) demonstrated similar performance to XGBoost. In contrast, the LR model ($\mu = 0.92$) had the lowest performance, likely due to its limited capability in predicting fire spreading involving both discrete and continuous data types. The KNN model ($\mu = 0.93$) indicated that unsupervised learning was less effective in distinguishing between fire and non-fire classes based on both data types.

Table 2. Performances metrics of ML models for fire spreading prediction.

Model	***AC***	***PR***	***RC***	***F1***	**Mean, μ**
LR	0.92	0.91	0.93	0.92	0.920
DR	0.95	0.95	0.95	0.95	0.950
RF	0.97	0.97	0.98	0.96	0.970
KNN	0.93	0.93	0.93	0.93	0.930
XGBoost	0.97	0.97	0.98	0.97	0.972

Figure 6 displayed the UEQ results with mean scores for six scales. The rating scale ranged from -3 to +3 and was normalized to a range from 0 to 6. A mean value below 3 indicated a negative attitude, above 3 indicated a positive attitude, and 3 indicated neutrality. Overall, the mean values for all scales were above 3, suggesting that the proposed SFSDTS received positive ratings from participants. The top three scales, with the highest mean values, were perspicuity, stimulation, and efficiency, all rated above 5.3. Attractiveness and dependability also performed well, with mean ratings above 5. Novelty received the lowest rating, below 5 but still above 3. Some participants noted that the virtual scenes were less enjoyable, less realistic, and had a lower level of immersion, but generally were satisfied with the SFSDTS.

The proposed SFSDTS differed from commercial products in several aspects. For example, the FDS [25] was a computational fluid dynamics model of fire-driven fluid flow used to address fire protection engineering problems and study fundamental fire dynamics and combustion. However, the FDS was complex and required a significant amount of time to simulate a scenario due to numerous parameters, limiting its effectiveness in real-time fire rescue missions. Similarly, Autodesk Revit [26] developed a design analysis tool for fire and smoke simulation in buildings, requiring users to specify building construction materials and initial fire types for accurate predictions. These building information modeling (BIM) software required substantial user training, and their complexity restricted their use to experts, making them less suitable for ordinary users. In contrast, the proposed SFSDTS offered advantages in accessibility and real-time simulation functionalities.

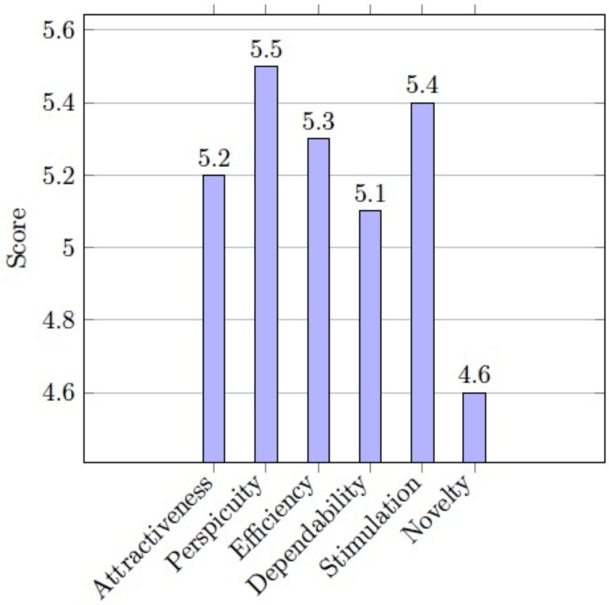


Figure 6. UEQ results displaying the mean scores for six scales, normalized on a 0 to 6 range. The x-axis represents the six GEQ scales, while the y-axis indicates the mean scores derived from participants' GEQ ratings

4. LIMITATION AND FUTURE WORK

The current study concentrated on developing a SFSDTS designed for a single building, along with an initial examination of indoor weather conditions. Future efforts will focus on expanding the system to simulate more complex fire scenarios, including the consideration of escape routes for multiple individuals. This will involve integrating computer vision-based human detection within indoor environments to track individuals and estimate escape routes for those still inside the building.

5. CONCLUSIONS

This study had proposed the design and implementation of SFSDTS which had demonstrated substantial benefits in the field of firefighting training and safety management. By utilizing different ML models, the SFSDTS effectively predicted fire spreading paths and estimated escape routes in real-time. The significant performance of the models highlighted the SFSDTS robustness in handling dynamic fire scenarios. Additionally, the use of the model for escape route optimization further improved the SFSDTS practicality and effectiveness. Compared to existing fire simulation tools, the SFSDTS offers improved accessibility and real-time functionalities, making it an important asset for firefighter training and emergency response planning. Future work could explore further integration of advanced AI techniques and expanded real-world applications to continue improving the proposed SFSDTS capabilities.

ACKNOWLEDGEMENTS

This work was supported by the UNNC Education Foundation through Li Dak Sum Innovation Fellowship under Grant LDS202307.

REFERENCES

[1] M. Singh, E. Fuenmayor, E. P. Hinchy, Y. Qiao, N. Murray and D. Devine, "Digital Twin: Origin to Future," *Applied System Innovation*, vol. 4, no. 2, pp. 36, 2021.

[2] B. R. Barricelli and D. Fogli, "Digital Twins in Human-Computer Interaction: A Systematic Review," *International Journal of Human-computer Interaction*, vol. 40, no. 2, pp. 79–97, 2022.

[3] G. P. Agnusdei, V. Elia and M. G. Gnoni, "Is Digital Twin Technology Supporting Safety Management? A Bibliometric and Systematic Review," *Applied Sciences*, vol. 11, no. 6, pp. 2767, 2021.

[4] X. Wu, X. Zhang, Y. Jiang, X. Huang, G. G. Huang and A. Usmani, "An Intelligent Tunnel Firefighting System and Small-Scale Demonstration," *Tunnelling and Underground Space Technology*, vol. 120, no. 1, pp. 104301, 2022.

[5] T. Kaarlela, S. Pieskä and T. Pitkäaho, "Digital twin and Virtual Reality for Safety Training," *2020 11th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, Mariehamn, Finland, 2020, pp. 115–120.

[6] X. Fang, H. Wang, G. Liu, X. Tian, G. Ding and H. Zhang, "Industry Application of Digital Twin: From Concept to Implementation," *International Journal of Advanced Manufacturing Technology*, vol. 121, no. 7, pp. 4289–4312, 2022.

[7] A. Harichandran, K. W. Johansen, E. L. Jacobsen and J. Teizer, "A Conceptual Framework for Construction Safety Training Using Dynamic Virtual Reality Games and Digital Twins," *Proceedings of the 38th ISARC*, Dubai, UAE, 2021, pp. 621–628.

[8] T. Zohdi, "A Digital Twin Framework for Machine Learning Optimization of Aerial Fire Fighting and Pilot Safety," *Computer Methods in Applied Mechanics and Engineering*, vol. 373, no. 1, pp. 113446, 2021.

[9] L. Jiang, J. Shi, C. Wang and Z. Pan, "Intelligent Control of Building Fire Protection System Using Digital Twins and Semantic Web Technologies," *Automation in Construction*, vol. 147, no. 1, pp. 104728, 2023.

[10] A. Sharma, E. Kosasih, J. Zhang, A. Brintrup and A. Calinescu, "Digital Twins: State of the Art Theory and Practice, Challenges, and Open Research Questions," *Journal of Industrial Information Integration*, vol. 30, no. 1, pp. 100383, 2022.

[11] R. K. Janardhan and S. Hostikka, "Predictive Computational Fluid Dynamics Simulation of Fire Spread on Wood Cribs," *Fire Technology*, vol. 55, no. 1, pp. 2245–2268, 2019.

[12] T. Zhang, Z. Wang, Y. Zeng, X. Wu, X. Huang and F. Xiao, "Building Artificial-Intelligence Digital Fire (AID-Fire) System: A Real-Scale Demonstration," *Journal of Building Engineering*, vol. 62, no. 1, pp. 105363, 2022.

[13] T. T. Verlekar and A. Bernardino, "Video Based Fire Detection Using Xception and Conv-LSTM," *In: Bebis, G., et al. Advances in Visual Computing. ISVC 2020. Lecture Notes in Computer Science*, Springer, Cham, vol. 12510, no. 1, 2022.

[14] Z. Wang, T. Zhang, X. Wu and X. Huang, "Predicting Transient Building Fire based on External Smoke Images and Deep Learning," *Journal of Building Engineering*, vol. 47, no. 1, pp. 103823, 2022.

[15] Y. Lei, Z. Shen, F. Tian, X. Yang, F. Wang, R. Pan, H. Wang, S. Jiao and W. Kou, "Fire Risk Level Prediction of Timber Heritage Buildings based on Entropy and XGBoost," *Journal of Cultural Heritage*, vol. 63, no. 1, pp. 11–22, 2023.

[16] X. Zhang, Y. Jiang, X. Wu, Z. Nan, Y. Jiang, J. Shi, Y. Zhang, X. Huang and G. G. Huang, "AIoT-Enabled Digital Twin System for Smart Tunnel Fire Safety Management," *Developments in the Built Environment*, vol. 18, no. 1, pp. 100381, 2024.

[17] G. P. Forney, *SmokeView (Version 6) A Tool for Visualizing Fire Dynamics Simulation*, Data Volume I: User's Guide, 2013.

[18] L. Han, S. Potter, G. Beckett, G. Pringle, S. Welch, S. Koo et al., "FireGrid: An E-infrastructure for Next-Generation Emergency Response Support," *Journal of Parallel and Distributed Computing*, vol. 70, no. 11, pp. 1128–1141, 2010.

[19] W. Jahn, G. Rein and J. Torero, "Forecasting Fire Dynamics Using Inverse Computational Fluid Dynamics and Tangent Linearisation," *Advances in Engineering Software*, vol. 47, no. 1, pp. 114–126, 2012.

[20] M. Almatared, H. Liu, O. Abudayyeh, O. Hakim and M. Sulaiman, "Digital-Twin-Based Fire Safety Management Framework for Smart Buildings," *Buildings*, vol. 14, no. 1, pp. 4, 2024.
[21] F. Abid and N. Izeboudjen, "Predicting Forest Fire in Algeria Using Data Mining Techniques: Case Study of the Decision Tree Algorithm," *Ezziyyani M. (eds) Advanced Intelligent Systems for Sustainable Development (AI2SD'2019)*, pp. 363–370, 2020.
[22] P. Cheng, S. Li, N. Wu and F. Meng, "Research on Fire Escape Path Planning based on Improved A* Algorithm," *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, 2020.
[23] L. Sun, B. G. Lee and W. Y. Chung, "Enhancing Fire Safety Education Through Immersive Virtual Reality Training with Serious Gaming and Haptic Feedback," *International Journal of Human–Computer Interaction*, pp. 1–16, 2024.
[24] B. G. Lee, H. Tang and F. Fang, "Enhancing Critical Thinking and Engagement through Puzzle Box Integration in Virtual Reality-based Digital Game-Based Learning," *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, pp. 1-8, 2023.
[25] K. McGrattan, R. McDermott, C. Weinschenk and G. Forney, "Fire Dynamics Simulator Users Guide," *Sixth Edition, Special Publication (NIST SP), National Institute of Standards and Technology*, Gaithersburg, MD, 2013.
[26] B. Wang, G. Ren, H. Li, J. Zhang and J. Qin, "Developing a Framework Leveraging Building Information Modelling to Validate Fire Emergency Evacuation," *Buildings*, vol. 14, no. 1, pp. 156, 2024.

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