GAN-enabled framework for fire risk assessment and mitigation of building blueprints

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Abstract. Fire risk posed by residential buildings endangers individuals' lives and safety but also severely impacts economic activities of a society. Consequently, minimising the risk of fire and reduce losses through the development of effective solutions for fire risk assessment and mitigation was, is and will remain crucial. This paper proposes a systematic framework for assessing and mitigating fire risk in buildings that incorporates hybrid of computer vision and artificial intelligence techniques. This framework relies on the automatic blueprint interpretation and can handle both manual and digital blueprints relying on the connectivity analysis of room layout. A well-trained connectivity-constrained generative adversarial network (cc-GAN) has been developed to redesign the original building blueprints to meet fire safety criteria. Overall, our work aims to offer building designers and engineers a practical tool for enhancing the fire safety performance of building layouts.

1. Introduction

Fire risk of residential buildings has been an integral part of the development of human society, and it poses a major threat to lives and properties in both urban and rural regions. In addition to physical devastation, fires have the potential to halt business operations and cause material financial losses. According to the statistics for China in 2010, the average risk of death due to fires in residential buildings is approximately 5.0×10^{-8} deaths per square meter per year, and the average property loss caused by building fires is 1.4×10^{-9} million GBP per square meter per year (Xin & Huang, 2013). By utilizing effective passive fire protection and active fire protection technologies, the fire risk in buildings can be significantly reduced, thereby enhancing safety measures.

Massive efforts have been made to assess and mitigate the fire risk of buildings, such as by how fire risk is formulated in insurance policies (Li, Yu, & Liu, 2018), property insurance marketing (Holland, 2019), fire prevention education and building design management (Xin & Huang, 2013; Lau, Lai, Lee, & Du, 2015; Lamberton, Brigo, & Hoy, 2017). However, previous research for fire risk assessment and mitigation mainly focused on hazard detection and warning notification after the occurrence of fire or explosion. There is little research that looks ahead to integrate mitigation into the fire risk assessment for buildings, based on their blueprints.

Fire risk assessment is a crucial step, which aims to determine the appropriate protective measures that need to be implemented. Such assessments serve as the foundation for identifying potential risks and hazards and developing a feasible plan to mitigate them. According to ISO 31000:2009, fire risk assessment includes three main stages of risk identification, risk analysis and risk evaluation (Purdy, 2010). To perform a thorough fire risk analysis and evaluation, it is crucial to carefully interpret and analyse the information gathered during the fire risk identification stage. This involves processing the extracted information to achieve three objectives: (i) successfully identifying the building layout (Chen, Ye, Milne, Hillier, & Oglesby, 2022), (ii) accurately recognizing and locating key passive protections such as firewalls, partition walls, fire doors, fire rolling shutters, evacuation routes, and building design and construction, and (iii) effectively identifying and locating active protections such as fire alarm systems, smoke extraction systems, sprinkle systems, and fire extinguishers (RIBA, 2021).

The first modern fire risk assessment method was proposed by the Dow Corning Company in the U.S. in the 1970s, in which they applied the fire and explosion index assessment method to conduct a systematic fire risk assessment of fire risk for enterprises (Wang, Li, Feng, & Yang, 2021). Afterward, various similar solutions were subsequently released, namely the SIA 81 by Max Gretener from Switzerland (Fontana, 1984), FRAME by De Smet from Germany (Smet, 2008) and FiRECAM by the National Research Council of Canada (NRC). With the continuous advancement of digital technology, there is an increasing demand for Machine Learning (ML), Artificial Intelligence (AI), Computer Vision (CV), and Optical Character Recognition (OCR) to support fire risk assessment, especially in identifying potential fire risks at the earliest stage of building design. The use of automated and intelligent techniques to interpret building blueprints is an emerging research field with significant applications in architecture and construction, including the identification of building fire risks. In the past, rule-based heuristics and image processing methods were commonly used to detect and classify structural primitives in blueprints. However, modern solutions utilizing machine learning (ML) and artificial intelligence (AI), such as fully connected neural networks and convolutional neural networks (CNN), are now widely employed for vectorization, segmentation, and detection of building blueprints (Paudel, Dhakal, & Bhattarai, 2021). Moreover, the utilization of digital technologies can minimize human effort in ensuring the accuracy of translating building information into digital form (Rica, Moreno-García, Álvarez, & Serratosa, 2020).

The integration of mitigation into fire risk assessment can be thought of as fire risk management. This ameliorates the biggest limitation of current fire protection strategies, which is the lack of a systematic framework to minimise the risk of building fire (Kodur, Kumar, & Rafi, 2020). It is worth noting that fire safety design is playing an increasingly crucial role in mitigating the risk of fires. In 2017, a study explored the potential benefits of incorporating fire safety into the building design process, as it is often viewed as an additional constraint in current design practices rather than a design parameter (Maluk, Woodrow, & Torero, 2017). When assessing fire risk and designing fire safety measures, it is crucial to consider the optimal evacuation distance in order to minimise response time and improve safety for life. While passive and active fire protections are essential in preventing building fires, in emergency situations, rapid evacuation is of utmost importance. Within this, the precise calculation of evacuation routes is one of the most critical operational considerations in mitigating the risk of building fires (Cheng, Chen, Wong, Chen, & Li, 2021). During the fire risk identification stage, a comprehensive blueprint interpretation has made it easier to calculate the layout connectivity and evaluate the fire risk, including counting evacuation distance.

Several studies have demonstrated the potential of using Generative Adversarial Networks (GANs) for interpreting building blueprints. GANs are a type of deep learning method that involves training generative models through game-theoretic principles of minimization and maximization (Luo & Huang, 2019). Huang and Zheng introduced a way of implementing GAN in the field for the recognition and generation of floor plans. They parsed floor plans by segmenting areas with different functions to design by data (Huang & Zheng, 2018). S. Kim et al. proposed a method to convert diverse floor plans into an integrated format also based on GAN in the vectorization process (Kim & Park, 2018). Sharma et al. applied the GAN convolutional network for blueprint detection and retrieval (Sharma, Gupta, Chattopadhyay, & Mehta, 2019). Furthermore, GANs possess the capability to generate a variety of building blueprints, which could potentially create an opportunity to enhance room connectivity and optimize evacuation routes by reconfiguring the building layout.

The aim of this study is to develop a proactive approach to assess and mitigate fire risk in buildings by utilizing a hybrid of AI techniques that rely on the connectivity analysis of room layouts in blueprints. The approach comprises four key stages, starting with standardizing building blueprints through pre-processing, followed by automated blueprint interpretation, automated building fire risk assessment, and GAN-supported building fire risk mitigation (as shown in Figure 1).

The method begins by interpreting building blueprints in a comprehensive manner, which includes segmenting rooms, extracting room information, verifying compliance with fire safety regulations, and obtaining and calculating room layout. By utilizing both digital and texture information, the building layout can be readily constructed, and the connectivity of each space is then analysed and checked for fire risk assessment. For building designs that do not comply with fire safety regulations, the layout is redesigned and reshaped by a connectivity-constrained Generative Adversarial Network (cc-GAN) until it meets the fire risk assessment criteria. This approach provides an effective tool for designers and engineers to enhance fire safety performance of building layouts, both in design and retrofitting phases, based on building blueprints.

This paper is structured as follows: Section 2 describes and explains the proposed framework. Section 3 presents the implementation and case study. The results and analysis are discussed in the subsequent section. Finally, the conclusions and future work are presented.

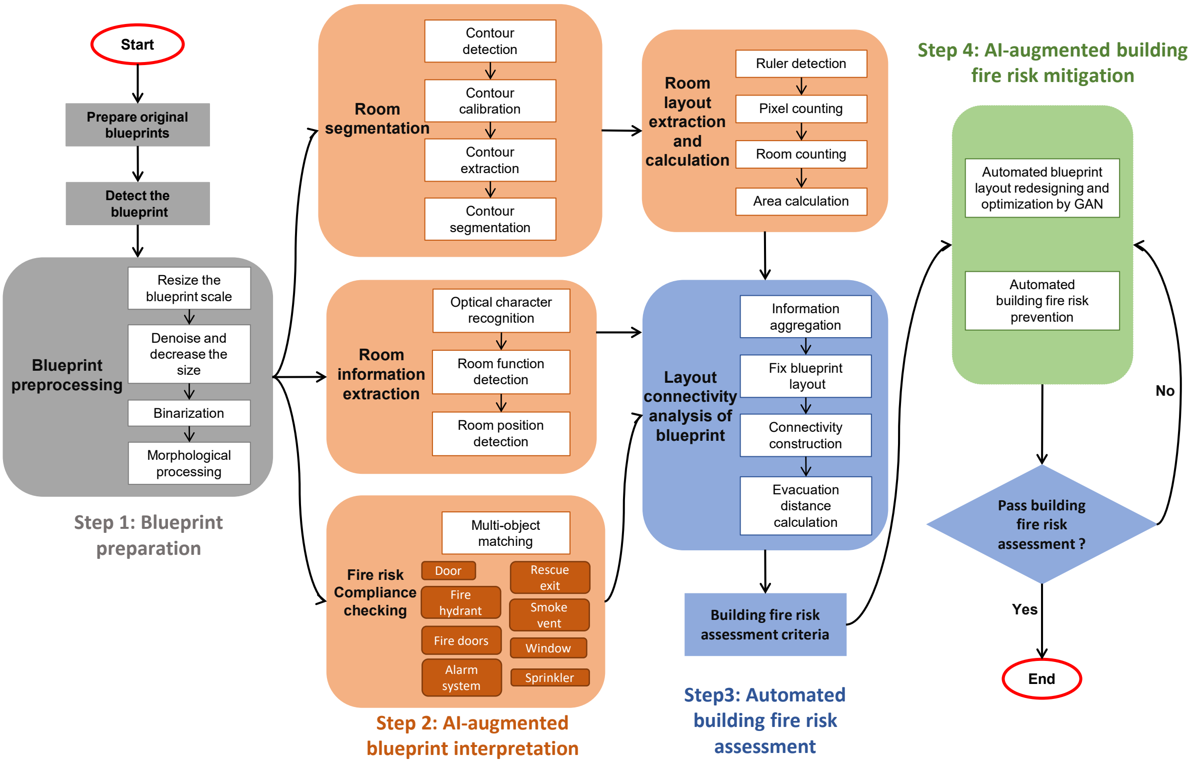


Figure 1. The federated framework of building fire risk assessment and mitigation

2. Proposed Framework

A systematic framework proposed to aid fire risk assessment and mitigation approach has been developed based on four interconnected steps (as shown in Figure 1): (i) Blueprint preparation, or pre-processing of building blueprints, including resizing, denoising, binarization and morphological processing; (ii) AI-augmented blueprint interpretation, which recognises structural and functional information of buildings, including contour, layout, space segmentation, room position and room types, based on computer vision (CV) and automatic information extraction techniques. This step also involves compliance checking fire risk based on automatic recognition of risk sources in building blueprints; (iii) Automated building fire risk assessment that aggregates information and analyse layout connectivity to determine fire risk; and (iv) AI-augmented building fire risk mitigation with layout improvement based on the connectivity-constrained generative adversarial network (GAN) and a knowledge base of building fire risk assessment. Steps 1 and 2 are summarised in *Section 2.1*, while steps 3 and 4 are concluded in *Section 2.2*. Our previous work (Chen et al., 2022) provides a detailed description of steps 1 and 2. It is also worth highlighting that the proposed approach can handle both digital and manual blueprints.

2.1 Automatic building blueprints interpretation

A. Building pre-processing

To ensure accurate interpretation of blueprints, it is important to pre-process them due to the varying qualities and standards. As shown in Figure 2, a systematic pre-processing approach will be applied to all types of original blueprints, which includes resizing, denoising, size reduction, binarization, and morphological processing. This pre-processing method will effectively improve the quality of the blueprint image by reducing noise and enhancing the necessary features for interpretation.

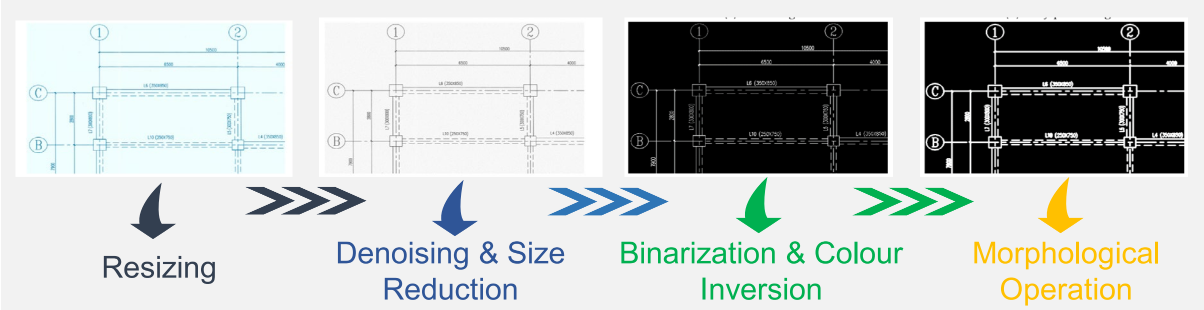


Figure 2. The systematic pre-processing approach

During the stage of image resizing, only its width and height of the image are altered which is beneficial for processing images in large quantities. Our framework incorporates Gaussian filtering as a means to decompose the image frequencies, using sigma and window size as parameters. Since many edge-detection algorithms are vulnerable to noise, the application of Gaussian filtering can lead to a significant increase in the accuracy of edge-detection outcomes. Additionally, to avoid any distortion when reducing the image size, we employ grey processing, which converts RGB images to grayscale. To effectively extract object features and edges, we employ binarization, which converts multicoloured images to black and white. Lastly, to enhance image clarity and facilitate feature extraction, we utilize morphological operations.

B. Automatic blueprint interpretation

In the realm of fire risk management, the technique of blueprint interpretation has been utilised to discern various visual attributes from building blueprints. These attributes comprise colour, texture, compactness, contrast, and edges, which collectively facilitate the identification of fire risks and hazards (Paneru & Jeelani, 2021). After the pre-processing stage, our framework undertakes several tasks, including room segmentation, room layout extraction and calculation, room information extraction, and fire risk compliance checking, as indicated by the orange-coloured boxes in Figure 1. Of note, the contour processing and room-related processing are pivotal parts of our blueprint interpretation approach. Specifically, the contour processing step is associated with the macro-level interpretation of the blueprint layout, while the room-related processing focuses on the micro-level interpretation of the blueprint's composition.

The initial stage of the automatic blueprint interpretation process involves identifying the fundamental outlines that serve as the foundation of the building's structure. This is accomplished through a series of processing elements, which encompass contour detection, contour calibration, contour extraction contour, contour segmentation and colour detection (when objects are coded by colour). In this context, ruler detection and pixel counting are employed to facilitate the process of room counting and area calculation. Following this, the interpretation system captures more nuanced information, such as objects of interest (e.g., doors, fire doors, fire sprinklers, etc.) and textual data (e.g., room function, room position, room area, etc.), which is achieved through the application of geometric recognition and optical character recognition algorithms.

Herein, several functions and algorithms are typically employed to interpret blueprints. The Cany edge detection function in computer vision (CV) is a commonly used approach that involves a sequence of steps, including noise reduction, gradient calculation, non-maximum suppression, double threshold, and edge tracking, to accurately delineate the contour of an image. By integrating vertical and horizontal line detection processes, the entire layout of the blueprints can be effectively segmented into multiple enclosed rooms with distinct colours, which can then be counted. Moreover, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique is utilised to improve the clarity of the scanned ruler scaler. By matching the number of pixels to each sector of the ruler, the scale factor can be obtained, enabling the calculation of the area of each enclosed room and the distance of the evacuation route. For ensuring compliance with fire safety regulations, both single object and multi-object matching methods are utilized to extract specific entities from the blueprint. Furthermore, an enhanced Optical Character Recognition (OCR) system is utilized to generate consecutive and accurate information with precise coordinates, facilitating the comprehensive interpretation of building blueprints.

2.2 Automatic building fire risk assessment and mitigation based on layout connectivity

A. Building fire risk assessment

The acquisition of a comprehensive interpretation of building blueprints yields crucial information pertaining to the layout connectivity and evacuation routes within a building. In light of the low population density of residential buildings, corridor width analysis is often disregarded, so the total length of evacuation pathways is prioritized within our framework. Furthermore, space access serves as a valuable metric for measuring building interconnectivity and calculating optimal evacuation routes. As depicted in Figure 3, the centre point of each room and its corresponding entryway exhibit a bidirectional interconnection in a connectivity graph. While the primary objective is to minimize the distance to a fire exit, government guidelines outlined in the Fire Exits and Regulations Information Guide state that, in the absence of multiple escape routes, the travel distance should not exceed 18 meters. In high-risk areas where fire is more prone to occur and spread, this distance is reduced to 12 meters. However, it may be increased to approximately 25 meters in low-risk areas. Therefore, in the context of residential buildings, a minimum evacuation distance of 15 meters is deemed suitable within our framework. Utilising the obtained connectivity graph, the length of an evacuation route is determined by the distance between the room's centre point and the room access point, in addition to the distance between the room access point and the nearest fire exit, which is illustrated in Figure 3. And the pseudocode to output the minimum evacuation distance and assess the fire risk is formulated in Algorithm 1.

Figure 3. The demonstration of evacuation routes

Algorithm 1: Automatic fire risk assessment

```
Input: room[i].center, exit_coordinate[i], safe_exit[j], scale_factor
Output: room[i].distance_to_safe_exit, assessment_result
// assume n rooms and m safe exit_coordinate
// calculate the minimum distance to the safe exit
for i=1 to n do
    distance_to_exit = calculate_distance(room[i].center, exit_coordinate[i]);
    room[i].distance_to_exit = distance_to_exit;
    min_distance_to_safe_exit = infinity;
    for j=1 to m do
        distance_to_safe_exit = calculate_distance(exit_coordinate[i], safe_exit[j]);
        if distance_to_safe_exit < min_distance_to_safe_exit;
            min_distance_to_safe_exit = distance_to_safe_exit;
        end if
    end for
    room[i].distance_to_safe_exit = min_distance_to_safe_exit;
end for
//automatic fire risk assessment by measuring the real evacuation distance
all_less_than_15 = True;
for i=1 to n do
    real_distance = room[i].distance_to_safe_exit * scale_factor;
    if real_distance > 15
        all_less_than_15 = False;
    end if
end for
if all_less_than_15 = True
```

```
        print ("Pass");
else
        print ("Redesign");
end if
```

B. Building fire risk mitigation with connectivity constrained GAN (cc-GAN)

In cases where building designs fail to adhere to fire assessment criteria, the generation and estimation of new building layouts much be conducted through trial and error. During the layout regeneration stage, the constraint of relational architecture derived from the connectivity graph ought to be encoded into the Generative Adversarial Network (GAN) to yield numerous realistic building layouts. Additionally, to enhance compatibility and minimize generation size, safety distance and realism checking may be employed. Through the computer-aided interpretation and redesign of building blueprints, the fire risk associated with the original building blueprints can be effectively assessed and mitigated. The specific procedure of cc-GAN is displayed in Figure 4.

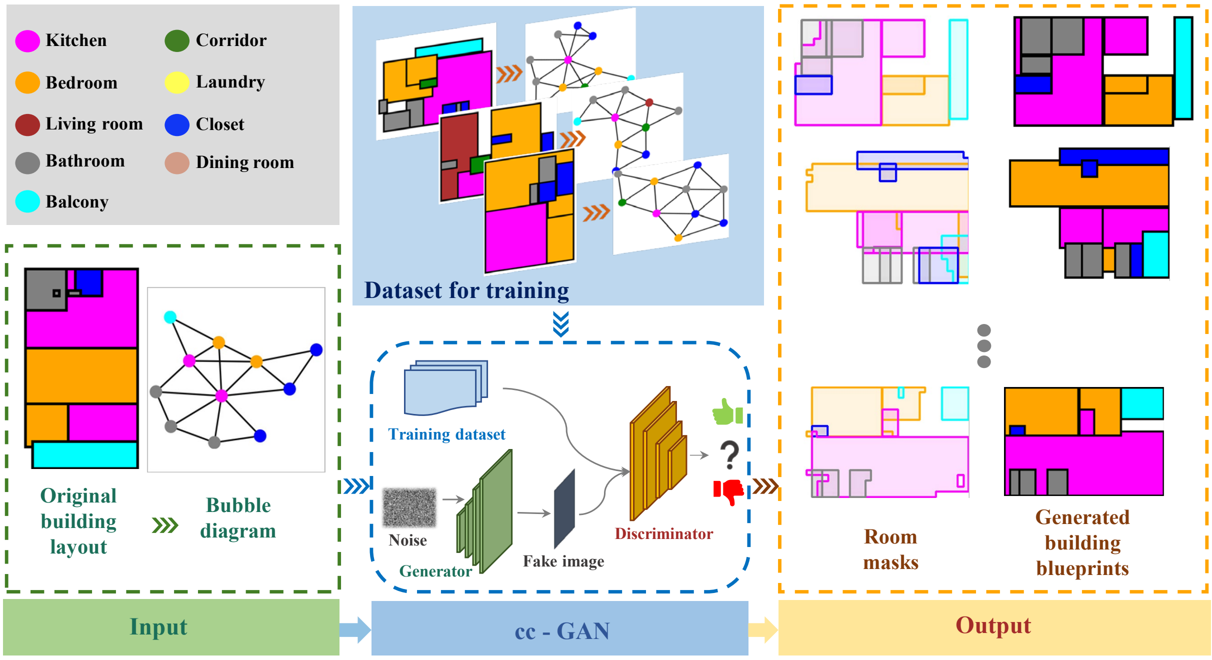


Figure 4. The procedure of connectivity constrained Generative Adversarial Network

The present procedure utilizes LIFULL HOME's dataset consisting of five million real blueprints. To train the cc-GAN, a subset of 10,000 blueprints is selected and standardized using the techniques described in Section 2.1. The floorplan vectorization algorithm is applied to convert these standardized blueprints into bubble diagrams, where each node represents a room and each line denotes the linkage between two rooms.

The cc-GAN architecture comprises a generator and a discriminator, which are trained using an adversarial approach. The generator aims to produce images that can deceive the discriminator. To reduce the generation size and improve the generation results, connectivity constraints are embedded into the neural networks. The generator takes as input the bubble diagram along with a noise vector, and employs Conv-MPN to store and update space-wise features via convolutional message passing (Nauata, Chang, Cheng, Mori, & Furukawa, 2020). The output of the generator is a graph of segmented room masks, which are fed into the discriminator. By comparing the masks obtained from real blueprints and those generated by the generator, the discriminator learns to distinguish between them and outputs a prediction of true or false. Both the generator and discriminator are optimized using an adversarial loss function.

3. Implementation and Case study

The proposed framework is developed using the Anaconda platform with CPU i7 and GPU GTX 1060. And the framework is implemented in Python language, utilizing various libraries and packages such as Imageio, Math, Matplotlib, Networkx, Numpy, OpenCV, Pillow, Pygraphviz, Pytesseract, Scipy, Tesseract-OCR, Scikit-image, Scipy, and Torch. The cc-GAN module for building fire risk mitigation is based on House-GAN (Nauata et al., 2020), employing ADAM optimizer with a constant learning rate of 0.0001.

By integrating multiple techniques described in Section 2.1, a unified platform is developed to analyze the comprehensive information of one input blueprint, as illustrated in Figure 5 and Figure 6.

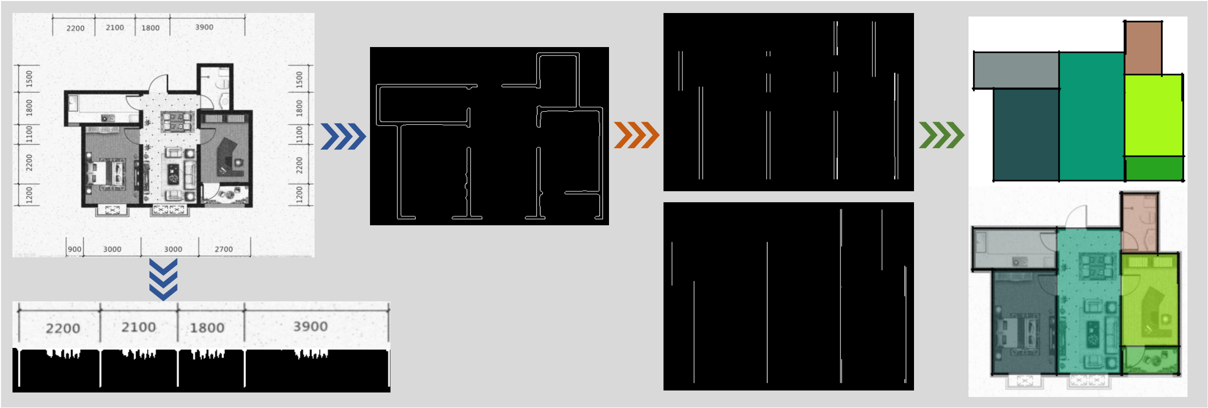
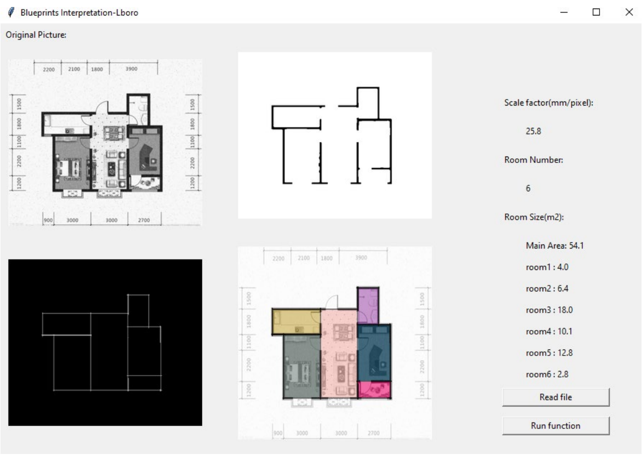
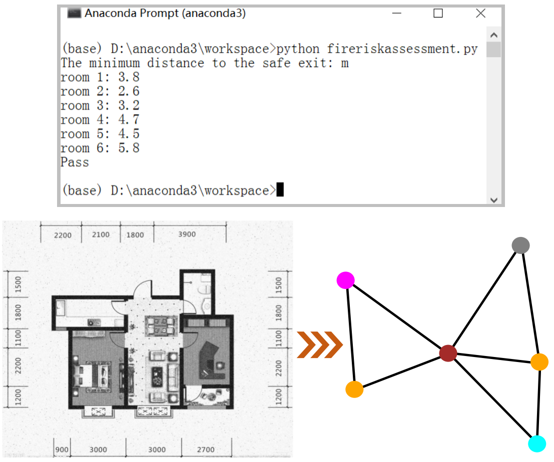


Figure 5. The demonstration of automatic blueprint interpretation



Scale factor(mm/pixel):
25.8
Room Number:
6
Room Size(m2):
Main Area: 54.1
room1 : 4.0
room2 : 6.4
room3 : 18.0
room4 : 10.1
room5 : 12.8
room6 : 2.8

Figure 6. The federated framework for blueprints interpretation



```
(base) D:\anaconda3\workspace>python fireriskassessment.py
The minimum distance to the safe exit: m
room 1: 3.8
room 2: 2.6
room 3: 3.2
room 4: 4.7
room 5: 4.5
room 6: 5.8
Pass

(base) D:\anaconda3\workspace>
```

Figure 7. Evacuation distance and layout connectivity

By leveraging the fully interpreted blueprints, the layout connectivity can be easily derived, and the evacuation distance of each room can be computed for fire risk evaluation, as demonstrated in Figure 7. The processed blueprint demonstrates a maximum evacuation distance of 5.8 meters, meeting the fire risk assessment criteria.

However, blueprints with evacuation distances greater than 15 meters will require cc-GAN for redesigning their room layouts, as shown in Figure 8. The same method of fire risk assessment, as described in Section 2.2, will be applied to these redesigned blueprints for safety inspection, until they meet the fire risk assessment criteria.

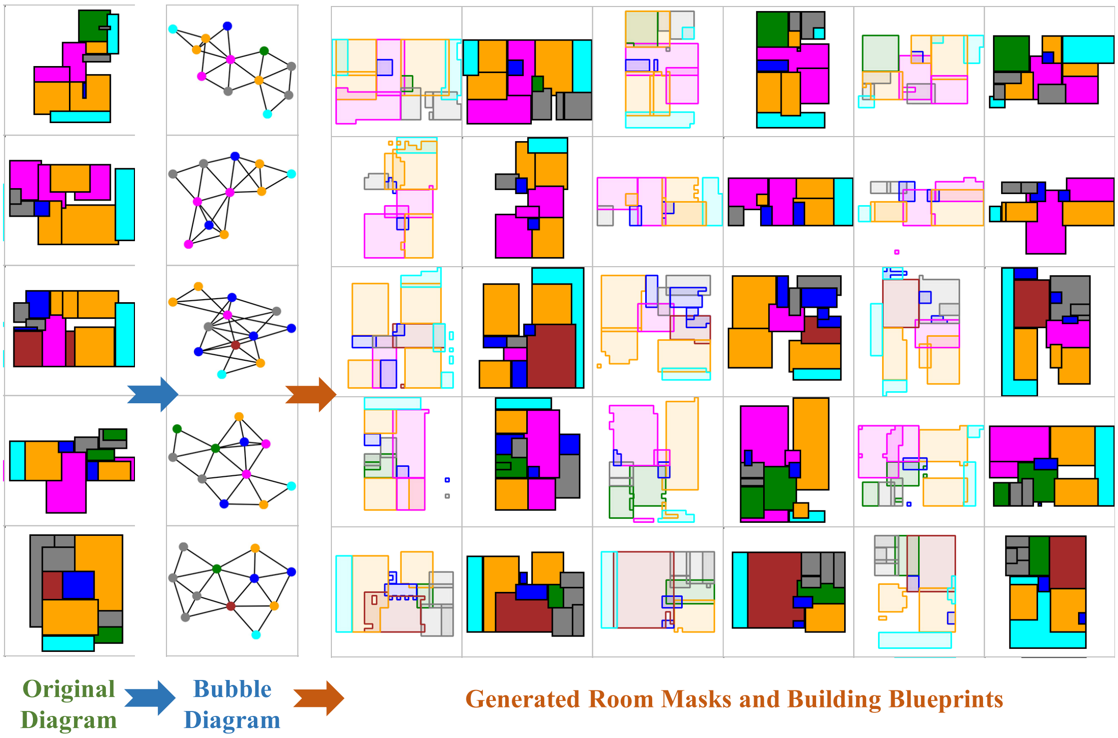


Figure 8. The redesigned building blueprints by cc-GAN for fire risk mitigation

4. Conclusions

This research developed a new framework for assessing and mitigating fire risk of buildings, cc-GAN, through employing a hybrid AI approach to building blueprints. This is an original work that aims to effectively identify the building entities and layout of blueprints, and proactively assess and mitigate the fire risk safety based on layout connectivity during the design phase. Without our assessment process, the building with design defects may have long evacuation distances, posing a threat to the lives and safety of individuals. The final case study illustrates the efficacy of the proposed framework in interpreting building blueprints and reducing their fire risk at the design and retrofitting stages. Future work will be focused on the filtering and optimization of redesigned blueprints and quantitative evaluations compared to other models using more datasets.

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