Z. Wang, T. Zhang, X. Huang (2022) *Predicting Real-time Fire Heat Release Rate based on Flame Images and Deep Learning*,
**Proceedings of the Combustion Institute**, 39. https://doi.org/10.1016/j.proci.2022.07.062

# Predicting Real-time Fire Heat Release Rate by Flame Images and Deep Learning

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## Abstract

The heat release rate (HRR) is the most critical parameter in characterizing the fire behavior and thermal effects of a burning item. However, traditional fire calorimetry methods are not applicable due to the lack of equipment in most fire scenarios. This work explores the real-time fire heat release rate prediction by using fire scene images and deep learning algorithms. A big database of 112 fire tests from the NIST Fire Calorimetry Database is formed, and 69,662 fire scene images labeled by their transient heat release rate are adopted to train the deep learning model. The fire tests conducted in the lab environment and the real fire events are used to validate and demonstrate the reliability of the trained model. Results show that regardless of the fire sources, background, light conditions, and camera settings, the proposed AI-image fire calorimetry method can well identify the transient fire heat release rate using only fire scene images. This work demonstrates that the deep learning algorithms can provide an alternative method to measure the fire HRR when traditional calorimetric methods cannot be used, which shows great potential in smart firefighting applications.

*Keywords:* Fire images; Flame dynamics; Fire calorimetry; Artificial intelligence; Fire-scenario database;

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## 1. Introduction

The fire heat release rate (HRR) or the power of fire is considered the most critical parameter in characterizing the fire behavior and thermal effects of a burning item [1,2]. The fire HRR is also an effective indicator for the fire growth rate and fire size [3] that has been extensively used in both building fire safety design and firefighting operation [4].

Many research efforts have been made to quantify the fire HRR of different burning fuels. Conventionally, there are two principal approaches in the laboratory experiments, (1) measuring the fuel mass burning rate and (2) the oxygen calorimetry [2]. For the fuel whose heat of combustion is known, the most direct way is to measure the fuel burning rate ($\dot{m}_f$) using a mass balance [3]. Then the HRR can be calculated as:

$$HRR = \dot{m}_f \eta \Delta H_c \tag{1}$$

where $\Delta H_c$ is the heat of combustion, and $\eta$ is the combustion efficiency. However, this method has two major issues, that is, the value of $\Delta H_c$ and $\eta$ are unknown for complex fuel; and its size and accuracy are limited by the scale.

Comparatively, measuring HRR by the oxygen calorimetry is more widely used for fire and fuel of different scales. By assuming the constant heat of oxidation for most common fuels [5] and complete combustion, the HRR of an arbitrary fuel is given by,

$$HRR = \Delta \dot{m}_{O_2} \Delta H_{O_2} \tag{2}$$

where $\Delta \dot{m}_{O2}$ is the oxygen consumption in fire, and $\Delta H_{O2}$ is the heat generated per unit mass of oxygen consumed. When considering incomplete combustion of fuels, the HRR is further corrected by measuring carbon monoxide [6]. This method only requires the measurement of fire emissions, so it is more convenient and accurate. The NIST forms a Fire Calorimetry Database (FCD) that contains transient HRR data for hundreds of fire experiments in the range of 50 kW to 20,000 kW [7].

Other methodologies, such as using temperature rise [8] and carbon dioxide generation [9], have also been developed to evaluate the fire HRR. However, the applications of these methods are limited by the measurement equipment, and most of them can only be used in the controlled lab environment. Thus, new methods are needed to achieve an easy and fast determination of fire HRR.

In most fire tests or actual fire incidences, fire videos are often available from CCTV cameras and mobile phone cameras that can record the flame and smoke to determine relevant fire parameters [10–12]. The flame images include the information of fire behaviors and characteristics, such as flame size, height, color, brightness, and oscillation frequency, as well as their time evolution. In-depth analysis of flame images can deliver valuable information about fire development. Our recent work [11] explores the use of flame sheet area quantified from the flame image to determine the HRR of microgravity flame. However, the accuracy and reliability of these methods by using traditional image processing [11] are sensitive to camera setting, background light, and experimental interferences. A long post-image process is also needed, so it is difficult for the real-time identification of fire HRR in a real fire incident.

With the development of artificial intelligence (AI) technology, especially deep learning methods, the capability of image analysis has been significantly improved and applied for facial recognition [13] and object detection [14]. More recently, AI methods have been widely applied to identify hidden fire information and predict the development of fire and smoke. For example, Hodges et al. [15] adopted transpose convolutional neural networks (TCNN) to predict spatially resolved temperatures and velocities in compartment fires. Wu et al. [16–18] also applied the deep learning method to forecast the tunnel fire development and smoke transportation 60 s in advance and demonstrated the smart firefighting system in a laboratory-scale tunnel model. Su et al. [19] used AI to train smoke images of numerical fire simulation to assist performance-based fire engineering design for the atrium. Ghosh et al [20] proposes a hybrid deep learning model based on convolutional neural network (CNN) and recurrent neural network (RNN) to detect forest fire, which provides a new insight to use computer vision for forest fire detection. Choi et al. [21] adopted convolutional neural networks (CNN) for semantic image segmentation in wildfire. Ban et al. [22] developed a deep learning-based framework for real-time wildfire progression monitoring through smoke, cloud and night.

Different deep learning algorithms have been adopted to automatically generate extensive features from massive amounts of training data [23] and pre-establish the complex relationship between complex images and target parameters so that real-time fire identification can be achieved. Our latest work [24] successfully used numerically generated smoke images outside the building to predict fire HRR inside the building. Given the excellent performance of AI methods in fire recognition, it is reasonable to believe that it is also feasible for image-based heat release rate identification.

This work explores the feasibility of using fire-scene images to identify the transient HRR of any burning item. The NIST database [7] is adopted to form a big fire-image database. The continuous fire images extracted from the test videos are labeled with time-varying HRRs determined in experiments to train the deep-learning model. Finally, the proposed AI-image fire calorimetry method is applied for fire images from new lab fire experiments and actual fire events to predict the real-time fire HRR.

## 2. Methodology

### 2.1. *Fire-image database*

To train the deep learning algorithm, a large number of fire-scene images labeled by their transient HRRs are needed. Thus, the NIST Fire Calorimetry Database is adopted for training the deep learning model, which measures the evolution of fire HRR from ignition to burnout by the oxygen calorimetry [25]. Different fire scenarios, such as single burning items, fully furnished rooms, controlled burners, well-characterized fuels, and fuels of unknown composition, are included in this database with the fire HRR from 50kW to 20,000 kW. For a given group of fire tests, the digital video camera with a fixed view angle was used to record the whole test process.

The current fire-image database includes fire tests in the transient combustion calorimetry (TCC) project [26,27] to train the deep learning model. Tests with no obvious flame and a maximum HRR of less than 10 kW are excluded. In total, 112 fire tests with the peak heat release rate (pHRR) ranging from 10 kW to 4,174 kW are selected to train and test the model. All items burned in these fire tests are commonly seen in our daily life, as shown in Fig. 1.

(a) Trash Can (b) Paper box

(c) Laptop cart (d) Wood pallets

**Fig. 1.** Typical burning items in the NIST Fire Calorimetry Database, (a) trash can, (b) paper box, (c) laptop cart, and (d) wood pallets.

All these tests with different fuel types and fuel loads are tested under the 100 kW, the 1 MW and 3 MW hoods, with the HRR uncertainty of 11% [28]. The test duration ranges from 4 to 115 minutes, depending on fuel type and fuel load. The HRR distribution in the fire image database is shown in Fig. 2(a), containing various fire scenario images and their corresponding HRRs, which can be used for the training of the deep learning model.

### 2.2. *Dataset pre-processing*

In the video, the fire behavior at each moment corresponds to a specific HRR. Thus, fire images in the video from ignition to extinction is extracted (one frame every 5 s) and paired with the HRR at that moment to obtain the final model training database. Finally, a database with a total of 69,662 fire images paired with HRR is formed, and its distribution of the HRR data is shown in Fig. 2(a). Afterward, data pre-processing is required before these images can be fed into a deep learning model for training.

Since the quality of the fire video images in the NIST database is sufficiently high (1920×1080), training raw images would greatly increase the computational complexity and cost. Thus, all fire images are first resized to 224×224. Afterward, these 69,662 images are further divided into two parts, the training set (80%) for training and validating the model and the test set (20%) for the demonstration purpose. Different fire tests with various fuels and ranges of HRRs are included in both datasets to avoid bias.

### 2.3. *Deep-learning algorithm*

Although human eyes can recognize the fire size in a qualitative way, telling the accurate value of fire HRR in a random fire is way beyond human's intuition and analytical calculations based on empirical laws. Thus, the deep-learning algorithm programmed in Python is adopted to get the relationship between the fire images and HRR. Previous research [24] has demonstrated that the VGG16 method [29] is an effective way to extract features from numerical smoke images and accurately identify the fire HRR, but such a method has not been applied to real fire images. Unlike the computer-rendered smoke images, real fire images are more complex, considering the background light, camera settings, and experimental interference. Thus, it is much more challenging to apply this AI-image fire calorimetry, and its performance is still unknown.

Fig. 2(b) shows the detailed architecture of VGG16 used for fire HRR identification, consisting of 13 convolutional layers, five max-pooling layers, and three fully-connected (FC) layers with 27,823,425 parameters. The feature maps can be generated from huge amounts of training data by the convolutional operation, and the max-pooling layer after the convolutional layer is responsible for reducing the dimension of the feature map and extracting dominant features. As a typical deep learning algorithm, VGG16 can automatically establish the relationship between fire images and HRRs through a hierarchical learning strategy without extra human interaction and expert knowledge, which is more advanced and effective than traditional image processing. Considering the convolutional layers can automatically extract the fire image feature, issues with background light, camera settings, experimental interference are not specially addressed. The resized flame image with the dimension of 224×224×3 is input directly into the network and reduced to 7× 7 × 512 by the convolution operation. Finally the corresponding HRR is output after 3 fully connected layers.

The entire network structure contains a total of 28 million parameters, which is sufficient to preserve the relationship between image data and fire HRRs. ReLU is selected as the activation function in convolutional layers and the first two fully connected layers, and the linear activation function is used as the activation function of the final output. The loss function of mean square error (MSE), mean absolute error (MAE), and $R^2$ value are used to compare the difference between actual and predicted values. Dropout is applied after each max pooling layer and fully connected layer with a dropout rate of 0.2 to avoid overfitting. It takes about 6 h in total for 50-step training on a server with 32 CPU cores and a Tesla P100 GPU card. After the model training, the deep learning model can achieve real-time prediction of HRRs based on the input fire scenario images.

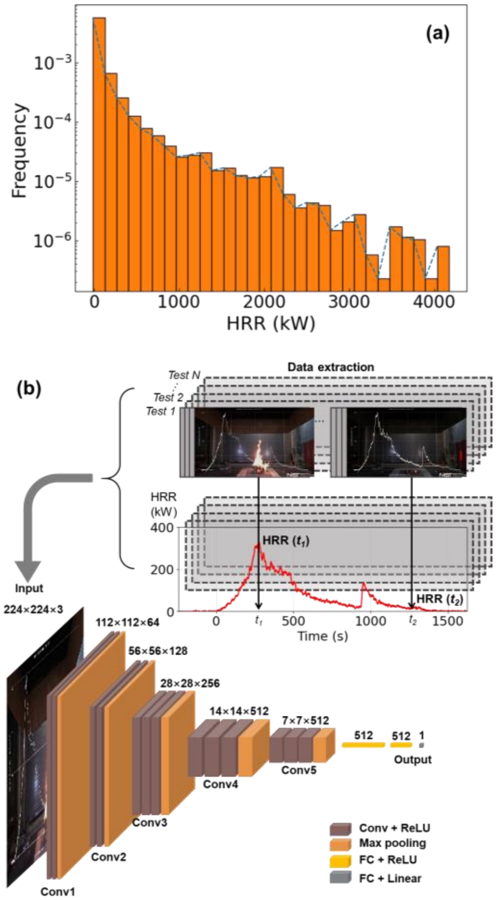
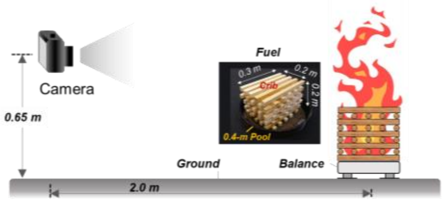


**Fig. 2.** (a) The distribution of the HRR data in the selected database and (b) paired training dataset and the architecture of VGG16 used for the AI-image fire HRR identification.

## 2.4. Demonstration of real fire events

One major feature of the NIST Fire Calorimetry Database is that for all fire-test videos, the camera view angle, the distance between fire and camera, and the background images are fixed. Thus, it is not sure if the trained AI model can be applied to predict the real-time HRR of fire images with a different view angle, distance, and background views.

(a) Additional fire tests in lab



(b) Vehicle fire
(c) Christmas tree fire

**Fig. 3**. Demonstration fire scenes, (a) the burning of the propanol pool and the small wood crib, (b) Vehicle fire [30], and (c) Christmas tree fire [31].

Therefore, another set of fire tests with different backgrounds and experimental setup is conducted in our lab, as illustrated in Fig. 3a. A video camera (Sony DSC-RX10M3) at 0.65 m from the ground is used to record flame behavior throughout the fire test. A circular propanol pool with diameters of 0.4 m and a 1/5 scale standard dry wood crib (30×20×20 cm$^3$) [32] were burnt. A balance with a precision of 0.1 g is placed under the fire source to measure the burning rate of fuel and the fire HRR by Eq. (1), which is compared with AI-image fire calorimetry for demonstration. Finally, videos of real fire accidents, a burning vehicle (Fig. 3b) and a Christmas tree fire (Fig. 3c) from the news are tested to demonstrate the reliability of real-time fire HRR identification by the proposed deep-learning method. It is worth noting that these fire scenarios are randomly selected that have different view angles, camera settings, distance, and background from the NIST database. The AI-predicted fire HRR will be compared with the measured HRR and literature data for validation.

## 3. Results and discussion

### 3.1. Model training

The model performance during the training is shown in Fig. 4. After 50 steps of training, the deep learning model reaches convergence with a minimum MSE loss of 885 and a maximum R$^2$ of 0.99, which indicates the deep learning model can accurately predict the transient HRR of fuels in the training data set.

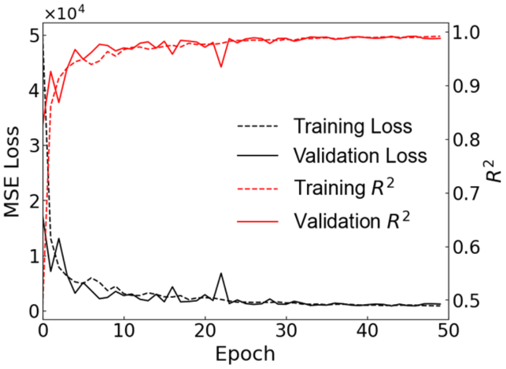


**Fig. 4.** Losses and $R^2$ of training and validation during the training process.

## 3.2. *Demonstration using NIST database*

After completing the training of the model, the test set was used to verify the identification performance of the model. Fire tests from the NIST Fire Calorimetry Database with different ranges of fire HRRs were selected for demonstration. Note that all these fire tests are within the 20% test set that is not involved in the training of the deep learning model. In other words, the AI model identifies the transient fire HRR of fuel in unseen fire scenarios by the knowledge learned from the training set.

Fig. 5 shows a comparison of the HRR evolution measured by the calorimeter and the predictions by the deep-learning model. The plastic bag (small HRR), trash can half-filled with crinkle paper (medium HRR), eight wood pallets (large HRR) were burnt in the fire test, respectively. The fire behaviors of each fire test and transient HRR identification are also displayed in Videos S1. It is found that the proposed deep-learning model can effectively evaluate the fire HRR as the fire develops, which shows comparable identification results to the oxygen calorimetry measurement, especially for fire scenarios with small HRR and medium HRR, with the $R^2$ larger than 0.8.

For the fire scenario with a large pHRR (Fig. 5c), the deep-learning model performs well at predicting fire HRRs at the growing and decaying stages. When the HRR approaches the peak value, the prediction of the deep learning model becomes relatively less accurate with a $R^2$ less than 0.7 [33]. To determine why the trained model fails to identify the large fire HRRs, the distribution of HRR in the training set should be analyzed, as shown in Fig. 2(a). Essentially, there are much fewer images of fire scenes higher than 2,000 kW, so the trained deep learning model is more effective in recognizing fire scenes within 2,000 kW. The underestimation is caused by three reasons.

The first reason is the unbalanced samples. There are more fire images for scenarios with small to medium HRRs than those with large HRRs, so the model tends to underestimate the HRRs of larger fires. Secondly, the peak HRR of the wood pallets fire reaches more than 4000 kW, far exceeding the range of HRRs identified by the model. Thus, the database should include more cases of larger fires. Thirdly, the wood pallet and the attached flame have a large depth that is not captured in 2-D images at a fixed location. To improve the AI-driven Fire ID, more large-scale fire scene videos and more fire images from different angles should be included in the training dataset.

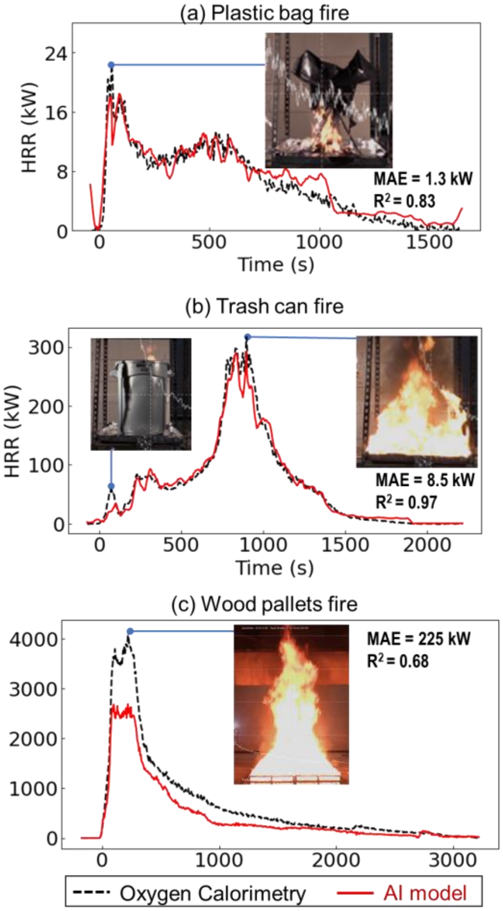


**Fig. 5.** Evolution of fire HRR by model prediction and the oxygen calorimeter by NIST, (a) plastic bag fire, (b) trash can fire, and (c) wood pallets fire.

In summary, all test cases show that the proposed AI-image fire calorimetry can well capture the characteristics of fire behavior and predict the transient HRR of burning fuel in the range of heat release rates for which sufficient image samples are available. Although the accuracy and measurement range of the model depends on the size of the training database, it shows an accuracy comparable to that of oxygen calorimetry and does not require the installation of complex equipment or additional sensors. Thus, compared with the conventional mass-burning calorimetry and oxygen calorimetry that are limited in the controlled laboratory environment, this AI-image fire calorimetry method is easier to apply in actual fire scenarios with wider application prospects.

### *3.3. Demonstration with new lab environment*

To further demonstrate the feasibility of the deep learning models to identify the fire HRRs, experiments in different backgrounds (Fig. 3a) were carried out to validate the deep learning model. A pool fire with a diameter of 0.4 m and 800 mL of propanol and a wood crib fire ignited by 100 mL of propanol was used as the target. Different backgrounds were used to exclude the effect of background on HRR identification. The burning process and the mass loss rate were recorded by the camera and balance, respectively.

For new experiments conducted in our laboratory, because the distance of the camera from the fire source is different from the distance of the training set used for model training, a direct input of the images would lead to false identification of the deep learning model. Therefore, the pre-processing of the image is needed to enable fire images taken at different distances from the fire source that can be used for deep learning identification. Note that the video taken under laboratory conditions needs to be scaled equally to the scale of the video in the FCD database to ensure that each pixel corresponds to the same actual length. Then, the distance between the camera and fire and zooming of view won't affect the fire identification. All images are first rescaled according to the scale of the training set images and restored to 1920×1080 using blank padding, and then, they are resized to 224×224. Rescaling and resizing of images allow the model to be adapted to different image sizes, enhancing the generalizability of the model.

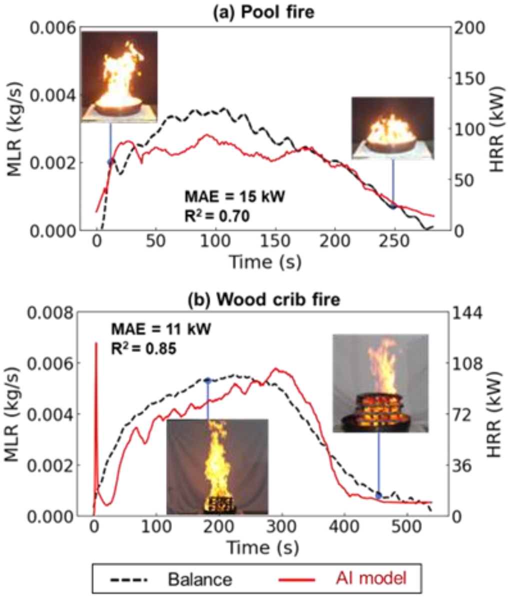


**Fig. 6.** Evolution of fire HRR by model prediction and the mass-balance measurement, (a) liquid fuel pool fire, and (b) small wood crib fire.

Fig. 6 summarizes the comparison between the fire HRR measured by the mass balance and the HRR predicted by the deep learning model. The detailed prediction process for the transient fire HRR using fire scene images is demonstrated in Video S2. In general, although completely different fire sources, background light, camera setting, and experimental setup are used, the prediction of the deep learning model showed high accuracy (overall error less than 15%) throughout the entire fire test process, considering that the uncertainty of repeating fire tests is about 10%.

Especially since the wood crib was ignited by the propanol, a large amount of propanol vapor could accumulate near the wood crib before it is ignited, which would result in violent combustion of propanol vapors when the crib was ignited without causing a change in the mass of the wood crib. However, this phenomenon can be clearly observed through the fire scene images and predicted by the deep-learning model, as shown in Fig. 6(b).

### *3.4. Demonstration with real fire events*

After the model validation using fire tests in a laboratory environment, real fire events are adopted to further demonstrate the transient HRR identification using the deep-learning model. Compared with the fire tests in the controlled laboratory, any actual fire event has more complex fire sources, background, and light conditions. Moreover, the view angle of shooting video, camera settings, and shooting distance also vary, so it is more difficult to predict the HRR in real fire scenarios.

To validate the reliability of the proposed AI-image fire calorimetry, a vehicle fire and dry Christmas tree fire are selected to represent real fire scenarios, see Fig. 3(b-c). All the fire scene images are also rescaled and resized to fit the scale of the deep learning model. The prediction of real fire evolution was demonstrated in Fig. 7. The detailed identification of fire HRR evolution can be seen in Videos S3. Visual observations show that for real fire events, the HRR prediction by the deep learning model qualitatively agrees with the trend of fire development in the video.

For the vehicle fire in Fig. 7(a), the deep learning model can also predict a pHRR of 750 kW, where half of the vehicle is burning. Such a value is 1/3-1/2 of the pHRR of 1.5-2 MW found in [34] when the whole vehicle is burning, so that AI's prediction is reasonable. It is worth noting that the generation of large amounts of smoke can lead to lower prediction results, probably due to the obscuration of the flame by the smoke, while the trained model identifies the fire HRR mainly based on the behavior of the flame.

For the Christmas tree fire in Fig. 7(b), the fuel load, including two Christmas trees and one chair, are discrete, and the tree on the left-hand side is specially processed to improve its fire retardancy. Despite the complex fuel load and more complex fire-spread process, the AI model still gives reasonable predictions and can accurately identify changes in fire HRR during the whole burning process. The predicted pHRR of 900 kW is well within the range (800 - 1,700 kW) for Christmas tree fires in the literature [35].

In summary, the proposed AI-image fire calorimetry method can effectively identify the transient fire HRRs within the training set for a variety of fire scenarios regardless of the background, fire source, or camera settings. However, for fire scenarios with very large HRRs, beyond the range in the training set, the method will generate an underestimation of heat release rates due to the lack of knowledge (Fig. 5c).

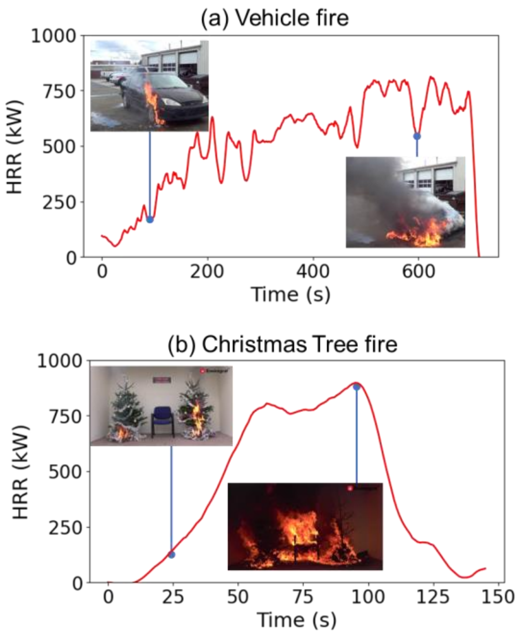


**Fig. 7.** Evolution of fire HRR in real fire events by model prediction, (a) vehicle fire, and (b) Christmas tree fire.

It is also noticed that the proposed deep learning method identifies fire HRR mainly through the dynamics flame behaviors. Thus, when a large amount of smoke is generated in the fire scene to obscure the flame, the recognition result will also be lower than the actual fire size (Fig. 7a).

Collecting more fire tests, including fire images partially covered by the smoke plume, to expand the training database is critical to improve the prediction capacity. Moreover, to illustrate the hidden process of image identification, an interpretable algorithm (e.g., the attention-based method) can be adopted that can help understand what exact features of the fire image are recognized by the algorithm. It is also meaningful to consider the synergistic effect of flame and smoke for a more accurate prediction of fire HRR because most fire scenarios produce flames along with large amounts of smoke that have different colors.

### *3.5. Application in smart firefighting*

After validating the effectiveness of the proposed deep learning model in identifying the fire size, this AI-driven technology can be used in the actual firefighting process as a key part of the smart firefighting system. Considering this AI-image fire calorimetry is based only on fire scene images, no additional gas sensors or temperature sensors are needed. The basic framework of applying this AI-image fire calorimetry is shown in Fig. 8.

When a vehicle fire, building fire, and other fires occur, we can use the camera in smartphones and unmanned aerial vehicles (UAVs) to collect images of fire scenes in real-time. Then, the collected fire images can be transferred to a cloud database via the network. Then, these streamed fire images can feed into the proposed deep learning model that can then output real-time fire HRR. The identified evolution of fire HRR then can be retransmitted to the firefighters' mobile devices, so they can keep tracking the fire scene development and make quick decisions before their arrival at the fire scene. Conventionally, firefighters can only rely on limited information and personal experience to judge the fire scenarios. In the future, this system can greatly improve fire situation awareness and assist firefighting and rescue [36].

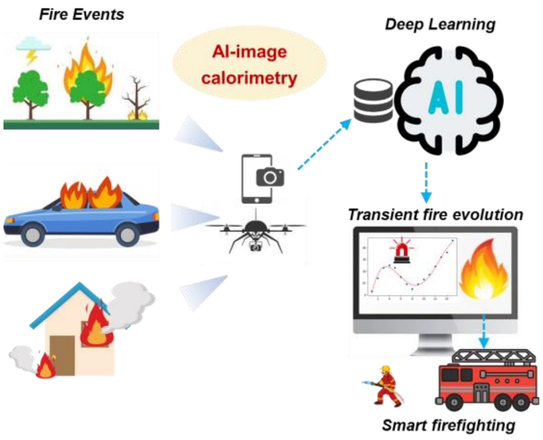


**Fig. 8.** AI-image fire calorimetry for smart firefighting.

Many challenges remain before the application of this AI method. Firstly, the fire image database should be further increased to include actual fire-incidence images and larger fires. Secondly, the flame is 3-D, so its depth cannot be captured in 2-D camera image. Future AI model should be trained by 3-D fire images reconstructed by multiple camera images taken from different angles. Thirdly, the distance and view angle of fire images have a great impact on the AI-image fire calorimetry. Additional sensors like Lidar and laser rangefinder can be used to find the fire distance and zoom in and out of fire images to match the database. Finally, influences of the image background (e.g., similar color with flame), blockage of fire view, camera setting (aperture, shutter and ISO), and the evolution of fire should also be considered. For example, it is necessary to explore the contributions of fire size, brightness and color on the AI-image fire calorimetry in future work.

## 4. Conclusions

In this work, the prediction for the real-time HRRs of burning fuels using flame images is proposed and demonstrated for the first time. The NIST Fire Calorimetry Database is adopted to train the deep learning model. Then, the proposed AI-image fire calorimetry is used to predict the transient fire HRRs of tests in the same and new lab environments, as well as the real fire events. Results show that the proposed AI-image fire calorimetry method can continuously predict the fire HRR using flame images regardless of the image background, camera settings, and view angles.

The image-based deep learning method is demonstrated as an effective way to extract features from fire scene images and achieve accurate HRR prediction in real-time. Moreover, it provides an alternative method to measure the fire HRR based on fire scene images when traditional calorimetric methods cannot be used. By expanding the fire image database, the measurement range of the model will be further improved. This work provides a simple and convenient way to measure the fire HRR and shows great potential in future smart firefighting applications.

## Acknowledgments

This work is funded by the Hong Kong Research Grants Council Theme-based Research Scheme (T22-505/19-N) and the PolyU Emerging Frontier Area (EFA) Scheme of RISUD (P0013879). TZ thanks the support from the Hong Kong PhD Fellowship Scheme. Authors thank Dr Andy Tam and Dr Matthew Bundy from NIST for providing the fire-test videos.

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