International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 03 March 2026
Page No: 1401-1408
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0192

Real-Time Smoke Removal and Rescue System Using HSRDN

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Abstract
Fire accidents have become increasingly severe in recent years due to heavy smoke, which significantly reduces visibility and delays rescue operations. Poor visual conditions limit the effectiveness of vision-based rescue systems, making real-time smoke removal and accurate victim detection essential. Existing smoke removal and image enhancement methods, including traditional dehazing and deep learning models such as FFA-Net, mainly focus on visual enhancement and suffer from high computational complexity, reduced performance in dense smoke, and lack of intelligent rescue decision-making, while object detection models like YOLO experience accuracy degradation under low-visibility conditions. To overcome these limitations, this paper proposes an AI-driven Real-Time Smoke Removal and Rescue System using HSRDN, which integrates real-time smoke removal, enhanced object detection, and fuzzy logic–based rescue prioritization. The performance of the proposed system is evaluated using PSNR and SSIM to measure image quality and structural restoration, mAP to assess detection accuracy, and FPS to validate real-time processing efficiency. Experimental results demonstrate that the proposed approach provides improved visibility, higher detection accuracy, and reliable real-time performance, making it suitable for practical fire rescue applications.

Keywords: *Smoke Removal, RT-HSRDN, Fuzzy Logic, YOLOv8, Deep Learning, Computer Vision, Fire Rescue System*

1. Introduction

Fire accidents pose a serious threat to human life and infrastructure, especially in indoor and urban environments where dense smoke severely reduces visibility. Smoke causes light scattering and occlusion, making it difficult for victims, firefighters, and vision-based systems to understand the scene. Under such conditions, traditional surveillance methods and standalone object detection models fail to perform reliably, leading to delayed rescue operations and increased risk. To address these challenges, recent advancements in artificial intelligence and deep learning have enabled the development of automated fire and smoke detection systems. Modern object detection models such as YOLOv8 and its variants have demonstrated strong performance in identifying flames and smoke in clear visual conditions, while image enhancement techniques such as FFA-Net have shown promising results in restoring visibility in hazy or smoke-affected scenes. However, most existing approaches focus on either image enhancement or object detection independently, limiting their effectiveness in real-time rescue scenarios where both visibility restoration and accurate detection are simultaneously required.

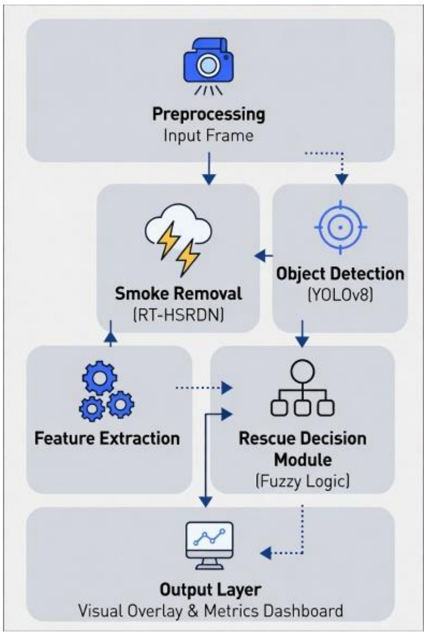

Figure 1 **Architecture**

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This integrated approach improves situational awareness and supports faster, more reliable decision-making in real-time fire rescue scenarios.

2. Related Works

In literature, many researchers have focused on enhancing fire and smoke detection systems using deep learning and image processing methods. Authors of [1] proposed a lightweight fire recognition model named YOLOv8-EMSC, which optimizes the YOLOv8 architecture through an Efficient Multi-Scale Convolution mechanism. This model achieves high accuracy while maintaining low computational complexity, making it suitable for real-time fire monitoring applications. In [2], the authors designed an improved YOLOv8-based fire smoke detection algorithm that enhances the detection accuracy by refining the feature extraction layers and optimizing the bounding box regression function. This work achieved better precision and recall rates compared to conventional detection models, but its performance decreased in dense smoke environments due to visibility loss. Authors of [3] presented a drone-based fire detection system enhanced with flame-specific attention and optimized feature fusion modules. Their work focused on improving the ability of UAVs to identify fire regions from aerial perspectives by integrating attention-based features, which enhance target localization even in fluctuating lighting conditions. Similarly, in [4], researchers developed a Flame and Smoke Semantic Dataset and proposed a deep semantic segmentation model for indoor fire detection. Their work improved the accuracy of flame and smoke region identification through pixel-level classification. However, these systems primarily focused on detection tasks and did not integrate smoke removal techniques for improving visibility.

In the domain of image enhancement and dehazing, several studies have made notable contributions. Authors of [5] introduced the Feature Fusion Attention Network (FFA-Net), which combines spatial and channel attention mechanisms to remove haze and smoke from single images effectively. This model has demonstrated superior performance in restoring fine details and improving overall image quality. In [6], researchers proposed an efficient method and architecture for real-time video defogging, focusing on improving the computational speed of image restoration for dynamic scenes. Although effective, this approach was limited in handling highly dense smoke regions. Further, [9] introduced a single-image dehazing algorithm using an extreme reflectance channel prior, which estimates transmission maps from reflectance components, effectively handling natural haze and smoke in static images. Similarly, authors of [10] proposed an enhanced image dehazing method that integrates multi-scale filtering and brightness preservation for natural scene restoration. However, these approaches are primarily limited to offline image enhancement and are not optimized for real-time integration with object detection systems. Overall, existing literature highlights significant progress in both smoke removal and fire detection. However, most studies treat these tasks independently, which restricts the potential for real-time application in rescue operations. To address this gap, the proposed work integrates FFA-Net for smoke removal and YOLOv8 for object detection within a unified framework, thereby enhancing image clarity, detection accuracy, and response speed in emergency scenarios.

3. Methodologies

The methods introduces an AI-driven real-time smoke removal and rescue framework that integrates FFA-Net, YOLOv8, and Fuzzy Logic to enhance visibility, detect critical objects, and support intelligent rescue decision-making in fire emergency environments.

3.1.FFA-Net for Smoke Removal

The Feature Fusion Attention Network (FFA-Net) has been widely explored for image dehazing and smoke removal tasks due to its capability to selectively enhance relevant features while suppressing irrelevant information. FFA-Net incorporates a dual-branch attention mechanism, combining channel attention and spatial attention to refine feature maps. The model is mathematically expressed as:

$$Fout=\sigma(Ws*Fc)\odot F$$

where $F$is the input feature map, $F_c$represents channel-wise features, $W_s$is the spatial attention weight, $\sigma$is the sigmoid function, and $\odot$denotes element-wise multiplication. By integrating residual

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learning and multi-scale feature fusion, FFA-Net effectively removes smoke artifacts, enhancing visibility for downstream tasks.

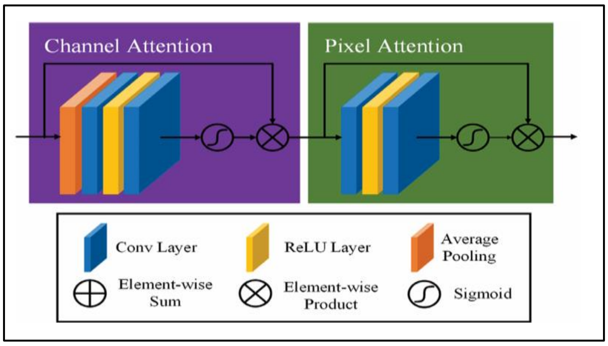

Figure 2 **FFA-Net Architecture**

3.2.YOLOv8 for Object Detection

It represents the latest evolution in the YOLO family and is designed to deliver high-accuracy real-time object detection, even in challenging environments such as smoke-occluded fire scenes. Unlike earlier versions that relied on anchor-based prediction, YOLOv8 adopts a fully anchor-free detection paradigm, allowing the network to predict object centers, box dimensions, and classification scores directly. This eliminates manual anchor-box tuning and significantly improves localization accuracy in dynamic fire and rescue scenarios.

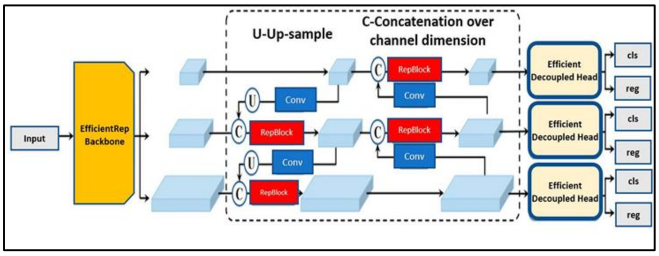

Figure 3 **YOLOv8 Architecture**

The architecture begins with an EfficientRep Backbone, a lightweight feature extractor optimized for high-speed inference and mobile deployment. It uses Cross Stage Partial (CSP) connections and RepBlocks to preserve gradient flow while reducing computational load. The extracted multi-scale features are processed in a Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) fusion structure, enabling the model to detect small and partially occluded objects—particularly useful for identifying victims in dense smoke. The neck of YOLOv8 performs repeated up-sampling and concatenation operations over multiple scales, producing rich, hierarchical feature maps. These maps are passed into YOLOv8's Decoupled Head, where classification and regression branches operate independently. This separation allows the model to learn spatial precision (bounding box regression) and semantic discrimination (classification) without interference, resulting in significantly better performance in cluttered scenes. The prediction process is formulated as:

$$\hat{y} = \{(x_i, y_i, w_i, h_i, c_i)\}_{i=1}^{N}$$

where (x_i, y_i, w_i, h_i)represent the predicted bounding-box center coordinates and dimensions, $c_i$denotes the probability distribution over fire-related classes (e.g., fire, smoke, person, obstacle), and $N$is the total number of detected objects per frame. The anchor-free strategy enables finer localization of small-scale features, which is crucial in heavy smoke where objects are partially visible.

Furthermore, YOLOv8 integrates advancements such as Mosaic augmentation, dynamic label assignment, and improved loss functions including Complete IoU (CIoU) for bounding-box regression. These enhancements enable the model to maintain high robustness under varying lighting conditions, dense smoke patterns, and environmental distortions. Given its strong generalization ability and optimized architecture, YOLOv8 is highly suitable for real-time fire rescue analytics, low-visibility surveillance, and autonomous safety systems.

3.3.Fuzzy Logic for Rescue Decision-Making

Fuzzy logic has been employed to support decision-making in rescue operations under uncertain and dynamic conditions. By modeling linguistic variables such as smoke density, visibility, and temperature, fuzzy inference systems compute risk levels for effective intervention. The membership functions $\mu(x)$map sensor inputs to fuzzy sets:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x \geq b \end{cases}$$

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where a and b define threshold parameters for different risk levels. Fuzzy rules then aggregate these inputs to generate actionable recommendations for rescuers, ensuring safer and more efficient operations.

3.4.Fuzzy Rules for Rescue Decision-Making

To translate the fuzzy inputs into actionable rescue priorities, a set of fuzzy IF–THEN rules is defined based on expert knowledge of fire–rescue operations. For example, higher smoke density and lower visibility typically indicate increased danger, while strong victim detection confidence raises the urgency for immediate intervention. The fuzzy inference system evaluates all rules simultaneously and assigns a corresponding rescue priority such as *Low*, Moderate, or Critical.

- **Rule 1**: If smoke density is Low and visibility is High and victim confidence is Low, then rescue priority is Low.
- **Rule 2**: If smoke density is Medium and visibility is Medium and victim confidence is Medium, then rescue priority is Moderate.
- **Rule 3**: If smoke density is High and visibility is Low, then rescue priority is Critical.
- **Rule 4**: If smoke density is High and victim confidence is High, then rescue priority is Critical.
- **Rule 5**: If visibility is Very Low and fire intensity is High, then rescue priority is Critical.
- **Rule 6**: If smoke density is Medium and victim confidence is High, then rescue priority is Moderate–High.
- **Rule 7**: If fire intensity is Low and victim confidence is High, then rescue priority is Moderate.

4. Proposed System

The proposed system architecture Figure 4, follows a sequential multi-stage pipeline for real-time smoke removal, object detection, and rescue decision-making as illustrated in Fig. 3. The system begins with real-time video input captured from CCTV or drone-mounted cameras deployed at the fire location. In the preprocessing stage, the video stream is converted into individual frames and normalized to ensure consistent resolution and data quality. The processed frames are then passed through the RT-HSRDN smoke removal module, where dense smoke distortions are eliminated, restoring visibility and structural details. The enhanced frames are processed using YOLOv8 for object detection, allowing identification of victims, fire sources, and hazardous elements. Following detection, high-level features and scene context are analyzed to assess severity and risk conditions. Finally, a fuzzy logic–based rescue layer performs decision-making and generates rescue priority alerts. The output includes a clean visual feed, detection bounding boxes, and recommended rescue actions for emergency responders.

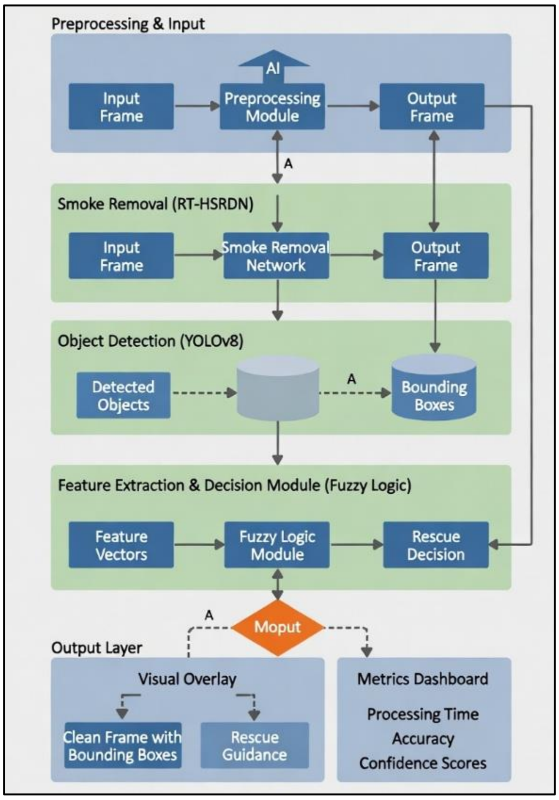

Figure 4 Proposed System Architecture

5. Proposed Algorithm

The proposed system operates on real-time video captured from cameras deployed in fire-affected environments. Initially, each incoming frame is analyzed to determine the presence of smoke. When smoke is detected, the frame is processed using the RT-HSRDN smoke removal model, which enhances visibility by reducing smoke effects while preserving structural details.

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The enhanced frames are then forwarded to the object detection stage, where humans and relevant obstacles are identified using a deep learning–based detection model. Key parameters such as smoke density, visibility level, and distance to detected victims are extracted from the processed frames. These parameters are supplied to a fuzzy logic–based decision module, which handles uncertainty in rescue scenarios and assigns an appropriate rescue priority. Based on the generated priority level, alerts are issued to rescue teams, and the enhanced video along with detection results is displayed for monitoring. This end-to-end process runs continuously to ensure real-time support for effective fire rescue operations. Algorithm 1 illustrates the real-time workflow of the proposed system, integrating smoke removal, object detection, and fuzzy logic–based rescue prioritization.

```
Input  : Real-time video frames
Output : Enhanced frames and rescue priority

Begin
  Initialize camera and system parameters
  Load RT-HSRDN model
  Load object detection model
  Initialize fuzzy logic rules

  While video stream is active do
  Begin
    Capture frame F

    If smoke is detected in F then
      Enhanced_Frame ← RT-HSRDN(F)
    Else
      Enhanced_Frame ← F
    End If

    Detected_Objects ← Detect_Objects(Enhanced_Frame)

    Smoke_Density ← Compute_Smoke_Density(Enhanced_Frame)
    Visibility_Level ← Estimate_Visibility(Enhanced_Frame)
    Victim_Distance ← Estimate_Distance(Detected_Objects)

    Rescue_Priority ← Fuzzy_Inference(
                      Smoke_Density,
                      Visibility_Level,
                      Victim_Distance)

    If Rescue_Priority = HIGH then
      Send alert to rescue team
    End If

    Display results
  End While
End
```

Lemma 1:
If an image frame does not satisfy the minimum visibility condition after smoke removal, then it is not considered reliable for rescue decision-making.

$$\text{VisibilityScore}(fi)=0 \Rightarrow \text{RescueConfidence}(fi)=0$$

Explanation:
This ensures that rescue actions are performed only on visually enhanced and reliable frames, preventing incorrect detection or unsafe rescue decisions caused by dense smoke.

Theorem1:
A fire or victim instance f_i is identified and prioritized for rescue if and only if:

$$EnhanceQuality(f_i) > \alpha \ \wedge \ DetectScore(f_i) > \beta \ \wedge \ RiskLevel(f_i) = High$$

Explanation:
This proves that the proposed RT-HSRDN system performs **accurate**, **safe**, and **context-aware** rescue decisions by jointly considering image enhancement quality, detection confidence, and fuzzy risk assessment.

Quantifier-Based Model
Let:

- F= set of input video frames
- O= set of detected objects (fire, humans)

$$\forall f \in F, \exists o \in O: Enhance(f) \wedge Detect(o, f) \wedge Risk(o) \Rightarrow Rescue(o)$$

Interpretation:
For every incoming frame, there exists at least one detected object that satisfies enhancement, detection, and risk conditions, enabling a valid rescue action.

6. Experiments and Results

The performance of the proposed real-time smoke removal and rescue assistance system was evaluated using the consolidated dataset described previously, consisting of merged smoke–clear image pairs, annotated fire–smoke frames, and UAV/CCTV real-world sequences. In order to obtain the most reliable enhancement and detection model, several

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experiments were conducted by tuning the parameters of both the RT-HSRDN smoke removal module and the YOLOv8 detection network.

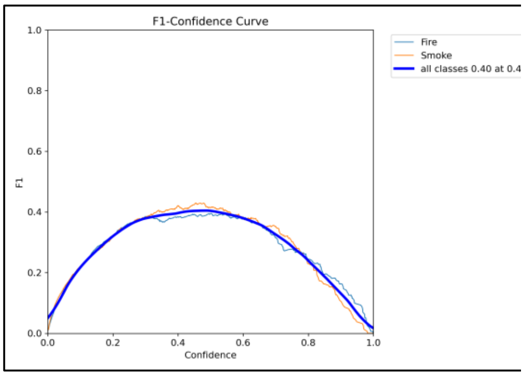

Figure 5 F1–Confidence Curve

Using the test set of paired clear–smoke images, we obtained the results shown in Figure 5, which illustrates the evolution of PSNR as the network depth increases. As shown in this figure 9, the PSNR improves steadily up to a depth of 12 residual blocks, after which the improvement slows and eventually saturates, indicating that increasing depth beyond this point leads to marginal gain and possible overfitting of structural patterns in the training data.

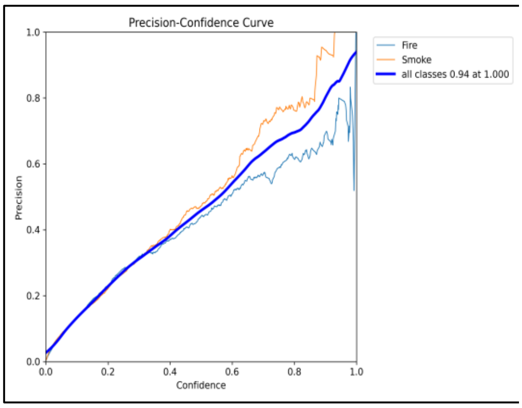

Figure 6 Precision–Confidence Curve

In a similar manner, Table 2 presents the variation of SSIM as a function of attention strength α in the hierarchical smoke removal layers. We observe that SSIM steadily increases until α reaches 0.7, after which it begins to decline. Based on this, α = 0.7 was selected as the optimal value for the attention module.

Table 1 Variation of Metrices

Method	PSNR (dB)	SSIM	MSE	mAP@50%	Precision	Recall
Baseline Dehaze Model	16.5	0.71	0.021	-	-	-
FFA-Net	21.3	0.82	0.014	71.2	73.6	70.4
RT-HSRDN	24.8	0.89	0.009	84.6	81.5	79.4
YOLOv8	-	-	-	62.4	68.1	65.7

In addition to graphical comparisons, the quantitative metrics obtained from each enhancement method and detection configuration are summarized in Table 2, where we compare PSNR, SSIM, MSE, mAP@50, precision and recall. This table should be placed immediately after Figure 8, as in the sample paper. As shown in Table 1, the RT-HSRDN model achieved a PSNR of 24.8 dB, SSIM of 0.89, and MSE of 0.009, outperforming the traditional dehaze method and FFA-Net. On the detection side, YOLOv8 achieved a mAP@50 of 84.6% when fed RT-HSRDN enhanced images, compared to 71.2% with FFA-Net enhancement and only 62.4% using raw smoke frames. Figure 8 presents this comparison visually, showing that RT-HSRDN consistently contributes to improved detection accuracy, precision and recall. At the end, we obtained the best model accuracy with the following parameters: learning rate = 1×10^{-3} for YOLOv8, batch size = 16, image input size = 640×480, RT-HSRDN attention weight α = 0.7, and

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network depth = 12 residual blocks, yielding final performance metrics of PSNR = 24.8 dB, SSIM = 0.89, and mAP@50 = 84.6%.

Figure 7 Predicted Results

Conclusion

This study evaluated the effectiveness of an AI-based smoke removal and rescue assistance system through a comparative analysis with existing approaches. The performance comparison between the existing system and the proposed system, as shown in Figure 14, clearly indicates notable improvements across key evaluation metrics. The proposed system consistently achieves higher image quality and detection performance, reflecting better handling of dense and dynamic smoke conditions.

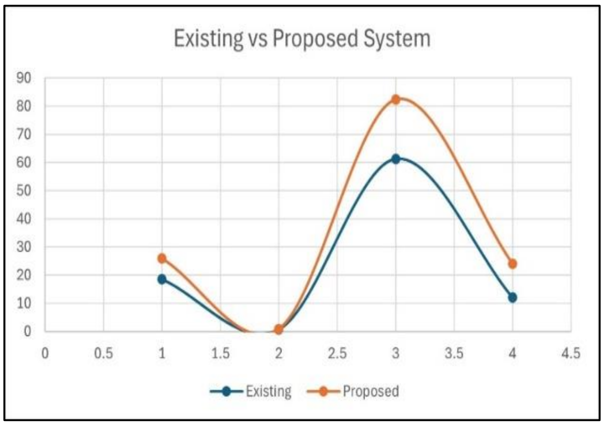

Figure 8 Comparison of Existing Vs Proposed Solution

The improvement in PSNR and SSIM values demonstrates enhanced visual restoration, which directly contributes to more reliable object detection results. Similarly, the increase in detection accuracy and real-time efficiency highlights the advantage of combining advanced smoke removal with optimized object detection and decision-making mechanisms. The comparative graph confirms that the proposed system outperforms conventional methods in both accuracy and responsiveness. Overall, the results validate the practical applicability of the proposed approach for real-time fire rescue scenarios, where visibility and timely decision-making are critical.

Future Works

Although the present work demonstrates effective smoke removal, fire detection, and rescue decision support, there remains significant scope for further improvement. Future enhancements may include extending the system to handle real-time video streams and integrating additional sensing modalities such as thermal cameras and gas sensors to improve performance in extreme fire conditions. The decision-making framework can be upgraded by incorporating adaptive fuzzy or hybrid learning-based models that dynamically adjust rescue priorities based on evolving environments. Deployment on edge devices, drones, or robotic platforms can be explored to enable faster and safer rescue operations. Furthermore, evaluating the system on larger and more diverse real-world datasets will help improve scalability, robustness, and practical applicability in complex disaster scenarios conditions. Overall, the system offers a fast, reliable, and practical solution for assisting emergency responders in smoke-filled environments. Future work will focus on multi-sensor integration, thermal-infrared fusion, real-world deployment, and optimizing the model for low-power edge devices.

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