Enhancing Coal-Fired Power Plant Efficiency Through Edge Computing And Video Processing For Real-Time Emission Monitoring

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To address limitations in real-time responsiveness, spatial perception, and long-term stability in emission monitoring of coal-fired power plants, this paper proposes an edge–cloud collaborative video-based monitoring framework. The system integrates video acquisition, image preprocessing, multi-scale target detection, emission-state recognition, and cloud-based collaborative analysis into a unified pipeline. An improved YOLO-FPN model is developed to enhance the detection of plume regions, flame instances, and abnormal operating zones. In addition, a multi-node edge collaboration strategy with dynamic model updating is introduced to reduce latency and improve adaptive performance over time. Experiments conducted on a real industrial testbed demonstrate improved detection accuracy, reduced processing delay, and lower network bandwidth consumption, while maintaining stable online deployment capability.

Keywords: Coal-fired power plants; edge-cloud collaboration; video monitoring; YOLO-FPN; edge computing; real-time emission monitoring; target detection

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1. Introduction

With the advancement of global energy transformation and "dual-carbon" goals, coal-fired power plants still play an important role in ensuring stable energy supply [1]. However, stricter environmental regulations and increasing demands for energy conservation and emission reduction have made real-time emission monitoring and operational optimization important research challenges [2, 3].

Traditional coal-fired power plant monitoring mainly relies on sensor networks, CEMS, and manual inspections. However, these methods have limitations in complex environments, including poor spatial awareness, limited real-time performance, and difficulty in identifying abnormal combustion or emission diffusion under multi-device operating conditions [4]. Therefore, intelligent monitoring methods with real-time capability, spatial perception, and practical deployability are highly important [5, 6].

Industrial vision and deep learning have made video-based monitoring a key approach for industrial state perception [7]. Compared to sensors, video analytics provides richer visual information such as flame behavior and plume diffusion, enabling better monitoring in coalfired power plants [8, 9]. YOLO-FPN and CNN-based methods perform well in complex scenes, but most existing work is limited to offline or laboratory settings, making real-time large-scale deployment still challenging [10]. Improves monitoring efficiency using an edge-cloud framework and enhances clarity and conciseness of the abstract and introduction. This paper proposes an edge-cloud collaborative YOLO-FPN-based system for real-time, accurate, and adaptive emission monitoring in coal-fired power plants. The main contributions and novelty of this work can be summarised as follows:

- Proposes a multi-node edge collaboration framework for emission monitoring.

- Introduces a dynamic edge-cloud learning mechanism for continuous updates.
- Validates using a real industrial experimental platform for performance and stability.

The framework enables multi-node collaboration with cloud updates, improving scalability, spatial awareness, and long-term stability over single-node static systems.

2. The scheme presented

2.1. Overall Architecture for Video Emission Monitoring

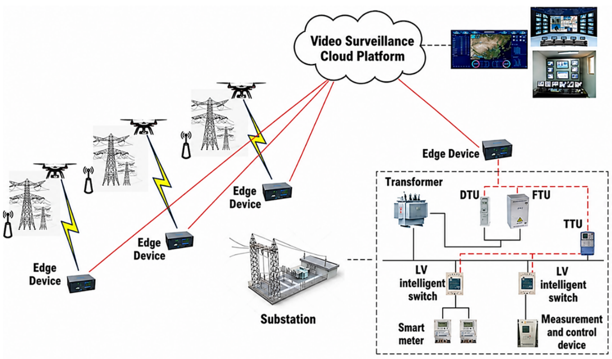

Fig. 1. Real-time video emission monitoring based on edge-cloud collaboration

As shown in Fig. 1, Edge-cloud architecture for real-time emission monitoring. The system pipelines video capture to multi-scale detection and edge-cloud analysis. Edge nodes enable real-time inference, reducing latency and bandwidth [11].

$$X_t = \{x_{t-n+1}, x_{t-n+2}, \ldots, x_t\} \tag{1}$$

X_t denotes the video sequence at time t, x_t represents an individual video frame, and n is the temporal window size. After the edge device extracts features from the video sequence, it obtains the corresponding spatiotemporal feature representation:

$$F_t = \Phi\left(X_t; \theta\right) \tag{2}$$

$\Phi(\cdot)$ is the lightweight edge model θ, and F_t is the spatiotemporal feature representation. It enables emission analysis with asynchronous edge-cloud updates for lower latency. At the control layer, cloud outputs are converted into commands to optimise emissions and efficiency.

$$\hat{Y}_t = f\left(F_t, Z_t\right), \quad \hat{\eta}_t = g\left(F_t, Z_t\right) \tag{3}$$

$\hat{Y}_t$ and $\hat{\eta}_t$ denote predicted emissions and thermal efficiency, while Z_t includes process variables like temperature, oxygen content, air-coal ratio, and load. It fuses process data with video features for combustion state representation and prediction. This architecture combines edge low-latency processing and cloud optimisation for closed-loop emission monitoring.

2.2. Model Training and Edge Online Inference Mechanism

Proposes a training and inference mechanism for low-latency monitoring with cloud-edge updates as shown in Fig. 2.

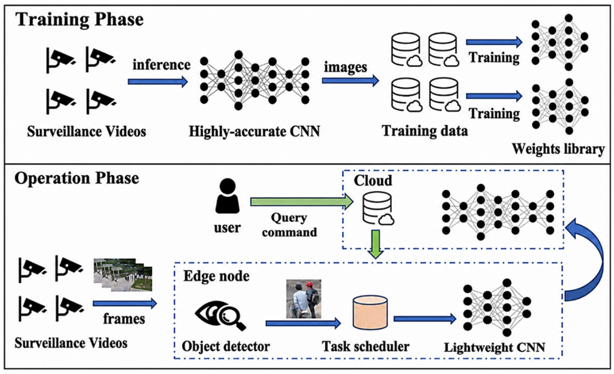

Fig. 2. Schematic diagram of model training and edge online inference mechanism

A CNN is trained in the cloud using preprocessed video frames to learn flame, flue gas, and emission features for accurate detection [12]. The video acquisition system uses industrialgrade cameras with a defined frame rate and resolution for stable and high-quality data capture. This supports scalable and robust performance in industrial environments. Video frames are used to train a cloud CNN to detect flame, flue gas, and emissions.

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{4}$$

D represents the training dataset composed of input-label pairs (x_i, y_i), where x_i is the input image, y_i is the corresponding label, and N is the total number of samples. The training objective of the high-precision model is defined as:

$$L = \frac{1}{N} \sum_{i=1}^{N} l\left(f\left(x_i; \theta\right), y_i\right) \tag{5}$$

L denotes the loss function, $f(\cdot)$ is the CNN model, θ are model parameters, and $l(\cdot)$ is the sample-wise loss function. Trained weights are stored in the cloud, and edge nodes handle realtime video detection. A timestamp-based synchronisation aligns video streams from distributed cameras, ensuring consistency before cloud analysis, while pruning and quantisation enable efficient deployment on resource-limited devices. Edge results are sent to the cloud for incremental learning, and updated models are returned to edge nodes in a closed loop. The system fuses multi-node edge outputs for low latency and robustness, with cloud updates for continuous learning and stable long-term performance.

2.3. Multi-scale emission target detection model based on improved YOLO-FPN

An improved YOLO-FPN model is deployed on edge nodes for real-time multi-scale detection of plume, emission, and combustion states in coal-fired power plants in Fig. 3.

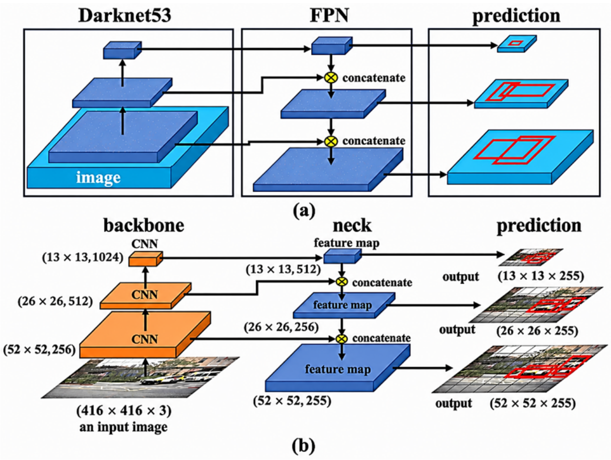

Fig. 3. Multi-scale target detection using improved YOLO-FPN

A CNN backbone extracts multi-level features such as plume edges, smoke contours, and flame patterns from video frames for stable detection [13]. Enhances YOLO with multi-scale fusion and lightweight convolutions for better plume, flame, and small-target detection.

2.4. Flame Image Preprocessing and Edge Feature Extraction

Images are preprocessed and edge features extracted to improve flame and plume detection accuracy before the model (Fig. 4).

Gaussian blur and Sobel reduce noise and extract edges [14, 15], while ROI processing improves flame features for YOLO-FPN.

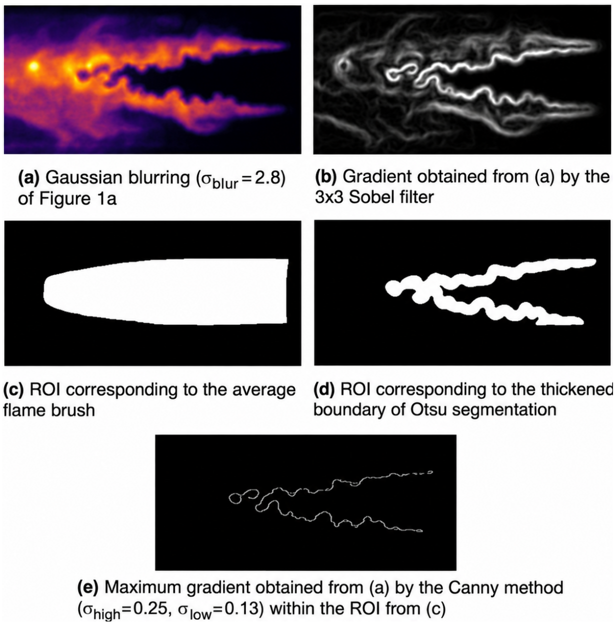

Fig. 4. Flowchart of flame image preprocessing and edge feature extraction

3. Experimental platform and field verification

3.1. Experimental Base and Field Deployment Environment

The actual scene of the experimental base is shown in Fig. 5.

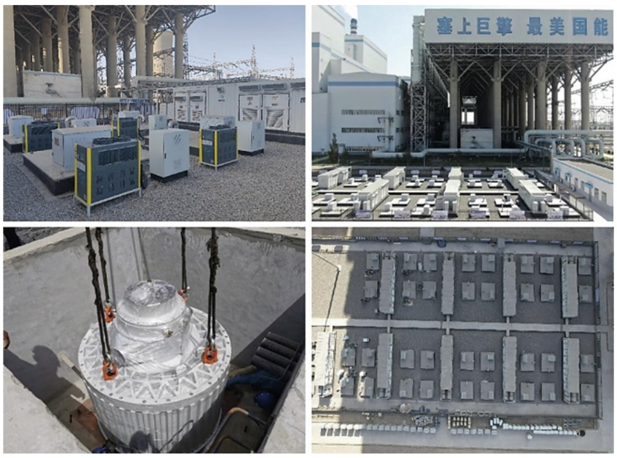

Fig. 5. Actual view of the experimental base and on-site deployment environment.

Fig. 5 shows an industrial testbed with edge devices and servers, supporting video acquisition, edge inference, cloud analysis, and control feedback.

3.2. Experimental System Deployment Scheme

Industrial cameras, edge nodes, and a central server form an edge-cloud collaborative system. The dataset has $\sim$ 120 videos and 58,000 labeled frames $(1920 \times 1080, 25\text{fps})$ for plume, flame, and emission regions, split 70:15:15. Edge inference runs on Intel i7 systems with NVIDIA GTX/RTX GPUs using Ubuntu, Python, PyTorch, and OpenCV.

3.3. Field Experiment Design

3.3.1. *Video Target Detection Experiment*

Experiments evaluate the improved YOLO-FPN model under industrial conditions for anomaly detection. Performance is assessed using accuracy, false positive rate, and false negative rate.

3.3.2. *Real-time Edge Inference Experiment*

The edge inference experiment evaluates latency, FPS, GPU usage, and memory, showing realtime efficiency and lower latency than cloud inference.

3.3.3. *multi-node collaborative experiment*

The multi-node experiment evaluates distributed edge monitoring for inference, stability, and bandwidth, verifying scalability and adaptability for large-scale deployment.

3.3.4. *Engineering Stability Test*

The stability experiments evaluate 24-72 hour operation, testing inference, device continuity, and transmission reliability to confirm robustness.

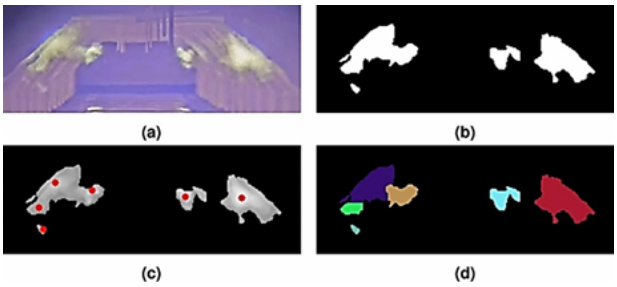

Fig. 6. Abnormal plume region detection and multi-target segmentation

Fig. 6 shows abnormal plume detection and multi-target segmentation, where YOLO-FPN accurately identifies plume regions with clear boundaries.

Fig. 7 presents flame segmentation and IoU evaluation results under different operating conditions. The baseline models (YOLOv5, YOLOv8, and Faster R-CNN) were evaluated on same dataset using identical training settings and evaluation metrics (IoU, precision, accuracy).

The Table 1 show that the proposed method consistently outperforms the baseline, achieving higher accuracy, precision, recall, and overall detection performance while reducing error rates.

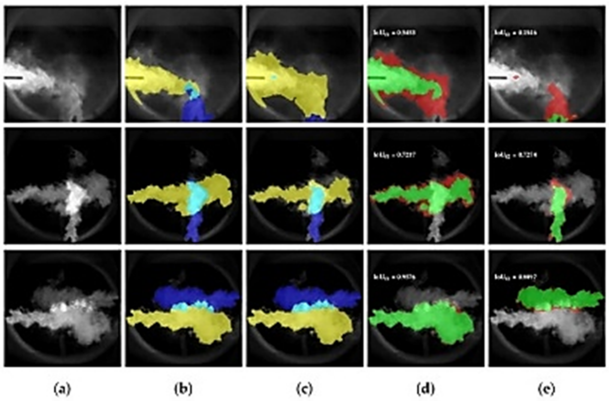

Fig. 7. Flame segmentation and IoU evaluation under multiple operating conditions

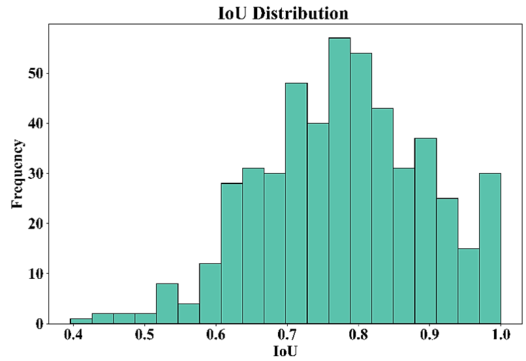

Fig. 8. Distribution of Intersection over Union (IoU) Scores

Fig. 8 illustrates the frequency distribution of IoU values, showing that most detections achieve high overlap accuracy concentrated between 0.7 and 0.9 .

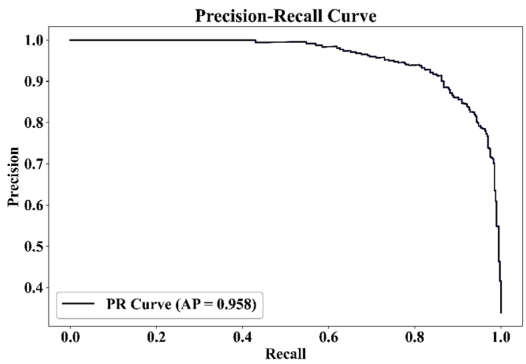

Fig. 9. Precision-Recall Curve of the Proposed Model

Fig. 9 shows the trade-off between precision and recall, indicating strong performance with a high average precision (AP $\approx$ 0.958).

Fig. 10 demonstrates the model's ability to distinguish

Table 1. Performance Comparison of Proposed YOLO-FPN Improved Model vs Baseline

Metric	Proposed Method (YOLOFPN Improved)	Baseline Method
Mean IoU (mIoU)	0.781	0.624
Precision	0.946	0.882
Recall	0.921	0.865
F1-score	0.933	0.873
mAP@0.5	0.952	0.891
mAP@0.5:0.95	0.874	0.732
False Positive Rate	0.054	0.118
False Negative Rate	0.079	0.135

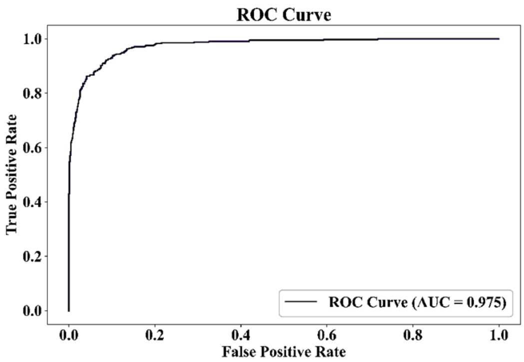

Fig. 10. Receiver Operating Characteristic (ROC) Curve of the Proposed Model

between classes, achieving a high AUC of approximately 0.975 , which reflects excellent classification performance.

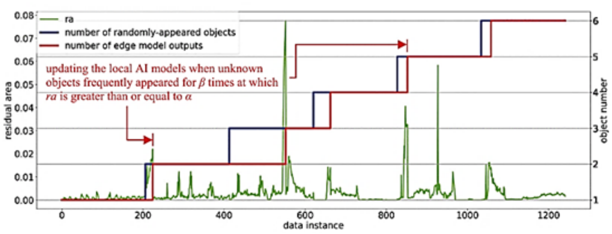

Fig. 11. Dynamic updating of edge AI models and adaptive learning for unknown targets.

Edge model updates adapt to unknown targets to maintain low errors (Fig. 11).

Fig. 12 shows the proposed method achieves low latency and balanced bandwidth. The system enhances combustion efficiency through edge-cloud detection and aligns well with CEMS for reliable emission monitoring.

Table 2 presents statistical results of latency and bandwidth for different deployment schemes, showing that edge-based and collaborative methods outperform the cloud-only approach.

Table 3 shows strong agreement between predicted emissions and CEMS measurements, confirming the system's

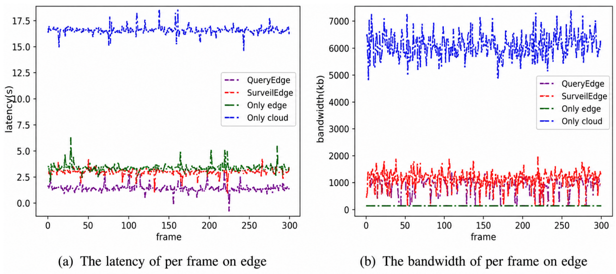

Fig. 12. Comparison of latency and bandwidth under different deployment schemes

reliability.

4. Conclusion

This paper proposes a real-time emission monitoring system for coal-fired power plants using edge-cloud collaboration and video processing. An improved YOLO-FPN model, combined with image preprocessing and edge feature extraction, enables accurate detection of abnormal plume and flame regions with strong robustness in complex dynamic environments. The system supports real-time edge inference, cloud-based analysis, and dynamic model updates for efficient closed-loop monitoring. Experimental results demonstrate reduced latency, lower bandwidth consumption, and stable long-term performance in industrial scenarios. At the system level, real-world experiments verified the proposed multi-node edge collaborative framework. Results show that the method reduces processing latency and network bandwidth usage while maintaining high detection performance. Dynamic model updates also enable adaptive online learning for unknown targets and new anomalies, improving long-term operational stability. Real-world deployment is affected by environmental noise, hardware degradation, and maintenance costs, which influence system reliability. These constraints are considered to ensure the practical feasibility of the proposed edge-cloud framework.

Table 2. Latency and Bandwidth Statistical Analysis

Method	Latency (ms) Mean	Min	Max	Std Dev	Bandwidth (MB/frame) Mean	Min	Max	Std Dev
Only Cloud	210	180	250	18	12.5	10	15	1.2
Only Edge	85	70	100	8	0.8	0.6	1.0	0.1
SurveilEdge	65	55	80	6	2.5	2.0	3.0	0.3
QueryEdge	52	45	65	5	2.0	1.5	2.5	0.2

Table 3. Comparison of Video-Based Emission Predictions with CEMS Measurements

Parameter	Video-Based Prediction	CEMS Measurement	Error (%)
SO_2(ppm)	42.5	41.8	1.67
NOx (ppm)	68.2	70.0	2.57
CO_2 (%)	12.4	12.6	1.59
Opacity (%)	18.7	19.0	1.58
PM (mg/m^3)	24.1	23.6	2.12

Declarations:

Data availability

Not applicable

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Author contribution

Lingyun Yang: Conceptualisation, methodology, writing—original draft, writing—review & editing.

Minglong Wang: Supervision, model design, validation.

Qianchuan Zhao: Data curation, analysis, and interpretation.

Wenfeng Yang: Feature extraction, experiments, and validation.

Yang Li: Visualisation, result interpretation, and manuscript editing.

All authors have read and approved the final manuscript.

Ethical approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent to participate

Not applicable.

Consent to publication

All authors have provided consent for publication of this manuscript.

Competing interests

The authors declare no competing interests

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