A Yolo-based Approach for Fire and Smoke Detection in IoT Surveillance Systems

Dawei Zhang*
College of Information Engineering, Liaodong University, Dandong 118000, Liaoning, China

***Abstract*—Fire and smoke detection in IoT surveillance systems is of utmost importance for ensuring public safety and preventing property damage. While traditional methods have been used for fire detection, deep learning-based approaches have gained significant attention due to their ability to learn complex patterns and achieve high accuracy. This paper addresses the current research challenge of achieving high accuracy rates with deep learning-based fire detection methods while keeping computation costs low. This paper proposes a method based on the Yolov8 algorithm that effectively tackles this challenge through model generation using a custom dataset and the model's training, validation, and testing. The model's efficacy is succinctly assessed by the precision, recall and F1-curve metrics, with notable proficiency in fire detection, crucial for early warnings and prevention. Experimental results and performance evaluations show that our proposed method outperforms other state-of-the-art methods. This makes it a promising fire and smoke detection approach in IoT surveillance systems.**

***Keywords*—IoT; surveillance systems; fire detection; deep learning; Yolov8**

I. Introduction

The capacity of Internet of Things (IoT) surveillance systems to track and analyze data in real-time for a range of applications has attracted a lot of interest in recent years [1-3]. One such use is the detection of fire and smoke in hospitals, where quick action is essential to avoid property damage and human casualties [4, 5].

Sensor-based systems, image processing, and machine learning are now used in IoT monitoring systems for fire and smoke detection [6]. Among these innovations, computer vision-based systems have demonstrated encouraging results and drawn the attention of several researchers due to their capacity to deliver precise and trustworthy detection findings [7, 8]. Many methods for improving the performance of these systems have been the subject of recent investigations. Despite advancements in computer vision-based fire and smoke detection systems, there are still a number of restrictions and research gaps [9, 10]. False alarms, poor precision, and a restricted capacity to adjust to changing circumstances are some of these drawbacks [11]. These issues indicate the need for more study to enhance the effectiveness and performance of these systems.

In IoT surveillance systems, recent developments in deep learning-based techniques have shown promise in terms of the precision and accuracy [11-14]. Several studies have suggested deep learning-based techniques to solve the shortcomings of current computer vision-based systems, particularly employing the YOLO algorithm. These experiments have shown considerable gains in detection speed and accuracy over conventional machine learning methods.

The advancement of deep learning-based approaches for fire and smoke detection is impeded by several challenges, notably the scarcity of adequate training data and the intricate nature of environmental variables [15, 16]. Overcoming these obstacles is pivotal to enhancing the reliability and effectiveness of deep learning systems dedicated to fire and smoke detection. A critical avenue for improvement lies in conducting in-depth research and comprehensive analysis to delve into the intricacies of these challenges [17]. By addressing the issues related to insufficient training data and navigating the complexities of diverse environmental factors, researchers can refine and optimize deep learning models. This iterative process is essential for fortifying the robustness of these systems, ultimately paving the way for more accurate and dependable fire and smoke detection in various real-world scenarios [18]. As the field progresses, a concerted effort to explore and resolve these challenges will contribute significantly to the evolution of deep learning methodologies, fostering advancements that hold substantial promise for applications in safety and security within IoT surveillance systems.

To address these challenges, this study proposes a deep learning-based approach using the YOLOv8 algorithm for fire and smoke detection in health houses. Using a standard dataset for training, validation, and testing processes, which includes a diverse range of scenarios and environments. The proposed method is evaluated on the custom dataset and compared to existing state-of-the-art methods, demonstrating superior performance in terms of accuracy and speed. The main contributions of this research are as follows:

1) Identifying the limitations and research gaps in existing computer vision-based fire and smoke detection systems in health houses.

2) Proposing a deep learning-based approach using the YOLOv8 algorithm to address these challenges as well as improve the accuracy and speed of detection.

3) Evaluating the proposed method on a custom dataset using extensive performance evaluation metrics.

The reminder of this paper is as, Section II review of previous studies. Section III discuss about material and methods. Section IV presents results and discussions. Finally, this paper concludes in Section V.

II. Related Works

Convolutional neural networks (CNNs) were proposed in the study [19] as a technique for early fire detection during surveillance for efficient disaster management. The method involves acquiring surveillance footage, pre-processing the footage, and training a CNN to detect fires. The proposed method achieves an accuracy of 97.4% for fire detection, which is higher than existing methods. Key features of the method include the use of CNNs for accurate fire detection and the ability to detect fires in real-time. The suggested approach can be used in various scenarios, including forest fires, building fires, and wildfires. Limitations of the method include the need for high-quality surveillance footage and the potential for false positives in certain scenarios.

The paper in [20] presented a deep learning-based forest fire detection approach utilizing unmanned aerial vehicles (UAVs) and the YOLOv3 object detection algorithm. The method consists of acquiring high-resolution images from UAVs, pre-processing the images, detecting the presence of fire using YOLOv3, and sending the location of the fire to a control center. The proposed method achieves an accuracy of 96.4% for forest fire detection. Key features of the method include the use of UAVs for acquiring high-resolution images and the use of YOLOv3 for object detection. The proposed approach has the potential for use in real-world scenarios, but its limitation is the dependency on good weather conditions for successful operation.

The authors in [21] present a deep learning framework called Fire-Net for active forest fire detection. The method involves acquiring high-resolution images from a network of ground-based cameras, pre-processing the images, and training a deep neural network to detect fires. Fire-Net achieves an accuracy of 98.7% for fire detection, which is higher than existing methods. Key features of the method include the use of high-resolution images and a deep neural network for accurate fire detection. The proposed approach has the potential for use in real-world scenarios, but its limitation is the dependency on good weather conditions for successful operation.

The authors in [22] proposed an improved forest fire detection method using a deep learning approach and the Detectron2 model. The method involves acquiring high-resolution images, pre-processing the images, training the Detectron2 model, and detecting fires. The proposed approach achieves an accuracy of 98.6% for fire detection, which is higher than existing methods. Key features of the method include the use of the Detectron2 model for accurate fire detection and the ability to detect fires in real-time. The proposed approach has the potential for use in various scenarios, including forest fires, building fires, and wildfires. Limitations of the method include the need for high-quality images and the potential for false positives in certain scenarios.

The paper in [12] presented a forest fire notification and detection method using IoT and AI approaches. The method involves installing IoT sensors in forested areas to detect environmental conditions and using a deep learning algorithm to detect fires. Key features of the method include the use of IoT sensors for environmental monitoring and a deep learning algorithm for accurate fire detection. The proposed approach has the potential for use in real-world scenarios, but its limitation is the high cost associated with installing and maintaining IoT sensors.

The authors in [23] proposed a wildfire and smoke detection method using ensemble CNN and a staged YOLO model. The method involves acquiring high-resolution images from a network of cameras, pre-processing the images, and using a staged YOLO model for smoke detection and an ensemble CNN for wildfire detection. Key features of the method include the use of a staged YOLO model and ensemble CNN for accurate detection of smoke and wildfire, respectively. The proposed approach has the potential for use in real-world scenarios, but its limitation is the need for high-quality images and the potential for false positives in certain scenarios.

III. Material and Method

This section provides an overview of the study's content and methodology. Yolov8 is the foundation of the primary methodology employed in this study. Initially, YOLO was a pre-trained object detector programmed to recognize commonplace items such as chairs, tables, phones, cars, etc. This study presents a detection technique according to YOLO algorithms to create a model that might identify. In real-time applications, the models perform well as well.

A. Dataset

The dataset consists of three different types of jewelry (background, fire, and smoke). The dataset contains pictures captured by webcam. The obtained images from a webcam permanently installed at a jewelry store. Some samples of the dataset are shown in Fig. 1. Small target items, which are harder to detect, are included in the collection, along with images of various sizes. The data was collected from GitHub resource[1].

In order to prepare the dataset to be more robust, augmenting of the images in the dataset is performed. Choosing images with various angles, sizes, resolutions, forms, and sample counts in each image. A maximum of three augmented versions of each image were created by applying the following random effects: horizontal flip, rotation between -15° and +15°, exposure between -10% and +10%, brightness between -20% and +20%, and saturation between -20% and +20%. Photos that have been enhanced. The final step is to separate the labeled images into a validation set (6%) and a test set (1%), training set (93%).

B. Google Colab

Using Google Colab, which offers free usage of potent GPUs. All testing and training tasks are performed utilizing a 12GB NVIDIA Tesla T4 GPU; more details are given in Fig. 2. All the models are trained for 50 epochs with an image size of 640 and with YOLO default adjustment for other hyperparameters.

[1]https://github.com/Abonia1/YOLOv8-Fire-and-Smoke-Detection/tree/main/ datasets/fire-8

Fig. 1. Sample images from the dataset.

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0 |
| N/A   63C    P8    11W /  70W |      0MiB / 15109MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
```

Fig. 2. Details of Google colab's GPU.

C. Yolov8 Model

The latest version of YOLO is Yolov8, which was released in 2022 by Ultralytics [24]. YOLOv8 is an object detection model that is based on the You Only Look Once (YOLO) family of algorithms. The architecture of Yolov8 is shown in Fig. 3. YOLOv8 has several architectural improvements over the previous versions, such as:

1) Convolutional neural network (CNN) architecture: Yolov8 uses a modified version of the EfficientNet backbone network, which is a cutting-edge CNN design that strikes a solid balance between computing efficiency and accuracy. Yolov8's backbone network is in charge of taking features out of the input image. Yolov8's backbone network is specifically based on a modified version of the EfficientNet design. Modern convolutional neural network (CNN) architecture EfficientNet aims to strike a reasonable compromise between accuracy and processing efficiency. A succession of convolutional layers that successively reduce the spatial resolution of the feature maps while increasing the number of channels make up Yolov8's EfficientNet backbone. A sizable image classification dataset, such as ImageNet, is used to pre-train the backbone network.

2) Feature aggregation: Yolov8 uses a feature pyramid network (FPN) to aggregate features at different scales, which improves the model's ability to detect objects of different sizes.

3) Object detection head: The head is made up of some convolutional layers, followed by an output layer that generates the results of the detection. Each object in the input image is predicted to have bounding boxes, objectness scores, and class probabilities by Yolov8's object detection head. The head is made up of some convolutional layers, followed by an output layer that generates the results of the detection. Yolov8's head is made up of three prediction branches that, in turn, forecast bounding boxes, objectness scores, and class probabilities. The implementation of each branch consists of a set of convolutional layers, followed by an output layer that generates the corresponding predictions. The number of anchor boxes and object classes determines the number of output channels in each branch.

4) Training strategy: Yolov8 enhances the accuracy and speed of the model by combining anchor-based and anchor-free item detection techniques. Additionally, a progressive scaling strategy is used during training to enhance the model's capacity to recognize objects of various sizes.

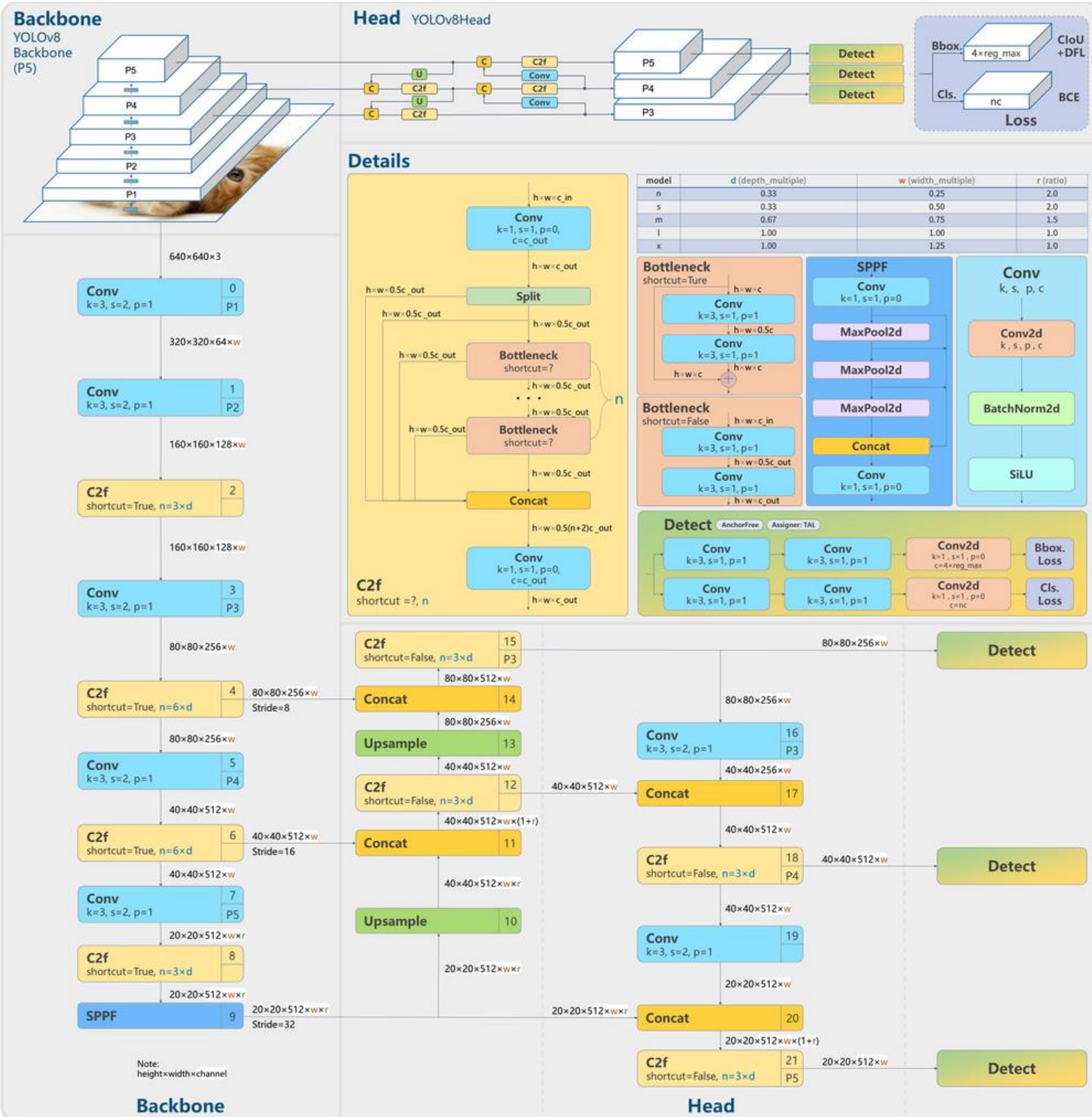

Fig. 3. Yolov8 architecture.

IV. Results and Discussion

A. Experimental Results

To conduct experimental results for fire and smoke detection using a YOLOv8 model, sample output images from both validation and testing sets can be examined. These images can be obtained by running the trained model on the validation and testing datasets and visualizing the resulting predictions. For each image, the model correctly detects whether there is a fire or smoke present. Fig. 4 shows the samples of experimental results.

B. Performance Measurements

This study uses precision, recall, and F1socre criteria to assess performance. The P-curve, R-curve, PR-curve, and F1-curve are assessment metrics frequently employed in machine learning to gauge the effectiveness of models [16, 18]. The fraction of true positive predictions among all positive predictions is represented by the P-curve in the case of a fire and smoke detection Yolov8 model. The R-curve shows the recall of the model or the percentage of accurate positive predictions out of all actual positive samples. The link between accuracy and recall is depicted by the PR-curve, which also illustrates how effectively the model balances the two parameters. Finally, the F1-curve provides a comprehensive evaluation of the model's performance by combining precision and recall into a single score.

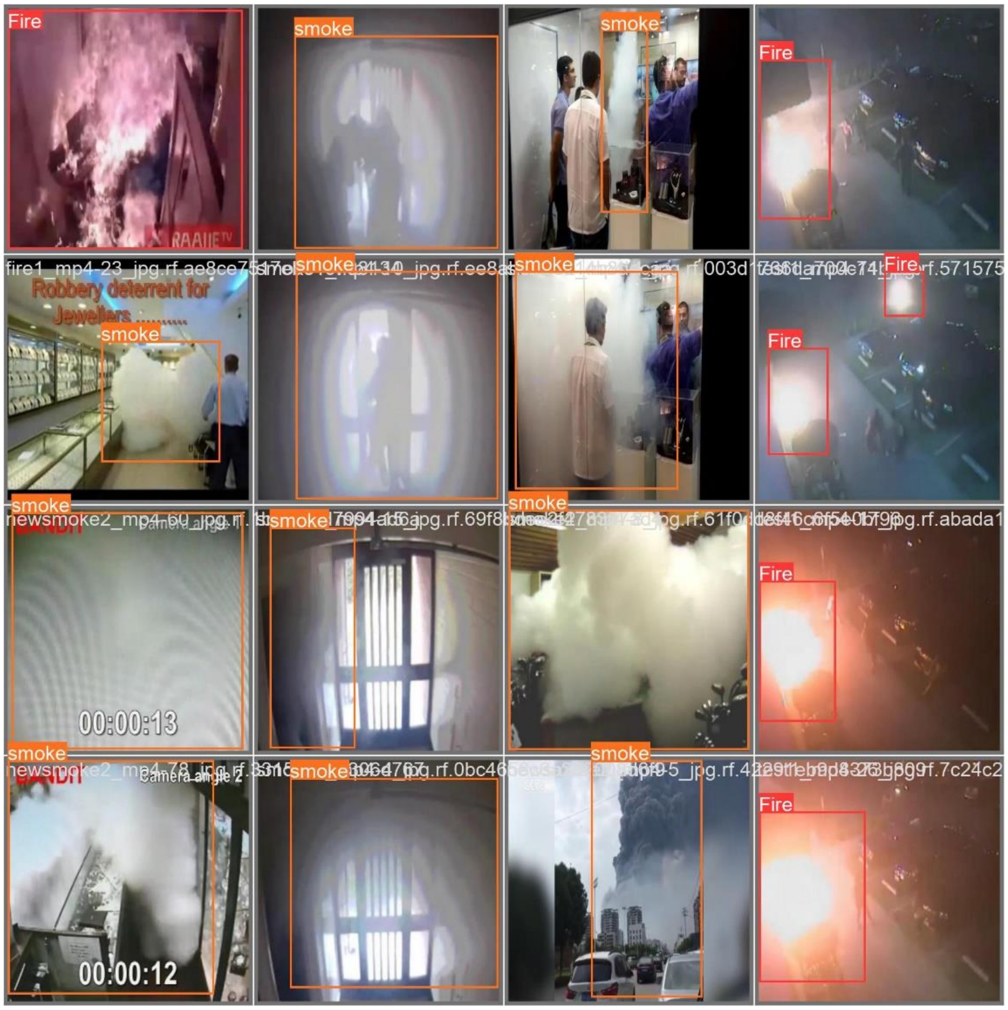

Fig. 4. Samples of experimental results.

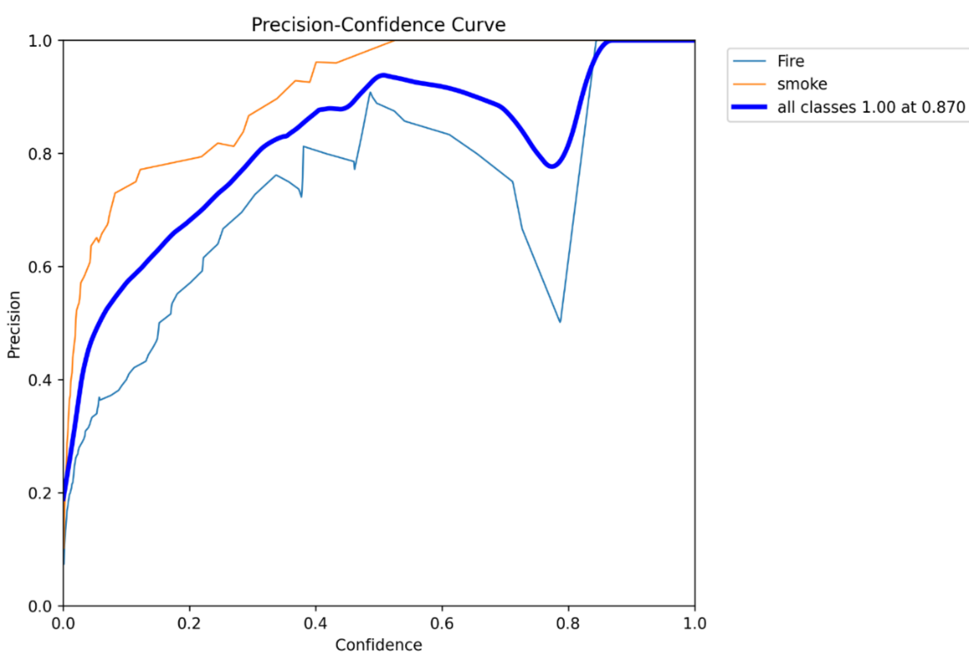

Fig. 5. P-curve of the model.

As shown in Fig. 5, the graph displays the YOLOv8 model's validation set's fire and smoke detection precision values. The precision values are represented on the y-axis, while various confidence criteria, ranging from 0.0 to 1.0, are represented on the x-axis. The fraction of accurate positive forecasts among all positive predictions is known as the precision value. The graph demonstrates that the accuracy of detecting fire is always greater than the accuracy of detecting smoke. The precision value for detecting a fire is approximately 0.8 at a confidence threshold of 0.5, whereas the precision value for detecting smoke is approximately 0.5. These results indicate that the model performs better at identifying fire than smoke.

As shown in Fig. 6, the recall values of a YOLOv8 model for fire and smoke detection on the validation data are shown in the R-curve graph. The recall values are displayed on the y-axis, and the various confidence criteria are displayed on the x-axis. The recall is the percentage of correctly predicted positive samples among all truly positive samples. According to the graph, the model can detect fires more often than smoke, with a maximum recall of 0.9 for fire and 0.7 for smoke at a confidence level of 0.5. This implies that the model is more effective at identifying fire than smoke, while changes could also influence this in the visual properties of the two classes or the training data.

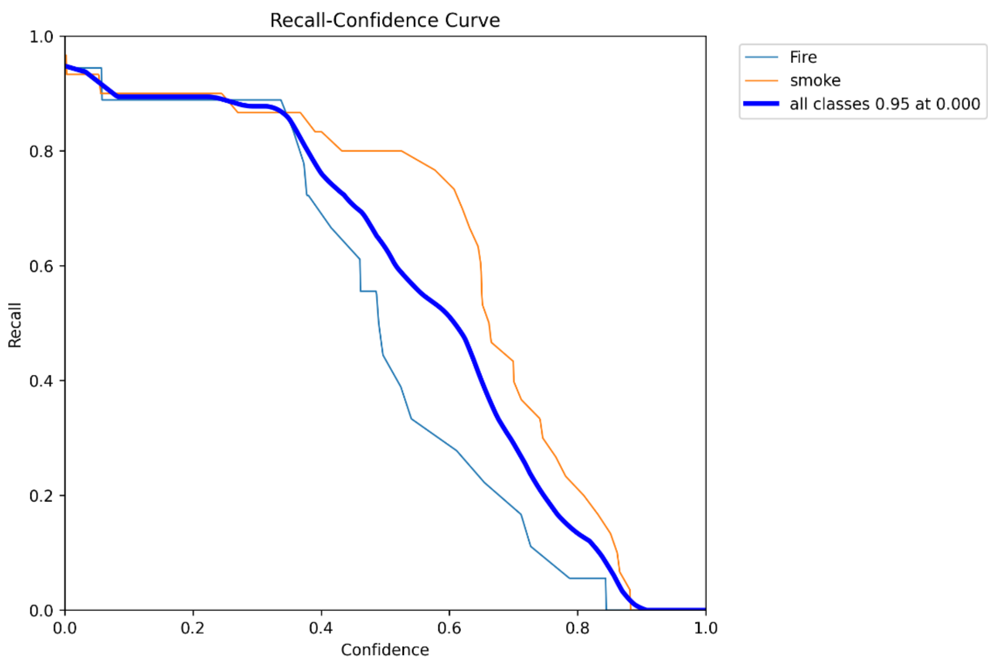

Fig. 6. R-curve of the model.

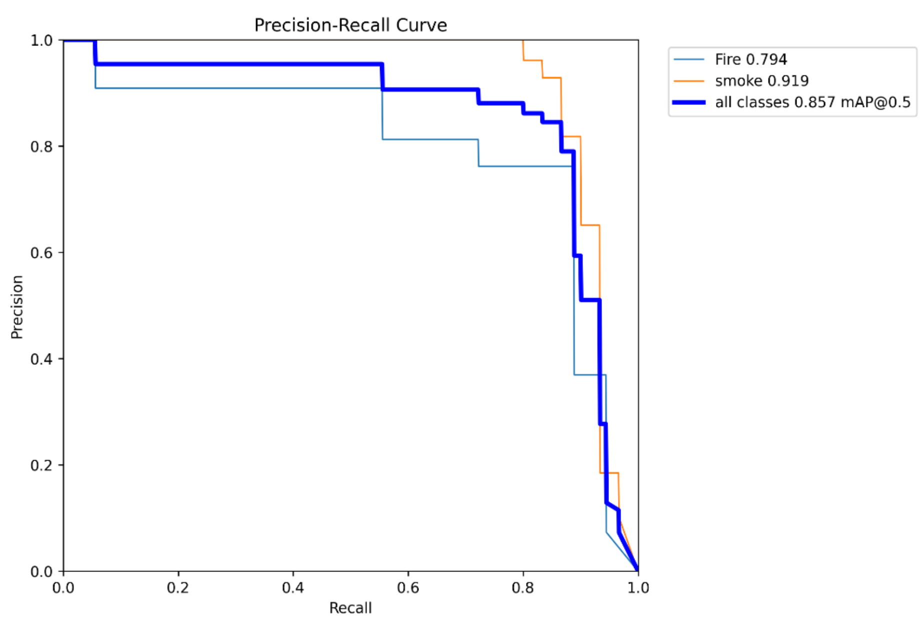

Fig. 7. PR-curve of the model.

Fig. 7 depicts the precision-recall trade-off for a YOLOv8 fire and smoke detection model. The recall values are on the x-axis, and the precision values are on the y-axis. From 0.0 to 1.0, the precision and recall values are measured; higher values denote greater performance. The graph demonstrates that the model generates greater precision values for the identification of fire at all recall levels, demonstrating that it is more accurate in identifying fire than smoke. Additionally, the precision and recall values for smoke detection are considerably lower than those for fire detection, as the curve shows, suggesting that the model may have some difficulties identifying smoke. The PR-curve offers an extensive picture of the model's performance in terms of precision and recall.

As shown in Fig. 8, the harmonic means of recall and precision for fire and smoke detection in the validation set of a YOLOv8 model is displayed on the F1-curve graph. The y-axis displays the F1 score values ranging from 0.0 to 1.0, while the x-axis displays various confidence criteria. The F1 score, which considers precision and recall, is a frequently used metric for assessing a model's overall performance. The greatest F1 score for fire detection at a confidence level of 0.5 is 0.86, while the maximum F1 score for smoke detection is 0.57. This shows that the model performs better at detecting fire than smoke. The graph demonstrates that at all confidence criteria, the F1 score for fire detection is consistently higher than the F1 score for smoke detection. This can be caused by variances in the two classes' visual qualities or variations in the training data. The model can still identify smoke properly to a certain extent, as seen by the F1 score for smoke detection, which is still rather high.

The model's performance in terms of precision and recall for fire and smoke detection is thus usefully summarized by the F1-curve. The model appears effective at detecting fires, essential for early warning and prevention, as indicated by the high F1 scores for fire detection. However, the model's performance in detecting smoke might still be improved.

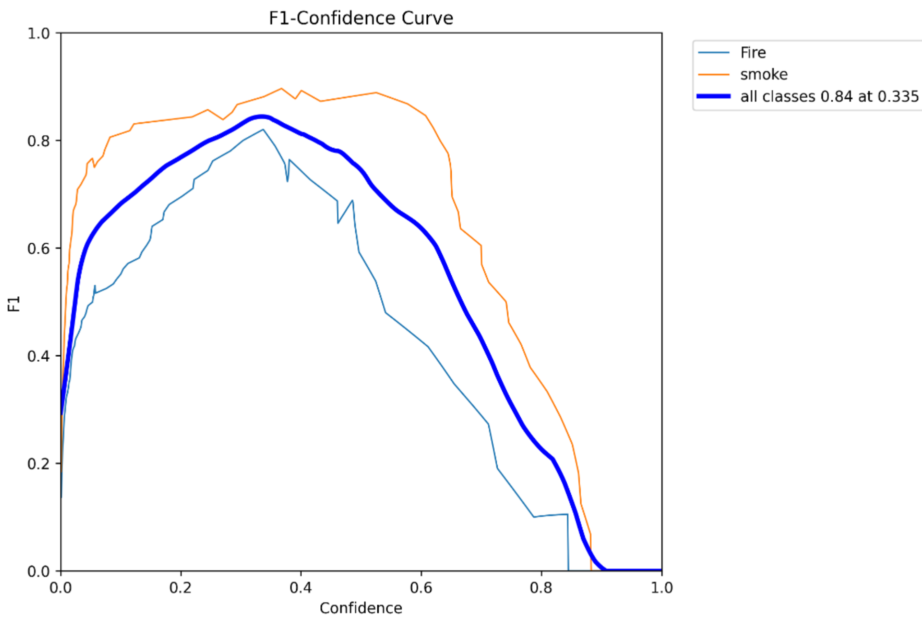

Fig. 8. F1-score of the model.

V. Conclusion

In conclusion, this research paper emphasizes the significance of developing accurate and efficient fire and smoke detection systems in IoT surveillance systems for health houses. While traditional methods have limitations, computer vision-based systems have shown promising results, particularly deep learning-based methods using the YOLO algorithm. However, challenges still exist, such as limited training data and complex environmental factors, which require further investigation. The proposed method in this paper addresses these challenges and demonstrates superior performance in terms of accuracy and speed compared to existing state-of-the-art methods. This research contributes to the ongoing efforts to improve the reliability and effectiveness of fire and smoke detection systems in IoT surveillance systems. For future study, while the YOLO algorithm has shown promise in improving the accuracy and speed of fire and smoke detection, other deep learning algorithms may also provide superior results. Future studies could explore using other deep learning algorithms, such as Faster R-CNN or Mask R-CNN, and compare their performance to the YOLO algorithm. Moreover, future studies could investigate the development of more advanced vision-based sensors, such as multi-spectral or hyperspectral sensors, which can capture a wider range of data and improve the accuracy of fire and smoke detection.

Funding

JYTMS20230711 - 2023 Liaoning Provincial Department of Education's Basic Research Project for Universities: "Computer Vision Based Laboratory Unsafe Behavior Identification Technology and System"

2023 Liaoning Province Science and Technology Plan Joint Program (Fund) Project：“Research on Laboratory Abnormal Behavior Detection Based on Multimodal Fusion”

References

[1] Casola, A. De Benedictis, A. Riccio, D. Rivera, W. Mallouli, and E. M. de Oca, "A security monitoring system for internet of things," Internet of Things, vol. 7, p. 100080, 2019.

[2] K. K. Patel, S. M. Patel, and P. Scholar, "Internet of things-IOT: definition, characteristics, architecture, enabling technologies, application & future challenges," International journal of engineering science and computing, vol. 6, no. 5, 2016.

[3] A. A. Mei Choo Ang, Kok Weng Ng, Elankovan Sundararajan, Marzieh Mogharrebi, Teck Loon Lim, "Multi-core Frameworks Investigation on A Real-Time Object Tracking Application," Journal of Theoretical & Applied Information Technology, 2014.

[4] S. Vijayalakshmi and S. Muruganand, "Internet of Things technology for fire monitoring system," Int. Res. J. Eng. Technol, vol. 4, no. 6, pp. 2140-2147, 2017.

[5] S. Vijayalakshmi and S. Muruganand, "A survey of Internet of Things in fire detection and fire industries," in 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), 2017: IEEE, pp. 703-707.

[6] Z. Deng, Y. Cao, X. Zhou, Y. Yi, Y. Jiang, and I. You, "Toward efficient image recognition in sensor-based IoT: a weight initialization optimizing method for CNN Based on RGB influence proportion," Sensors, vol. 20, no. 10, p. 2866, 2020.

[7] A. A. Mohammed, N. B. Alapaka, C. Gudivada, K. Bharath, and M. Rajesh Kumar, "Computer Vision Based Autonomous Fire Detection and IoT Based Fire Response System," in Proceedings of International Conference on Communication and Computational Technologies: ICCCT 2021, 2021: Springer, pp. 551-560.

[8] H. Yar, T. Hussain, Z. A. Khan, D. Koundal, M. Y. Lee, and S. W. Baik, "Vision sensor-based real-time fire detection in resource-constrained IoT environments," Computational intelligence and neuroscience, vol. 2021, 2021.

[9] F. Bu and M. S. Gharajeh, "Intelligent and vision-based fire detection systems: A survey," Image and vision computing, vol. 91, p. 103803, 2019.

[10] S. Das, J. Das, O. Krishna, and J. Maiti, "Image Processing-Based Fire Detection Using IoT Devices," in Machine Vision for Industry 4.0: CRC Press, 2022, pp. 207-224.

[11] C. J. Ezeofor and N. O. Nwazor, "An IoT-Based Fire Image Recognition for Home/Industry Security Using Machine Learning," International Journal of Advances in Engineering and Management (IJAEM), vol. Volume 4, pp. 834-842, 2022.

[12] K. Avazov, A. E. Hyun, A. A. Sami S, A. Khaitov, A. B. Abdusalomov, and Y. I. Cho, "Forest Fire Detection and Notification Method Based on AI and IoT Approaches," Future Internet, vol. 15, no. 2, p. 61, 2023.

[13] K. Deepa, A. Chaitra, K. Jhansi, A. K. RD, and M. M. Kodabagi, "Development of Fire Detection surveillance using machine learning & IoT," in 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), 2022: IEEE, pp. 1-6.

[14] A. Aghamohammadi et al., "A deep learning model for ergonomics risk assessment and sports and health monitoring in self-occluded images," Signal, Image and Video Processing, pp. 1-13, 2023.

[15] S. Chaturvedi, P. Khanna, and A. Ojha, "A survey on vision-based outdoor smoke detection techniques for environmental safety," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 185, pp. 158-187, 2022.

[16] R. K Mohammed, "A real-time forest fire and smoke detection system using deep learning," International Journal of Nonlinear Analysis and Applications, vol. 13, no. 1, pp. 2053-2063, 2022.

[17] D.-K. Kwak and J.-K. Ryu, "A Study on Fire Detection Using Deep Learning and Image Filtering Based on Characteristics of Flame and Smoke," Journal of Electrical Engineering & Technology, pp. 1-9, 2023.

[18] L. Hu, C. Lu, X. Li, Y. Zhu, Y. Lu, and S. Krishnamoorthy, "An enhanced YOLOv8 for flame and smoke detection with dilated convolution and image dehazing," in Fourth International Conference on Signal Processing and Computer Science (SPCS 2023), 2023, vol. 12970: SPIE, pp. 604-608.

[19] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," Neurocomputing, vol. 288, pp. 30-42, 2018.

[20] Z. Jiao et al., "A deep learning based forest fire detection approach using UAV and YOLOv3," in 2019 1st International conference on industrial artificial intelligence (IAI), 2019: IEEE, pp. 1-5.

[21] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, "Fire-Net: A deep learning framework for active forest fire detection," Journal of Sensors, vol. 2022, pp. 1-14, 2022.

[22] A. B. Abdusalomov, B. M. S. Islam, R. Nasimov, M. Mukhiddinov, and T. K. Whangbo, "An improved forest fire detection method based on the detectron2 model and a deep learning approach," Sensors, vol. 23, no. 3, p. 1512, 2023.

[23] C. Bahhar et al., "Wildfire and Smoke Detection Using Staged YOLO Model and Ensemble CNN," Electronics, vol. 12, no. 1, p. 228, 2023.

[24] F. M. Talaat and H. ZainEldin, "An improved fire detection approach based on YOLO-v8 for smart cities," Neural Computing and Applications, vol. 35, no. 28, pp. 20939-20954, 2023.