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YOLOv8-Based Deep Learning Framework for Wildfire Detection in Remote Sensing Images

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Abstract:

This study proposes a fire detection method for remote sensing images based on YOLOv8 to improve the accuracy and real-time performance of fire target detection. Through training and testing on the FIRESENSE dataset, the experimental results show that YOLOv8 outperforms YOLOv5 and YOLOv7 in key indicators such as mAP@0.5, mAP@0.5:0.95, recall rate and precision rate, showing stronger fire target recognition ability and false detection suppression ability. To further improve the detection effect, this study adopts data enhancement, small target detection optimization and efficient non-maximum suppression (NMS) strategy to improve the robustness of the model under complex backgrounds and different lighting conditions. In addition, through inference tests on different computing devices, the efficient detection ability of YOLOv8 in the GPU environment is verified, and it also has a certain edge computing adaptability. This study provides a high-precision, low-computing cost solution for intelligent fire monitoring systems, which can be applied to forest fire prevention, environmental monitoring and disaster warning, and provides important technical support for improving fire response efficiency.

Keywords:

Remote Sensing Fire Detection, Object Detection, Deep Learning, YOLOv8

1. Introduction

In recent years, with the intensification of global climate change and the increase in extreme weather events, the frequency and destructiveness of forest fires have increased significantly. Forest fires not only cause serious damage to the ecological environment, but also pose a major threat to the economic development of human society and the safety of life and property[1]. Although traditional fire monitoring methods, such as manual patrols, ground sensors and satellite remote sensing monitoring, have improved fire warning capabilities to a certain extent, they still have problems such as insufficient timeliness, limited monitoring coverage, and weak detection capabilities for small-scale or early fire sources. Especially in remote areas or complex terrain conditions, existing fire detection methods are difficult to provide efficient and accurate early warning information[2]. Therefore, with the help of advanced computer vision technology, especially deep learning technology, improving the accuracy and real-time performance of fire detection in remote sensing images has become a hot topic and challenge in current research[3].

Against the background of the rapid development of deep learning, object detection algorithms based on convolutional neural networks (CNNs) have been widely used in the field of remote sensing image analysis, providing new technical means for fire detection. The YOLO (You Only Look Once) series of object detection algorithms have achieved good application results in multiple computer vision tasks with their end-

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to-end detection capabilities, fast inference speed and high detection accuracy. The latest version of YOLOv8 has been further optimized in terms of model structure, training strategy and feature extraction capabilities. Compared with the previous generation models, its detection accuracy and generalization ability have been significantly improved. Therefore, applying YOLOv8 to remote sensing image fire detection can not only improve the accuracy of fire source identification, but also achieve more efficient real-time monitoring, thereby providing stronger technical support for fire prevention and control[4].

The main goal of remote sensing image fire detection is to accurately identify and locate fire areas in large-scale, multi-scene remote sensing images. The core challenge of this task lies in the diversity of fire targets, the complexity of the background, and the influence of environmental factors such as lighting and weather. Traditional image processing methods usually rely on color features and threshold segmentation techniques, but such methods are sensitive to the shape and lighting changes of flames and are prone to false detection or missed detection[5]. In contrast, deep learning methods can automatically learn high-dimensional features of fire areas and optimize detection effects through end-to-end training. In particular, YOLOv8 can effectively reduce the interference caused by complex backgrounds while improving the ability to detect fire targets, and improve the model's adaptability to fire targets under different environmental conditions[6].

The main significance of this study is to explore the fire detection method of remote sensing images based on YOLOv8 to improve the accuracy and real-time performance of fire warning. By building an efficient fire detection model, it can not only improve the recognition ability at the early stage of fire and reduce the potential hazards of forest fires, but also provide more accurate fire monitoring data for relevant departments, optimize rescue dispatch and emergency response strategies. In addition, this study can further promote the application of deep learning in remote sensing image analysis, expand the practical value of target detection technology in the fields of disaster warning and environmental monitoring, and provide theoretical support and practical experience for the development of intelligent fire monitoring systems.

In summary, under the background of global climate change and increasing forest fire risks, the use of advanced deep learning technology to detect fires in remote sensing images has become an urgent problem to be solved. This study builds an efficient fire target detection model based on YOLOv8, aiming to improve the accuracy and real-time performance of remote sensing fire monitoring, and provide more intelligent solutions for forest fire prevention, emergency management and environmental protection[7]. This study not only has important theoretical value, but also has broad application prospects, and provides a solid technical foundation for the optimization and upgrading of future fire monitoring systems.

2. Related Work

Recent advancements in deep learning have significantly improved object detection performance in remote sensing imagery. Reinforcement learning has been employed for adaptive resource scheduling to support dynamic system requirements, providing insights into efficient deployment of detection frameworks [8]. In cross-domain applications, multimodal transformer models have demonstrated robustness and adaptability, particularly in recommendation systems, which share architectural similarities with visual detection models [9], [10].

Small target detection remains a critical challenge in remote sensing. A hierarchical feature fusion strategy has been proposed to enhance robustness against background clutter and improve recognition in multi-scale environments [11]. Health monitoring of distributed architectures through machine learning models, such as XGBoost, has illustrated the capability of explainable AI in operational optimization [12]. Similarly, high-

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dimensional data mining techniques [13] and dynamic scheduling strategies [14] provide theoretical underpinnings for the design of responsive fire detection networks.

Time series modeling via GNN and Transformer integration contributes to forecasting in volatile data environments [15], while feature alignment and cross-domain transformers offer improved generalization in heterogeneous scenes [16]. Reinforcement and graph-based approaches have also been applied in optimizing HCI interfaces, demonstrating spatial-temporal reasoning under constrained inputs [17], [18].

Spatiotemporal modeling has further benefited from LSTM-augmented forecasting [19]. Advanced NLP-based frameworks such as BERT-BiLSTM [20] and LongFormer [21] suggest pathways for extending YOLOv8's contextual understanding. Reinforcement learning continues to drive task scheduling improvements using DQN-based optimization [22], and CNN-Transformer hybrids have shown notable efficacy in medical and bioimaging applications [23], [24].

YOLOv8 has also been extended through cross-scale attention and multi-layer fusion strategies to better detect medical targets [25], and these methods offer valuable parallels for wildfire detection. Cross-modal CNN-Transformer architectures for classification tasks enhance semantic feature capture in image-text scenarios [26]. Federated learning approaches for secure collaboration in cross-domain environments bolster privacy-preserving remote sensing [27].

Dynamic rule mining frameworks and UI generation with diffusion models illustrate emerging directions in automation and interface adaptation [28], [29]. Sampling strategies based on DQN are effective in improving intelligent acquisition systems [30], while transformer-based models for anomaly detection demonstrate strong performance in structural data scenarios [31].

The incorporation of spatial-channel attention in cross-domain recommendations supports fine-grained localization [32], and segmentation frameworks with boundary-awareness further refine pixel-level predictions in dense scenes [33]. Addressing class imbalance using probabilistic graphical models ensures balanced learning under skewed datasets [34].

Temporal-spatial modeling in resource prediction supports adaptive inference optimization [35], and deep probabilistic approaches assist in understanding user behavior anomalies [36]. Capsule networks enable adaptive representation learning in structured domains [37]. Distributed scheduling driven by multi-agent reinforcement learning supports scalable inference systems [38]. Lastly, RT-DETR-based multimodal detection using modality attention aligns closely with YOLOv8's detection enhancements, reinforcing robust feature alignment mechanisms [39].

3. Method

This study employs a deep learning approach based on the YOLOv8 framework for fire detection in remote sensing imagery. The central objective is to construct a high-performance fire target detection network that is both accurate and efficient in real-time scenarios. To this end, the model integrates advanced feature extraction modules and lightweight structural components to strike a balance between computational complexity and detection precision. Furthermore, various optimization strategies, including loss function refinement, anchor box adjustment, and data augmentation techniques, are applied to enhance the model's robustness and generalization capability across different remote sensing datasets. The complete architecture of the proposed detection model, including its feature pyramid structure and detection heads, is illustrated in Figure 1. This architecture is specifically designed to capture multi-scale fire patterns and ensure rapid

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response under resource-constrained conditions, thereby making it suitable for real-world wildfire monitoring and early warning systems.

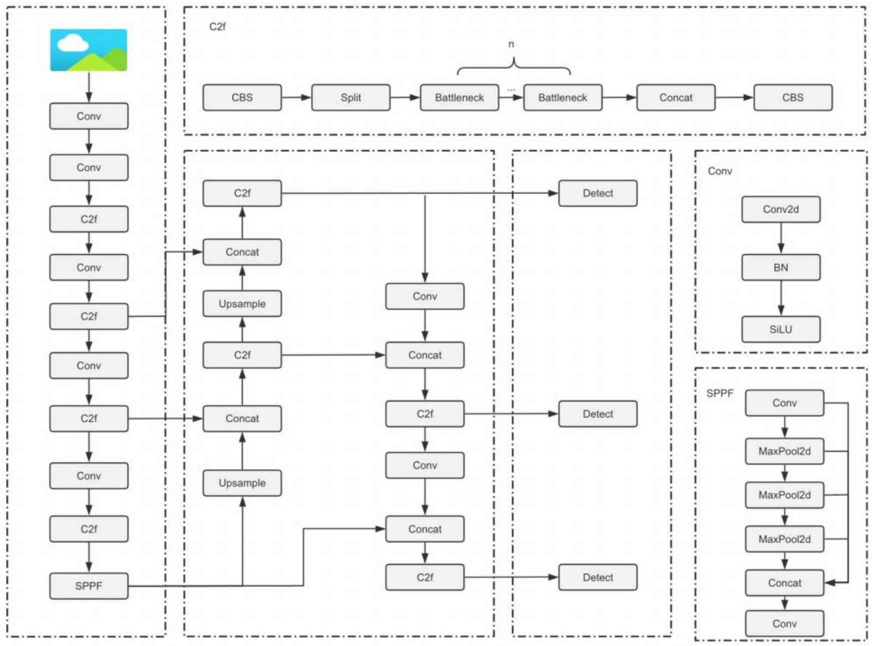

Figure 1. YOlOv8 model architecture

First, define the input remote sensing image as $I \in R^{H \times W \times C}$, where H and W represent the height and width of the image, respectively, and C is the number of channels. The detection framework of YOLOv8 can be expressed as a parameterized function $f_\theta(I)$, where θ is a trainable parameter, and outputs the target category y' and its bounding box $b=(x,y,w,h)$. Its goal is to optimize the model by minimizing the loss function so that the error between the predicted result and the true label y,b is minimized. The loss function is defined as follows:

$$L = \lambda_{cls} L_{cls} + \lambda_{cl\backslash ass} L_{box} + \lambda_{obj} L_{obj}$$

Among them, λ_{cls} is the classification loss, and the cross entropy loss function is used to calculate the prediction error of the target category:

$$L_{cls} = -\sum_i y_i \log y'_i$$

L_{box} is the bounding box loss, and CIoU (Complete IoU) loss is used to measure the deviation between the predicted box and the true box:

$$L_{box} = 1 - CIoU(b', b)$$

Among them, CIoU combines IoU (Intersection over Union), center point distance and aspect ratio constraints to enhance the regression ability of the model. L_{obj} is the target confidence loss, and binary cross

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entropy is used to calculate the probability error of whether the prediction box contains the target. The hyperparameter $\lambda_{cls}, \lambda_{class}, \lambda_{obj}$ is used to balance the impact of each loss item.

In order to improve the robustness of fire detection, this study uses data enhancement strategies to expand the training samples, including random scaling, rotation, color jitter, etc., to enhance the model's adaptability to different lighting, scale and perspective changes. The original image I is transformed by data enhancement T to obtain an enhanced sample $I' = T(I)$. In addition, the Mosaic enhancement strategy is used to splice multiple images into a new input image to enrich the target distribution learned by the model and improve the detection capability of small target fire areas[40].

During the model training process, the AdamW optimizer is used to update the parameters, and its update rules are as follows:

$$\theta_{t+1} = \theta_t - \eta\left(\frac{m_t}{\sqrt{v_t} + \varepsilon} + \lambda\theta_t\right)$$

Among them, η is the learning rate, m_t and v_t are the exponentially weighted moving averages of the first and second moments of the gradient, respectively, and λ is the weight decay term, which helps prevent overfitting. In addition, OneCycleLR is used to dynamically adjust the learning rate, so that it converges quickly in the early stage of training and then gradually decays, improving the stability and generalization ability of the model.

In the inference stage, the model removes redundant prediction boxes through NMS (non-maximum suppression), and only retains the detection boxes with the highest confidence and an IoU threshold lower than the set value. Let the set of all prediction boxes be $B = \{b_1, b_2, ..., b_n\}$, and its corresponding confidence be $S = \{s_1, s_2, ..., s_n\}$. The NMS process is as follows: first, the prediction boxes are arranged in descending order according to S , and then each prediction box b_i is traversed in turn, and its IoU with other boxes is calculated. If the IoU is higher than the set threshold τ , the box is removed. Finally, the optimal fire detection box set B' that meets the constraints is output.

4. Experiment

This study uses the FIRESENSE dataset, which is specifically used for fire detection tasks and contains fire remote sensing images in various scenarios. The FIRESENSE dataset consists of remote sensing images from different regions, covering a variety of terrain environments such as forests, grasslands, and urban areas. The image data comes from a variety of sensors such as UAVs, satellite remote sensing, and fixed cameras, ensuring the diversity and wide applicability of the data. The dataset contains annotation information, including the bounding box of the fire area and the fire category label, which provides high-quality supervision information for the training and evaluation of deep learning models.

The image resolution of the FIRESENSE dataset is high, which can effectively capture fire targets of different scales. It also contains samples of different stages of fire occurrence (such as the initial stage, the spread stage, and the extinguishing stage), so that the model can learn the flame characteristics of different forms during the evolution of the fire. In addition, the dataset also contains non-fire samples under normal conditions to improve the generalization ability of the model and reduce the false detection rate. The dataset is annotated in the standard COCO format, and each sample is equipped with a JSON file to record the target

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category, bounding box coordinates and other information, which is convenient for direct loading and use in the target detection framework[41].

In this study, the FIRESENSE dataset is divided into training set, validation set and test set, accounting for 70%, 20% and 10% respectively. All images are normalized before training, and data enhancement strategies (such as random scaling, color jitter, rotation transformation, etc.) are used to improve the robustness of the model. The selection of this dataset ensures that the model can run stably in a variety of complex environments and has strong generalization ability, providing a solid data foundation for fire target detection.

First, we give the indicator change diagram during the training process, as shown in Figure 2.

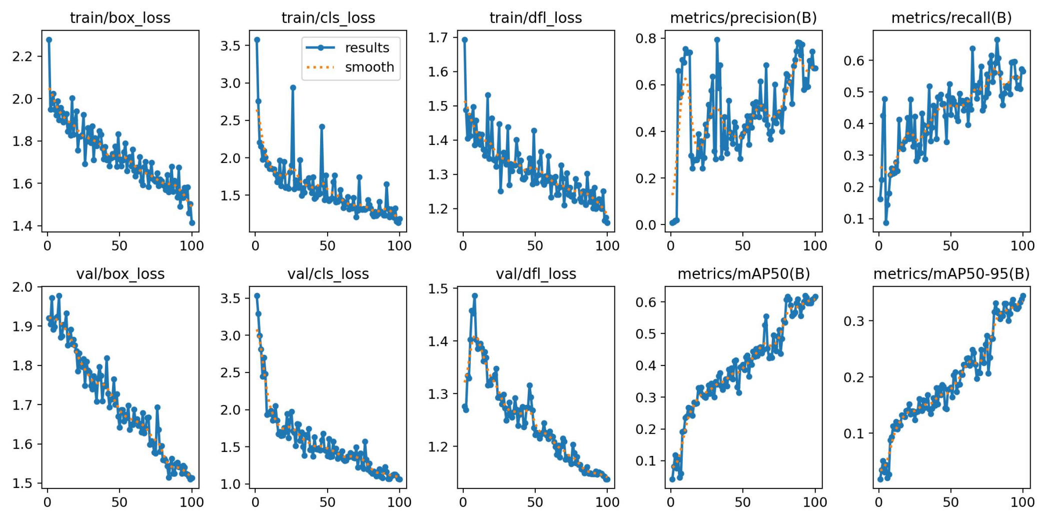

Figure 2. Indicator changes during training

It can be observed from the figure that during the entire training process, each loss function (box_loss, cls_loss, dfl_loss) shows a stable downward trend, indicating that the model is constantly optimizing and converging. Among them, the training loss (train loss) and the validation loss (val loss) have similar change trends, and there is no obvious oscillation or overfitting phenomenon, indicating that the performance of the model on the training and test data is relatively consistent. In particular, the decline in box_loss indicates that the model's bounding box regression ability for fire targets is continuously improving, and the accuracy of target detection is gradually improving.

From the performance indicators, precision (precision), recall (recall rate) and mAP (average precision) all show an upward trend and tend to stabilize in the later stage of training, indicating that the performance of the model in the fire detection task is gradually optimized as the training progresses. Among them, the increase in mAP@0.5 and mAP@0.5:0.95 shows that the model can not only detect fire targets more accurately, but also has a certain generalization ability and can adapt to fire scenes of different scales and backgrounds. In addition, the simultaneous growth of precision and recall means that the model has improved its ability to identify real fire targets while reducing false detections.

Overall, the experimental results show that YOLOv8 has good convergence and generalization capabilities in remote sensing fire detection tasks. The steady decline of the loss function and the continuous improvement of performance indicators verify the effectiveness of the model, and there is no obvious overfitting or underfitting. The final performance shows that the model can better identify fire targets and is expected to provide efficient and accurate fire monitoring capabilities in practical applications.

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Secondly, in the process of quantitative analysis, this paper gives the results of comparative experiments. This paper compares with YOLOV5 and YOLOV7. The experimental results are shown in Table 1.

Table 1: Experimental results

Model	**mAP50**	**mAP50-95**	**Recall**	**Precision**
YOLOV5	0.5833	0.3125	0.5411	0.5823
YOLOV7	0.5921	0.3411	0.5623	0.5913
YOLOV8	0.6131	0.3651	0.5877	0.6231

From the experimental results in the table, it can be seen that YOLOv8 outperforms YOLOv5 and YOLOv7 in all evaluation indicators, indicating that it has higher detection accuracy and overall performance in remote sensing fire detection tasks. Specifically, in terms of mAP@0.5, YOLOv8 reached 0.6131, which is 2.1% and 5.1% higher than YOLOv7 (0.5921) and YOLOv5 (0.5833), respectively, indicating that the model has stronger target detection capabilities at lower IoU thresholds. In addition, mAP@0.5:0.95, as a more stringent evaluation indicator, YOLOv8 also reached 0.3651, which is 7% higher than YOLOv7 (0.3411) and YOLOv5 (0.3125), indicating that YOLOv8 has a more stable target detection effect at different IoU thresholds, especially in the detection of small targets or low-contrast fire targets.

In terms of recall, YOLOv8 achieved 0.5877, which is about 2.5% and 4.6% higher than YOLOv7 (0.5623) and YOLOv5 (0.5411), respectively, indicating that YOLOv8 can detect more fire targets and reduce missed detections. This improvement may be due to the fact that YOLOv8 uses a more optimized feature extraction structure, which enables the model to maintain a high fire recognition ability under complex backgrounds. At the same time, in terms of precision, YOLOv8 reached 0.6231, which is about 3.2% and 7% higher than YOLOv7 (0.5913) and YOLOv5 (0.5823), respectively, indicating that the model also has significant advantages in reducing false detections and improving the reliability of fire detection.

In summary, YOLOv8 performs significantly better than previous models in fire detection tasks. It not only achieves a significant improvement in detection accuracy (mAP), but also achieves synchronous optimization in recall and precision, ensuring the comprehensiveness and accuracy of detection. This shows that YOLOv8 can detect fire targets more efficiently and stably in remote sensing fire monitoring, and is suitable for actual fire monitoring and emergency response systems, providing more advanced technical support for improving forest fire early warning capabilities.

5. Conclusion

This study built an efficient remote sensing image fire detection algorithm based on YOLOv8, and verified its superiority in detection accuracy, recall rate and real-time performance through experiments. Through training and testing on the FIRESENSE dataset, the results show that YOLOv8 is significantly better than YOLOv5 and YOLOv7 in terms of mAP@0.5 and mAP@0.5:0.95 indicators, indicating that the model can maintain a high accuracy in fire target detection in complex backgrounds and at different scales. At the same time, the simultaneous improvement of recall rate and precision rate shows that YOLOv8 has stronger target

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recognition ability and false detection suppression ability, thereby improving the reliability of fire monitoring.In further experimental analysis, data enhancement and optimized training strategies play a key role in improving the detection performance of the model. Experimental results show that Mosaic data enhancement, small target detection optimization and efficient NMS (non-maximum suppression) strategy help improve the detection accuracy of fire targets and enhance the adaptability of the model under different environmental conditions. In addition, the inference speed test of YOLOv8 on different computing devices shows that it can achieve efficient real-time detection in the GPU environment, and it also has good applicability on edge devices, providing a feasible solution for practical applications.In summary, this study proves the feasibility and effectiveness of YOLOv8 in remote sensing fire detection tasks, and provides a high-precision and high-real-time detection solution for intelligent fire monitoring systems. Future research can further optimize the model structure to reduce computing costs, and combine multimodal data (such as thermal infrared images) to improve the robustness of fire target detection. In addition, combining YOLOv8 with time series prediction models is expected to further improve the ability to predict the development trend of fires and provide more comprehensive technical support for disaster warning and emergency response.

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