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Deep Learning Wildfire Detection to Increase Fire Safety with Yolov8

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Abstract: Object detection involves using computer vision algorithms to identify and locate objects in an image or video. In the context of wildfire detection, object detection can be used to identify features such as flames, smoke, and heat sources in satellite or drone imagery and to alert authorities to the presence of a wildfire. YOLOv8 (You Only Look Once) is a popular object detection algorithm widely used for various applications, including wildfire detection. The YOLOv8 object detection algorithm could be used to help reduce the impact of wildfires on communities and the environment. After extensive preprocessing and a well-structured 25-epoch experimental phase, the model performed well with a mean Average Precision (mAP) of 0.6, precision of 0.7, and recall of 0.57. This study advances wildfire detection methods and provides significant information.

Keywords: *computer vision, deep learning, forest fire, wildfire detection, YOLO*

1. Introduction

The data shows that fires that hit residential or residential buildings are increasing due to the use of flammable materials and elements. Not only that, but fires can also occur in forests, which human or natural factors can cause. Wildfire is one of the most common hazardous threats to human society. The expense of fighting fires and the rehabilitation that follows is unreasonably high, and the cost of controlling wildfires is rising at an exponential rate every year. The 2018 Camp Fire in California was the most expensive disaster in history, with a total loss of $12.5 billion. Other nations had comparable financial costs due to wildfires, with public spending rising by millions of dollars [1].

Wildfire detection is an essential aspect of fire safety that involves identifying and monitoring the presence of wildfires in a specific area. There are various methods for detecting wildfires, including satellite-based systems [2]–[4], ground-based sensors [5]–[7], and aerial surveillance using drones or aircraft [8]–[11]. The primary focus of the study was to examine advanced technologies to enhance early wildfire detection and real-time situational awareness to enhance firefighting efforts. Computer vision techniques were employed in analyzing satellite or drone imagery to identify critical characteristics of wildfires, such as flames, smoke, and heat sources, to notify relevant authorities promptly.

One of the challenges in detecting forest fires is the many environmental influences, such as similar background elements such as clouds, surface air, and fog, so the range varies. Natural lighting fluctuations that influence each other further exacerbate this problem. With the increasing development of artificial intelligence technology, especially in computer vision, object detection can solve this problem. Object detection is a technique that can be used in conjunction with these methods to increase the accuracy and efficiency of wildfire detection. Object detection involves using computer vision algorithms to identify and locate objects in an image or video. In the context of wildfire detection, object detection can be used to identify features such as flames, smoke, and heat sources in satellite or drone imagery and to alert authorities to the presence of a wildfire.

Object detection algorithms can be trained to recognize specific patterns and features indicative of a wildfire, such as flames' shape and intensity or smoke's color and texture. By analyzing the data from satellite, drone, or ground-based sensors, object detection algorithms can help to quickly and accurately identify and locate wildfires and provide important information about their size, location, and potential trajectory. Using object detection for wildfire detection can help reduce response times and improve the effectiveness of wildfire management efforts. It can also help to minimize the impact of wildfires on communities and the environment by allowing authorities to respond more quickly and effectively to the threat.

YOLO (You Only Look Once) [12] is a popular object detection algorithm widely used for various applications, including wildfire detection. YOLOv8 is the latest version of the YOLO algorithm and is the current state-of-the-art for object detection. One of the critical advantages of YOLOv8 is its ability to detect objects in real-time, making it well-suited for applications that require fast response times, such as wildfire detection. YOLOv8 uses a single convolutional neural network (CNN) to analyze an entire image or video frame in one pass rather than breaking it down into smaller regions like other object detection algorithms do. This allows YOLOv8 to process images and videos quickly and make predictions in real-time.

Using YOLOv8 for wildfire detection can help to improve the efficiency and accuracy of wildfire management efforts and help minimize the impact of wildfires on communities and the environment. However, it is essential to note that object detection

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algorithms like YOLOv8 are only one aspect of a comprehensive wildfire detection and management system. They should be used with other methods, like satellite-based systems and ground-based sensors. This article aims to assess the performance capabilities of YOLOv8 in detecting "fire" and "smoke". The architecture adhered to the YOLOv8 architecture and was constructed from the ground up. Subsequently, it was trained to utilize datasets obtained from Roboflow [13].

2. Related Works

Traditional methods of detecting and monitoring wildfires rely heavily on human observation and reporting, which often leads to delays in response and causes fires to spread uncontrollably [14]. Therefore, there is an urgent need for advanced technologies to enable early detection and provide real-time situational awareness to facilitate quick and effective firefighting efforts [15]. The authors [16] present a proposed forest fire detection system using drones to capture images of forests and analyze them with YOLOv3 and a small convolutional neural network. The test results show that the system is exact and fast, far exceeding expectations, proving its efficiency and practical utility as an autonomous aerial vehicle platform and fire detection system based on deep learning. Testing has determined that the algorithm's recognition rate is approximately 83%. Alireza et al. [17] also proposed using drones with the FLAME dataset. The FLAME (Fire Luminosity Air-borne-based Machine Learning Evaluation) dataset was taken in Northern Arizona. The images and videos were taken in four color palettes: normal, Fusion, White-Hot, and Green-Hot. The dataset uses both thermal and regular cameras. An ANN technique with a 76% classification accuracy was created for frame-based fire classification. Additionally, the authors employ segmentation techniques to identify fire borders precisely. The FLAME solution achieved a recall of roughly 84% and a precision of 92%.

Furthermore, Yifan et al. [18] created Light-YOLOv4, a portable detector for real-time smoke and flame detection. They made the YOLOv4 method better by using lightweight backbone networks instead of the YOLOv4 backbone network, splitting the convolution, and computing the channel and geographic region separately. Regarding flame and smoke detection tests, the Light-YOLOv4 detector demonstrated an accuracy of 86.43%, 84.86%, mAP@0.5, 70.88%, and FPS of 71 detections. The authors [19] developed an ABi-LSTM to detect smoke from forest fires. The temporal attention subnet, the bidirectional LSTM network, and the spatial feature extraction network make up the ABi-LSTM. After candidate patches are identified using the spatial feature extraction network, the ViBe background subtraction technique extracts spatial characteristics from them. An attention network concentrates on discriminative frames, while the bidirectional LSTM network uses spatial features to learn long-term smoke-related information. Using 1920 × 1080 footage from the forest fire monitoring system, the ABi-LSTM model obtained 97.8% accuracy.

From the previous research that has been discussed, frequently used metrics include accuracy, recall, precision, F1 score, map, etc. To evaluate the efficacy of object detectors, appropriate metrics tailored to the specific problem must be used. Object detection is challenging since every recognized object in an image must have a bounding box drawn precisely around it. We chose three metrics, namely precision, recall, and mAP. Equations (1) to (3) describe commonly used metrics of precision, recall, and mAP (average precision) to evaluate detection accuracy.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (1)$$

$$precission = \frac{TP}{(TP+FP)} \quad (2)$$

$$recall = \frac{TP}{(TP+FN)} \quad (3)$$

The accurate identification of an object corresponding to the dataset's actual label is known as TP (True Positive). False Positives, or FPs, result from the model incorrectly detecting an object that is not in the picture. A false negative, or FN, is an object that the model does not see but is, in reality, present. The area of overlap between the predicted bounding box and the ground truth bounding box of the actual object is measured in object detection using the intersection over unity (IoU) technique.

3. Method

In this research, the process begins with the collection of datasets pertinent to wildfire. Once the datasets are amassed, they proceed to the annotation and labeling phase, ensuring that the utilized data aligns with the research objectives. Following the annotation and labeling, the datasets undergo a preprocessing stage to prepare them for model training.

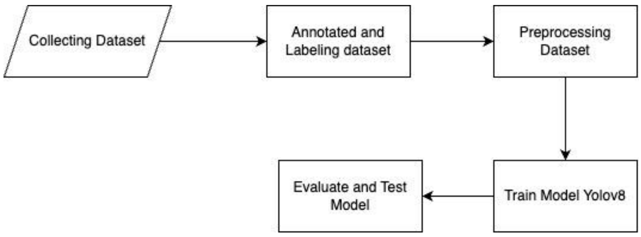

Fig. 1. Research methodology

The chosen model for this research is YOLOv8, which is trained using pre-processed datasets. Upon completion of the model training, the model undergoes evaluation and testing to ensure that its performance aligns with the expectations and objectives of the research. The evaluation and testing of the model are iterative, enhancing its performance and accuracy in detecting and classifying wildfires from the utilized datasets.

3.1. Dataset

In this research section, we focus on the dataset utilized for wildfire analysis. A comprehensive dataset consisting of 3,104 images has been curated for this study. The images are sourced from a public dataset available on Roboflow Universe, supplemented with additional wildfire images obtained from various internet sources. Each image within the dataset has been meticulously annotated, categorizing the visual content into two distinct labels: 'fire' and 'smoke'. This structured approach to labeling and categorization aims to enhance the precision and reliability of the subsequent model training and evaluation phases of the research.

3.2. Preprocessing dataset

In the preprocessing stage of the research, the curated dataset is strategically divided, allocating 70% of the images for training, 20% for validation, and the remaining 10% for testing purposes.

This allocation is meticulously done to ensure balanced and effective data utilization for various phases of the model's development. Additionally, an auto-orientation process is applied to each image, ensuring they are correctly oriented for consistent analysis. Furthermore, every image in the dataset is resized to a standard dimension of 640 x 640 pixels, promoting uniformity and consistency in the data processed and analyzed in subsequent stages of the research.

3.3. Experiment

In the experimentation phase, the YOLOv8 model is subjected to a training process utilizing the pre-processed dataset. The training is meticulously conducted over 25 epochs, ensuring that the model has adequate exposure and learning from the dataset to develop its predictive capabilities effectively. Following the training process, the model undergoes a rigorous evaluation and testing phase. In this stage, the prepared dataset assesses the model’s performance, accuracy, and reliability in identifying and classifying wildfire elements. This ensures the model is calibrated and refined for accurate wildfire prediction and analysis.

4. Result and Discussion

The primary focus of the study was to examine advanced technologies to enhance early wildfire detection and real-time situational awareness to enhance firefighting efforts. Computer vision techniques were employed in analyzing satellite or drone imagery to identify critical characteristics of wildfires, such as flames, smoke, and heat sources, to notify relevant authorities promptly.

The utilization of 3,104 annotated images served as a robust basis for the training and evaluation of the model. The results of the experimentation phase are elucidated through various performance metrics and visual assessments. A notable achievement is the model's mean Average Precision (mAP) of 0.63. This indicates balanced precision and recall in the model’s predictions. The precision of the model is recorded at 0.7, highlighting the model’s ability to identify positive instances among the predicted positives correctly. The recall of the model is 0.57, representing the model’s capability to identify positive cases in the dataset.

Referring to the provided Figure 2, the graphical representations depict the progression and optimization of the model throughout the training epochs. The training loss, validation loss, and various metrics, such as precision and recall, are meticulously plotted to visualize the model's learning trajectory and performance enhancement over the epochs.

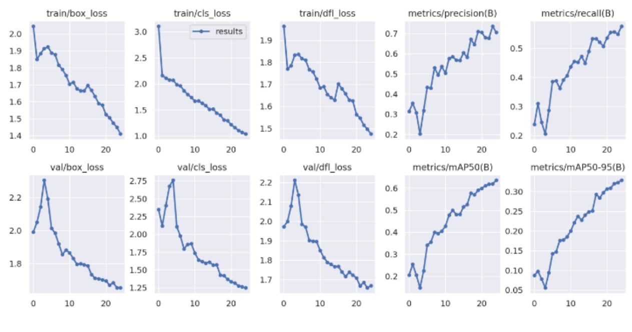

Fig. 2. Metrics evaluation

Figure 3, generated during the experiments, showcases the model's proficiency in identifying and labeling ‘fire’ and ‘smoke’ within the images, with respective confidence scores. These visual outputs corroborate the model's capabilities in effectively recognizing and distinguishing between elements pertinent to wildfires, showcasing practical applicability and reliability in a real-world wildfire identification and classification scenario.

Fig. 3. Evaluation results on the test dataset

5. Conclusion

This research demonstrated a meticulous approach to leveraging a comprehensive dataset and a robust YOLOv8 model to address wildfire detection and classification. However, it is essential to acknowledge the limitations of the study, which include the utilization of a small dataset and the absence of real-world testing. The dataset comprising 3,104 images may not encompass the entirety of wildfire scenarios. Without empirical validation, the model's efficacy in real-life scenarios may be compromised.

Subsequent investigations will aim to address these constraints and enhance the efficacy of the model. There is a need for a more extensive and diverse dataset to train the model effectively and conduct thorough real-world testing to evaluate its performance. The enhancement of accuracy and efficiency in wildfire detection systems can be achieved by exploring alternative deep-learning algorithms and techniques.

Using YOLOv8 for wildfire detection can bring about a paradigm shift in wildfire management through enhanced operational efficiency and heightened precision, thereby mitigating the adverse impacts on the environment and local communities.

The utilization of YOLOv8 for wildfire detection has the potential to bring about a paradigm shift in wildfire management through enhanced operational efficiency and heightened precision, thereby mitigating the adverse impacts on the environment and local communities.

The findings of the study are expected to enhance the efficacy of early wildfire detection and real-time situational awareness technologies. The potential impact of deep learning algorithms such as YOLOv8 on wildfire detection and management is significant, although further investigation is warranted to comprehend its implications fully.

6. References

Author contributions

Pandu Wicaksono: Conceptualization, Methodology, Data curation**,** Writing-Original draft, Validation.

Rezki Yunanda: Data curation, Writing-Original draft preparation, Coding, Implementation.

Panji Arisaputra: Coding, Visualization, Investigation, Writing-Reviewing and Editing.

Zahra Nabila Izdihar: Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] J. V Barbosa, R. A. O. Nunes, M. C. M. Alvim-Ferraz, F. G. Martins, and S. I. V Sousa, "Health and Economic Burden of the 2017 Portuguese Extreme Wildland Fires on Children," *Int J Environ Res Public Health*, vol. 19, no. 1, 2022, doi: 10.3390/ijerph19010593.

[2] G. Mazzeo *et al.*, "Integrated Satellite System for Fire Detection and Prioritization," *Remote Sens (Basel)*, vol. 14, no. 2, 2022, doi: 10.3390/rs14020335.

[3] K. Thangavel *et al.*, "Autonomous Satellite Wildfire Detection Using Hyperspectral Imagery and Neural Networks: A Case Study on Australian Wildfire," *Remote Sens (Basel)*, vol. 15, no. 3, 2023, doi: 10.3390/rs15030720.

[4] Y. Chen *et al.*, "California wildfire spread derived using VIIRS satellite observations and an object-based tracking system," *Sci Data*, vol. 9, no. 1, p. 249, 2022, doi: 10.1038/s41597-022-01343-0.

[5] D. Stipaničev *et al.*, "Vision based wildfire and natural risk observers," in *2012 3rd International Conference on Image Processing Theory, Tools and Applications (IPTA)*, 2012, pp. 37–42. doi: 10.1109/IPTA.2012.6469518.

[6] A. K. Agirman and K. Tasdemir, "BLSTM based night-time wildfire detection from video," *PLoS One*, vol. 17, no. 6, pp. e0269161-, Jun. 2022, [Online]. Available: https://doi.org/10.1371/journal.pone.0269161

[7] J. Shi, W. Wang, Y. Gao, and N. Yu, "Optimal Placement and Intelligent Smoke Detection Algorithm for Wildfire-Monitoring Cameras," *IEEE Access*, vol. 8, pp. 72326–72339, 2020, doi: 10.1109/ACCESS.2020.2987991.

[8] T. Barmpoutis Panagiotis and Stathaki, "A Novel Framework for Early Fire Detection Using Terrestrial and Aerial 360-Degree Images," in *Advanced Concepts for Intelligent Vision Systems*, P. and P. W. and P. D. and S. P. Blanc-Talon Jacques and Delmas, Ed., Cham: Springer International Publishing, 2020, pp. 63–74.

[9] K. Govil, M. L. Welch, J. T. Ball, and C. R. Pennypacker, "Preliminary Results from a Wildfire Detection System Using Deep Learning on Remote Camera Images," *Remote Sens (Basel)*, vol. 12, no. 1, 2020, doi: 10.3390/rs12010166.

[10] K. Dimitropoulos, P. Barmpoutis, and N. Grammalidis, "Higher Order Linear Dynamical Systems for Smoke Detection in Video Surveillance Applications," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 5, pp. 1143–1154, 2017, doi: 10.1109/TCSVT.2016.2527340.

[11] P. Barmpoutis, T. Stathaki, K. Dimitropoulos, and N. Grammalidis, "Early Fire Detection Based on Aerial 360-Degree Sensors, Deep Convolution Neural Networks and Exploitation of Fire Dynamic Textures," *Remote Sens (Basel)*, vol. 12, no. 19, 2020, doi: 10.3390/rs12193177.

[12] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 779–788, 2015, [Online]. Available: https://api.semanticscholar.org/CorpusID:206594738

[13] B. Dwyer, J. Nelson, J. Solawetz, and others, *Roboflow (version 1.0)[software]*.

[14] D. Kinaneva, G. Hristov, G. Georgiev, P. Kyuchukov, and P. Zahariev, "An artificial intelligence approach to real-time automatic smoke detection by unmanned aerial vehicles and forest observation systems," in *2020 International Conference on Biomedical Innovations and Applications (BIA)*, 2020, pp. 133–138. doi: 10.1109/BIA50171.2020.9244498.

[15] S. Jazebi, F. de León, and A. Nelson, "Review of Wildfire Management Techniques—Part II: Urgent Call for Investment in Research and Development of Preventative Solutions," *IEEE Transactions on Power Delivery*, vol. 35, no. 1, pp. 440–450, 2020, doi: 10.1109/TPWRD.2019.2930095.

[16] 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, pp. 1–5. doi: 10.1109/ICIAI.2019.8850815.

[17] A. Shamsoshoara, F. Afghah, A. Razi, L. Zheng, P. Z. Fulé, and E. Blasch, "Aerial imagery pile burn detection using deep learning: The FLAME dataset," *Computer Networks*, vol. 193, p. 108001, 2021, doi: https://doi.org/10.1016/j.comnet.2021.108001.

[18] Y. Wang, C. Hua, W. Ding, and R. Wu, “Real-time detection of flame and smoke using an improved YOLOv4 network,” *Signal Image Video Process*, vol. 16, no. 4, pp. 1109–1116, 2022, doi: 10.1007/s11760-021-02060-8.

[19] Y. Cao, F. Yang, Q. Tang, and X. Lu, “An Attention Enhanced Bidirectional LSTM for Early Forest Fire Smoke Recognition,” *IEEE Access*, vol. 7, pp. 154732–154742, 2019, doi: 10.1109/ACCESS.2019.2946712.