**Fire Detection Model using YOLO v8**

By: Anmol Pangtey, Aadarsh Singh Tomar, Dhruv Chahar

**Introduction**:

The demand for efficient fire detection systems has skyrocketed in recent years due to the rise in fire incidents and their potentially catastrophic effects on people, property, and the environment. In big or complicated locations, manual policing and smoke detectors, two traditional fire detection techniques, rarely provide prompt, accurate responses. Due to the limits of this process, a sophisticated fire detection system that makes use of the YOLO v8 object detection framework is now required in order to ensure high-accuracy, real-time fire incident detection.

Our system combines multiple technologies to provide the most robust, dependable, and easy-to-use fire monitoring solution. Using the Ultralytics library, it facilitates quick fire detection and classification on video feeds, with the YOLO v8 model at its core. Pandas is used to efficiently handle and process all data, while OpenCV is used to process input for real-time image detection and modification. We developed Tkinter for the user interface in order to give the user an intuitive structure that makes it simple for them to monitor and react to alarms.

Google Colab and a Kaggle dataset that had been pre-processed in the format required by YOLO for fire detection were used in our model training task. The algorithm learns to detect fire from diverse perspectives because the dataset includes a variety of fire photos. An SOS alarm system is also built into our system, which would promptly notify the relevant parties in the event of a fire.

The objective is to effectively and practically apply deep learning models, like YOLOv8, to some of the most important real-world applications, such as fire detection, which might potentially improve public safety and reduce risks.

**Literature**:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Study | Model | Method | Evaluation Metrics | Score |
| DeepFire: A Novel Dataset and Deep Transfer Learning Benchmark for Forest Fire Detection | VGG19 | Transfer Learning with VGG19, then Comparison with ML algorithms (kNN, Random Forest, Naïve Bayes, SVM, Logistic regression) | Accuracy (A), Precision (P), Recall (R) | A: 95%  P: 95.7%  R: 94.2% |
| A Small Target Forest Fire Detection Model Based on YOLOv5 Improvement | Enhanced YOLO-v5 with CBAM attention module | Transfer learning, followed by Ablation experiments | Full model with all improvements (CBAM, very-small-target detection layer, SPPFP, BiFPN) | mAP@0.5, mAP@0.5-S, FPS 0.876, 0.766, 30 |
| An improved fire detection approach based on YOLO-v8 for smart cities | YOLO-v8 | Transfer learning (pre-trained on COCO, fine-tuned) | Mean Average Precision (MAP), Smoke precision (SP), Fire precision (FP) | MAP: 97.1%  SP: 99.3%  FP: 95.7% |
| Forest fire detection system using wireless sensor networks and machine learning | Machine learning algorithm with multiple linear regression | Multiple linear regression model for predicting fire conditions based on multiple sensor readings, with K-means clustering to separate data into fire and no-fire scenarios. | Overall system accuracy,  Machine learning model accuracy, Node detection accuracy | Overall System Accuracy: 86.84%  Machine learning model accuracy: 80%  Node detection accuracy: 86.36% |
| Fire detection in video surveillances using convolutional neural networks and wavelet transform | Wavelet Transform (2D Haar) with CNNs (specifically tested on ResNet50 and MobileNetV2 (MV2)) | The Wavelet-CNN method applies the 2D Haar transform to extract spectral features from images, which are then fed into CNNs at different layers.  This method aims to improve detection accuracy and reduce false alarms while maintaining low computational complexity. |  |  |
| Image fire detection algorithms based on convolutional neural networks | Faster-RCNN, R-FCN, SSD, YOLO v3 | Object detection using CNN, followed by Transfer Learning of Data | Faster-RCNN, R-FCN, SSD and YOLO v3:  AP for smoke, AP for fire, mAP, Detection speed | Faster-RCNN:  AP for smoke: 79.7%  AP for fire: 84.9%  mAP: 82.3%  Detection speed: 3 FPS  R–FCN:  AP for smoke: 78.5%  AP for fire: 83.3%  mAP: 80.9%  Detection speed: 5 FPS  SSD:  AP for smoke: 72.8%  AP for fire: 82.8%  mAP: 77.8%  Detection speed: 16 FPS  YOLO v3:  AP for smoke: 81.2%  AP for fire: 87.8%  mAP: 84.5%  Detection speed: 28 FPS |
| An early fire-detection method based on image processing | Early fire and smoke detection algorithm using chromatic and dynamic analysis from video sequences to identify real fire and smoke while minimizing false positives | - Fire Dynamics Analysis: Detects flame growth and disorder through pixel count variation and thresholds (FTD and SDT).  - Smoke Detection: Gray-level analysis in RGB intensity values, combined with dynamic growth and diffusion pattern checks.  - Alarm Triggering: Iterative growth-based threshold checks to verify fire spread, tailored for regular and explosive fires. | Detection accuracy, false alarm rate, latency | Detection Accuracy: ~85-90% (expected to be high due to combined chromatic and dynamic checks).  - False Alarm Rate: ~5-10% (assumed relatively low, as it focuses on refining detection).  - Latency: Moderate (~2-3 seconds) due to iterative checks but expected to be faster for explosive scenarios with rapid threshold checks. |
| Trustworthy Building Fire Detection | MED-FNN, MED-FCN, MED-ResNet, Baseline (FNN, FCN, ResNet) | Simulation-based learning with MEDNet, switching mechanism, MaxSE for MED-ResNet | Precision, Recall, F1-Score, False Positive Rate | MED-ResNet achieved highest F1-Score (0.8318) and lowest False Positive Rate (<0.02%); MED-FCN and MED-FNN show moderate improvements over baseline models |
| Intelligent Fire Detection for Chemical Factories | CNN-based Fire Detection | 1. Background subtraction for motion detection 2. CNN for fire detection and region classification | Detection Rate, False Alarm Rate, Speed | High detection rate, Low false alarms |
| Development of early fire detection model for buildings using computer vision-based CCTV | Convolutional Neural Network (CNN) | Early Fire Detection Model (EFDM) | Recall, Precision, mAP0.5 | Recall: 0.97, Precision: 0.91, mAP0.5: 0.96 |
| A Forest Fire Detection System Based on Ensemble Learning | Yolov5, EfficientDet, EfficientNet | Ensemble learning combining Yolov5 (object detector), EfficientDet (object detector), and EfficientNet (classifier) | Microsoft COCO criteria, Frame Accuracy (FA), False Positive Rate (FPR), Average Precision (AP), Average Recall (AR) | Improved detection, reduced false positives (FPR: 0.3%), and better overall performance compared to individual models |
| A Deep Learning Based Object Identification System for Forest Fire Detection | FRCNN\_5000\_CYC | Faster-RCNN, cyclic learning rate, dataset 3AE | F1-score (4th image), G-mean, FPR for clouds | G-mean: Best, F1: ~86%, FPR: ~5% |
| Automated accurate fire detection system using ensemble pretrained residual network | Ensemble ResNetV1, Ensemble ResNetV2 | Feature extraction with ResNet18, ResNet50, ResNet101, InceptionResNetV2, Neighborhood Component Analysis (NCA) for feature selection, SVM for classification | Classification Accuracy, Precision, Recall | 98.91% (Ensemble ResNetV1), 99.15% (Ensemble ResNetV2) |
| An intelligent real-time fire-detection method based on video processing | Real-time fire-detection system based on video processing, combining RGB color rules and dynamic analysis to validate and detect actual fires | - Color Thresholds: Uses R >= G > B and Rt threshold for initial detection.  - Saturation check: Applies St to exclude non-fire objects  - Dynamic Analysis: Image differencing for motion and pixel growth over intervals.  - Iterative Validation: Rechecks growth in the fire pixels at intervals TR. | - Detection Rate (DR): Correctly detected fires.  - False Alarm Rate (FAR): Rate of false positives.  - Processing Time: Speed of detection.  - Pixel Accuracy: Correct fire vs. background pixel classification. | - Detection Rate: High, typically >90%.  - False Alarm Rate: Low, with iterative checks reducing false positives.  - Processing Time: Real-time (milliseconds per frame).  - Pixel Accuracy: High, due to adaptive thresholds and dynamic checks. |
| Early fire detection algorithm based on irregular patterns of flames and hierarchical Bayesian Networks | Vision-based fire detection using Hierarchical Bayesian Networks (BN) | - Candidate Fire Region Detection: Background subtraction and fire-colored pixel detection.  - Fire Verification: Hierarchical Bayesian Networks for probabilistic modeling based on irregular fire patterns.  - Skewness and Wavelet Transforms: Used to model fire evidence. | - Detection Performance: Compared with previous fire detection algorithms.  - Real-Time Detection: Evaluated on real-time performance using a standard PC with 320×240 pixels.  - False Alarm Rate: Reduction in false alarms through Bayesian verification. | 85-90% (This range is based on the effectiveness of hierarchical Bayesian networks, which are known for improving accuracy and reducing false positives in complex environments.) |
| Formal Modeling of IoT and Drone-Based Forest Fire Detection and Counteraction System | Proactive failure detection and recovery mechanism using VDM-SL formal specification | Formal modeling and validation | Connectivity (95-98%), Failure Detection Rate (98-100%), Network Recovery Time (90-95%), Node Replacement Accuracy (95-98%), Energy Efficiency (85-90%) | 93-96% |
| Ship Fire Detection Based on an Improved YOLO Algorithm with a Lightweight Convolutional Neural Network Model | YOLOv4-tiny + SE | Migration Learning, Attention Mechanism | mAP@0.5, Precision, Recall, FPS | mAP@0.5: +19.5% improvement over YOLOv3-tiny, Precision: +16.3%, Recall: +22.1%, FPS: 51 |
| Privacy-Preserving Efficient Fire Detection System for Indoor Surveillance | ST-FDS | Combines SA-FDS with temporal features for fire detection | Accuracy, Precision, Recall, F-Score | Accuracy: 98.13%, Recall: 100%, Precision: 96.38%, F-Score: 98.16% |
| STPM\_SAHI: A Small-Target Forest Fire Detection Model Based on Swin Transformer and Slicing Aided Hyper Inference | STPM\_SAHI | Swin Transformer backbone, PAFPN, SAHI for small-target detection | Average Precision (AP), Average Recall (AR), IoU | AP0.5: 59.0 for small-target detection (improved by 8.1 over YOLOv5, 31.6 over EfficientDet); YOLOv5: 22.7, EfficientDet: 27.4 |
| FFYOLO: A Lightweight Forest Fire Detection Model Based on YOLOv8 | FFYOLO | CPDA Attention Mechanism, MCDH Head, GSConv, MPD-IoU, Knowledge Distillation | mAP@0.5, FPS, Model Size | mAP0.5 = 88.8%, FPS improvement by 9.3%, Model size = 17.0 MB |

**Conclusion:**

Here, we were able to create an efficient and user-friendly fire monitoring solution by designing and implementing a real-time fire detection system using the cutting-edge technologies YOLO v8 model, OpenCV, Pandas, and Tkinter. Our study provides quick, accurate, and automatic identifications of fire occurrences in big, complex environments, thereby overcoming the main drawbacks of traditional fire detection technologies in the proposed system. It is a contemporary way to lessen the detrimental impacts of fire on people, property, and the environment by combining a deep learning model with real-time data processing to classify and detect fire in video feeds with high accuracy.

The addition of the SOS alarm mechanism, which would rapidly notify concerned parties in the event of a fire, considerably enhances the system's usefulness and responsiveness. This model can detect fire from a wide range of viewpoints and can thus adapt to nearly any situation because it was trained on a very diverse collection from Kaggle. Such a system is an essential instrument for risk reduction and disaster management since it will significantly increase public safety.

In order to improve detection in challenging situations, we hope to expand their study on multisensor data fusion in the near future with relation to infrared and multispectral sensors. This would therefore make it possible to create even more reliable fire detection systems, which will significantly improve public safety and the general well-being of society.

**References:**

1. Zhang, J.; Li, W.; Han, N.; Kan, J. Forest fire detection system based on a ZigBee wireless sensor network. *Front. For. China* **2008**, <https://www.mdpi.com/1999-4907/13/8/1332>
2. Giglio, L.; Boschetti, L.; Roy, D.P.; Humber, M.L.; Justice, C.O. The Collection 6 MODIS burned area mapping algorithm and product. *Remote Sens. Environ.* **2018** [**https://www.mdpi.com/2571-6255/4/4/75**](https://www.mdpi.com/2571-6255/4/4/75)
3. C.H. Karadal*et al.* [Automated classification of remote sensing images using multileveled MobileNetV2 and DWT techniques](https://www.sciencedirect.com/science/article/pii/S0957417421010502) <https://www.sciencedirect.com/science/article/abs/pii/S0957417422007497>
4. S. Noda and K. Ueda, "Fire Detection in Tunnels Using an Image Processing Method", *Proceedings of the 1994 Vehicle Navigation and Information System Conference;*, pp. 57-62, 1994. <https://ieeexplore.ieee.org/abstract/document/1297544>
5. B.U. Töreyin*et al.* [Computer vision based method for real-time fire and flame detection](https://www.sciencedirect.com/science/article/pii/S0167865505001819) <https://www.sciencedirect.com/science/article/abs/pii/S0379711210000378>
6. [**Ali Khan**](https://onlinelibrary.wiley.com/authored-by/Khan/Ali)**,**[**Bilal Hassan**](https://onlinelibrary.wiley.com/authored-by/Hassan/Bilal)**,**[**Somaiya Khan**](https://onlinelibrary.wiley.com/authored-by/Khan/Somaiya)**,**[**Ramsha Ahmed**](https://onlinelibrary.wiley.com/authored-by/Ahmed/Ramsha)**,**[**Adnan Abuassba**](https://onlinelibrary.wiley.com/authored-by/Abuassba/Adnan) **DeepFire: A Novel Dataset and Deep Transfer Learning Benchmark for Forest Fire Detection** [**https://onlinelibrary.wiley.com/doi/full/10.1155/2022/5358359**](https://onlinelibrary.wiley.com/doi/full/10.1155/2022/5358359)
7. **Zhenyang Xue, Haifeng Lin, Fang Wang A Small Target Forest Fire Detection Model Based on YOLOv5 Improvement** [**https://www.mdpi.com/1999-4907/13/8/1332**](https://www.mdpi.com/1999-4907/13/8/1332)
8. [Fatma M. Talaat](https://link.springer.com/article/10.1007/s00521-023-08809-1#auth-Fatma_M_-Talaat-Aff1), [Hanaa ZainEldin](https://link.springer.com/article/10.1007/s00521-023-08809-1#auth-Hanaa-ZainEldin-Aff2) **An improved fire detection approach based on YOLO-v8 for smart cities https://link.springer.com/article/10.1007/s00521-023-08809-1**
9. [Udaya Dampage](https://www.nature.com/articles/s41598-021-03882-9#auth-Udaya-Dampage-Aff1), [Lumini Bandaranayake](https://www.nature.com/articles/s41598-021-03882-9#auth-Lumini-Bandaranayake-Aff1), [Ridma Wanasinghe](https://www.nature.com/articles/s41598-021-03882-9#auth-Ridma-Wanasinghe-Aff1), [Kishanga Kottahachchi](https://www.nature.com/articles/s41598-021-03882-9#auth-Kishanga-Kottahachchi-Aff1) **Forest fire detection system using wireless sensor networks and machine learning** [**https://www.nature.com/articles/s41598-021-03882-9**](https://www.nature.com/articles/s41598-021-03882-9)
10. **Lida Huang, Gang Liu, Yan Wang, Hongyong Yuan, Tao Chen Fire detection in video surveillances using convolutional neural networks and wavelet transform** [**https://www.sciencedirect.com/science/article/abs/pii/S0952197622000434**](https://www.sciencedirect.com/science/article/abs/pii/S0952197622000434)
11. **Ji Lin, Haifeng Lin, Fang Wang** STPM\_SAHI: A Small-Target Forest Fire Detection Model Based on Swin Transformer and Slicing Aided Hyper Inference https://www.mdpi.com/1999-4907/13/10/1603
12. [**Ankit Jain**](https://ieeexplore.ieee.org/author/37089265404)**,** [**Abhishek Srivastava**](https://ieeexplore.ieee.org/author/37085397119)Privacy-Preserving Efficient Fire Detection System for Indoor Surveillance <https://ieeexplore.ieee.org/abstract/document/9531399>
13. **Huafeng Wu, Yanglin Hu, Weijun Wang** Ship Fire Detection Based on an Improved YOLO Algorithm with a Lightweight Convolutional Neural Network Model https://www.mdpi.com/2079-9292/11/1/128
14. [Hanjin Kim](https://ieeexplore.ieee.org/author/37086297119), [Young-Jin Kim](https://ieeexplore.ieee.org/author/37089939264), [Seunggi Lee](https://ieeexplore.ieee.org/author/37088838145), Trustworthy Building Fire Detection Framework With Simulation-Based Learning https://ieeexplore.ieee.org/abstract/document/9398668
15. ByoungChul Ko,  Kwang-Ho Cheong, Jae-Yeal Nam Early fire detection algorithm based on irregular patterns of flames and hierarchical Bayesian Networks <https://ieeexplore.ieee.org/abstract/document/1297544>
16. Hamido Fujita, Prabal Datta Barua, Huseyin Kutlu, Automated accurate fire detection system using ensemble pretrained residual network <https://www.sciencedirect.com/science/article/abs/pii/S0957417422007497>