AI PART

Artificial intelligence (AI) has become an increasingly integral part of our lives, permeating numerous fields and transforming the way we interact with the world. From healthcare and finance to transportation and entertainment, AI is driving innovation and efficiency. One particularly impactful application of AI lies in object detection, where it excels at identifying specific items within images or videos. This capability has profound implications for various sectors, including security, manufacturing, and environmental monitoring. In this project, we are specifically interested in leveraging AI for fire detection.

Historically, detecting fires was a challenging and often delayed process, leading to significant property damage, environmental destruction, and tragic loss of life. Traditional methods, such as smoke detectors and sprinkler systems, often proved insufficient in rapidly identifying and responding to fires, especially in remote or expansive areas.

AI offers a powerful solution to this problem. By analyzing visual data from cameras or sensors, AI algorithms can quickly and accurately detect the unique signatures of fire, such as flames, smoke, and heat patterns. This rapid detection enables faster response times, minimizing the spread of fire and ultimately saving lives and property. AI-powered fire detection systems can be deployed in various settings, from homes and businesses to forests and industrial facilities, providing a crucial layer of protection against the devastating consequences of fire.

Dataset Description

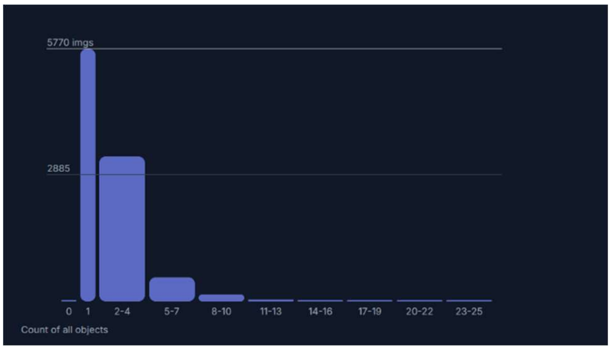
https://universe.roboflow.com/detection-e83li/smokeandfire

This dataset contains **9,848 images** used for object detection, specifically focusing on Smoke and Fire detection
and it includes a variety of images captured in both indoor and outdoor environments, ensuring that our model is trained on diverse scenarios. This improves its ability to detect objects accurately across different settings, lighting conditions, and backgrounds

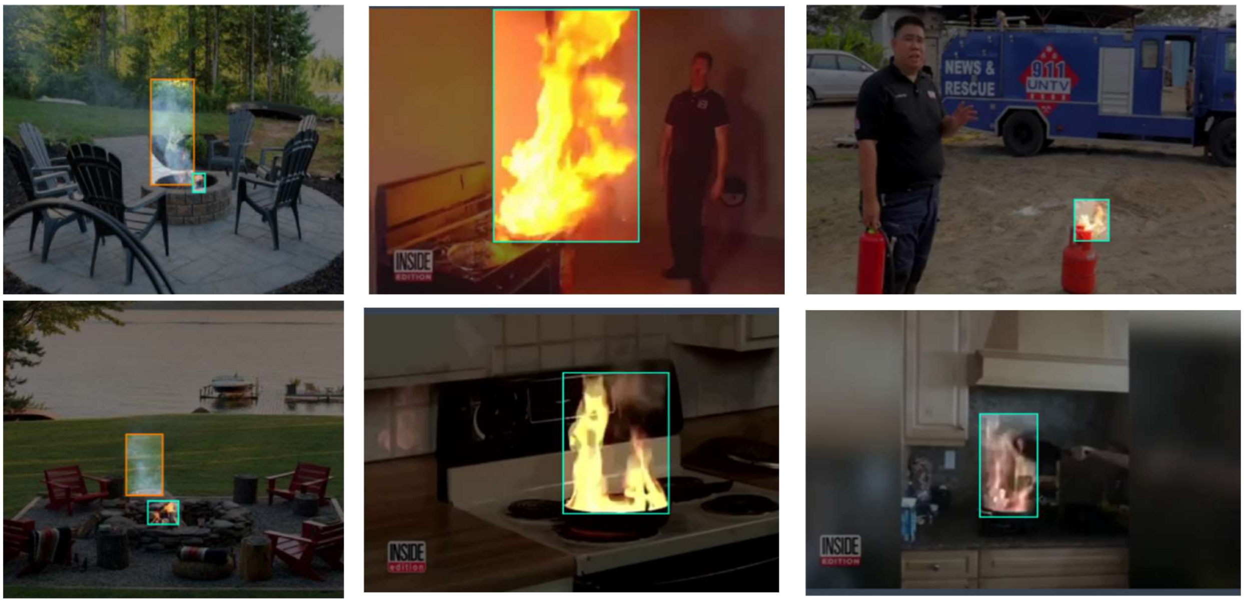
Annotations: **19,511** total annotations

- **Classes**:
  - **Fire: 13,307** annotations
  - **Smoke**: **6,204** annotations
- **Image Sizes**:
  - median size of **640x640** pixels.

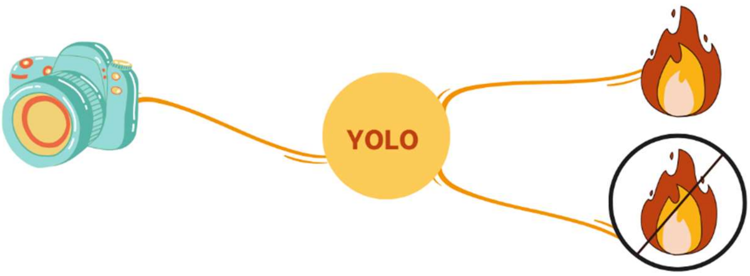
- **Object Distribution**:
    - 5,770 images contain only 1 object.
    - 2,885 images have 2-4 objects.
    - A few images contain more than 5 objects.



Samples from dataset



Our project focuses on fire detection using an AI model. As we know, early and accurate fire detection is crucial, and we're leveraging the power of YOLO (You Only Look Once) to achieve this.

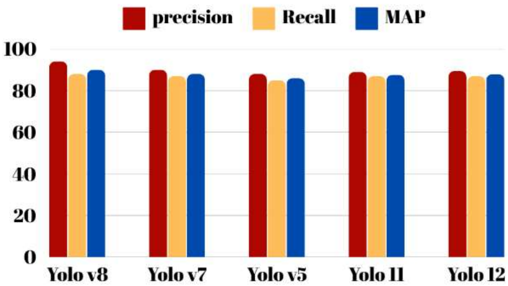


Simple Background on YOLO

YOLO is a real-time object detection algorithm that predicts bounding boxes and class probabilities for objects in a single image pass. Unlike earlier methods that relied on separate stages for region proposal and classification, YOLO performs both tasks simultaneously, making it fast and efficient.

We tested different models for fire detection, including YOLOv5, YOLOv7, YOLOv8, YOLOv11, and YOLOv12. YOLOv8 performed the best, achieving a detection accuracy (mAP) of 0.90. **YOLOv8 stands out as the best model for real-time fire detection systems.**

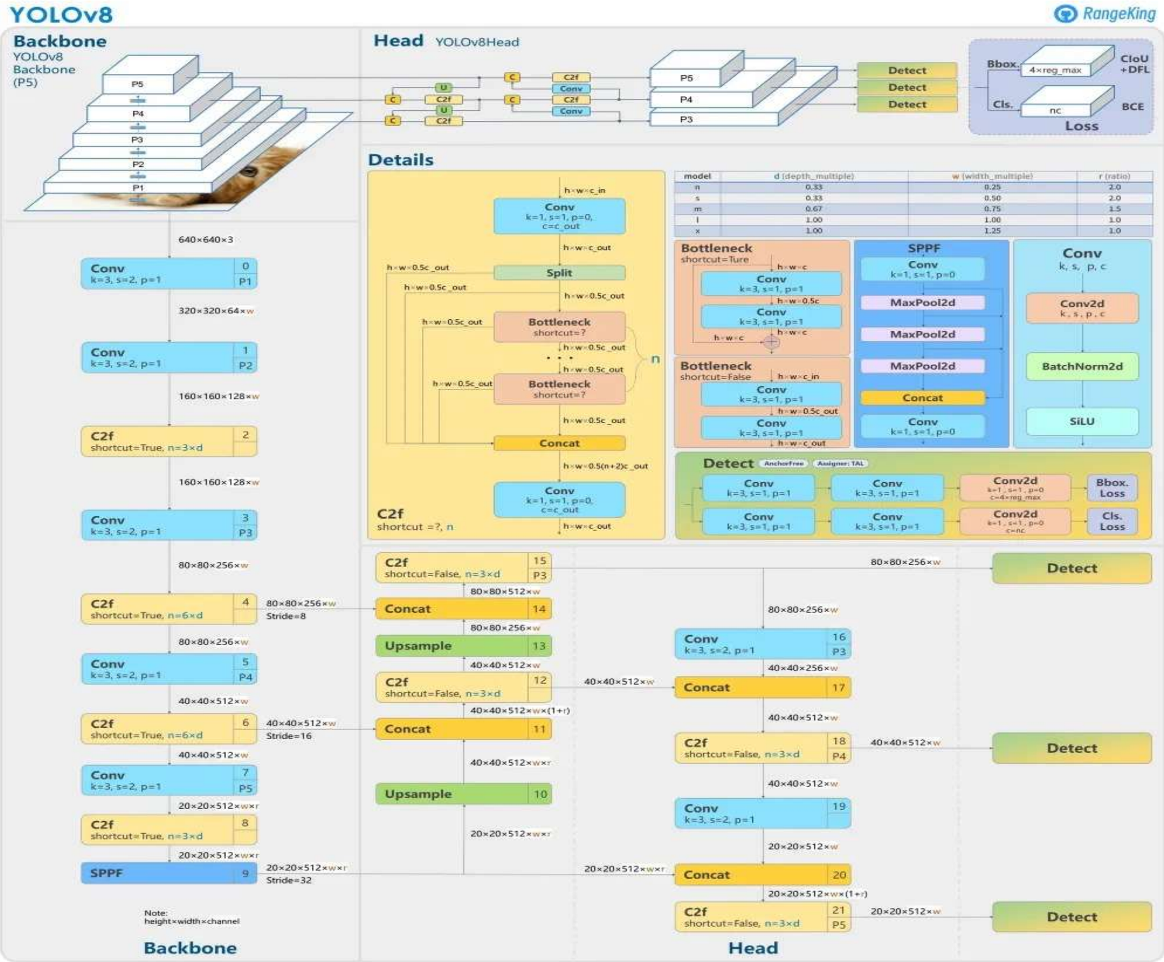
Model	MAP	precision	recall
YOLO V5	0.86	0.88	0.85
YOLO V7	0.87	89	86.2
YOLO V8	0.90	0.943	0.881
YOLO V11	0.876	0.895	0.871
YOLO V12	0.879	0.894	0.869



Also we test different sizes from yolov8

We tested different sizes of YOLOv8: Nano, Small, and Medium, training each model for 80 epochs to ensure a fair comparison. YOLOv8-Small performed the best, offering both high accuracy and fast processing.At first, YOLOv8-Medium performed well, showing promising results. However, as training progressed, it became unstable, leading to fluctuations in accuracy and performance. This instability made YOLOv8-Small the more reliable and efficient choice for real-time fire detection.

Yolo 8(Our model)



Parameters we used

parameters	Value
epochs	120
imgsz	640
batch	32
Augment	true
Lr0	0.005
weight_decay	0.0005
optimizer	SGD

Data Augmentation: The use of augmentations like mosaic, flipping, rotation, scaling, helps the model become more robust to variations in the data, improving generalization.

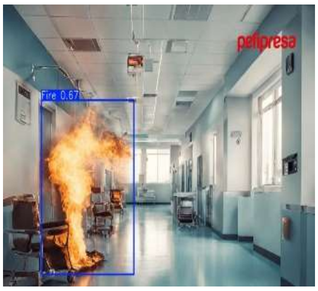
Learning Rate & Optimizer: we've chosen a relatively low learning rate with SGD optimizer, which is commonly used for fine-tuning models. This will help in steady and controlled learning

Regularization: Techniques like weight decay and augmentation help avoid overfitting, ensuring the model generalizes better on unseen data.

Results

```
Ultralytics 8.3.48 🚀 Python-3.10.12 torch-2.4.0+cu121 CUDA:0 (Tesla P100-PCIE-16GB, 16269MiB)
val: New cache created: /kaggle/working/smokeandfire-2/test/labels.cache
                   all        543       1065      0.943      0.881      0.902      0.788
                  Fire        528        748      0.965      0.951      0.963      0.819
                 Smoke        190        317      0.921      0.811      0.841      0.757
Speed: 0.6ms preprocess, 4.5ms inference, 0.0ms loss, 0.8ms postprocess per image
Results saved to runs/detect/val2
```

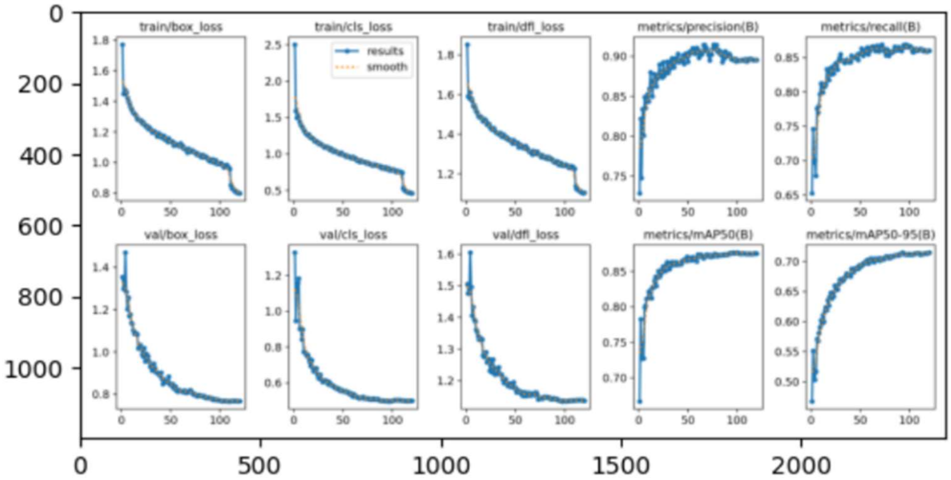
Test on new images




Test on videos

https://drive.google.com/file/d/1zXrvtEXBHXu9cwNwGDzt7nQhF6tF2L5q/view?usp=sharing

Training and validation loss



[compared our model with other models from previous research.](https://thesai.org/Publications/ViewPaper?Volume=15&Issue=3&Code=IJACSA&SerialNo=18)

https://thesai.org/Publications/ViewPaper?Volume=15&Issue=3&Code=IJACSA&SerialNo=18

One of the studies we reviewed is a paper titled "A Fire and Smoke Detection Model Based on YOLOv8 Improvement," where the authors presented an improved YOLOv8-based model with modifications such as the use of lightweight architectures and attention blocks to enhance detection performance.

After comparing the results, we found that our model outperforms in terms of accuracy

Model	Parameter	GFLops	P/%	R/%	mAP@.5/%
YOLOv8n	3011238	8.2	73.1	63.4	71.9
YOLOv8n-C2f-faster	2306038	6.4	76.8	63.2	73.4
YOLOv8n-EMA	3011252	8.2	74.4	64.2	72.6
YOLOv8n-BiFF	3122100	8.5	74.1	64.9	73.2
YOLOv8n-EBF	2416914	6.7	77.8	65.3	75.0

TABLE IV. THE RESULTS OF COMPARATIVE EXPERIMENTS

Model	Parameter	GFLops	Size/MB	P/%	R/%	mAP@.5/%
YOLOv3t	12133156	19.0	23.2	67.8	61.0	66.5
YOLOv4t	6056606	16.4	46.3	30.4	69.9	43.1
YOLOv5n	2508854	7.2	5.0	73.7	63.4	71.6
YOLOv6n	4238342	11.9	8.3	75.7	62.8	71.5
YOLOv7t	6017694	13.2	11.7	67.9	67.2	69.6
YOLO8n	3011238	8.2	6.0	73.1	63.4	71.9
YOLOv8n-EBF	2416914	6.7	4.8	77.8	65.3	75.0

Also we reviewed a paper titled "Research on Fire Smoke Detection Algorithm Based on Improved YOLOv8" https://ieeexplore.ieee.org/document/10644114
where the authors proposed an enhanced YOLOv8 model by adding a large target detection head to improve fire and smoke detection. While their approach focuses on detecting large-scale fire and smoke targets, our model achieves a higher mAP (90%) with better stability and real-time performance, making it more suitable for practical fire detection applications.

Models	P(%)	R(%)	mAP50(%)	FPS
YOLOv3-Tiny	60.3	59.6	60.3	132
YOLOv5s	71.1	62.0	69.8	125
YOLOv7-Tiny	68.6	63.7	68.3	181
YOLOv8n	70.1	64.6	71.5	426
YOLOv8n-World	73.4	65.2	72.4	413
YOLOv9-Tiny	74.3	64.3	74.1	172
YOLOv8-FEP	75.9	66.7	74.6	395

we also compared its performance with recent state-of-the-art approaches, including the Light-YOLOv8-Flame model. Light-YOLOv8-Flame reported a precision of 75.40%, recall of 63.40%, and mAP@0.5 of 68.17% on a flame detection dataset comprising 7,431 images

https://arxiv.org/abs/2504.08389

In contrast, our YOLOv8-based model achieved significantly higher performance, with a precision of 94.3%, recall of 88.1%, and mAP@0.5 of 90.2% across two classes (fire and smoke).

TABLE VI
PERFORMANCE COMPARISON OF MAINSTREAM ALGORITHMS

Model	Precision	Recall	mAP@50	FPS	Param/10^6	FLOPs
YOLOv5s	74.81%	61.04%	64.93%	70	9.11	23.8G
YOLOv6s	74.37%	61.53%	63.88%	83	16.30	44.0G
YOLOv8s	76.22%	61.35%	67.39%	77	11.13	28.4G
YOLOv9s	72.61%	63.59%	64.69%	80	7.17	26.7G
YOLOv10s	72.97%	61.83%	63.81%	75	8.04	24.4G
YOLOv11s	74.45%	62.12%	65.46%	82	9.41	21.3G
YOLOv12s	72.67%	63.40%	65.25%	79	9.23	21.2G
Light-YOLOv8-Flame	75.40%	63.40%	68.17%	78	8.31	21.4G

Compared to the state-of-the-art models reviewed in the study by Khan et al. (2024),

https://www.researchgate.net/profile/Ijist-Jr/publication/382398338_Smart_Fire_Safety_Real-Time_Segmentation_and_Alerts_Using_Deep_Learning/links/669b6fcecb7fbf12a45fbe9f/Smart-Fire-Safety-Real-Time-Segmentation-and-Alerts-Using-Deep-Learning.pdf

our fine-tuned YOLOv8 model significantly outperforms the reported versions. Their best-performing YOLOv8-large model achieved a mAP@0.5 of 74.9% and mAP@0.5:0.95 of 51.0% .In contrast, our YOLOv8 model reached a mAP@0.5 of 90.2% and mAP@0.5:0.95 of 78.8%, with a precision of 94.3% and recall of 88.1%.

	Performance Evaluation Metrics				
Model	**F1 score**	**Precision**	**Recall**	**mAP-50**	**mAP50-90**
YOLOv5-n	70.8%	79.4%	63.9%	68.7%	39.8%
YOLOv5-s	74.5%	**87.9%**	64.7%	72.5%	43.6%
YOLOv5-m	73.9%	83.9%	66.1%	72.2%	44.3%
YOLOv5-l	74.3%	87.3%	64.8%	72.7%	44.4%
YOLOv7	74.7%	86.9%	65.6%	70.7%	41.7%
YOLOv8-n	73.3%	84.9%	64.5%	72.6%	47.5%
YOLOv8-s	73.5%	85.7%	64.4%	72.3%	48.1%
YOLOv8-m	75.0%	84.7%	67.4%	**74.9%**	48.9%
YOLOv8-l	**75.7%**	85.7%	**67.9%**	**74.9%**	**51.0%**

Test against the results reported by Catargiu et al. (2024) on the FireAndSmoke dataset

https://www.mdpi.com/1424-8220/24/17/5597

Compared to their reported YOLOv8 model, our approach achieved higher performance in key metrics. Specifically, for fire detection, our model reached a Precision of 0.965 and Recall of 0.951, outperforming the paper's 0.86 Precision and 0.85 Recall.

Similarly, the mAP@50-95 for our model was 0.819, notably higher than the paper's 0.69. For smoke detection, although their model had a slightly higher recall, our model offered better mAP@50-95 and overall precision.

Model	Fire					Smoke					Other					Speed (fps)
	P	R	mAP @50	mAP @50–95	F1	P	R	mAP @50	mAP @50–95	F1	P	R	mAP @50	mAP @50–95	F1	
YOLOv5	0.86	0.86	0.91	0.69	0.86	0.88	0.82	0.89	0.66	0.85	0.80	0.78	0.84	0.69	0.79	210
YOLOv6	0.84	0.86	0.91	0.64	0.85	0.89	0.81	0.91	0.63	0.84	0.78	0.73	0.81	0.56	0.75	215
YOLOv7	0.83	0.88	0.91	0.64	0.85	0.87	0.84	0.90	0.62	0.86	0.76	0.79	0.84	0.58	0.77	230
YOLOv8	0.86	0.85	0.91	0.69	0.85	0.88	0.84	0.91	0.68	0.85	0.82	0.77	0.85	0.63	0.79	230
YOLOv9	0.85	0.85	0.91	0.69	0.85	0.88	0.85	0.91	0.68	0.85	0.76	0.68	0.84	0.63	0.72	115
YOLOv10	0.86	0.85	0.91	0.69	0.85	0.89	0.83	0.91	0.68	0.86	0.82	0.74	0.84	0.63	0.78	210

Also here

https://www.mdpi.com/2571-6255/7/4/135

Our YOLOv8-based model outperforms existing fire and smoke detection methods. Compared to models like YOLOv5, Faster R-CNN, and SSD reviewed in recent studies, our model achieves higher accuracy and faster inference. It reaches a precision of 0.965 for fire and 0.921 for smoke, with an overall mAP@0.5 of 0.902 and mAP@0.5:0.95 of 0.788

Table 1. Comparative analysis of YOLO models for smoke and fire detection.

Model	Precision	Recall	mAP:50	mAP:50-95
YOLOv8n	0.919	0.793	0.869	0.658
YOLOv8s	0.929	0.828	0.891	0.721
YOLOv8m	0.935	0.831	0.895	0.745
YOLOv8l	0.949	0.837	0.901	0.753
YOLOv8x	**0.954**	**0.848**	**0.926**	**0.772**
YOLOv7	0.881	0.778	0.854	0.647
YOLOv7-X	0.918	0.817	0.882	0.715
YOLOv7-W6	0.922	0.824	0.887	0.745
YOLOv7-E6	0.937	0.824	0.896	0.748
YOLOv6l	0.582	0.605	0.852	0.496
Faster-RCNN	0.437	0.374	0.471	0.348
DETR	0.443	0.362	0.413	0.291