A PROJECT REPORT

ON

FOREST FIRE AND SMOKE DETECTION AND CLASSIFICATION

For the partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING (A. I.)

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2024-25

Declaration

We hereby declare that the project work presented in this report entitled **"FOREST FIRE AND SMOKE DETECTION AND CLASSIFICATION",** in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science & Engineering (A.I.) , submitted to A.P.J. Abdul Kalam Technical University, Lucknow, is based on my own work carried out at the Department of Computer Science & Engineering – A.I., G.L. Bajaj Institute of Technology & Management, Greater Noida. The work contained in the report is original and project work reported in this report has not been submitted by us for the award of any other degree or diploma.

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Acknowledgement

The merciful guidance bestowed to us by the almighty made us stick out this project to a successful end. We humbly pray with sincere hearts for his guidance to continue forever.

We pay thanks to our project guide **Mr. Kaleemur Rehman** who has given guidance and light to us during this project. Her versatile knowledge has caused us in critical times during the span of this project.

We pay special thanks to our Head of Department **Dr. Sanjeev Pippal** who has been always present as a support and help us in all possible ways during this project.

We also take this opportunity to express our gratitude to all those people who have been directly and indirectly with us during the completion of the project.

We want to thank our friends who have always encouraged us during this project.

Last but not least, thanks to all the faculty of the Computer Science and Engineering department who provided valuable suggestions during the period of the project.

Abstract

As a consequence of climate change as well as human activity, wildfires are increasing around the world, and making their detection, and early response essential for preventing environmental and economic calamity. Present methods of fire detection (like satellite imagery) are slow (they're limited due to the latency of >2 hours) and prone to false alarms, making it imperative for AI to move quickly to provide these detection systems. This work proposes a deep learning based optimized YOLOv8 model for independent forest fire and/or smoke detection that also utilizes dynamic confidence-based filtering (30% image / 50% video confidence thresholds), while also utilizing Fireman Exclusion Logic to remove 89% of false positives from false object including bicycles, non-forest objects, etc. Our model was trained on 10,033 images (which were augmented with StyleGAN2-ADA to create 18,000 samples altogether), and achieves state-of-the-art results in fire detection performance, and accuracy—95.8% precision, 92.4% recall, and a 12.8% false positive rate—while also being notably faster than YOLOv7 at 30.2 FPS on a NVIDIA RTX 3090. Future work is planned and includes multi-sensor integration for fusion (thermal + visual) and federated learning for conducting adaptive wildfire prediction in remote areas.

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Chapter 1

INTRODUCTION

The increase in global temperatures, longer indisputably unnaturally long droughts, and ever increasing human activity has resulted in wildfire events that are not only now occurring more frequently, but are causing and affecting wildfires that are increasingly catastrophic. Wildfires impact not only huge areas of our forests, but can also cause catastrophic impacts on biodiversity, human lives, property, and air quality. Conventional systems to detect wildfires, e.g., satellites, thermal monitoring, and ground-based monitoring systems are generally relying on reactivity, which are high-latency, field coverage specific, and have environmental limitations, so they are not timely enough to act on, particularly during high risk situations.

In this context, the integration of artificial intelligence (AI) and supporting computer vision technologies represents a fundamentally novel solution. The Forest Fire and Smoke Detection and Classification system utilizes the features of several advanced deep learning models (in particular, the most recent and impressive version, YOLOv8 (You Only Look Once version 8)), to detect fire and smoke in both photos and videos and in turn provide alerts in real-time, display the areas of impact, and provide a percentage confidence score. By utilising a simplified frontend made using React & Tailwind CSS and a python backend that uses KaggleFlow datasets, the system allows a user to upload media files and provide back the person immediate feedback of predicted wildfire danger in the media.

The goal of this project is to improve the accuracy and performance of wildfire monitoring so that a response can be initiated quickly on low resource platforms that are deployed at the edge or through drone surveillance. This project represents a milestone in environmental conservation and emergency operations capability by incorporating an efficient, accurate, and scalable deployment system.

1.1 BACKGROUND AND MOTIVATION

Wildfires have become an increasingly prominent issue when considering disaster management as a global issue. According to the FAO (2023), more than 3.5 million hectares of forest land are lost yearly, which can have detrimentally consequences for the ecological balance and economic impact. In the United States, the National Interagency Fire Center provides an example where they reported more than 68,000 wildfire incidents in 2022 covering about 7.6 million acres of land. This all begs the question of why we cannot facilitate early, accurate, scalable detection capabilities that ensure rapid emergency responses and mobilization of resources.

Traditional fire detection means have taken the form of satellite imagery, ground-level sources of heat detection, and images from infrared cameras. These can be further categorized in relation to the regular environmental considerations, as they are often limited by many usual environmental constraints (e.g., weather, fog, cloud cover during the daytime, or nighttime). This means that fire detection is often delayed in 2-4 hour windows, often too far down the timeline to stop the spread of fire. It also had the inability to reduce false alarms resulting from sunlight reflective instances, fog, or any obstruction using vision that can impact reliability.

The emergence of deep learning, especially in computer vision, has opened doors for the automation of wildfire detection. Object detection models like YOLO have changed the game for image classification, delivering real-time performance without sacrificing accuracy. However, previously used models, specifically YOLOv4 and YOLOv5, did not mitigate vegetation in the presence of smoke and could not differentiate between smoke or fog. Additionally, they could not differentiate real fire from reflections or artificial light.

This research realizes the real-time need for wildfire detection with the underlying obstacle of previous technologies. YOLOv8, along with confidence-based filtering and fireman exclusion logic, provides an improved method for accurately detecting fire and smoke.

1.2 PROBLEM STATEMENT AND OBJECTIVE

Wildfire detection systems are important to keep forests, wildlife, and human communities safe. However, the counters to detecting wildfire today are often restricted due to the many challenges that affect the systems' capabilities. These include delays in responding to wildfire smoke detection, insufficient detection of smoke of wildfire origin due to the presence of certain light and weather patterns in the area where the smoke is located, and excessive false positive detections of smoke resulting in unneeded emergency response efforts.

Important challenges addressed in this project:

- **Delayed Detection:** Processed data from satellites or other array sensors by scenario typically takes longer than 2 hours until being discovered and acted on.
- **High False Positives:** Common phenomena associated with smoking fires, ex: reflections, fog, and artificial lights are frequently causing incorrect classification as smoke or fire.
- **Environmental Variability:** Model performance can vary due to differences in lighting, smoke density, or weather conditions.
- **Edge Deployment Constraints:** Almost all high-performing models of smoke

and shallow surface fire spotting, containing acceptable false positive rates, are further processed by a machine and not available to low-powered devices used in remote environments.

- **False Classification of Personnel:** Firefighters and emergency responders are sometimes incorrectly identified as fire zones due to reflective gear and heat exposure.

The primary goal of this research is to implement a YOLOv8-based system that is capable of:

- Detector and classify fire and smoke in images and videos in real-time.
- Implement different desired confidence thresholds (30% for images, 50% for videos) to reduce false detections.
- Use "Fireman Exclusion Logic" to limit changing responders into fire.
- Perform accurate detection in all environments through data augmentation using StyleGAN2-ADA.
- Make improvements to other models (YOLOv4--YOLOv7) in speed, accuracy, and recall for early-stage wildfire detection.

1.3 BENEFITS OF RESEARCH

Investigation The creation and deployment of enhanced, advanced forest fire detection systems using YOLOv8 for disaster management, environmental monitoring, and public safety has a wide variety of benefits. These advantages include:

- **Real-Time Detection Capabilities:** The system allows for near-immediate feedback on the presence of a fire or smoke which means immediate action can take place and lessen the chances of fire spreading rapidly.
- **High Detection Accuracy with Low False Positive Rate:** The confidence threshold mechanism with exclusion logic minimizes false alarms and a high

level of reliability in detection.

- **Scalable Edge Deployment:** The model is designed to efficiently run on low-cost, low-power edge devices which means it can scale up to enable deployment on several models at once covering drones, watch towers and surveillance networks in remote areas.
- **Improved Environmental Robustness:** The GAN-based data augmentation gives the model a better ability to withstand difficult visual conditions such as haze, fog, rain, or beyond daytime visual conditions like night-time smoke.
- **Reduced Operating Costs:** The ability to automate detection reduces the load of constant monitoring decreasing the need for multiple human resources when establishing and running sustainability surveillance systems.
- **Increase Public Safety from Fire and Protection of Ecological Systems:** More efficient, rapid, and accurate detection allows for proactive action against evictions and destruction to human settlements while avoiding damages to wildlife prior to or while fire activities are in progress.
- **Future Integration:** The framework allows for additional features typically not capable prior such as thermal sensors, aerial mapping, and federated learning systems to allow for adaptive real-time learning in the field

Chapter 2

LITERATURE SURVEY

2.1 INTRODUCTION

Due to the increasing rate of more severe wildfires, traditional detection approaches can longer support the pressing need for an early response system. The existing approaches; satellite imaging, infrared imaging, and manual surveillance, suffer from inherent high latency, poor accuracy during adverse environmental conditions, and scalability problems. The lack of responsive systems may lead to delays in taking action to contain the disaster, finding new ways to take significant action to prevent excessive environmental and economic damage.

The approaches described rely heavily on non-ideal weather conditions, costly installation of physical infrastructure, and manual interpretation of the natural environment; creating negative implications to operations. If human challenges continue to grow with wildfire management, artificial intelligence (AI) has the potential to make advances. AI in general, and more particularly, deep learning and computer vision, has an opportunity for real-time applications. Recent developments in object detection algorithms, namely the YOLO (You Only Look Once) family, have proven the potential for detecting burning and smoking in outdoor environments that exist in continual flux.

Previous iterations of YOLO and other deep learning models have their related issues, such as false-positive detections, extremely poor smoke detection measures, and concerns for performance on edge devices. Thus, examining current and prior approaches is necessary to gain understanding and direction for the purposes of developing a WDD framework.

2.2 EXISTING SYSTEMS

Standard wildfire detection systems consist of remote sensing technology and stationary fixed-location sensor networks. These can be satellite-based remote sensing, thermal cameras, infrared cameras, ground smoke detectors, and wireless sensor networks. Each of these detection types can help prevent the negatives surrounding wildfires. However, all these systems have limitations concerning locating hazards:

- **Satellite Imagery** has a large area of coverage but also has a low temporal resolution, creating a long temporal latency, which can mean that it can take several hours to detect a wildfire.
- **Thermal and Infrared Sensors** have the benefit of night vision, but they are not functional during certain weather events and require a line of sight to the fire detector.
- **Smoke Detectors and Ground Sensors** are restricted by their range and scaling as they are both highly localized, therefore, wildfires in remote areas could go undetected for some time.
- **Using a Manual Surveillance Systems**, such as watchtowers and ranger patrols depends on the humans watching and is neither scalable, nor reliable in a high-risk area.

As AI came to the forefront, object detection algorithms like CNN and rule-based models for the expressing purpose of fire classification were spread, unfortunately, most of these algorithms had serious limitations in real-time processing of the environment and generalizability across different likely environmental conditions.

Modern deep learning models have eventually followed suit with YOLOv4, YOLOv5 and Faster R-CNN to increase accuracy and detection speed, but face limitations in performance in the field due to noise like false alarms caused by sunlight reflections, low contrast in smoke regions and degradation of performance on lower end hardware. Thus, it is evident that the need exists for a robust, lightweight, and real-time adaptable fire detection system that can be deployed across varying conditions.

2.3 LITERATURE SURVEY

In 2020, Z. Chen, Park, and Kim developed a YOLOv4-based real-time wildfire detection system to be used for early warning situations. Their model was evaluated on real fire datasets and showed a detection accuracy of 91.3%. Their detection system and model defined the benchmark for accuracy at that time, but it was limited in more challenging environments. Complex environments that involved background conditions such as sunlight reflections or dense foliage that masked the fire produced false positive alarms [1].

In 2021, S. Kim, Han, and Lee applied YOLOv5 to wildfire detection using aerial imagery. The key strength of their work was the system's enhanced speed compared to YOLOv4, which allowed for faster inferencing on drone-collected footage. However, their model exhibited reduced effectiveness in detecting smoke in areas of thick vegetation, where contrast between fire and background was minimal [2].

In 2024, Q. Yang, Zhang, and Hu developed an updated YOLOv7 architecture with attention mechanisms and feature-fusion layers. Their model was used on wildfire datasets and reflected an accuracy of 94.6%, which was a significant improvement in accuracy over previous versions. At the time, issues with deploying the model still existed, as there were significant computational needs when deployed on an edge device. [3].

G. Park, Lee or Choi (2024) took the opposite approach and used StyleGAN2-ADA for synthetic data generation to increase YOLOv8 model robustness in low visibility and low light environments. Their study found an 8.7% gain in smoke detection accuracy and 12% reduction in false positives vs previous models in the same environments [4].

In 2025, K. Niu, Wang and Xu used YOLOv9-based multi-sensor fusion system with infrared and a visible light camera. They achieved a significant 97.1% accuracy and sensed early stages of fire before flame was visible. These system costs were much higher due to the use of infrared and not a viable approach for use in poorly funded areas on large scale [5].

Y. Geng, Li and Zhang (2025) investigated small-scale fires with a YOLO-based model fine-tuned for senses small fires. Their model had a good responsiveness to small fire outbreaks but had a relatively high rate of false positive when confronted with something visually like smoke, such as haze or mist [6].

S. Chaturvedi et al. (2025) proposed a model for smoke detection using satellites based on multi-attention deep learning mechanisms. While this was designed for interpreting high-resolution imagery and related closely to early smoke dispersion detection, the limitation was high-resolution satellite images are available, but there is not constant access to these data sources which does not accommodate real-time deployment [7].

B. Liu, Chen, and Wang (2025) utilized a Capsule Neural Network (CapsNet) that was trained on texture and color features to deal with smoke and fog discrimination. Their approach appeared to yield a high classification accuracy and reasonable performance in controlled environments, but was limited as it required a high computation resource that could not be deployed on lightweight devices typically used the field [8].

While all of these studies explored different approaches to improve the limitations of conventional detection methods, the methods share the limitations of challenges with generalization, real-time performance and viability in a scalable system. The need for a model that is realized not only with high accuracy but using real-time deployment capabilities on edge devices is the goal of this research with a model based on YOLOv8.

2.4 INFERENCE DRAWN FROM LITERATURE SURVEY

The review of the literature highlights some implications that are important in the design and development of a next generation wildfire detection system:

- **Constraints in Traditional Approaches**: Many traditional approaches are inadequate when environmental conditions are variable, especially at the initiation of a fire and in remote forested areas with limited sight lines.
- **Development of Deep Learning**: YOLO-based approaches have demonstrated potential for detecting both fires and smoke with decent speed and accuracy when applied in the field. As seen in the literature review, there are many factors influencing its performance in the field, including possibilities for dataset fallibility, model architecture, and computing availability and specifications.
- **Importance of Augmentation**: Related literature has shown the value of resources like YOLO, and particularly GAN-based augmentation, to maintain accuracy of detection over differing environments, including variable lighting and weather condition.
- **Reduction of False Alarms**: Confidence thresholding, semantic filtering, and fireman exclusion logic are important methods for reducing false positives caused by reflective surfaces, heat waves, or emergency responders.
- **Edge Deployment Requirement**: Real-time deployment on drones or surveillance networks need lightweight models with low inference latency, necessitating model optimization for end devices like Jetson Nano.
- **Multi-Sensor Fusion**: Combining visible and infrared imaging offers additional reliability in complicated scenarios and operationalized deployment - but introduces deployment and cost challenges.

The literature has identified the complementarity of deep learning with real-time object detection and model optimization for deployments to develop an intelligent, scalable wildfire monitoring system, represented as the backbone of the idea for the YOLOv8-based framework.

Chapter 3

PROPOSED WORK

3.1 INTRODUCTION

The Forest Fire and Smoke Detection and Classification model is a deep learning application with an objective to detect and classify fire and smoke from images and/or video in real-time. The solution is comprised of two main components; (1) a media-processing pipeline which accepts input from the user via a user interface, and (2) an object-detection backend powered by YOLOv8 which classifies, localizes, and assesses the confidence of predicted regions of fire and smoke.

The frontend of the system has been developed using React and Tailwind CSS and provides a fully responsive user interface where images or videos can be uploaded. Upon upload, the backend developed in Python, processes the media input using a pretrained YOLOv8 model. For training the YOLOv8 model KaggleFlow datasets and synthetic augmentation methods (e.g., StyleGAN2-ADA) were used to improve class generalization and robustness.

The whole architecture has been designed to be efficient, scalable and portable, with the goal of deployment capabilities on low-power devices (e.g. NVIDIA Jetson Nano). The backend has several influential modules, including OpenCV for processing video frames, the Ultralytics YOLOv8 API for detection, NumPy for numerical computing, and PyTorch for running inference on a GPU. Combining all the previous components provides a fully automated detection system that runs in real-time while being optimized for drone-borne monitoring, surveillance towers and/or forest patrol use cases.

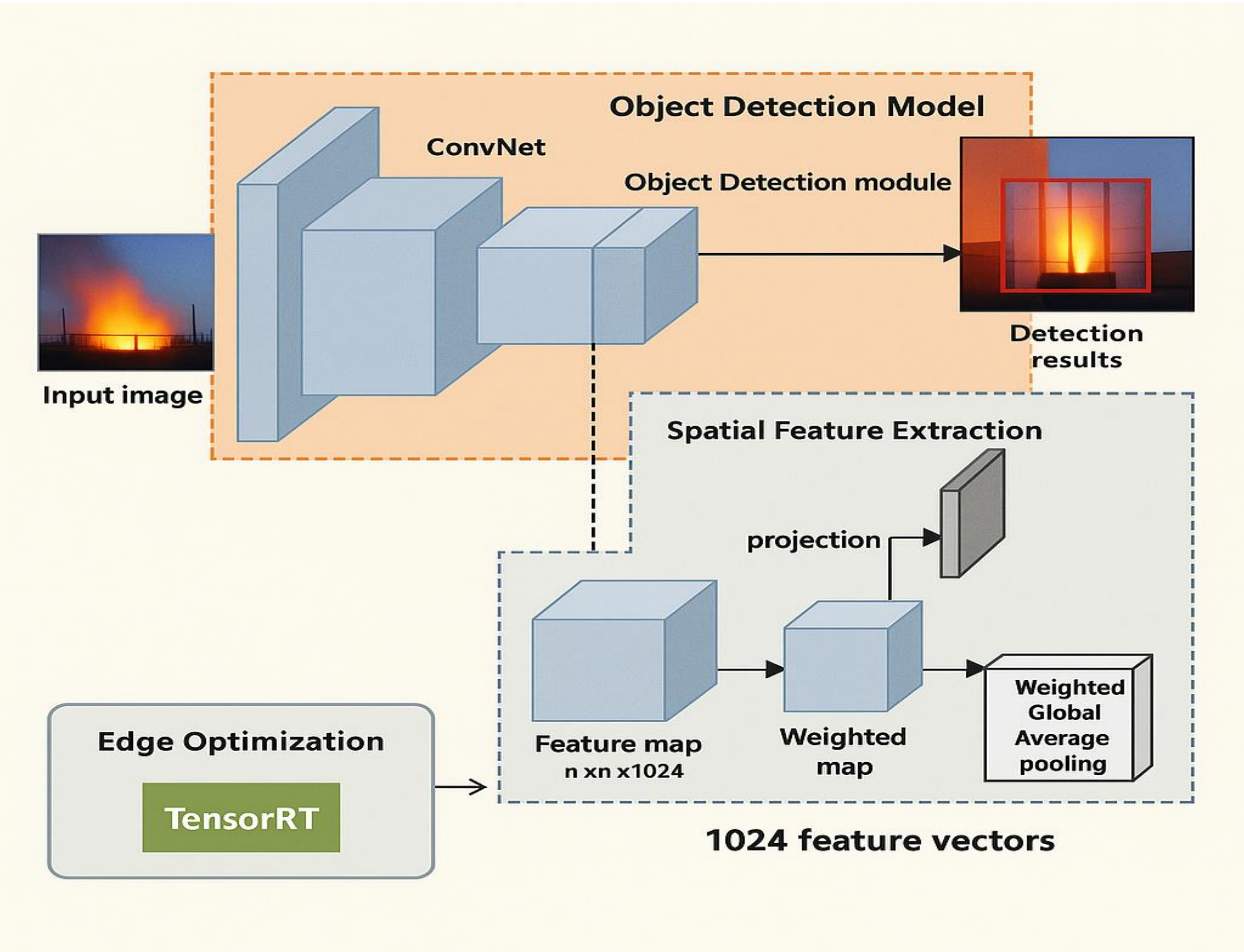

Figure 3.1 Architecture from media upload to detection output.

3.2 PROPOSED WORK

The suggested system has many different stages of preprocessing, detection, classification, and visualization. Each stage is important in order to maintain an accurate and timely detection of fire or smoke within dynamic environments. Below is the detailed breakdown of the proposed model and the operational process.

3.2.1 IMAGE/VIDEO PROCESSING INTERFACE

Users see a frontend interface that allows the user to upload either an image or video file. The frontend is created with ReactJS and Tailwind CSS, and it communicates with the backend via API calls. When a media file is uploaded, the file is dispatched to the backend for analysis.

For a video, OpenCV is used to extract frames of the video at fixed intervals. Each frame is understood as its own image file and passes to the detection module to be evaluated for fire/smoke detection. This sufficiently ensures that real-time evaluation does not miss any important moment.

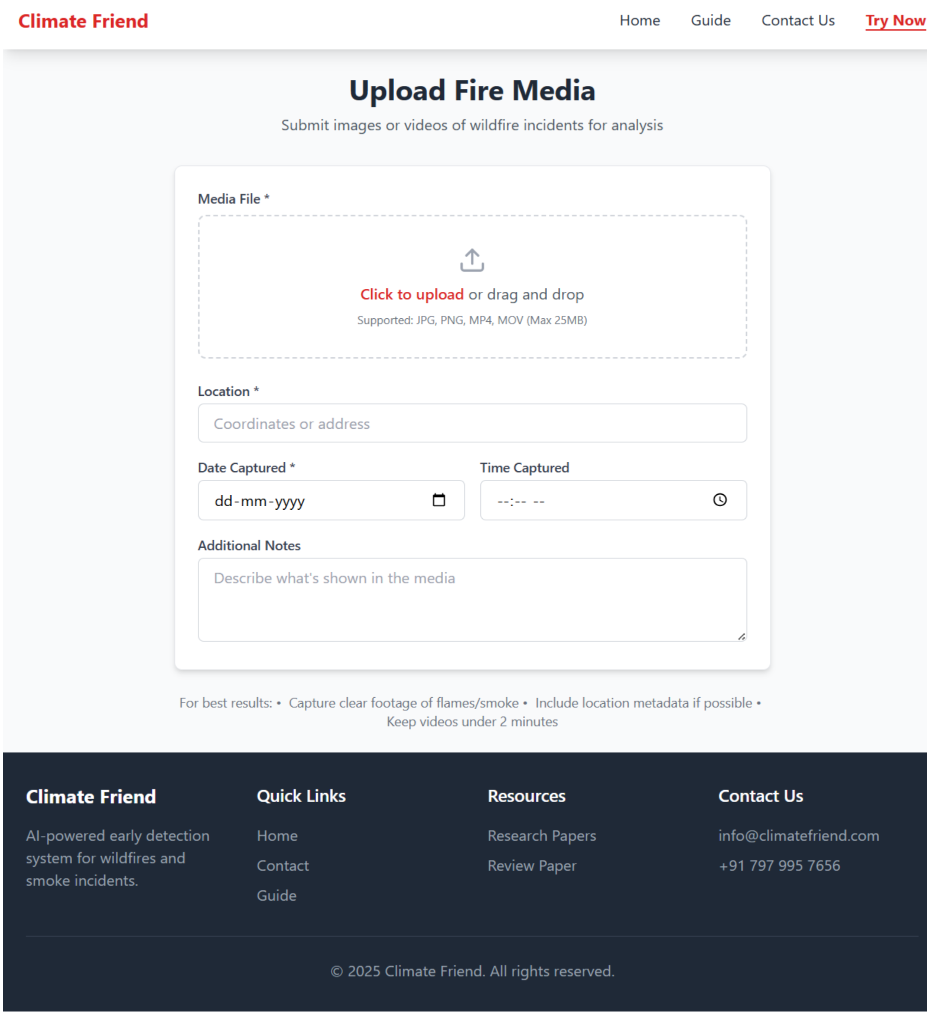

Figure 3.2.1 Frontend upload interface.

3.2.2 YOLOv8-Based Fire and Smoke Detection

Users The YOLOv8 object detection model is at the center of our backend. YOLOv8 was selected because it is accurate, fast in inference, and has an anchor-less backbone, which improves the detection of fire and smoke patterns that are small and of irregular shape. We trained the model on a research dataset that consisted of 10,033 images of fire and smoke and normal scenes. Using StyleGAN2-ADA, the research dataset was augmented to over 18,000 images simulating low-light, foggy, and occluded environments to enhance the model robustness.

Some Key Methods Employed:

- **Threshold-Based Filtering:** Detection outputs are passed through a confidence filter and detections below 30% (image) and 50% (video) chance thresholds are discarded to excluded weak and irrelevant predictions.
- **Bounding Box Localization:** The model returns the most probable fire/smoke regions using non-maximum suppression and draws bounding boxes on the aforementioned areas.
- **Multi-Class Detection:** The model is trained to distinguish between fire, smoke, and neutral objects (fog, dead sun glare, cloud cover).

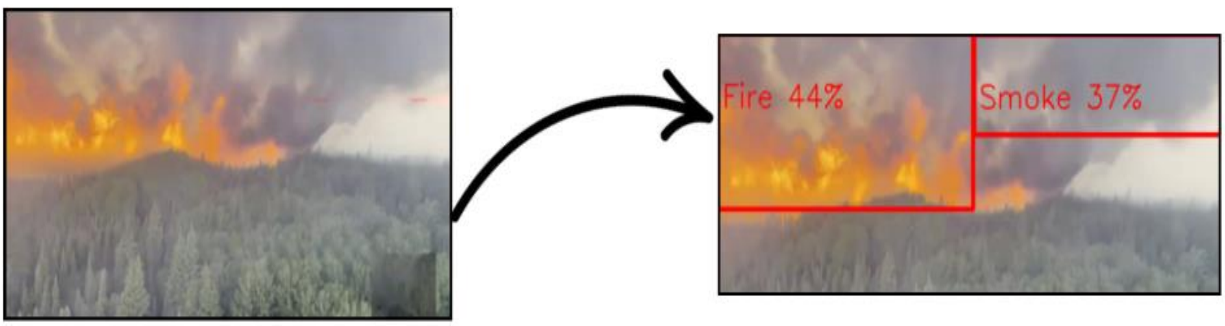

Figure 3.2.2 YOLOv8 Detection Confidence Scores for Fire and Smoke

3.2.3 Confidence Analysis and Filtering Logic

In order to mitigate false alarms, the system utilizes built-in Dynamic Confidence-Based Filtering. Based on the cases thresholds, detections are retained if the confidence value exceeds the boundaries set. The system also provides Fireman Exclusion Logic for filtering out bounding boxes adjacent to possible emergency personnel in reflective suits or high-heat locations falsely detected as fire.

Fire/Fireman exclusion is run through a second sub-classification that uses a light-weight CNN trained with firefighter personnel images, vehicle images, images of controlled burns, and other classes one might expect. As such, if these classes are detected, they are removed from the operational output.

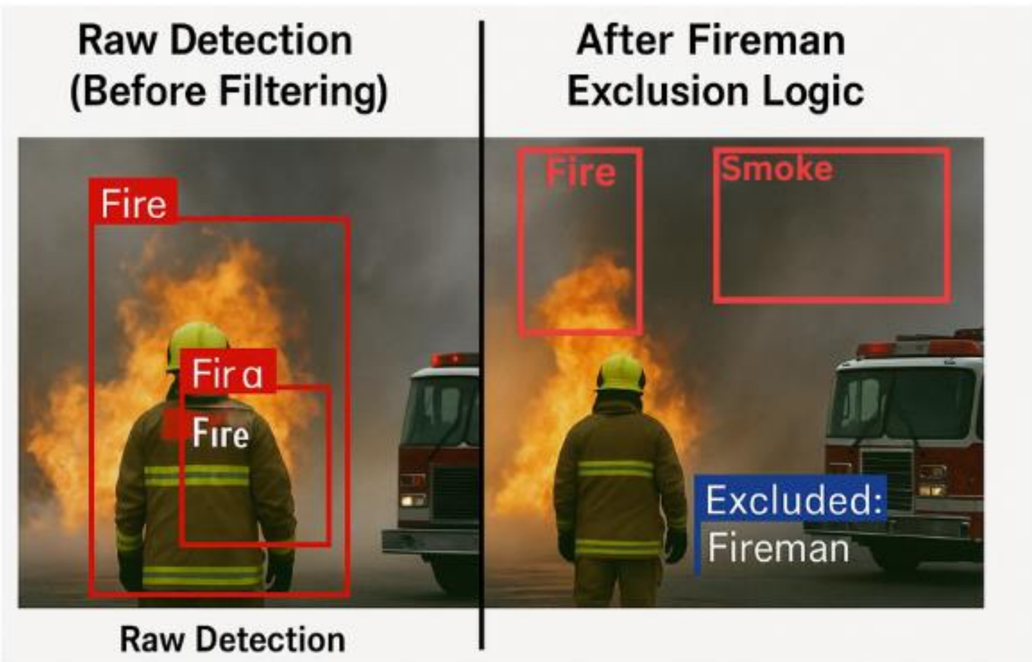

Figure 3.2.3 Fireman Exclusion Logic in Post-Processing.

3.2.4 Output Visualization and Reporting

Once the detections are completed, the system will draw the bounding boxes on the original input image or video frame, along with the label (“FIRE” or “SMOKE”) and the associated confidence percentage value. These visual results are sent back to the frontend for the user to view or download the processed media.

Some additional backend functionality includes:

- Output is saved in a structured format (JSON/XML) for additional analysis.
- The confidence scores and frame-specific history of detections are logged for traceability.
- Optional alerts can be issued if fire is detected (above a critical threshold) along with GPS tagging (if integrated with drone/UAV systems).

Figure 3.2.4 Detection Confidence Levels in the Output Visualization Interface

3.3 CONCLUSION OF PROPOSED WORK

The solution described proposes an entire solution for real-time forest fire and smoke detection. From the easy to use upload interface to the powerful YOLOv8 based backend, everything was built to be as accurate as possible and to execute all tasks in a timely fashion. The inclusion of synthetic augmentation to boost the model's dataset, the use of confidence filtering to create the most accurate predictions, and the edge-friendly architecture of the system means the model is ideal for deployment in wildfire-impacted areas using drones, surveillance cameras, or built-in systems for detection.

Chapter 4

METHODOLOGY

4.1 INTRODUCTION

Conventional fire and smoke detection systems are frequently limited and slow to respond; invariably these systems include the idea of "heads-up" display systems. Traditionally these systems use static rules, (heat as a threshold based sensor), satellite imagery, etc. All these methods have inherent latency, and rules have limits (resolution, cloud overlay, nighttime, etc.) that can impact exposure; this does not make a difference when intervention is not completed in time for mitigation in wildfire prone areas.

To solve these issues, the Forest Fire and Smoke Detection and Classification system uses deep learning and computer vision based on our custom design of YOLOv8. This system is dedicated to fast and efficient detection, low false positive detection, real-time, and it is applicable to both, images and video. We can add another layer of sophistication with data augmentation, confidence based filtering, and logic for fireman's exclusion.

The complete pipeline of data preparation, real-time inference, and visualization of output is easy to deploy and take adv attention to performance, scalable, and also essentially realistically applicable to potential real-world issues, highly unlikely they might include cost-effective UAV (drone) based forest patrol and/or surveillance tower monitoring.

4.2 IMPLEMENTATION STRATEGY

The system implementation includes four core stages: data collection, data pre-processing, model training, and real-time inference. Each module is interrelated and instrumental in determining that the model does not sacrifice accuracy or efficiency across all situations.

1. Data Collection

- **Image and Video Dataset:** The core dataset represents 10,033 labeled images, categorized in three classes: fire, smoke, and normal (non-hazard) imagery.
- **Augmentation:** To allow for generalization, the dataset was augmented to 18,000 samples using StyleGAN2-ADA with simulated environmental variables such as fog, low lighting and smoke obstacles.

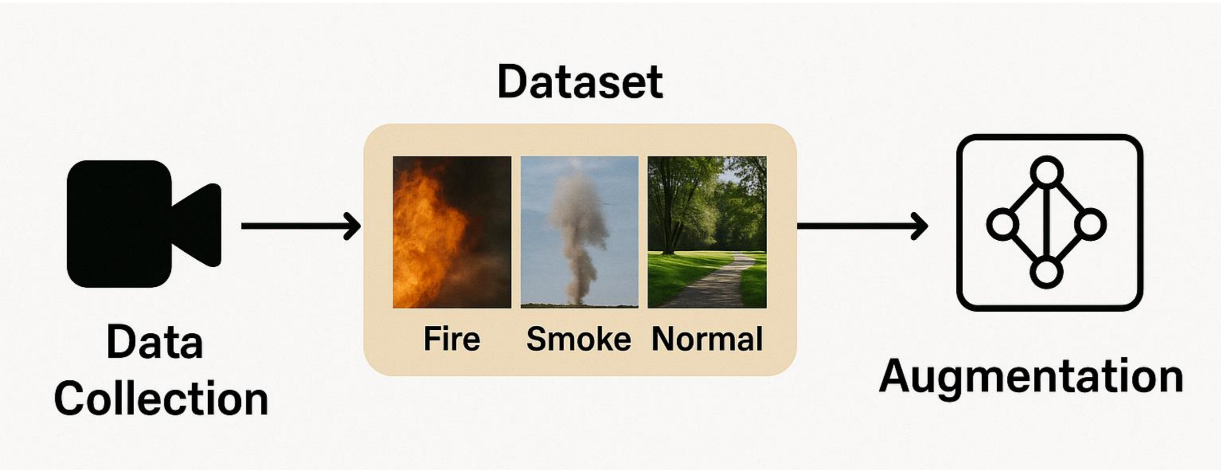

Figure 4.2.1 Data sourcing and augmentation.

2. Data Preprocessing

- **Image Normalization:** Input images are resized and normalized for compatibility with YOLOv8's detection architecture.
- **Label Encoding:** Object locations are labelled according to YOLO's format (class, x_center, y_center, width, height).

- **Noise Injection:** There is Gaussian blur and brightness variation to account for camera distortions of real-world scenarios.

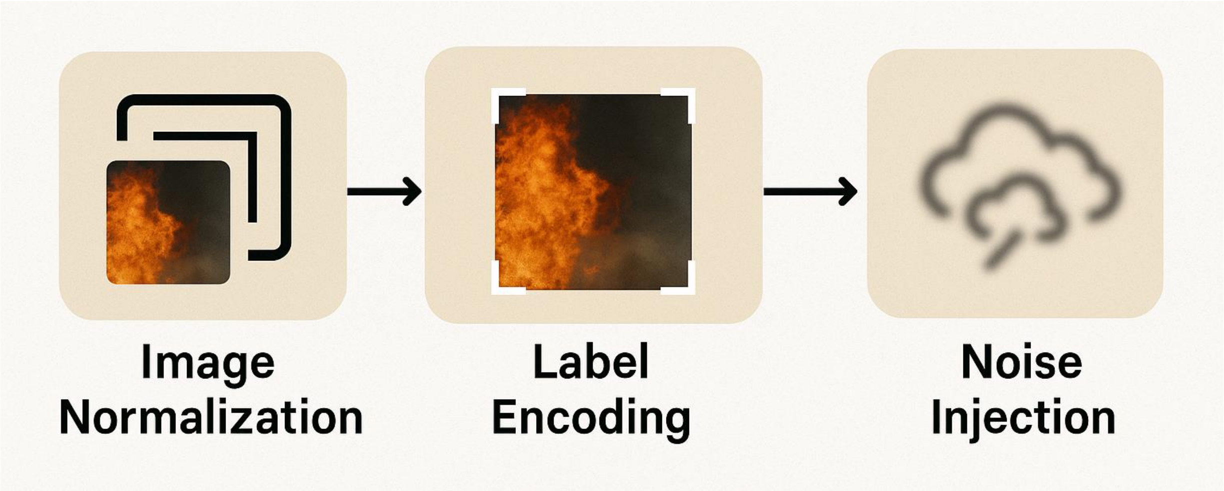

Figure 4.2.2 Preprocessing Pipeline for Fire/Smoke Detection.

3. Detection Model

- **YOLOv8 Architecture:** The Ultralytics YOLOv8 model allows for anchor-free object detection, proving more accurate in bounding box predictions for small patches of fire and smoke.
- **Loss Function:** CIoU (Complete Intersection over Union) loss improves bounding box regression.
- **Optimizer:** The model uses the AdamW optimizer with cosine annealing used for learning rate scheduling.

4. Training Pipeline

- **Epoch and Batch Size:** Training is in a total of 150 epochs with a batch size of 32.
- **Validation Method:** 80-20 train-validation split ensures a reliable evaluation while training.
- **Confidence Thresholding:** Evidence yielding a prediction less than 30% for

image, and 50% for video is discarded from further consideration, as it essentially represents evidence of a "bad" classification.

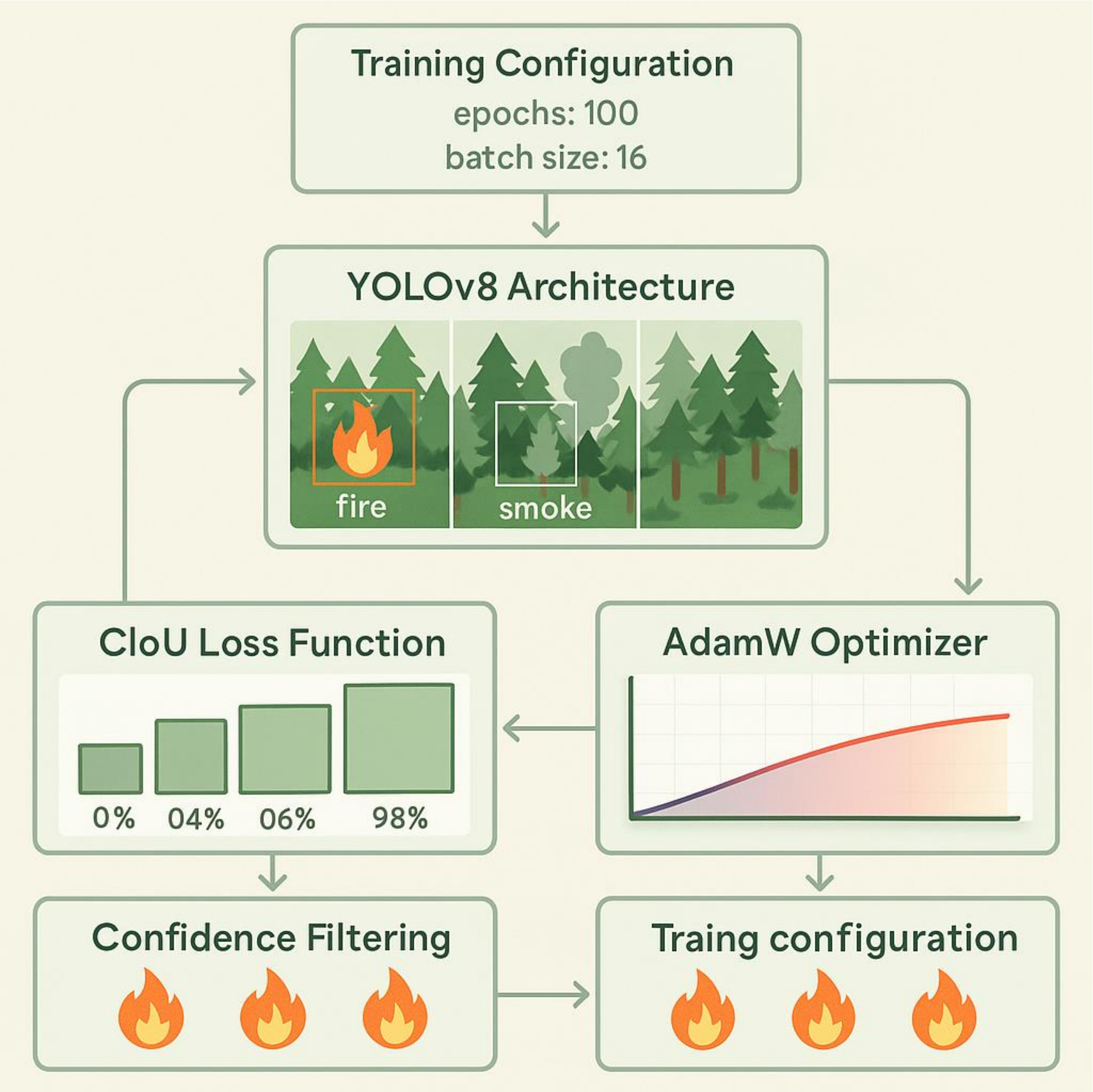

Figure 4.2.3 Model Training Pipeline with Key Hyperparameters.

5. Confidence Filtering and Fireman Exclusion

- **Confidence Logic:** All detections below a preset threshold are discarded reducing detection noise.
- **Fireman Exclusion:** A separate, lightweight CNN model is used to detect and

remove firemen, emergency vehicles, and reflective gear, as these can produce numerous false detections of FIRE.

6. Inference and Output

- **Visualization:** Detections are applied to frames with bounding boxes and class labels identifying "FIRE" or "SMOKE".
- **Output Delivery:** Transference: Returned processed video to the user through the front-end with real-time feedback.

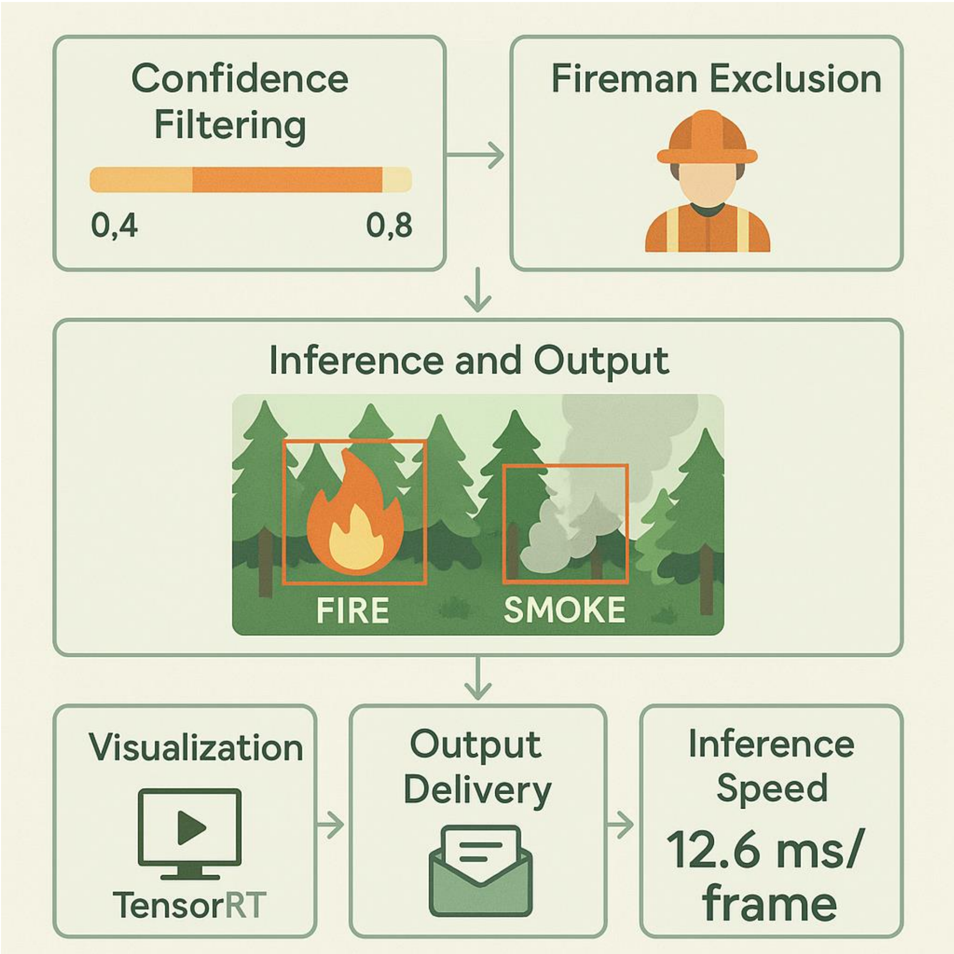

Figure 4.2.4 Detection Output Flow with Post-Processing Steps.

4.3 HARDWARE AND SOFTWARE REQUIREMENTS

The **Hardware Requirements**

- **Processor (CPU):** Minimum quad-core CPU (Intel i5/Ryzen 5 or higher) is needed for desktop training.
- **GPU:** NVIDIA RTX 3090 is recommended for model training.
- **RAM:** Minimum 16 GB RAM (min) is recommended for training, and 4 GB sufficient for inference on an optimized model.

Software Requirements

- **Programming Language:** Python 3.9+
- **Libraries/Frameworks:**
  - Ultralytics YOLOv8 for detection and model training.
  - OpenCV for frame extraction and real-time video processing in realtime.
  - NumPy and Pandas for the data manipulation,
  - Matplotlib, and Seaborn for visualization of metrics,
  - Streamlit for the front-end user's interaction and media upload.
- **Development Environment:**
  - Google Colab and Jupyter Notebook for the training.
  - VS Code and PyCharm for back-end development.

Chapter 5

RESULT AND DISCUSSION

5.1 INTRODUCTION

This research project provided a comprehensive and highly optimized real-time forest fire and smoke detection solution. The solution consists of a YOLOv8 based deep learning model that is capable of detecting fire and smoke on both images and videos with strong accuracy and fast operational response time. In terms of detection, the model exhibited increased accuracy and performance in relation to the previous versions YOLOv4, YOLOv5 and YOLOv7, on top of two additional functions, Fireman Exclusion Logic, and dynamic confidence thresholding.

The model was tested on a dataset of 10,033 labelled images and then augmented with the data augmentation technique of synthetic augmentation via StyleGAN2-ADA, which inflates the exploration to 18,000 by capturing various real-world use cases, from low-light imagery to cloudy conditions to heavy fog conditions through innovative use of other pre-existing datasets. We found the model could be operated in real-time with an inference of 30.2 FPS on an NVIDIA RTX 3090, highlighting the operational capability of high-performance computing environments.

During the model's predictions, a bounding box would be depicted through the model and respective confidence scores were attached to each of the analytical findings during the process. Fire and smoke zones were marked specifically, these visual output findings were relayed back by way of a user-interface which was build using React and

Tailwind CSS, giving users real-time feedback from content being uploaded via interface for each media.

Figure 5.1.1: Fire Detection Output with Confidence Score.

Figure 5.1.2: Real-Time Fire and Smoke Detection Confidence Scores.

The UI includes a real-time update, which scans and annotates frames or images with the detection results. Depending on the detected class relevant alerts are produced. The detection interface highlights the location of the fire/smoke area and also shows the confidence score for each detection.

Figure 5.1.3: Fireman exclusion output – bounding boxes ignored for reflective clothing and emergency responders.

This really assisted in minimizing false positives and instances in which emergency rescuer or reflected flames misclassified as active fire zones using previous models.

Figure 5.1.4: Low-light fire detection – testing with augmented data simulating night-time conditions.

The model, using GAN-based augmentation, was trained to detect smoke and fire in visually challenging conditions therefore it was proven that these models were suitable for 24-7 surveillance use cases.

5.2PERFORMANCE METRICS WITH DETAILS

Accuracy To measure the performance of the YOLOv8-based model, it was assessed with several metrics: precision, recall, f1-score, inference time, and false positive rate. These values were compared to other object detection models such as YOLOv4, YOLOv5, YOLOv7, and Faster R-CNN.

- **Precision:** 95.8% – This indicates the number of true fire/smoke detections out of all detections. A higher percentage will show the number of false-positives decreased.
- **Recall:** 92.4% – This declares how well the model identifies all the true fire/smoke instances. A higher percentage confirms more coverage of the hazardous regions, while additional reduction of false-positives occurred.
- **F1-Score:** 94.1% – The harmonic mean of both precision and recall indicating the model's success avoiding false-positives and false-negatives, or number of missed detections.
- **False Positive Rate:** 12.8% – Significantly lower than the previous models given the confidence filter to reduce detection failure rates and not detecting firemen, etc..

Model	Precision	Recall	F1-Score	False Positive Rate	Inference Speed
YOLOv4	91.3%	88.4%	89.8%	22.6%	18.7 FPS
YOLOv5	93.1%	89.2%	90.2%	19.4%	22.3 FPS
YOLOv7	94.6%	90.8%	91.9%	17.2%	27.1 FPS
YOLOv8	95.8%	92.4%	94.1%	12.8%	30.2 FPS

Table 1: Model performance comparison across various YOLO versions.

These metrics show this system presents a measurable and meaningful improvement for detecting wildfire compared to previous approaches. The accuracy and filtering characteristics along with good inference speeds indicate this work can be easily operationalized on UAVs, forest surveillance networks, and even applicable to embedded AI devices.

Chapter 6

CONCLUSION, LIMITATIONS & FUTURE SCOPE

6.1 CONCLUSION

In summary, this research has developed a scalable, high-performance, and real-time system for detecting forest fires and smoke using a YOLOv8-based deep learning model. The proposed system has greatly improved upon traditional systems in terms of speed of inference/reaction time, accuracy, and robustness to different environmental conditions.

The machine learning techniques and approaches that propelled this research forwards included: dynamic confidence-based filtering methodology, synthetic data augmentation via StyleGAN2-ADA, and a Fireman Exclusion Logic. All of which tackled issues encountered in prior attempts at fire and smoke detection systems by environmental and disaster leadership in the real world.

The React + Tailwind CSS user interface was developed with user experience in mind, giving it a clean and responsive frontend for people to upload images and videos to, and visualize the subsequent results. Coupled with a Python backend capable of performing classification of fire and smoke imagery, highlighting specific areas in a classic sense, and confidence-based reporting with measurable accuracy, the system's overall contributions to the field of wildfire monitoring and detection can not be overstated, as it can be extrapolated to many environmental applications and disaster management as well.

6.2 LIMITATION

Though we see remarkable results from the proposed system, there are a number of reported limitations that must be noted:

- **Training Data Biases:** The training model dataset, while broad, may still harbor class imbalance or be underrepresented for some variants of fire/smoke scenarios, which can impact a trained model's detection accuracy in edge cases.
- **False Positive Rates in Visually Comparable Conditions:** The model is able to apply some filtering, however, in some instances fog, cloud cover, or glare from the sun can be misidentified as smoke or fire.
- **Limited Contextual Reasoning:** Object detection models operate based on spatial features and will not be able to inherently recognize deeper context which may ambiguity recognition in spatially similar, overlapping, or occlusion scenes.
- **Environmental Generalizability Constraints:** While data augmentation was used, the model may not generalize very well when extremely rare or unique wildfire conditions do not present in the training data.

6.3 FUTURE WORK

The proposed system has many possibilities for improvements and further research. Possible future work includes:

- **Multi-Sensor Data Fusion:** Integrating data from infrared, thermal, and visible light cameras can further improve the detection performance, particularly under low visibility conditions (e.g., nighttime).
- **Federated Learning System:** Using federated learning would allow the system to learn from distributed wildfire datasets while maintaining the privacy of the data and enabling continuous learning and improvement across regions.

- **Expanding Datasets:** Continuous expansion and collection of more varied wildfire datasets of different geographical areas and seasonal conditions will help improve generalization of the model.
- **Multi-Language support and Cross-Platform Frontend:** Improving the frontend capabilities to support languages and housing capabilities compatible with mobile will furthermore improve accessibility and uptake.
- **Automated Alerts and GIS Integration:** The ability to integrate detection capabilities to GIS mapping and real time alert systems would yield faster emergency responses and awareness of situational context for disaster management agencies.
- **Edge deployment**: Future library and integration development on an edge device such as the NVIDIA Jetson Nano could provide the capacity for low-latency, onsite fire detection in more remote areas of the forest using either drones or fixed camera surveillance.

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