

FIRE AND SMOKE DETECTION FOR WILDFIRE USING YOLOV5 ALGORITHM

Bharathi K, Jawahar Jonathan K, Satyabhama, Shobharani C N,
Sridevi, Bhagyashree K Itagi

Department of Computer Science and Engineering, Acharya Institute of
Technology, Bangalore, India

ABSTRACT

This research paper presents a realtime fire and smoke detection system using the YOLOv5 object detection algorithm. The system aims to detect fire and smoke in images and video streams captured by a camera in real-time, without the need for any preprocessing or manual intervention. The proposed system uses the YOLOv5 algorithm to detect the fire and smoke regions in the input images and videos. The YOLOv5 model is trained on a dataset of annotated images to recognize fire and smoke patterns accurately. The proposed system has been tested on different datasets and has achieved high accuracy and precision in detecting fire and smoke in real-time. The experimental results demonstrate that the proposed system is robust and efficient, and it can detect fire and smoke in real-time with high accuracy and low latency. The proposed system can be used in various applications, such as early warning systems, fire safety, and disaster management. It can also be integrated with the CCTV network directly. The testing findings show how reliable and effective the suggested system is, as well as how accurately and quickly it can detect fire and smoke in real time. Numerous applications, including early warning systems, fire safety, and disaster management, are suitable for the suggested system. Direct integration with the CCTV network is another option.

1. INTRODUCTION

The development of human civilization has been greatly aided by fire. Conversely, it is one of the world's worst calamities, with a staggering loss of life and property worldwide. Early fire detection can save lives and property by raising awareness of the danger and averting these tragedies. Usually, smoke is released before an object catches fire and starts to burn. Smoke can thus be used as a signal to spot fires early. In India, the number of fire events has increased within the last several years. An analysis by Accidental Deaths and Suicides in India (ADSI), kept up to date by the National Crime Records Bureau, shows that in the five years between 2016 and 2020, fire-related incidents claimed the lives of 35 individuals on average every day.

Division of Records. Such incidents demolish properties valued at millions of rupees. Early fire detection without false alarms is essential to reducing such tragedies. Numerous autonomous fire detection technologies are being developed and are commonly employed in real-world situations because traditional detection systems proved to be unsuccessful in outside contexts.

The advent of computer vision-based detection systems may be attributed to the rise of artificial intelligence and its offshoots. These vision based detection systems provide greater surveillance coverage and overcome size and location constraints. They also provide less false alarms, quicker detection, and less need for human intervention. When it comes to computer vision

technology, researchers have worked very hard to overcome the problems of false detection and system complexity.

Therefore, we want to apply this development for the good of society by creating a more straightforward system for detecting fire and smoke using convolutional neural networks. This system will be able to analyze a picture and determine whether or not it includes smoke or fire. Enhancement of data has been used to add slightly altered copies of previously existing data to increase the amount of data. These copies are derived from original images that have undergone some minor geometric transformations (such as flipping, translation, rotation, or the addition of noise) to increase the diversity of the training set. or using already existing data to create new, synthetic data. When the machine learning model is being trained, it serves as a regularizer and lessens overfitting.

2. LITERATURE SURVEY

[1] The accuracy, efficiency, and speed of flame and smoke detection algorithms have been addressed by recent advances. Low precision and lengthy processing are common problems with traditional approaches, especially for tiny targets like smoke plumes or flames. Researchers have used YOLOv5s, a state-of-the-art object identification model, into their algorithms to get around these restrictions. Accuracy is increased and real-time detection capabilities are made possible by this integration. Furthermore, the backbone network's technologies like ODConvBS improve feature extraction and make it possible to identify faint patterns of smoke and flame. The spatial interaction and feature extraction efficiency are further improved by methods such as Shuffle Attention (SA) module and recursive gated convolutions (Gnconv). By taking into account the vector angles between regressions, specialized loss functions like SIOU speed up model training and produce faster and more accurate detections.

[2] The literature study included in the material supplied highlights how crucial it is to identify wildfire smoke early in order to reduce casualties and property damage. It emphasizes the use of camera networks for prompt detection, highlighting the significance of clever video smoke detection algorithms and cost-effective camera placement techniques. Two modules make up the suggested effective video smoke detection framework: one handles wildfire camera location optimization as a binary integer programming issue, while the other uses dense optical flow and local binary patterns for smoke detection in video frames. The framework makes use of deep learning methods such as MobileNetV2 in conjunction with physics-based features to improve detection accuracy while preserving computational and storage economy. The paper also discusses the computational difficulties that deep learning-based methods face in situations with limited resources, arguing in favor of simple solutions ideal for embedded local applications as wildfire camera systems.

[3] Research on improving fire detection systems has increased significantly in recent years, especially in response to the growing threat of forest fires. The failure of conventional sensor-based techniques has led to research into computer vision algorithms. There are benefits to vision-based methods in terms of precision, coverage, and instantaneous response. By extracting complex information from photos, the development of Deep Learning— particularly convolutional neural networks like YOLOv5 and U-Net—has revolutionized the detection of fires. In order to overcome issues like false alarms and lengthy inference times, this article suggests a novel architecture for fire detection and segmentation that blends YOLOv5 with U-Net. The suggested architecture integrates YOLOv5 with U-Net in an attempt to overcome the obstacles that persist in obtaining high accuracy and speed despite developments. This integration offers enhanced performance in detecting and segmenting fires, including small-size fire objects, while decreasing false alarms. These results highlight the increasing interest in

deep learning (DL) approaches to fire-related problems and point to a viable path for further fire detection and monitoring system development.

[4] The two primary strategies for smoke detection included in the literature review are those based on computer vision and those based on deep learning. Computer vision techniques make use of classifiers like rule-based systems, SVMs, and shallow neural networks, as well as characteristics including color, motion, texture, form, and energy. For smoke detection tasks, deep learning approaches, on the other hand, use CNN architectures such as AlexNet and Faster R-CNN. In order to achieve equivalent detection accuracy but requiring less computing and storage, the suggested approach combines lightweight CNNs with conventional feature extraction techniques. The methodology solves the shortcomings of previous methods and can be used in resource-constrained wildfire monitoring camera systems by integrating mobilenetV2 CNN for classification with local binary patterns (LBP) and dense optical flow for feature extraction.

3. METHODOLOGY

The process for detecting fire and smoke starts with recognizing the special difficulties that come with being in a region that is prone to wildfires and real-time and accurate monitoring. Gathering various datasets of videos and photos from wildfires and annotating them is the process of collecting data for model training. YOLOv5 is chosen due to its precision and instantaneous response times; it is trained and refined to efficiently identify fire and smoke occurrences. Deployment in wildfire-prone areas is made easier by integration with a real-time surveillance platform, which also ensures compatibility and extensive testing across a range of situations. Testing and validation studies are used in assessment to evaluate performance, and continuing maintenance and enhancements guarantee dependability and efficacy. The goal of this methodical approach is to improve safety protocols in regions susceptible to wildfires by tackling the intricacies of smoke and fire detection.

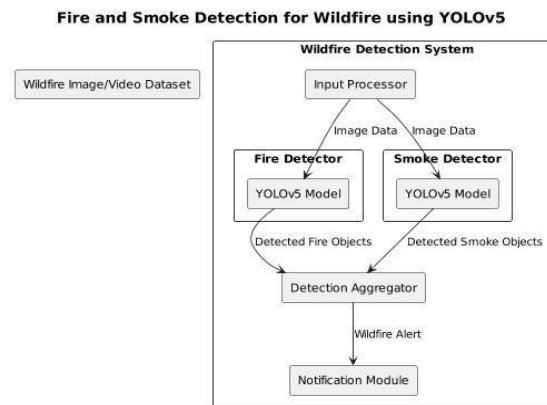


Fig.3.1 Methology of fire and smoke detection.

- **Problem Understanding and Requirement Analysis:**

Recognize the unique difficulties and specifications related to smoke and fire detection in regions vulnerable to wildfires. Determine the necessity of robustness, high precision, and real-time monitoring for the detection of fire and smoke incidents.

- **Gathering and Preparing Data**

Compile a varied dataset with pictures and videos of wildfire episodes that show different situations, the weather, and the time of day. To produce ground truth data for training the YOLOv5 model, preprocess the dataset by categorizing the areas of fire and smoke in the photos and videos.

- **Model Selection and Training:**

Due to its accuracy and real-time performance, choose YOLOv5 as the object identification model.

To modify the YOLOv5 model to detect fire and smoke incidents, train it on the annotated dataset using transfer learning techniques. To boost the variety of the training set and enhance the model's capacity for generalization, apply data augmentation approaches.

- **Model Enhancement:**

In order to retain real-time performance and get high detection accuracy, adjust the YOLOv5 model's parameters and hyperparameters. Optimize the model architecture and training procedure to enhance the model's capacity to identify fire and smoke occurrences in wildfire situations.

- **Integration and Deployment:**

Combine a real-time surveillance platform appropriate for detecting wildfires with the trained YOLOv5 model.

Install the integrated system where wildfires are likely to occur, making that it is compatible with the infrastructure and monitoring systems already in place.

- **DATASET ACQUISITION**

The dataset used for training and validation had a major impact on the deep learning model's accuracy level. From open-access sites like GitHub and Roboflow, we collected fire photos that showed a variety of situations (form, color, size, inside and outdoor setting).

To verify the system's dependability and efficacy in identifying fire and smoke incidents, test it in a variety of lighting and environmental scenarios.

- **Assessment and Confirmation**

Analyze the deployed system's performance in terms of processing speed, dependability, false positives, and detection accuracy

Conduct validation studies and field testing to verify the system's efficacy in identifying fire and smoke occurrences in wildfire zones.

- **Constant Maintenance and Improvement**

Track the functioning of the implemented system and gather input from users and stakeholders. Update and enhance the system often in response to user input and fresh advancements in

object and wildfire detection technologies. To guarantee the system's continued functioning and performance, undertake routine maintenance and upgrades.

4. TESTING

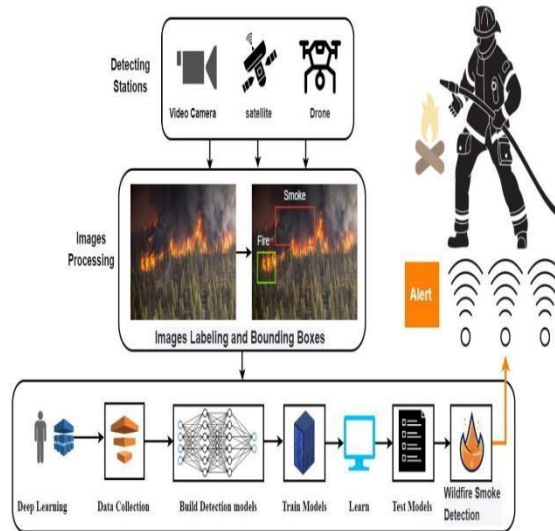


Fig.4.1 Wildfire smoke detection operation using deep learning.

There were 2462 fire photos in our fire image dataset.

- **DATA PREPROCESSING**

Roboflow was used to store the dataset. Pictures without annotations were eliminated. Then create a dataset by combining them. The roboflow framework was used to preprocess the photos . There was no augmentation used by us. They were extended to 416×416 after being resized. Lastly, split them into 50% training and 50% validation. Next, we export the dataset in Pytorch format (YOLO v5), and it creates an API connection that we immediately utilized in our model.

5. IMPLEMENTATION

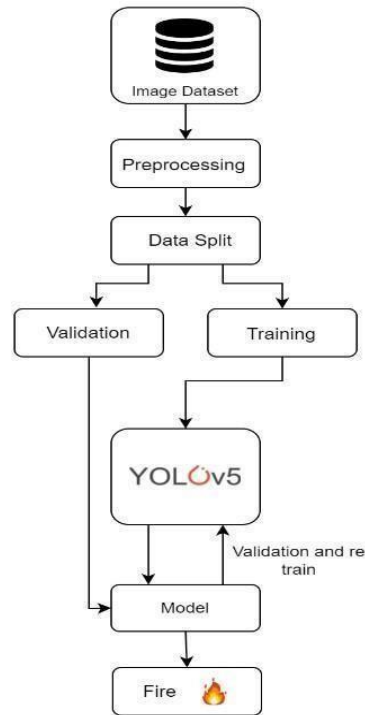


Fig.5.1 Overall design of the proposed system.

- **Data Preparation:**

Compile a varied dataset with pictures and videos showing smoke and fire incidents in different settings. Using programs like Roboflow or Makesense, annotate the dataset to identify the fire and smoke zones of interest. Divide the dataset into subgroups for testing, validation, and training.

- **Model Training for YOLOv5:**

To train the YOLOv5 model on the annotated dataset, use Google Colab. To ensure effective training, set up a Google Colab laptop with GPU capability. For training, use the YOLOv5 repository from GitHub and adhere to the guidelines given. Utilizing the provided dataset, fine-tune the YOLOv5 model to maximize detection accuracy.

- **Validation:**

Using the dataset's validation subset, validate the trained YOLOv5 model. Analyze the model's performance measures, including mean average precision (mAP), recall, and accuracy. To enhance performance, modify the model's hyperparameters or training settings as necessary.

- **Testing:**

To evaluate the model's performance in the actual world, test it using the testing subset of the dataset. Use inference on unseen photos and videos to find occurrences of smoke and fire. Analyze the model's processing speed, false positive rate, and accuracy of detection.

- **User Interface Development:**

Provide an intuitive user interface so that users can communicate with the smoke and fire detection system. Create an interface that can display detection results and take in photos or videos as input. Provide tools for monitoring detection confidence ratings, changing detection thresholds, and handling alarms.

- **Integration with Makesense and Roboflow**

Use Makesense and Roboflow to integrate data preparation and annotation into the training workflow. For dataset maintenance, augmentation, and format conversion, use Roboflow. To improve annotations and confirm label correctness, use Makesense.

- **User Examination:**

Allow testers to experience the operational smoke and fire detection system. Give the testers preestablished test scenarios to work with while they are doing the tests. Get tester input about the performance, efficacy, and usability of the system. Utilize the input to pinpoint areas that need work and make iterative changes to the implementation. Include tools for controlling warnings, monitoring detection confidence ratings, and changing detection thresholds.

- **Refinement and Optimization**

Adjust the implementation iteratively in response to user testing input. Optimize the YOLOv5 model even further to boost robustness and detection accuracy. For real-time deployment, optimize the system's performance and resource use.

- **Deployment:**

Implemented smoke and fire detection system should be put to use in an actual setting. Make sure there is a smooth interface with any current networks or surveillance systems. Keep an eye on the system's dependability and performance in use, and take appropriate action when problems occur.

6. RESULTS

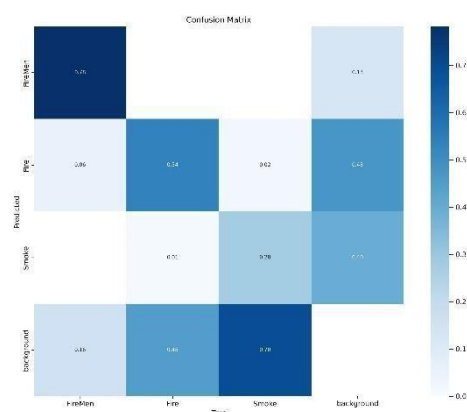


Fig.6.1.Confusion Matrix

A table that lists a classification model's performance in summary form is called a confusion matrix.

It displays the number of forecasts that are true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TP:

Properly anticipated positive cases. TN: Accurately forecasted adverse events. FP: False alarms caused by incorrectly projected positive cases. FN: Negative incidences that were incorrectly anticipated (missed detections).

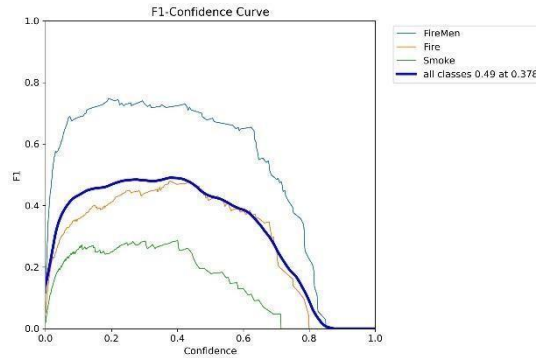


Fig.6.2.F1 and Confidence Curves

The model's performance in the event of a class imbalance is assessed using the F1 score, which is the harmonic mean of accuracy and recall. Plotting the F1 score against various forecast confidence criteria is known as the F1 curve. It aids in figuring out the ideal cutoff point that strikes a balance between recall and accuracy. The F1 score's variation with the confidence threshold is depicted by the curve.

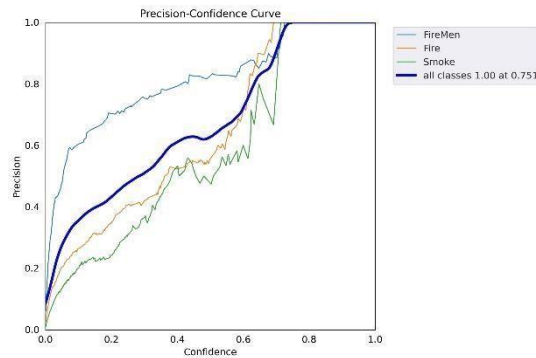


Fig.6.3.Precision and Confidence Curves

The precision of a prediction is the percentage of accurate positive forecasts among all positive predictions. Plotting precision versus various confidence criteria is done using the precision curve. It facilitates the visualization of the model's accuracy at various degrees of confidence. More accurate detections result from fewer false positive predictions, which are shown by a greater precision.

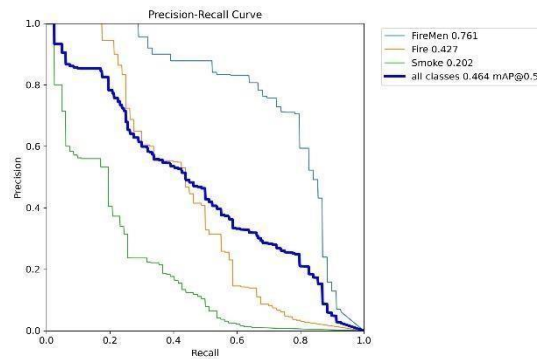


Fig.6.4.Accuracy and Recall Curves

At various confidence levels, accuracy and recall are traded off. These curves show this tradeoff. Plotting recall is done on the xaxis and precision on the y-axis.

The graph illustrates how, with fluctuating confidence levels, accuracy changes when recall varies or vice versa.

It aids in evaluating how well the model captures all positive occurrences while producing accurate positive forecasts.

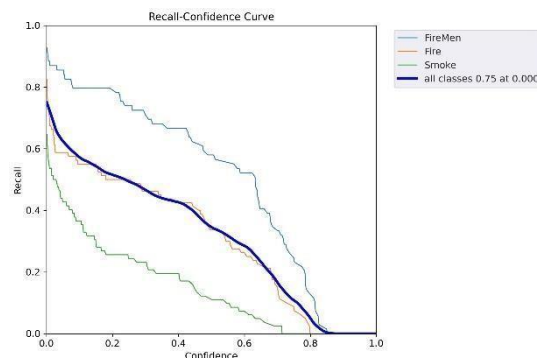


Fig.6.5.Confidence curves and recall

recall calculates the percentage of accurate positive predictions among all real positive occurrences. Plotting recollection versus various confidence criteria is done using the recall curve. It facilitates the visualization of the model's recall at various confidence levels. More accurately detected positive cases are indicated by a better recall, which also means fewer incorrect negative predictions.

7. DISCUSSION

The YOLOv5 object identification method is used in the research article to propose a realtime fire and smoke detection system. The introduction emphasizes how important it is to identify fires early since they offer serious hazards. It is decided that conventional detection techniques are insufficient, which leads to the investigation of automated, higher level systems. The suggested solution uses YOLOv5 architecture and deep learning approaches to try to overcome these drawbacks. It highlights how crucial improved accuracy, on-the-spot monitoring, and automation are to the detection process. High detection accuracy, the ability

to monitor in real-time, and easy connection with current surveillance systems are important advantages. The research is driven by the pressing need to enhance fire detection systems, particularly in settings where conventional approaches are inadequate. The project's scope includes all phases, from development and research to assessment and integration. The study presents a clear architectural foundation for the proposed system by identifying modules and using UML diagrams. The efficacy of the YOLOv5-based smoke and fire detection system is emphasized in the conclusion, underscoring its capacity to improve safety precautions and lessen the risks connected with fire occurrences.

8. CONCLUSION

In summary, the YOLOv5-developed fire and smoke detection system has shown to be an efficient and successful means of accomplishing the project's goals and functional requirements. YOLOv5 has been chosen as the foundational technology for object detection. Allowed the system to precisely identify incidents of fire and smoke in pictures and videos in real time, achieving the project's main goal. The accuracy and performance of the system have been greatly enhanced by YOLOv5's cutting-edge object identification capabilities and architecture, which guarantee dependable detection even in challenging and dynamic contexts.

Additionally, the monitoring interface, alert notification module, and surveillance system integration with YOLOv5 have made things easier. Smooth cooperation and communication, enabling thorough observation and prompt reaction to fire and smoke occurrences. The technology has improved operating efficiency and reduced the danger of possible disasters by automating the detection process, setting off alarms, and notifying the appropriate authorities. Overall, it has been quite successful in meeting the project's goals and functional requirements to use YOLOv5 as the primary technology for smoke and fire detection. Due to its precision, efficiency in real-time, and integration potential, the system has established itself as a dependable means of improving safety protocols and lowering the risks connected with fire-related incidents.

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