# Improving the Performance of the YOLOv11 Model for Fire and Smoke Detection Using Hyperparameter Tuning

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Abstract: Reducing losses and responding quickly to events depends on early detection of fires. Artificial intelligence has contributed significantly to the development of accurate and reliable detection systems for detecting and classifying the presence of objects. The most prominent shortcomings observed in this study are the possibility of the model encountering difficulties in determining dim lighting or the presence of materials similar to smoke, which affects the model's performance. In this research study, we created an intelligent model for detecting smoke and fires based on images. The YOLOv11 model is the latest and most advanced deep learning model in object identification applications. In order to determine the true set of hyperparameters to determine the best performance of the model, this information was modified through trial and error and evaluation of different settings including batch size, learning rate, optimizer type, and adding dropout rate. A large database collected from surveillance cameras, internet images and other sources was also used, showing high accuracy results, with the model achieving 98% accuracy. It was found that the improved model was better than the default model. In addition, there was a 73% decrease in false alarms compared to the default model before the improvement. These results highlight the importance of tuning hyperparameters to improve detection accuracy and reduce errors, resulting in a more robust, efficient, and reliable model that can be used to detect smoke and fires in a variety of indoor and outdoor environments.

## 1 INTRODUCTION

Fires are among the most dangerous natural disasters that threaten people's lives and environmental properties worldwide [1], [2], [3]. International organizations have reported that fires suffers hundreds of thousands of deaths and injuries annually, in addition to economic losses estimated at billions of dollars. They destroy buildings and infrastructure and hinder commercial and industrial operations [6], [7]. The devastating environmental impacts of fires include deforestation and the emission of massive amounts of harmful gases and substances, leading to a major climate change problem. [8], [9]. California saw 8527 fires in 2018 alone, burning 1.9 million acres (7700 km2), or about 2% of the state's total territory, at an estimated cost of USD 148.5 billion. [10], [11]. An excellent illustration of significant fire disasters is the Australian bushfire crisis of 2019, which highlights the vital importance of fire detection during the pre-suppression stage. Numerous systems equipped with visible light, thermal infrared, and multispectral instruments have been developed and extensively used, including platforms that are ground-based, airborne, or space borne [12], [13].

It takes a lot of fire or smoke to set off an alert because conventional smoke/fire sensors that rely on photometry, thermal, or chemical detection can react in a matter of minutes [14]. Additionally, they are not applicable to outdoor settings and are unable to provide information regarding the location and size of the fire. By addressing the shortcomings of earlier systems, the creation of new camera-based solutions increases the resilience and dependability of smoke and fire detection [15]. The majority of human surroundings, including public transportation, industry, and city streets, already have cameras and closed-circuit television (CCTV) systems installed for surveillance purposes [16], [17].

To avoid these serious risks to these serious risks, it has become necessary to develop smarter and more accurate early warning systems, and this is where YOLOv11 comes in as an effective model for monitoring and responding to fires in real time. One of the latest methods used in artificial intelligence to detect fires is the YOLOv11 model, which is characterized by high speed and accuracy in determining the location of smoke and flames, especially in difficult situations such as places with little or dim lighting [4]. Due to significant progress in models and methods for fire and smoke detection, previous studies have faced many challenges, most notably high rates of false alarms, the inability of traditional models to distinguish between smoke and similar environmental elements such as fog and clouds, and poor performance in low-light environments or complex scenes [5]. Some models also suffered from slow response times, which limited their use in early warning systems. In this study, the YOLOv11 model was used after improving hyperparameters to solve these problems. The results showed significant improvements in accuracy and recall, in addition to lower false alarm rates, making the model more efficient and reliable in detecting fires and smoke in different environments. The structure of the research paper is as follows: Section 2 outlines previous work related to fire and smoke detection. Section 3 covers the methodology and recommended techniques for achieving optimal results. Section 4 presents and discusses the results obtained, along with previous studies. Section 5 concludes the paper's conclusions and future work.

## 2 LITERATURE SURVEY

The subject of detecting smoke and fire using computer vision techniques is presently being worked on by a number of researchers. Creating precise automated detection systems is their goal. Recently, deep learning techniques have been used to increase these solutions' accuracy [21]. Several deep learning-based methods that are suitable for smoke and fire detection are covered in this section.

Wang et al [18] (2022) This study considered a lightweight model called lightweight YOLOv4 to achieve a balance between performance and efficiency in flame detection. The study replaced the basic network CSPDarknet53 with CSPDarknet53 while adopting the BiFPN network to enhance bidirectional communication across domains. In addition, the feature extraction unit was improved by adding a separate attention unit, which led to replacing the traditional 3×3 convolution. The results showed that lightweightYOLOv4 reduced the number of trainable parameters by 19% compared to YOLOv4, while maintaining similar accuracy (85.64% mAP) and processing speed of 71 frames per second, making it suitable for real-time applications.

Al-samdi et al (2023) [19] presented a new framework to improve the accuracy of smoke detection. The performance and speed of three YOLO models, YOLOv3, YOLOv5, and YOLOv7, were compared with Fast R-CNN and Faster R-CNN, using a dataset that included different detection regions (far, near, and medium). According to the data, with an accuracy of 96% of mAp atInseryion Over Union IoU, YOLOv5 outperformed YOLOv3, and YOLOv7 outperformed YOLOv3 with an accuracy of 95% versus 94%. Comparing the modified approach with other models confirmed the satisfactory results. Dalal et al. (2024) [20] Using LBP-CNN and YOLOv5, this work demonstrated a hybrid model for detecting urban fires. The study relied on a dataset from Kaggle to focus on normal and foggy conditions. The results showed an accuracy rate of 96.25% in the typical environment 93% and the (mAP) 94.59%, showing that the hybrid model outperformed traditional models for smoke detection.

Khan et al. (2025) compared three models YOLOv5, YOLOv7, and Transformers with an improved, lightweight Yolov8 model for fire and smoke detection that has higher performance and faster speed. Control components were added to improve the extraction of important features. In addition, a C3Ghost module was also added to try to reduce the computational complexity without affecting the model's performance in terms of accuracy. There are several datasets that were used in this study from Kaggle, where the improved model achieved mAP@50 of 89%. This improved model is believed to be reliable for detecting a variety of fires and smoke. In 2024, Chetoui et al. [22] used deep learning detection methods such as YOLOv8 and YOLOv7 to quickly and accurately identify and detect smoke. They constructed a dataset of approximately 11,000 smoke and fire images and achieved a mAP@50 of 92%, a classification accuracy of 83%, and a recall of 95% compared to other models including DEtection Transformer, Faster-RCNN, and YOLOv6. YOLOv8 performed better in terms of accuracy and speed. The model showed a clear superiority in performance and speed, making it suitable for applications in safety and fire prevention. J. Hu and Y. He et al [23] proposed a system DS-YOLO to detect fire and smoke detection model which is based on DP-ELAN to enhance accuracy and reduce the number of parameters along with SlimNeck to reduce computational complexity. The IoU criterion is replaced by Gaussian Wasserstein distance to improve small object detection. The model achieves mAP of 70.1% with lower complexity, outperforming the baseline model by 1.3%, making it suitable for comprehensive fire safety applications.

Wei and X. Liu et al [24] The paper proposed an improved YOLOv8-FD model for fire detection in different scenarios with the aim of addressing the accuracy and detection error problems. The model was improved using EfficientViT to extract features more efficiently, which helps to identify the flame perimeter more clearly and reduce errorsbuildingC2f_EMSC is designed to improve detection accuracy and reduce computational operations. Additionally, SPPF and LSKA modules are integrated to easily detect small targets, reaching mAP@0.5 of 94.2%. Table 1. Shows the details of previous studies.

Table 1: Summarize of previous studies.

| Name researcher | Year | Model | mAP |
|---|---|---|---|
| Wang et al | 2022 | YOLOv4 | 85.64% |
| Al-samdi et al | 2023 | YOLOv3,YOLOv5,YOLOv7 | 95% |
| Dalal et al | 2024 | YOLOv5 | 94.25% |
| Khan et al | 2025 | YOLOv5,YOLOv7 | 89% |
| Chetoui et al | 2024 | Detection Transformer, Faster-RCNN, and YOLOv6. YOLOv8 | 92% |
| J. Hu and Y. He et al | 2024 | DS-YOLO | 70.1% |
| Wei and X. Liu et | 2024 | YOLOv8-FD | 94.2% |

# 3 PROPOSED METHODOLOGY

This research paper presented a set of deep learning techniques to attempt to detect smoke and fires accurately and systematically. The first step was to collect a variety of data from fires and smoke in indoor and outdoor environments. After that, the pre-processing process was carried out using image cropping technique, then the most appropriate and efficient model was chosen due to its additional improvements, which is the YOLOv11 model. After that, the model's performance was improved by adjusting the hyperparameters. Finally, the model's performance was evaluated through a set of metrics, the most prominent of which is (mAp). The Figure 1. Shows proposed methodology.

## 3.1 Fire and Smoke Image Collection

The database for fire and smoke detection collected from Tensorflow, which is one of the most important and best sites specialized in preparing data for researchers and developers in various fields of artificial intelligence. The database consists of 8785 images distributed into Train 75%, Val 20%, and Test 5%. Thus, the Train file contains 6593 images, Val file contains 1751 images, and Test file contains 441 images. All images in the database are 640x640 pixels in jpg format and were collected from surveillance cameras, Internet images, and other sources to cover different scenarios of fires in different places such as house fires, forest fires, car fires, and smoke from industrial fires. The data was manually annotated with fire and smoke zones to enable it to be used in various detection projects. The database contains 21697 annotations (15668 for fire class and 6029 for smoke class). Table 2 below shows the details of the dataset and Figure 2 shows samples from the dataset.

Table 2: Database properties.

| Dataset split | Number of images | Images percentage | Number of annotations |
|---|---|---|---|
| train | 6593 | 75% | 16335 |
| val | 1751 | 20% | 4312 |
| test | 441 | 5% | 1050 |
| Total | 8785 | 100% | 21697 |

## 3.2 Fire and Smoke Image Preprocessing

Image cropping technique was adopted as one of the effective methods to improve the accuracy of fire and smoke detection, as the images may contain many unnecessary details that may affect the performance of the model. The clipping process allows focusing on areas that contain clear visual evidence of fires and smoke, which contributes to improving prediction. In addition, random cropping was incorporated during the training process to increase data diversity and improve the model's ability to generalize and recognize different types of fires and smoke. Figure 3 illustrates image preprocessing when cropping is used.

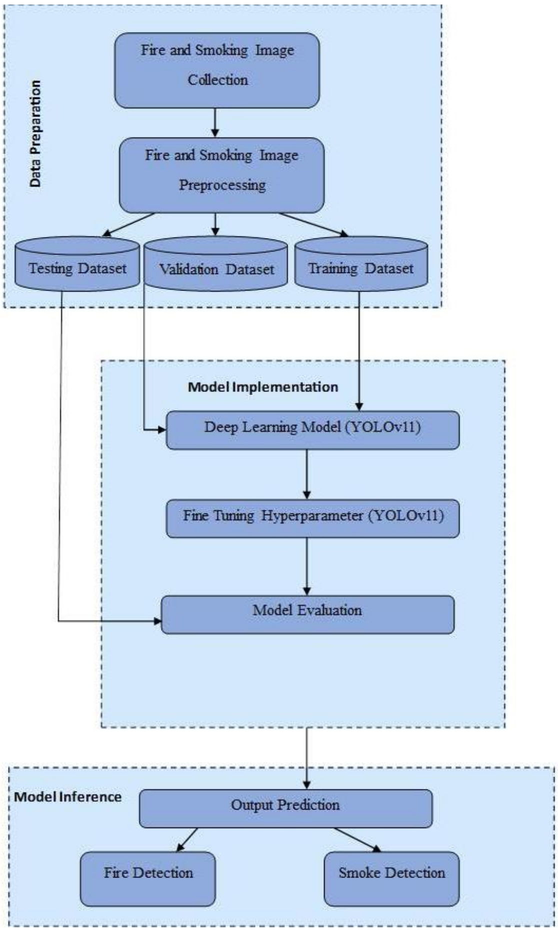


Figure 1: Proposed methodology.

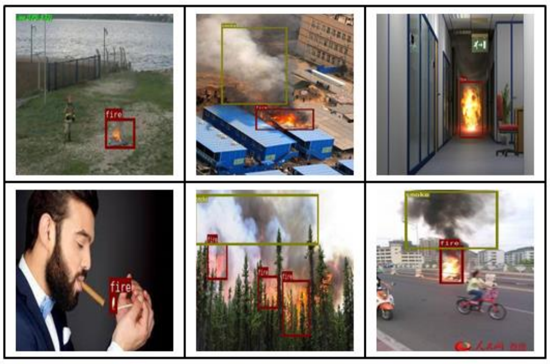

Figure 2: Dataset samples.

## 3.3 Deep Learning Model YOLOv11

Because of its exceptional object detection capabilities—which include faster and more accurate object identification than other models—the YOLOv11 model was selected for the fire detection challenge. One of the newest variants in the YOLO (You Only Look Once) family, the yolov11 model was introduced by Ultralytics in October 2024. . maintained the multitasking capabilities of Yolov8 while enhancing efficiency with the C3k2 block and adding the C2PSA module for improved spatial attention, which is especially advantageous for the identification of small and overlapping objects. Significant advancements over earlier iterations are seen in its ability to achieve more accuracy with fewer parameters, which makes it more effective, resource-efficient, and quicker than many other conventional models, like SSD and Faster R-CNN. Therefore, It is perfect for a variety of uses, including intelligent picture analysis, autonomous driving, and security surveillance. Because of Google Colab's robust cloud computing environment and fast graphics processing units (GPUs), which enable running deep models without requiring a lot of local computing resources, the model was constructed and trained utilising this platform. The YOLOv11 model's architecture is shown in Figure 4.


Figure 3: Image cropping: a) before cropping, b) after cropping.

## 3.4 Fine Tuning Hyperparameter YOLOv11

The hyperparameter tuning stage and its procedures are one of the most important and accurate steps in creating an accurate and robust model, while many studies ignore this step and instead use default hyperparameter settings, which are not suitable for all applications, especially those that require speed and high efficiency, such as our task of detecting fires and smoke in different environments. After evaluating the performance of the YOLOv11 model and its results using the default hyperparameters, our study found some shortcomings that indicate that modifying and changing some of the main hyperparameters may significantly improve the reliability of the model. Adam was replaced with the SGD optimizer, which is characterized by balance and the ability to generalize better, especially when working with large amounts of data. Also, to prevent overfitting and increase in accuracy levels at each epoch, a so-called dropout rate layer of 0.2 was added. The batch size was also increased from 16 to 32, which improves stability and prevents accuracy fluctuations throughout the training process. In addition, the learning rate was increased to 0.01 to improve stability and convergence, especially in more difficult tasks that appear to have low light or are caused by the presence of clouds, etc. These changes in the hyperparameters improved the accuracy of our model and its effectiveness in identifying smoke and fires across a variety of environments [27]. This highlights the importance of carefully and precisely tuning the hyperparameters to create a model with high accuracy and reliability. Table 3 shows the modified hyperparameters compared to the default hyperparameters of the YOLOv11 model.

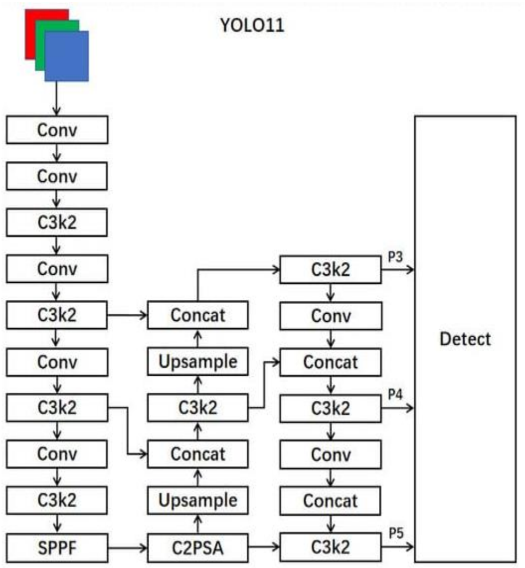


Figure 4: The architecture of YOLOv11 [25].

Table 3: Yolov11 default and proposed fine tuning hyperparameters.

| Hyperparameters | Default values | Proposed values |
|---|---|---|
| Image size | 640 | 640 |
| Dropout ratio | 0.0 | 0.2 |
| Batch size | 16 | 32 |
| Optimizer | Adam | SGD |
| Learning rate | 0.001 | 0.01 |
| Momentum | 0.93 | 0.93 |
| Epochs | 20 | 20 |

### 3.5 Model Evaluation

The performance evaluation of the suggested model is a crucial stage in wrapping up our work technique. The most popular performance metrics, such as F-Score, Accuracy, Precision, and Recall, were used [26], [28]. Furthermore, the most crucial of these is the average accuracy (mAp). In essence, mAP assesses the model's capacity to strike a balance between recall (making sure the objects detected are accurate) and precision (finding all pertinent objects).a fundamental performance indicator that illustrates the degree of the model's effectiveness in identifying objects at various levels [29], [30].

## 4 RESULTS AND DISCUSSION

### 4.1 Analyzing the Metrics of Recall, Accuracy, mAp, Precision and F1-Score

The performance of the YOLOv11 model was evaluated using a number of measures after implementation using virtual hyperparameter. The model achieved an mAP of 94%, with a precision of 94% and a recall of 95%. However, the model showed a high rate of false alarms (false positives = 565), indicating that the model tends to misclassify some images as fires or smoke, which can lead to false alarms in real-world environments. Additionally, training took longer (45 m) due to the use of the Adam optimizer and a small batch size.

Based on these results, the hyperparameters were returned to improve the model's performance in terms of accuracy, training speed, and reducing prediction errors. This resulted in a significant improvement in performance after these modifications, with the model's accuracy rising to mAP =98%, and its precision improving to 99%, meaning the model was more selective in classifying fires, meaning it no longer generated false alarms as frequently. The recall also improved to 99%, indicating that the model was better able to detect all actual fires without missing many. The results also show that the largest improvement was in reducing false alarms to just 150, a 73% reduction, indicating that the model was more accurate in classifying fires and smoke and distinguishing them from other backgrounds. Due to its training on diverse data, the model's reliability has increased compared to previous models. It is now able to accurately distinguish flames and smoke in diverse conditions, as previously mentioned, distinguishing them from strange objects other than smoke, including low and high lighting. This has been particularly prominent after improving the super-information and its stability on diverse data through improving this super-information. Table 4 compares the results before and after tuning the hyperparameters for the YOLOv11 model, demonstrating how the modifications improved all key metrics, underscoring the importance of tuning the hyperparameters for achieving optimal model performance. Figure 5 shows the confusion matrix for the Yolov11 model before and after tuning the hyperparameters, also Figure 6 shows the confusion matrix for the Yolov11 model after tuning.

Table 4: Results before and after tuning the hyperparameters for the YOLOv11 model.

| Performance measures | Before tuning | After tuning | Improvement percentage |
|---|---|---|---|
| mAP | 94% | 98% | 4% |
| Precision(p) | 94% | 99% | 5% |
| Recall(r) | 95% | 99% | 4% |
| false alarms (false positives) | 565 | 150 | 73% |
| Training time | 45m | 30m | 33% |


Figure 5: Confusion matrix for the Yolov11 model before tuning the hyperparameters.

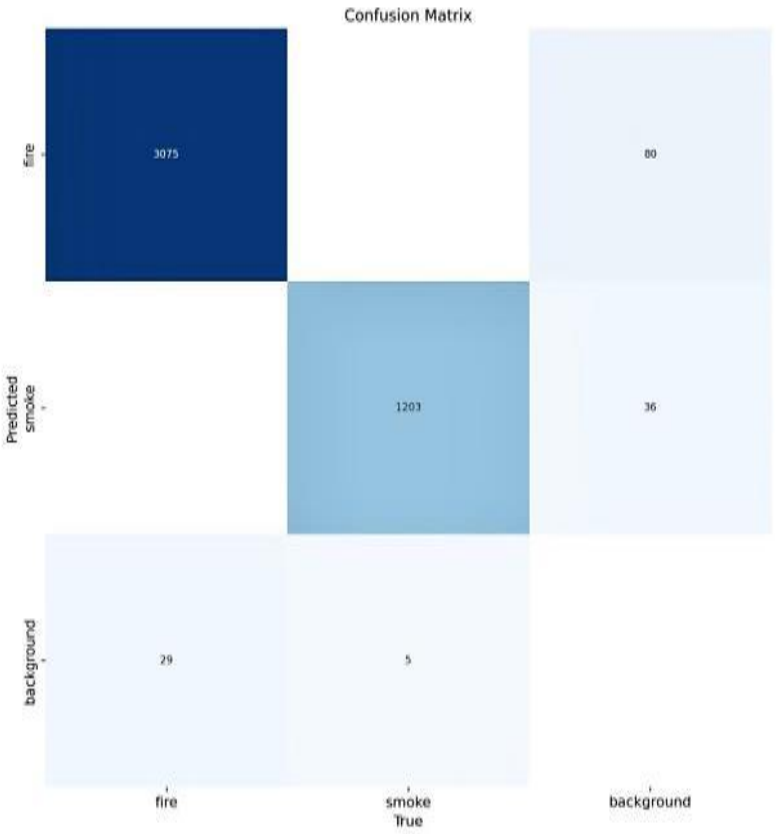


Figure 6: Confusion matrix for the Yolov11 model after tuning the hyperparameters.

Through this research, four main curves were examined to evaluate the performance of the YOLOv11model. Accuracy varied across confidence levels, as shown by the precision-confidence curve. After optimization, the model demonstrated its ability to accurately identify fires while minimizing false positives and maintaining high accuracy levels even at low confidence levels. The recall-confidence curve illustrates how recall with confidence thresholds compares. In a similar way, the model accumulates more fires without compromising sensitivity, as shown by the improved recall across different thresholds. Throughout the precision-confidence curve, both positive and negative results were carefully considered. While f-score achieves an optimal equilibrium of missed detections and false alarms, it also maintains high accuracy in fire detection. Figure 7 illustrates the curves for both the Precision-Confidence, the Recall-Confidence, the Precision-Recall, and the F1 Score.

The improved YOLOv11 model was evaluated using a sample image as shown in Figure 8. The model demonstrated excellent accuracy in detecting smoke and fires. The model also became more effective and reliable in both outdoor and indoor work environments due to its increased ability to detect fires with high accuracy and fewer false alarms.

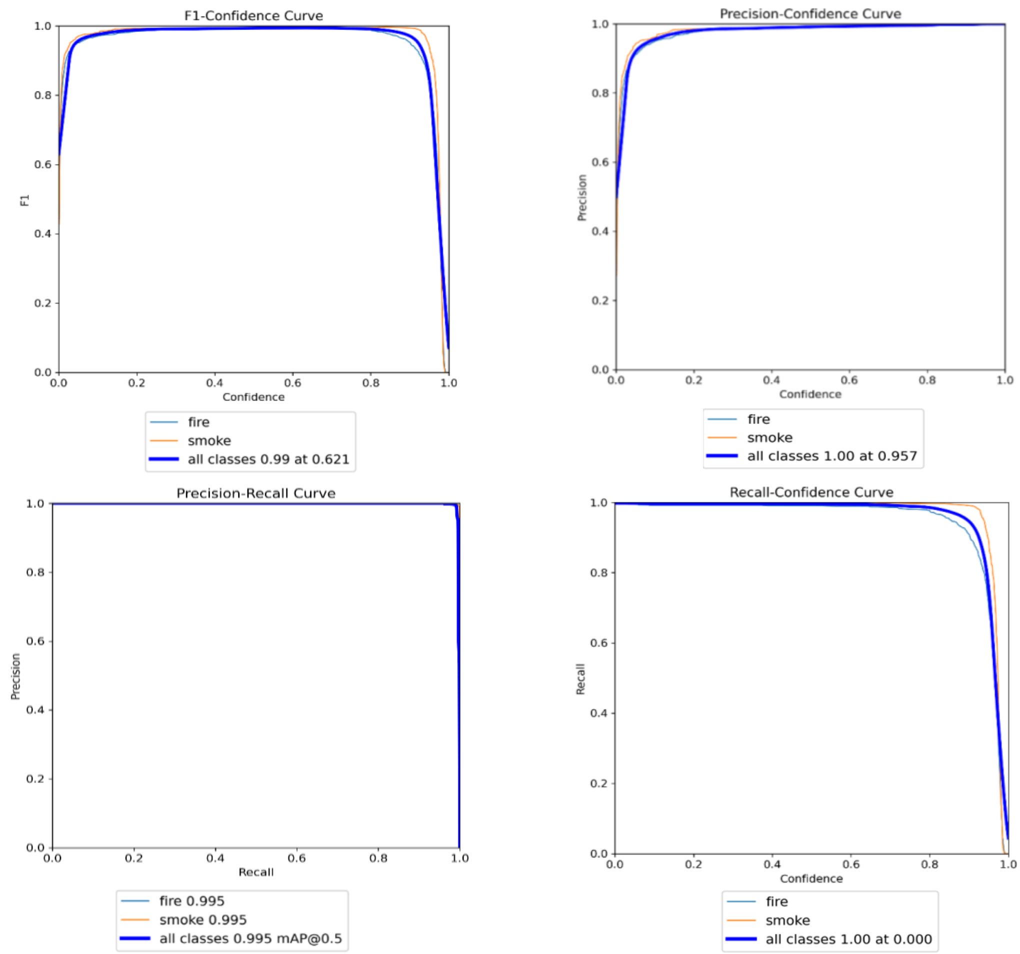


Figure 7: Shows the precision, recall, and F1 curves for the modified model.

## 4.2 Comparison with Provisos Studies

When compared to J. Hu and Y. He et al [23] study, which relied on DS_YOLO, the models used in their research suffered from a high rate of false alarms due to the difficulty in distinguishing between light smoke and natural clouds. These common errors were greatly reduced in the study by adjusting the hyperparameter and the best results were obtained in the research. The map of the Chetoui et al. [22] dropped to 92%, indicating that there are problems in detecting fires and smoke. On the other hand, the YOLOv11 model showed its ability to deal with detecting fires at different lighting levels, which makes it more reliable in detecting these fires. These results show that the YOLOv11 model helped it overcome these difficulties that it faced in previous studies. Table 5 shows a comparison with previous studies.

Table 5: Comparison with previous studies.

| Paper | Model | n.Class | Results(mAP) |
|---|---|---|---|
| [22] | YOLOv8 | 2 | 92% |
| [23] | DS_YOLO | 2 | 70.1% |
| Proposed model | YOLOv11 | 2 | 98% |


Figure 8: Samples of the modified model's predictions on the test data.

## 5 CONCLUSIONS

The need for an accurate system is increasing as the likelihood of fires breaking out in indoor and outdoor spaces increases. Smoke and fires behave in ways that are difficult to detect. Using the YOLOv11 model and tuning its hyperparameters, this study demonstrated how deep learning can improve the accuracy and reliability of smoke detection. Its performance has improved significantly, reducing false alarms and achieving high accuracy and high reliability. Since the average precision (mAP) criterion measures the model's efficiency in classifying items across different probability threshold levels, it was chosen as the primary indicator for model evaluation. The results demonstrate the importance of modifying hyperparameters to enhance the capabilities of fire and smoke detection systems, as well as their robustness. Future studies should focus on improving the model's efficiency while developing an additional dataset. Moreover, the proposed method demonstrates that deep learning can offer a substantial advantage over traditional detection techniques. Future research should focus on further improving model efficiency, exploring more diverse and challenging environmental conditions, and developing additional high-quality datasets to support broader real-world applications.

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