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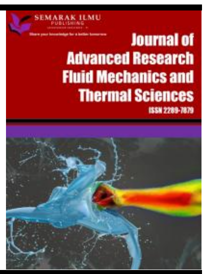

Fire Detection System using YOLOv5 and IoT Integration for Real-Time Alerts in Safety Applications

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ABSTRACT

The rising threat of heat-related and fire incidents underscores the urgent need for advanced thermal and fire detection systems to ensure timely and accurate responses. This report presents a smart fire detection project utilizing the YOLOv5 deep learning model. The project aims to design an early fire detection system with real-time capabilities. The proposed system implements a convolutional neural network (CNN) and the YOLOv5 real-time object identification system, enhancing fire detection through anchor box optimization. In the incident of a fire, the system sends an alert to the user's Telegram app bot via the Internet of Things (IoT), assisting in taking necessary precautions. The project demonstrates notable efficiency in fire detection and alerting capabilities, with system evaluation metrics showing an F1 score of 95%, mAP@50 of 97%, accuracy 96.3%, and a recall rate of 89%. These results underscore the system's reliability and precision. The project contributes significantly to Sustainable Development Goals (SDG), goal 9 for industry, innovation, and infrastructure, and 11 for sustainable cities and communities highlighting its potential to enhance fire safety measures in various settings.

1. Introduction

A fire can spread through different heat transfer mechanisms conduction, convection, and radiation. Understanding these mechanisms is essential for fire prevention and control. In the context of fire, the three heat transfer mechanisms conduction, convection, and radiation play crucial and interrelated roles in the spread and intensity of the fire. Conduction allows heat to travel through solid materials, such as walls or metal structures, potentially igniting other parts of a building or object. Convection involves the movement of hot gases and smoke, which can transfer heat to

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surrounding areas, raising temperatures and spreading the fire vertically, especially in enclosed spaces. Radiation emits heat through electromagnetic waves, allowing the fire to spread to nearby objects even without direct contact, further intensifying the fire's reach. These mechanisms work together to propagate and sustain fires, making them critical factors in fire safety and control.

The present of fires, are significant risk to human life, infrastructure, and the environment. Timely and accurate, detection of fire incidents is crucial for effective emergency response and mitigating potential damages. Traditional fire detection systems often face challenges in accuracy, real-time detection, and integration with modern technologies. This technical report introduces a smart fire detection project that leverages the power of deep learning and the you only look once (YOLO) model to address these limitations. Utilizing computer vision techniques, the system aims to enhance the accuracy, speed, and real-time detection capabilities. The system also uses, integration with the Telegram IoT platform. This will give instant notifications from remote monitoring, enhancing the fast response compared to smoke detection. This report provides an in-depth exploration of the smart fire detection project, encompassing its objectives, methodology, experimental results, and implications for fire safety and emergency management. The project's significance lies in its potential to enhance fire safety measures, reduce response time, and minimize property damage, ultimately contributing to a safer environment for individuals, communities, and society.

Existing fire detection systems face significant limitations in accuracy and real-time detection, leading to delayed emergency responses and potential property damage. Additionally, these systems often lack effective integration with IoT platforms like Telegram, hindering instant notifications and remote monitoring during fire incidents, which are crucial for timely fire management.

This study aims to develop an intelligent fire detection system to address these deficiencies. The objectives include creating a smart fire detection model using YOLOv5 to enhance its performance and integrating fire detection systems with IoT platforms to establish a robust notification system for immediate response and monitoring.

The innovation of this research lies in its comprehensive approach to improving traditional fire detection systems. Taking advantage of YOLOv5's speed and accuracy enhances real-time detection efficiency, reducing property damage risks and increasing occupant safety [1]. Integrating with IoT platforms like Telegram ensures instant, remote-access notifications, improving coordination among first responders and continuous situation monitoring, thus setting new standards in fire safety management.

Extensive references have been made to several research papers that focus on different approaches to fire detection using popular object detection methods and computer vision-based strategies. The reviewed literature underscores the evolution and improvement in real-time fire detection capabilities, contributing valuable insights and advancements to the field. The selected papers include Fire accidents in any place such as industrial operations, schools, homes, or even offices [2-4]. Early fire detection is crucial and plays a higher priority and important role in protecting and saving lives and properties. Harnessing fire detection systems, can significantly reduce damages and maximize fire control efforts. It is also one of the most fundamental steps for fire safety measures. Traditional fire detection systems detect fire via physical sensors, and locating the fire will consume time, especially outdoor environment. Thus, the concentration of fire combustion products needs to be high in the open air to trigger the alarm [5].

This project proposed a fire detection method by optimizing the anchor box for the object detection model using a Convolutional Neural Network (CNN) which is the YOLO v5 algorithm because the YOLO v5 network detects is more consistent with the extraction algorithm of areas of interest in the experiment such as in studies by Yu *et al.,* [6] and Xu *et al.,* [7]. This project will also include a notification system via IoT through the Telegram application which most of the research (in

Table 1) lacks. The system is expected to have a relatively lower model size, higher accuracy, and detection speed than conventional fire detection such as smoke detectors. This system also aims to be implemented in any setting whether indoors or outdoors without any errors.

Recent research has focused on enhancing fire detection systems through various deep-learning methods to improve accuracy, efficiency, and real-time capabilities. The study by Wu and Zhang [8] employed R-CNN, YOLOv3, and SSD for real-time forest fire detection, achieving high accuracy rates of 99.7%, 92%, and 99.88%, respectively. However, the study noted the limitation of less integration with IoT for fire notifications. In 2020, Huimin *et al.,* [9] developed a fire monitoring system using YOLOv3 with Online Hard Example Mining (OHEM), which achieved an accuracy of 83.33%. The primary limitation was insufficient fire images, under complex scenes in the training dataset.

Another study by Hongyu *et al.,* [10] improved multi-scale fire detection using YOLOv4, resulting in an accuracy of 86.2%, yet it lacked an IoT-based notification system. In the same year, Chaoxia *et al.,* [11] focused on flame detection using R-CNN, which enhanced efficiency and achieved 99.5% accuracy but suffered from large computational redundancy. The study by Wang *et al.,* [12] explored lightweight YOLO combined with MobileNet, achieving 64.8% accuracy. However, the result is still lower, compared to the YOLOv4.

Table 1
Summary of recent research on fire detection methods using deep learning techniques

Reference	Method	Accuracy	mAP	Limitation
Wu *et al.,* [8]	R-CNN, YOLOv3 and SSD	99.88%	-	Less fire notification system involving IoT
Huimin *et al.,* [9]	YOLOv3 with OHEM	83.33%	-	Data limitations, false positives, training complexity, generalization, no IoT reported.
Hongyu *et al.,* [10]	YOLOv4	-	86.2%	Limited data variety, complex training, high computational cost, generalization challenges, not involving IoT
Chaoxia *et al.,* [11]	R-CNN	99.5%		Large computational redundancy, no IoT used.
Wang *et al.,* [12]	YOLO + MobileNet	-	64.8%	Using YOLOv4, the accuracy is still quite low
Mseddi *et al.,* [13]	YOLOv5 and U-net	99.6 %	-	Challenges: fire-like objects, high false alarms, small fires.
Pincott *et al.,* [14]	R-CNN Inception V2	95%	-	High false alarm rate, low training sample
Mahdi and Mahmood [15]	YOLOv5	96%	-	Non-existence of an integrated IoT notification system

Research by Mseddi *et al.,* [13] utilized YOLOv5 and U-Net for fire detection and segmentation, achieving a dice coefficient of 92% and an accuracy of 99.6%. However, it faced challenges such as fire-like objects, high false alarms, detection of small fires, and high inference time. In a study by Pincott *et al.,* [14] Faster R-CNN and Inception V2 for indoor fire detection, achieving 95% accuracy but struggled with a high false alarm rate and low training sample size. A recent study by Mahdi and Mahmood [15] implemented a wildfire detection system using YOLOv5, achieving 98% accuracy with the proposed process achieving 96%, but noted the absence of IoT integration for notifications.

Collectively, studies show advancements in fire detection methods, but challenges in IoT integration, computational efficiency, and dataset limitations still need addressing for further improvement [16]. There are other studies conducted where they do not use images for detecting the presence of fire [17-25]. Instead, the alert system uses IoT with various online platforms. The IoT system is also used by Hanafi *et al.,* [26] for tracking and monitoring for safety purposes.

This research supports SDG 9 (industry, innovation, infrastructure) and SDG 11 (sustainable cities) by developing an intelligent fire detection system using YOLOv5 and IoT [27-30]. It enhances infrastructure resilience, promotes innovation, and ensures timely emergency responses. The system improves urban safety through real-time fire detection, reducing false alarms, and contributing to resilient, sustainable, and inclusive cities. There are also other methods using acoustics for fire detection [31-33]. However, inaudible acoustic sensing has limitations, including susceptibility to false alarms from background noise and lacking the detailed visual information and fire type distinction provided by image detection.

The novelty of this research lies in the combination of anchor box optimization with IoT integration for enhanced fire detection. By leveraging anchor box optimization within the YOLOv5 model, detection accuracy is significantly improved. The system integrates real-time notification via Telegram, enabling immediate alerts and timely responses. This unique combination of optimized detection with IoT-based alerting offers a significant improvement over traditional fire detection systems, ensuring a practical and efficient solution for early warning and proactive fire management.

2. Methodology
2.1 Project Flowchart

In Figure 1, a flowchart shows the steps and processes involved in developing the proposed system. It contains three phases where the first process is data preparation involving data collection, data augmentation, data labeling, and data division. Next, this project continues with the second phase: the model development cycle This includes the YOLOv5 model training and testing the performance of the trained model. Lastly, the notification system phase starts after developing the YOLOv5 model which involves communication between the YOLOv5 model and the IoT platform, using Telegram.

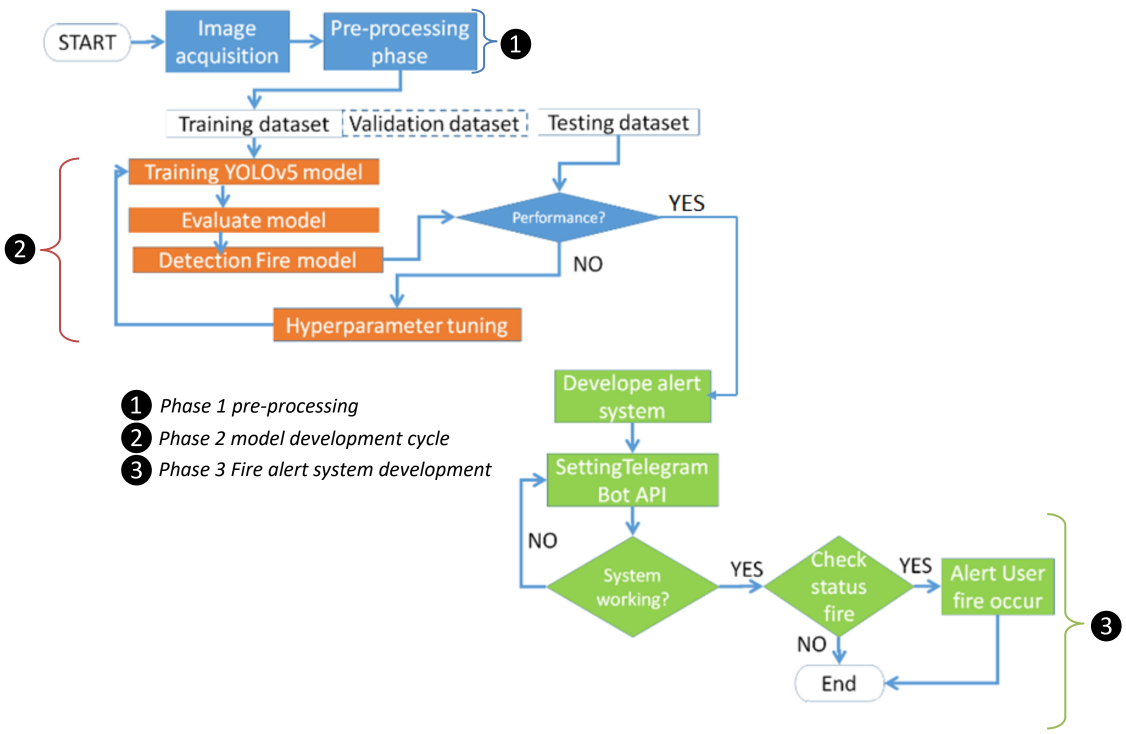

Fig. 1. Workflow for anchor box optimization in fire detection and notification system via IoT

2.2 Data Preparation

The data collection process for the smart fire detection project is critical for acquiring relevant datasets to train and evaluate the fire detection system. It involves several steps to ensure quality and diversity. Initially, the existing fire-related datasets are identified from public repositories like Roboflow, containing video footage and images covering a variety of fire scenarios and environmental conditions. 2,707 fire images were extracted from various fire accident videos, allowing the model to learn from diverse shapes, textures, colors, and lighting conditions. After selection, the datasets were downloaded for further analysis and augmentation operations, including image rotation, mirror symmetry, brightness adjustment, and PCA jittering, to increase training set diversity and improve model generalization. The data samples then undergo image labeling using Roboflow Annotate, where the region of interest (ROI), for each sample, is manually determined. Once annotated, the labeled images are converted to YOLOv5 format and downloaded for model development. The samples are divided into train, validation, and test sets in a 70:20:10 ratio, and cross-validation is employed to optimize training parameters like learning rate and cost function.

2.3 Model Development

The YOLOv5 architecture is chosen as the base model for fire detection due to its speed and accuracy. Anchor boxes, aspect ratios, and scales are determined to handle objects of different sizes and orientations. Project-specific hyper-parameters and input image sizes are configured accordingly. The YOLOv5 model is initialized with pre-trained weights on a large-scale dataset like common objects in context (COCO), and the annotated dataset is used for training. Stochastic gradient descent (SGD) or Adam optimization is employed, monitoring metrics like loss and learning rate. The trained model is evaluated using the validation dataset, computing precision, recall, and mean average precision (mAP). Fine-tuning the YOLOv5 model occurs based on evaluation results, adjusting hyper-parameters if necessary. Advanced techniques like focal loss or IoU loss may be explored. Iteration and refinement are performed to achieve the desired performance and capabilities in fire detection using YOLOv5.

2.4 Notification System Development

The development process of the Telegram notification system for this project involves key steps for successful integration and functionality. These steps include setting up a dedicated Telegram account, integrating with the Telegram API, implementing event detection and notification logic, determining notification content, managing user access, establishing real-time communication, conducting thorough testing and validation, deploying the system, and ensuring ongoing maintenance and updates. These steps collectively contribute to the effective function of the Telegram notification system for fire detection.

The process begins with the acquisition and pre-processing of the images. The fire images are collected from various sources, such as fire accident videos, and prepared through enhancement, resizing, and necessary transformations. Following this, the dataset is divided into three subsets: training, validation, and testing datasets.

The YOLOv5 model is then trained using the training dataset, and its performance is evaluated with the validation dataset. The trained model is subsequently implemented for fire detection. If the model's performance meets the desired criteria, the process advances to developing an alert system; otherwise, hyper parameter tuning is set to improve the model's performance, followed by reevaluation. An alert system is developed upon satisfactory model performance, and a Telegram Bot API is configured to send notifications. The system's functionality is verified, and if it operates correctly, it proceeds to monitor the status of fire detection in real time. If a fire is detected, the user is alerted immediately; if not, the system continues to monitor. This approach ensures that the object detection model is optimized for accuracy and efficiency. At the same time, the integration process with IoT technologies facilitates real-time fire detection and user notification, thereby enhancing safety and responsiveness.

3. Results

3.1 Model Training

The model was trained using PyTorch on Google Colab with an NVIDIA T4 GPU, utilizing 2,707 fire accident images. Table 2 provides a detailed illustration of the dataset distribution, systematically segmented into 70% for training, 20% for validation, and 10% for testing.

Table 2
Distribution of images in the dataset for fire detection model

Dataset	Numbers images
Training set	1,897
Validation set	541
Testing set	271

The dataset in Table 2, consists of fully labeled fire images in PNG format with bounding boxes saved in .TXT files for YOLOv5 training. Uploaded to Google Colab, the model was trained using PyTorch with 60 epochs, a 640 image size, a batch size of two, and YOLOv5x pre-trained weights. Training beyond 60 epochs, showed no further improvement, potentially leading to overfitting due to a constant learning rate and lower gains in mean Average Precision (mAP). Besides, the learning rate decreases and eventually becomes constant, indicating no further improvement and potential overfitting. It will cause the model to memorize the data, reducing its accuracy. The batch size was set to 2 due to Google Colab's limited GPU memory capacity. A higher batch size would exceed the maximum GPU memory allocated; thus, batch size adjustments were necessary to fit within the available resources. After training, the model learning process and training results are shown in Figure 2 and Figure 3. In simpler terms, these are the YOLOv5 metrics and losses while training and validating the model. YOLO loss function consists of three classifications; *box loss*: bounding box regression loss (Mean Squared Error), *obj loss*: the confidence of object presence is the object-ness loss and *cls loss*: the classification loss (Cross-Entropy).

3.2 Evaluation Metrics

A confusion matrix is a performance measurement tool used in machine learning and statistical classification tasks. It is a tabular representation that visualizes the performance of a classification model by summarizing the predictions made by the model against the actual ground truth labels of the dataset. Table 3 shows the result of this model.

Table 3
The overall results

Evaluation Metrics	Values (%)
F1 Score	95
Precision	100
Recall	89
mAP@50	97

True positives (TP) are instances where the fire detection system correctly identifies and classifies a fire incident as positive, and true negatives (TN) are instances where the system accurately identifies and classifies a non-fire incident as negative. False positives (FP) occur when the system incorrectly identifies a non-fire incident as positive, leading to a false alarm or Type I error. Conversely, false negatives (FN) are instances where the system fails to detect and classify a fire incident, resulting in a missed detection. Precision is a metric used to evaluate the accuracy of the fire detection system in correctly identifying and classifying fire incidents. Precision specifically focuses on the proportion of correctly classified fire incidents out of all instances classified as fire by the system. Recall, also known as sensitivity or true positive rate, is a metric used to evaluate the effectiveness of the fire detection system in correctly identifying and capturing all fire incidents present in the dataset. The F1 score is a metric used to assess the performance of the fire detection system relative to both precision and recall. Mean Average Precision (mAP) is a metric used to evaluate the performance of the fire detection system in object detection tasks. It is particularly relevant when using a model like YOLOv5, for detecting and localizing multiple objects, including fires, within an image or video.

The four graphs in Figure 2, show the performance metrics displayed in the four graphs reflect the fire detection model's progress throughout training, showcasing its improvement in key areas such as precision, recall, and mean Average Precision (mAP). Both precision and recall increase significantly early in the training process and stabilize around 0.9, indicating that the model effectively identifies true fire instances while minimizing false positives. High precision and high recall indicate that it successfully detects most of the actual fire occurrences. The mAP@0.5 curve reveals that the model achieves approximately 0.9, demonstrating excellent performance at the 50% Intersection over Union (IoU) threshold. This metric suggests that the model can accurately localize and classify fire-related objects with a moderate overlap criterion. Additionally, the mAP@0.5:0.95 curve, which measures performance across a range of more stringent IoU thresholds, increases steadily to reach 0.7. This indicates that the model is not only performing well under lenient conditions but also maintains strong detection capabilities across stricter IoU requirements, reflecting its robustness and generalizability. These metrics highlight the model's strong performance, stability, and effectiveness in fire detection tasks, making it a reliable tool for real-world applications where accuracy and precision are critical.

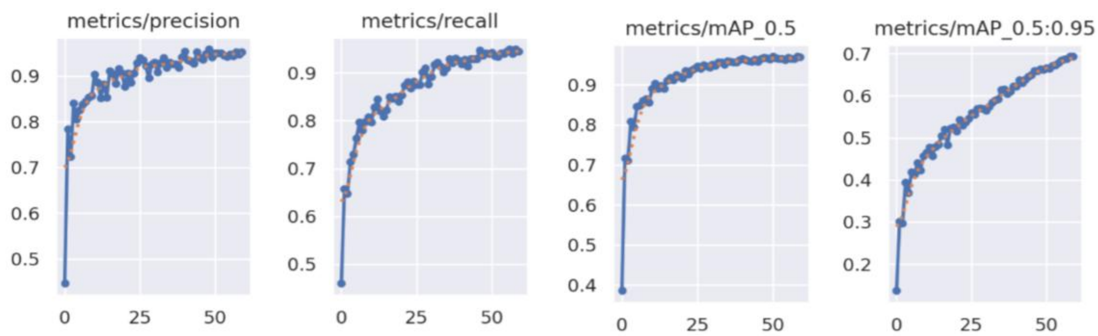

Fig. 2. Training results

The four graphs illustrate key performance metrics for a fire detection model. The precision-confidence curve Figure 3(a) shows precision increasing as the confidence threshold rises, reaching 1.0 at a confidence level of 0.903, indicating near-perfect accuracy at high thresholds. The recall-confidence curve Figure 3(b) demonstrates that recall remains high (0.98) at lower confidence levels but drops significantly as confidence increases, suggesting the model detects most fires at lower thresholds. The F1-confidence curve Figure 3(c) balances precision and recall, peaking at 0.95 at a confidence level of 0.534 before declining as higher thresholds reduce recall. The precision-recall curve Figure 3(d) indicates consistently high precision as recall increases, with a mean Average Precision (mAP) of 0.970 at an IoU threshold of 0.5, reflecting strong performance in identifying fires while minimizing false positives. These metrics suggest the model achieves optimal balance at a confidence level of 0.534, performing well across different thresholds.

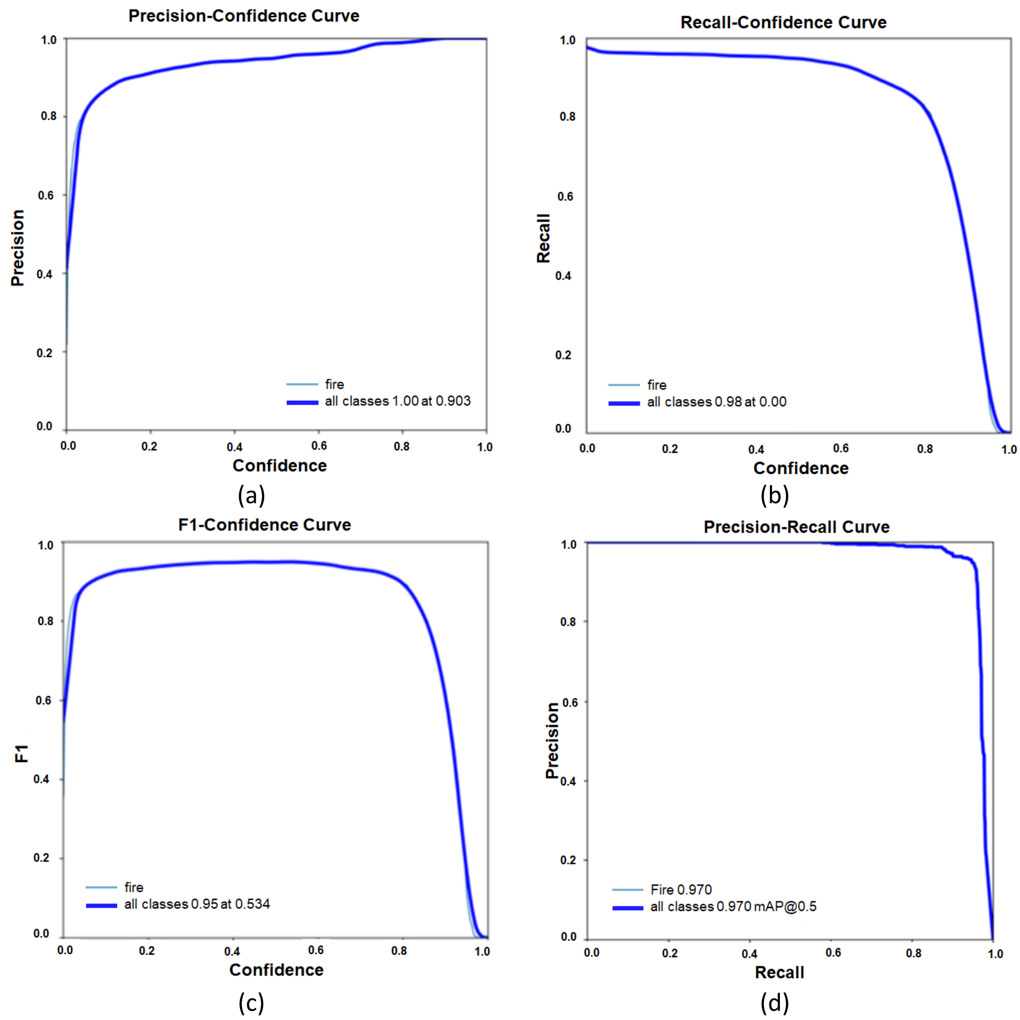

Fig. 3. Performance Metrics for Fire Detection Model (a) Precision results, (b) Recall results, (c) F1 score results, and (d) mAP@50 results

3.3 Model Inferencing

After training the data, the model is used to identify the occurrence of fires. The specific command used in the Windows virtual environment or command prompt

```
# Run inference on YOLOv5 model
!python run.py --weights /content/yolov5-master/best.pt --img 640 --conf 0.25 --source 0
``` &#8203;:citation[oaicite:0]{index=0}&#8203;
```

The YOLOv5 model that has been trained is then tested to run inference on multiple images of fire and also videos containing fire in the test dataset. Figure 4 below shows the result after running inference on the YOLOv5 model. The area containing fire is automatically marked with a bounding box including its confidence value on the top right. In the YOLOv5, the confidence value is the object score associated with each bounding box prediction. It represents the model's certainty about the presence of an object in that bounding box. By adjusting the confidence threshold, the model's precision and recall trade-off can be controlled. A Telegram channel, the 'SmartFireBot' was created to send the detected results from the trained YOLOv5 model. This channel will notify the users when the trained model detects a firing accident happening around the area. This Telegram channel the 'SmartFireBot' as in Figure 4(c), is important as this is the IoT platform being selected in this research to create a seamless communication between a YOLOv5 model with IoT to help achieve safer cities and communities. The YOLOv5 model is then tested to be implemented in a real-time camera application. This is crucial as real-time fire detection is needed for early fire detection, localizing the fire incidents and is more reliable when compared to existing fire detection systems. Inference results that are detected will be sent to the Telegram channel 'SmartFireBot', and messages will be published to warn users that a fire incident is happening in the area.


(a) (b) (c) (d)

**Fig. 4.** Result for fire detection model (a) Video before testing, (b) Inference result on video, (c) Notifications are sent via 'SmartFireBot' in the Telegram platform, providing images and short videos related to the fire incident
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The findings in Table 4 underscore the significant advancement presented by the proposed YOLOv5 model, which achieves an impressive mAP of 97%, markedly outperforming YOLOv4 (86.2%) and YOLO integrated with MobileNet (64.8%). This model stands out not only for its high accuracy but also for its suitability for IoT applications, a critical requirement for real-time deployment. While R-CNN demonstrates marginally higher accuracy at 99.5%, it falls short in IoT compatibility. Therefore, the proposed YOLOv5 model emerges as an optimal solution, combining high precision with IoT adaptability, thereby contributing to the advancement of real-time, IoT-enabled computer vision systems. Additionally, it demonstrates novelty compared to other models in this study.

Table 4
Comparison with others' results

Model	Accuracy (mAP)	Accuracy	IoT implement
YOLOv3 with OHEM [9]	-	83.3%	X
YOLOv4 [10]	86.2%	-	X
R-CNN [11]	-	99.5%	X
YOLO + MobileNet [12]	64.8%	-	X
R-CNN Inception V2 [14]	-	95%	X
YOLOv5 [15]	-	96%	X
Proposed using YOLOv5	97%	-	✓

4. Conclusions

This project developed an innovative fire detection system using YOLOv5, enhancing real-time detection accuracy. Rigorous testing demonstrated the model’s precision in fire localization, enabling prompt response. Integration with the Telegram IoT platform allows instant notifications and remote monitoring, improving public safety and asset protection through timely emergency response. This aligns with SDG, particularly Goal 9 and Goal 11. This project supports sustainable development and community resilience. This project opens up exciting prospects for further optimization of the fire detection system. Future work could explore advanced techniques to improve performance under diverse environmental conditions and expand the dataset for more comprehensive training approaches. Addressing intelligent challenges such as handling occlusions, improving detection in low-light conditions, and integrating multiple sensor inputs will enhance accuracy and robustness. Continued research and development in fire detection technology promises significant advancements, contributing to smarter and safer communities and ensuring a more secure and sustainable societal future.

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