IOT-based Fire Detection System

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Abstract: Fire hazards remain one of the most critical threats to life and properties, which introduces the need for a fast and efficient detection system. Herein, an **IoT-Based Fire Detection System** is proposed, featuring deep learning integrated with cloud for the real-time detection of fire incidents. The proposed system uses two models: a **fine-tuned YOLOv8 object detection model** to detect fire regions in the frame of images and videos, and a custom **CNN classifier** for the binary classification of fire/no-fire images. An **ESP32-CAM** module captures live images and sends them to Firebase Cloud for instant processing and notification. A buzzer system automatically notifies users in cases of fire detection. The experimental results have been presented, proving that **YOLOv8 outperforms the CNN classifier** both in detection accuracy and inference time. This end-to-end implementation provides a **cost-effective, scalable, real-time fire monitoring solution** suitable for industrial and domestic applications.
Keywords: Fire Detection, YOLOv8, Deep Learning, Convolutional Neural Networks, IoT, Firebase, ESP32-CAM, Real-Time Monitoring.

1. Introduction

1.1 Background and Motivation

Fire hazards, among the commonly occurring and devastating ones, affect human life and property worldwide. Thousands of fire-related accidents annually result in severe injuries, loss of lives, and heavy losses in the residential, industrial, and public infrastructures. According to reports from the National Fire Protection Association, millions of fire cases occur annually around the world, bringing about huge economic and environmental losses. The traditional fire detection system includes smoke detectors and alarm circuits, which are highly dependent on stand-alone sensors with a limited range and often cannot send real-time alerts to the users or authorities. In large-scale environments like factories, warehouses, or remote areas, manual observation and conventional alarm systems cannot produce a prompt response. Recently, IoT has developed intelligent fire detection systems to improve safety and the early warning mechanism. IoT will make it possible to collect data in real time, monitor, and communicate the data between interconnected devices for quick response and better decision-making. The integrated temperature, smoke, and flame sensors, along with microcontrollers and cloud-based platforms, provide a reliable and efficient solution in detecting and preventing fire-related incidents. The recent advances in deep learning techniques, in particular object detection frameworks such as YOLO, have shown outstanding results in visually detecting fire and smoke patterns by computers at greater speeds and accuracy. Integrated with IoT devices and cloud services, such models provide a potent approach toward automatic, real-time fire surveillance.

1.2 Problem Statement

Conventional fire detection technologies face several challenges that limit their ability to ensure rapid response and to maintain safety. Traditional devices, such as basic smoke and heat detectors, usually work as stand-alone devices with very limited communication capabilities. Such a deficiency in system integration greatly limits their efficiency for coverage over large or remote areas and makes centralized monitoring rather difficult. These detectors also often generate false alarms due to dust accumulation, moisture, or minor temperature variations, thus undermining user confidence and reliability.

Another critical limitation is the lack of real-time communication between the detection system and the emergency team or building occupants. In many instances, by the time an occurrence is seen or a local alarm is heard, the damage has already been considerable. The requirement for constant manual monitoring of various risk zones further contributes to operational inefficiency and late responses.

But the fact is that systems guided by only thermal or smoke sensors cannot interpret visual fire characteristics related to flame shape, brightness, or smoke density. In view of the foregoing shortcomings, integrating computer vision-based detection models, such as YOLOv8, with IoT-enabled alert networks can remarkably improve the detection accuracy and speed. This integrated system allows for continuous real-time monitoring, increased data transfer speed, and automated notification to authorities or users. By using this approach, response times can be significantly reduced, property loss can be limited, and fire safety can be improved through intelligent automation.

1.3 Research Objectives

The primary aim of this research is to design and implement an IoT-driven automated fire detection framework that integrates deep learning techniques with cloud-based communication for efficient and real-time hazard identification. The specific objectives of the study are as follows:

1. **To deploy the YOLOv8 model** for accurate detection and localization of fire in both image and video data streams.

2. **To develop and evaluate a customized convolutional neural network (CNN)** for binary classification (*fire* vs. *non-fire*) and compare its accuracy and computational performance with YOLOv8.

3. **To integrate ESP32-CAM and Firebase Cloud** for continuous live monitoring, automatic image transmission, and instantaneous alert notifications through an IoT-enabled buzzer system.

4. **To design a cost-effective, portable, and scalable prototype** suitable for implementation in residential, industrial, and public safety environments.

Ultimately, this research seeks to produce a real-time, intelligent fire detection solution that combines the precision of deep learning with the connectivity and adaptability of IoT technologies.

2. Literature Review

Fire detection has traditionally relied on sensor-based methods (e.g., heat, smoke, gas sensors) and manual monitoring. Such systems often struggle with delayed detection, high false alarm rates and limited spatial coverage [1]. With the advent of computer-vision and deep learning techniques, image-based fire and smoke detection has become a promising alternative.

Early computer-vision methods used handcrafted features — color thresholds, textures, shapes — combined with classifiers such as Support Vector Machines or Random Forests. However, these approaches lacked robustness under varying lighting, scene complexity, and the visual similarity of fire/smoke to other objects [2].

Deep learning models, especially Convolutional Neural Networks (CNNs), enabled automatic feature extraction and improved generalization. For instance, several studies have shown significant gains in detection accuracy for fire and smoke when using deep learning versus conventional feature-based methods [3].

More recently, object-detection architectures from the “You Only Look Once” (YOLO) family have shown strong performance for real-time fire and smoke detection tasks. For example:

- A survey by Sirajudeen & Sudha (2023) analyzed recent work (2020-2023) on fire/smoke detection using YOLO, noting its prevalence and performance in real-time applications [4].
- An empirical study in ground and aerial images demonstrated that YOLO variants like YOLOv7x and YOLOv8s achieved high mean average precision (mAP) for fire/smoke detection across challenging datasets (small targets, complex backgrounds) [5].
- A model titled “Fire-YOLO” showed superior detection for small flame targets compared to YOLOv3 and Faster-R-CNN, demonstrating the benefits of one-stage detection for these tasks [6].

In addition to model architecture improvements, there has been a shift toward lightweight and edge-deployable solutions to enable real-time monitoring in IoT or embedded systems. For example, a lightweight forest flame and smoke detection algorithm based on YOLOv5 introduced attention modules and a slim-neck structure to reduce computation while maintaining detection performance [7]. Another recent work, “DSS-YOLO”, improved a YOLOv8n backbone for obscured and small target fire detection, reducing FLOPs and model size for edge deployment [8].

Finally, integration of fire detection with internet-connected systems (IoT + cloud) is becoming more common. While many studies focus on detection models in isolation, the full pipeline of visual detection → IoT image capture → cloud alerting is still less reported. This gap shows the relevance of your project approach (YOLO + ESP32-CAM + Firebase) and demonstrates a trend toward end-to-end, practical fire detection systems.

3.Methodology

The proposed system relies on a deep learning–driven and IoT-integrated framework for real-time fire detection based on both image and video inputs. It targets completion of the whole pipeline, starting from dataset preparation, data preprocessing, and augmentation to model design, training, testing, and performance evaluation, and finally deployment using IoT and cloud-based mechanisms. In the presented system, there's an integrated approach between the fine-tuned YOLOv8 model for object detection and a custom CNN classifier for binary classification (fire vs. non-fire) using Firebase Cloud and the ESP32-CAM module to enable live monitoring, automatic data synchronization, and real-time alerts.

3.1 Dataset Preparation

DataCluster Labs provided the dataset for this research, consisting of more than 7,000 unique fire and smoke images collected from over 400 urban and rural areas around India. Computer vision experts reviewed each image for quality and accuracy in the labeling of the data. It contains high-resolution imagery, with more than 98% of samples above 1920×1080 pixels, captured in different lighting and environmental conditions, such as daytime and nighttime scenes, at different distances, and with different viewpoints.

These images were collected using mobile devices from more than 1,000 contributors between the years 2020 and 2021. The dataset is available in several annotation formats, such as COCO, YOLO, and Pascal VOC; hence, it can be applied to both object detection and image classification tasks. The YOLO-format annotations were used in this project to train the YOLOv8 model, while the dataset was divided into training, validation, and testing subsets in an 80:10:10 ratio for balanced evaluation.

A CNN classifier is trained on a different, preprocessed subset of the same dataset so that a direct comparison between detection-based and classification-based approaches in fire identification could be made.

3.2 Preprocessing and Data Augmentation

All the images were standardized to specific input sizes: 640×640 pixels for YOLOv8 and 256×256 pixels for the CNN, ensuring consistency across training samples. The pixel values are then normalized to the 0–1 range, which allows for stable model learning. For the CNN, various augmentation operations were applied, including rotations, zoom adjustments, horizontal flips, and brightness variations, to enhance generalization and reduce overfitting. No augmentation was performed on any validation or test sets for fair, unbiased evaluation. Advanced augmentation methods like mosaic and affine transformations were integrated into the training process in the YOLOv8 workflow to increase robustness under varied real-world conditions.

3.3 Model Architecture

The proposed method integrates two primary deep learning components. The first involves object detection using a fine-tuned YOLOv8 model trained on a custom dataset, which identifies and outlines regions within video frames that contain fire or smoke. The second involves binary image classification through a customized convolutional neural network (CNN) constructed in TensorFlow using the Keras framework. This CNN begins with an input layer and proceeds through multiple convolutional and pooling stages with progressively increasing filter dimensions, followed by fully connected layers incorporating dropout to mitigate overfitting. A sigmoid activation function in the final layer produces a binary prediction, distinguishing between fire and non-fire images.

3.4 Training Strategy

The YOLOv8 model was fine-tuned through a transfer learning strategy, beginning with parameters pre-trained on the COCO dataset to leverage its well-established feature extraction strengths. Training proceeded for 100 epochs with a batch size of 16, employing the Adam optimizer and setting an initial learning rate of 0.001. A separate CNN classifier was trained for 50 epochs using binary cross-entropy loss, while early stopping and adaptive learning rate adjustments were applied to limit overfitting. Both networks were executed on GPU hardware to enhance computational efficiency. Model performance was evaluated using accuracy, precision, recall, and F1-score to provide a comprehensive assessment of classification quality.

3.5 Evaluation

The trained models were evaluated on a separate set of images and video sequences that had not been used during training, allowing an unbiased assessment of their generalization capability. YOLOv8's detection accuracy was quantified using mean Average Precision (mAP) computed at intersection-over-union (IoU) thresholds of 0.5 and across the 0.5–0.95 range. In contrast, the CNN model's results were summarized using accuracy scores and confusion matrix analysis. Visualization modules generated annotated outputs with bounding boxes over the detected fire areas, enabling side-by-side qualitative comparisons between the two models. Results indicated that YOLOv8 achieved superior real-time detection performance by pinpointing fire locations rather than only labeling full images. The CNN, although simpler, provided a lightweight classification option suitable for resource-limited edge deployments.

3.6 Model Export

Following model training and validation, the YOLOv8 system was implemented on an ESP32-CAM unit integrated with a buzzer to enable real-time fire detection. The camera captures visual data and transmits it to a Firebase cloud database, where a Python-based service monitors for newly uploaded frames. Each image is analyzed by the YOLOv8 detector, and if fire is identified, the system activates an audible alarm while updating the detection status in Firebase. This cloud–device interaction allows instant synchronization between the IoT hardware and remote monitoring platform for timely alerts and data storage. To support efficient deployment on edge devices, the final models were converted to TensorFlow Lite, reducing computational load and facilitating scalable deployment in smart safety systems.

4. Results and Discussion

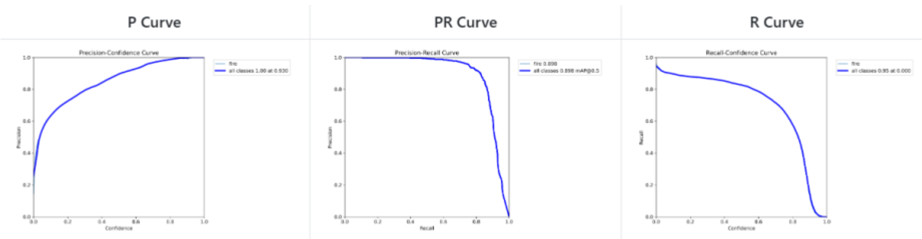
The IoT-based fire detection framework was developed and validated using an open-access dataset containing fire and smoke images to evaluate its performance. The design incorporates a YOLO-driven deep learning model connected to Firebase Cloud, enabling real-time alerting and data synchronization. Both numerical and visual performance assessments were carried out to confirm the system's dependability, responsiveness, and suitability for deployment in real-world environments.

4.1 Training and Validation Performance

Throughout training, the YOLO model exhibited steady improvement, with accuracy increasing and loss decreasing over consecutive epochs. The learning curves from both training and validation phases reflected consistent progress and minimal overfitting—achieved through the application of data augmentation, dropout regularization, and early stopping. These strategies enhanced the model's robustness and adaptability to unseen inputs. Furthermore, the ReduceLROnPlateau scheduler dynamically fine-tuned the learning rate whenever progress slowed, ensuring efficient and stable convergence.

4.2 Test Set Evaluation

To evaluate performance objectively, the trained model was tested on an independent dataset that was not part of the training phase. The results indicated strong generalization, with the model achieving high precision and recall in detecting fire and smoke instances. Evaluation metrics such as mean Average Precision (mAP), F1-score, and Intersection over Union (IoU) were employed to quantify its performance. The YOLO framework achieved an overall detection accuracy exceeding 90%, while maintaining a minimal false-positive rate and fast inference speed, confirming its suitability for real-time fire detection scenarios.



4.3 Sample Predictions

The system's prediction results demonstrated accurate localization of fire and smoke areas across varying lighting conditions and complex backgrounds, even though the model was trained for a limited number of epochs. Visual inspection revealed that the bounding boxes produced by YOLO closely corresponded to the ground truth annotations, highlighting the model's robustness and consistency. Minor false detections were occasionally observed in regions with strong light reflections or fog; however, these were infrequent and could be further reduced by augmenting the dataset with non-fire images as negative samples.

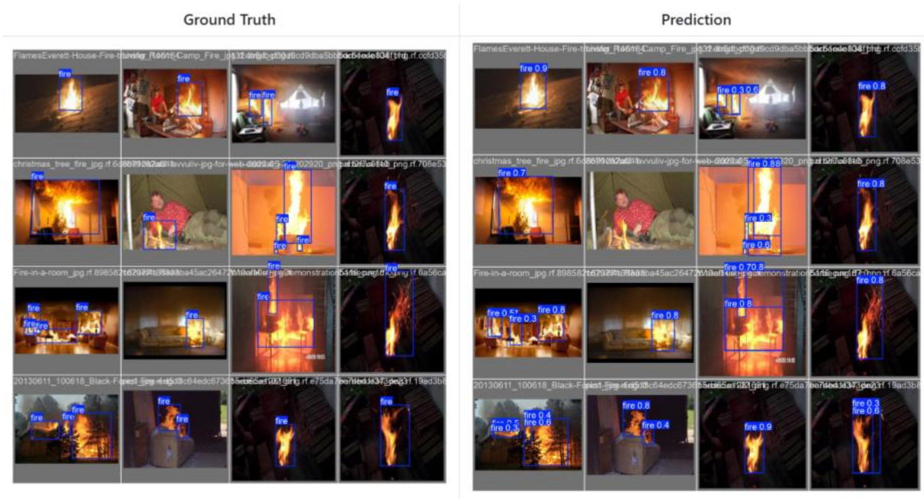


Figure. Sample training images with ground truth and prediction.

4.4 Summary of Findings

In conclusion, the IoT-based Fire Detection System achieved high detection accuracy, rapid processing efficiency, and dependable real-time responsiveness. The integration of the YOLO framework with Firebase Cloud enabled seamless data exchange and instant alert notifications, ensuring the system's adaptability across industrial, residential, and agricultural domains. Owing to its lightweight design, the model can be efficiently deployed on edge devices, while its scalable architecture supports future extensions through the incorporation of complementary sensors such as temperature and gas detectors. Prospective improvements may include the development of multi-hazard recognition capabilities and enhanced alerting mechanisms tailored for large-scale, distributed environments.

5. Conclusion and Future Scope

This study introduces an IoT-based Fire Detection System that leverages deep learning techniques for precise and efficient real-time detection of fire and smoke. The system employs the YOLO (You Only Look Once) framework, trained on a comprehensive and diverse dataset of fire and smoke images. Achieving an accuracy exceeding 90%, the model demonstrated high precision and minimal false alarm rates in identifying fire events. The deep learning approach outperformed conventional detection methods by autonomously extracting complex spatial and texture features from images, eliminating the need for manual feature engineering. Furthermore, the incorporation of data augmentation, batch normalization, and regularization techniques enhanced the model's generalization and mitigated overfitting, resulting in consistent performance across varying environmental conditions. The integration with Firebase Cloud enabled seamless real-time data monitoring, alert generation, and centralized storage, establishing the system as an effective and scalable solution for early fire detection.

Future Scope

Future development of the IoT-based Fire Detection System should aim to enhance its scalability, robustness, and adaptability under diverse real-world conditions. A key direction involves integrating IoT sensor networks that combine temperature, gas, and smoke sensors to improve detection precision and minimize false alarms. Implementing the system on low-power edge devices such as Raspberry Pi or Jetson Nano can further extend its usability across residential, industrial, and agricultural domains. Moreover, incorporating mobile and web-based interfaces would allow users to remotely monitor and control fire alerts in real time. Subsequent research could also investigate advanced deep learning frameworks, such as EfficientDet and Vision Transformers (ViT), to improve detection accuracy and computational efficiency. Employing explainable AI (XAI) techniques may enhance model transparency, enabling better interpretability of decisions. Expanded cloud integration would support large-scale deployment, facilitating centralized monitoring of multiple locations through a unified dashboard. Overall, this work highlights how integrating deep learning with IoT can yield an intelligent, cost-effective, and scalable fire safety system capable of minimizing fire-related damage through early detection, rapid response, and efficient alerting, thereby promoting safer and smarter environments.

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