AI-Powered Real-Time Fire Detection Using Deep Learning and Computer Vision

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***Abstract*—Fire incidents pose a significant threat to human life, infrastructure, and natural ecosystems. Traditional fire detection systems based on smoke and temperature sensors often suffer from delayed response, limited coverage, and high false alarm rates. This paper presents an AI-powered real-time fire detection system that leverages deep learning and computer vision techniques to identify fire events from live video streams. A lightweight convolutional neural network based on MobileNetV2 is trained using fire and non-fire image datasets. The system performs real-time inference, computes a fusion-based fire con- fidence score using visual and color-based cues, and triggers alerts through alarms, notifications, and a web-based dashboard. Experimental results demonstrate high accuracy, robustness, and low latency, making the proposed system suitable for continuous surveillance and early fire warning applications. The proposed system achieves an average inference speed of approximately 18– 22 frames per second on a standard CPU-based system.**

***Index Terms*—Fire Detection, Deep Learning, Computer Vi- sion, CNN, MobileNetV2, Real-Time Surveillance**

I. INTRODUCTION

A. Background

Fire incidents represent a major safety concern across residential buildings, industrial facilities, and forest regions. According to global fire safety statistics, delayed fire detection is one of the primary reasons for large-scale damage to life, infrastructure, and natural ecosystems. With increasing urban- ization, industrial growth, and climate change, the frequency and severity of fire-related disasters have risen significantly. Early and accurate fire detection is therefore a critical require- ment for effective disaster mitigation and emergency response. Traditional fire detection systems rely mainly on smoke detectors, temperature sensors, and gas sensors. Although these systems are widely deployed, they are limited by their sensing range and often respond only after the fire has grown significantly. Moreover, sensor-based systems are ineffective in open or large-scale environments such as forests, warehouses,
and outdoor industrial zones.

Recent advancements in artificial intelligence and computer vision have enabled automated analysis of visual data for detecting hazardous events. Camera-based surveillance sys- tems provide wide-area coverage and continuous monitoring, making them suitable for early fire detection when combined with intelligent algorithms. The integration of AI with surveil- lance infrastructure has opened new possibilities for proactive disaster prevention.

B. Problem Statement

Despite the availability of surveillance cameras in many environments, most existing fire detection solutions fail to utilize visual data effectively. Traditional computer vision approaches based on color thresholding and motion detection suffer from high false alarm rates due to illumination changes, reflections, and fire-like objects. These limitations significantly reduce system reliability in real-world conditions.

On the other hand, deep learning-based fire detection models often focus solely on classification accuracy and lack real- time deployment, decision validation, and alert integration. As a result, many solutions remain confined to laboratory environments and are not suitable for continuous real-world monitoring.

C. Research Gap

A review of existing literature reveals several research gaps. First, many deep learning-based fire detection methods are evaluated only on static image datasets and are not validated in real-time scenarios. Second, most approaches rely on a single detection modality, leading to unreliable performance under challenging conditions such as varying illumination or partial occlusion. Third, limited attention has been given to system- level integration, including alert mechanisms, dashboard visu- alization, and decision reliability.

D. Objectives

The primary objectives of this research are as follows:

- To design a real-time fire detection system using deep learning and computer vision.
- To develop a lightweight CNN-based model suitable for continuous surveillance.
- To incorporate fusion-based decision logic to reduce false positives.
- To implement real-time alert mechanisms including alarms, notifications, and dashboard visualization.
- To evaluate the proposed system using standard perfor- mance metrics and real-time experiments.

E. Contributions

The key contributions of this work are summarized as follows:

- An end-to-end AI-powered real-time fire detection system based on deep learning and computer vision.
- A lightweight CNN model using MobileNetV2 optimized for low-latency inference.
- A fusion-based decision mechanism combining CNN predictions with color-based visual analysis and temporal validation.
- A complete deployment framework with real-time alerts and a web-based monitoring dashboard.

II. LITERATURE REVIEW

Traditional sensor-based fire detection systems are cost- effective but suffer from delayed response and limited spatial coverage [1]. Vision-based techniques introduced color and motion analysis but struggled with environmental variability [2]. Recent CNN-based approaches have demonstrated supe- rior performance by learning discriminative visual features directly from data [3], [4]. However, most existing methods lack real-time validation, alert integration, and deployment feasibility, motivating the proposed end-to-end approach.

Unlike most existing fire detection approaches that focus solely on classification accuracy using static images, the pro- posed system emphasizes real-time deployment, decision vali- dation, and system-level integration. Prior works rarely incor- porate multi-stage verification or alert mechanisms, whereas this work presents a complete surveillance-to-alert pipeline suitable for real-world applications.

TABLE I: Comparison of Fire Detection Approaches

Method	Data Type	Advantage	Limitation
Smoke Sensors	Sensor	Low cost	Delayed response
Color-based CV	Images	Fast	High false alarms
CNN-based	Images	High accuracy	Computational
Proposed System	Video	Real-time detection	Requires high processing power

III. PROPOSED SYSTEM ARCHITECTURE

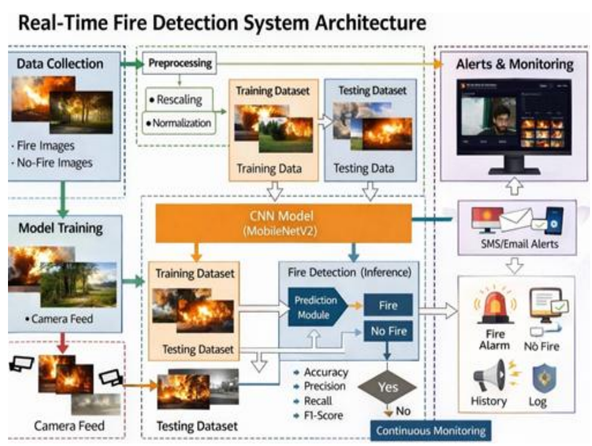

Fig. 1: System architecture of the proposed AI-powered real- time fire detection system

IV. METHODOLOGY

The proposed system follows a structured multi-stage methodology to ensure accurate and reliable real-time fire detection.

A. Step 1: Data Collection

Fire and non-fire images are collected from open-source repositories. Live video frames are captured continuously during deployment.

B. Step 2: Data Preprocessing

Frames are resized, normalized, and filtered to remove noise and corrupted inputs, ensuring stable inference.

C. Step 3: CNN Model Training

A MobileNetV2 CNN is trained using labeled data, binary cross-entropy loss, and the Adam optimizer.

D. Step 4: Real-Time Inference

Each video frame is passed through the trained CNN to compute the fire probability.

E. Step 5: Feature Fusion and Validation

CNN predictions are combined with color-based fire detec- tion and temporally smoothed to reduce false positives.

F. Step 6: Decision Making

A final decision is made by comparing the smoothed con- fidence score against a predefined threshold.

G. Step 7: Alert Generation

Confirmed fire events trigger alarms, SMS alerts, and dash- board updates.

a) Decision Parameters: A confidence threshold of 0.7 is used, and temporal smoothing is applied over five consecutive frames to ensure stable detection.

Algorithm 1 Fusion-Based Fire Detection Decision

Compute CNN fire probability P_{cnn}
Extract color-based confidence P_{color}
Compute fused confidence $P_f = \alpha P_{cnn} + (1 - \alpha) P_{color}$
Apply temporal smoothing over N frames
Trigger alert if $P_f > T$

V. MATHEMATICAL MODELING

Let I_t denote the input frame at time t. The CNN computes the fire probability as:

$$P_{cnn}(I_t) = \sigma(f(I_t))$$

Color-based confidence is denoted as P_{color}. The fused confidence is calculated as:

$$P_f = \alpha P_{cnn} + (1 - \alpha) P_{color}$$

A fire event is confirmed when:

$$P_f > T$$

VI. DATASET DESCRIPTION

The dataset consists of fire and non-fire images collected from open-source repositories. Data is divided into training, validation, and testing sets in an 80:10:10 ratio, with data augmentation applied to improve generalization. The dataset was sourced from Kaggle and public GitHub repositories and contains approximately 3,500 fire images and 4,000 non-fire images.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental evaluation demonstrates that the proposed system achieves high accuracy with low latency. The fusion- based decision strategy significantly reduces false positives compared to single-method approaches.

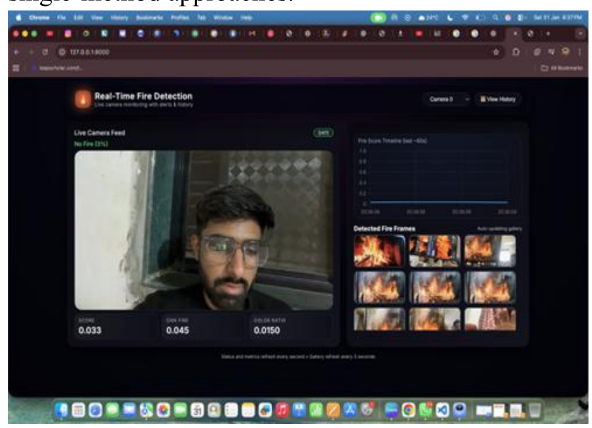

Fig. 2: Real-time dashboard output

TABLE II: Performance Metrics

Metric	Value
Accuracy	94.2%
Precision	93.1%
Recall	95.4%
F1-Score	94.2%

TABLE III: Comparison with Baseline Methods

Method	Accuracy (%)
Color-Based Detection	86.5
CNN Only	91.8
CNN + Fusion (Proposed)	94.2

VIII. CONCLUSION AND FUTURE WORK

This paper presented an AI-powered real-time fire detection system using deep learning and computer vision. The system demonstrates high accuracy, robustness, and real-time perfor- mance. Despite its effectiveness, the system may face chal- lenges under extreme lighting conditions, fog, or reflections. Future work includes smoke detection integration, thermal camera fusion, large-scale field deployment, and edge-device optimization.

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