VISION-BASED FIRE ALERT SYSTEM

Real-Time Fire Detection System with Alarm and Notification: A Deep Learning Approach

SUBJECT :- DATA SCIENCE TOOLS WORKSHOP

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INTRODUCTION

Fire detection systems play a critical role in preventing catastrophic damage, preserving lives, and protecting property. This research presents a comprehensive MobileNetV3-based real-time fire detection system with integrated alarm and notification capabilities for early intervention in fire emergencies.

Fire incidents represent one of the most destructive and life-threatening emergencies across industrial, commercial, and residential settings worldwide. Traditional fire detection systems typically rely on sensors such as smoke detectors, heat detectors, and gas sensors that require direct exposure to the products of combustion. While effective in many scenarios, these conventional methods often suffer from delayed response times, high false alarm rates, and limited coverage areas.

The emergence of computer vision and deep learning technologies has created new possibilities for fire detection that overcome many limitations of traditional systems. Vision-based fire detection offers several distinct advantages, including the ability to monitor large areas with a single device, detect fires at greater distances before they trigger conventional sensors, and provide visual verification to reduce false alarms.

Recent advancements in deep learning architectures, particularly convolutional neural networks (CNNs), have dramatically improved the accuracy and efficiency of image-based fire detection systems. Among these architectures, MobileNet stands out for its balance between computational efficiency and detection accuracy, making it particularly suitable for real-time applications on edge devices with limited processing capabilities.

This research presents a comprehensive real-time fire detection system that leverages the lightweight MobileNetV3 architecture to classify video frames into fire and non-fire categories with high accuracy. The system extends beyond mere detection by incorporating multimodal alerting mechanisms, including an audible alarm for immediate local notification and email alerts for remote monitoring. This integrated approach ensures rapid response to fire incidents, potentially reducing damage and saving lives through early intervention.

LITERATURE SURVEY

Evolution of Fire Detection Technologies:- Fire detection has evolved significantly over decades, progressing from simple manual observation to sophisticated automated systems. Early automated detection relied primarily on physical and chemical sensors that detect the byproducts of combustion. Blazequel categorizes the primary types of conventional detectors as smoke detectors (optical, photoelectric, and ionic), heat detectors (thermal and thermovelocimetric), flame detectors (infrared, ultraviolet, and combined), linear infrared detectors, gas detectors, and temperature sensor cables[5]. These systems, while effective, often require the fire to develop to a certain stage before triggering an alarm.

As noted by VisionTIR, fires progress through several distinct phases: warm-up (pre-combustion), ignition and initial combustion, development (growth and spread), stabilization, and extinguishing[6]. Conventional detection methods typically only identify fires during the later stages of this progression, highlighting the need for systems capable of earlier detection.

Computer Vision for Fire Detection:- The integration of computer vision technologies into fire detection systems represents a significant advancement in the field. PyImageSearch highlights that computer vision can be employed in various contexts for fire detection, including IoT/edge devices strategically placed in high-risk areas, drones for aerial surveillance, and satellite imagery for monitoring large areas[2]. These approaches enable fire detection at greater distances and with broader coverage than conventional sensor-based systems.

A systematic literature review by researchers at Universiti Kebangsaan Malaysia identified several advantages of vision-based fire detection over conventional methods, including the ability to monitor large areas, detect fires at earlier stages, and provide visual verification[8]. However, the review also noted challenges in this approach, including variable lighting conditions, complex fire patterns, and computational requirements.

Deep Learning Approaches in Fire Detection:- The application of deep learning, particularly convolutional neural networks (CNNs), has dramatically improved the accuracy and reliability of vision-based fire detection systems. The International Journal of Scientific Development and Research (IJSDR) reports that CNN-based models significantly outperform traditional algorithms in terms of fire detection accuracy[11]. Various architectures have been explored for this purpose, including Faster R-CNN, R-FCN, SSD, and YOLO variants, with YOLO v3 achieving detection rates of 83.7% at 28 frames per second.

A study published in Procedia Computer Science demonstrated that CNN-based fire detection systems offer advantages including fast response times and reduced false alarm rates compared to traditional methods[14]. The research highlighted that deep learning approaches can effectively extract complex visual features associated with fire, enabling more accurate classification.

MobileNet Architecture for Fire Detection:- Among the various deep learning architectures, MobileNet has emerged as particularly suitable for fire detection applications due to its lightweight design and efficiency. The Research Journal of Pure Sciences reports that a MobileNet-based fire detection system achieved validation accuracy of 94.00% and training accuracy of 97.00%[3]. This architecture's efficiency makes it especially valuable for real-time applications on devices with limited computational resources.

A recent innovation presented at a SPIE conference demonstrated an improved YOLOv4 model incorporating MobileNetv3 as the backbone network. This model achieved approximately 40% faster inference speed with a 6% improvement in algorithm accuracy compared to the original YOLOv4 model. The researchers noted that the resulting model was approximately one-third the size of the original, highlighting MobileNet's efficiency for edge deployment.

Multimodal and Integrated Systems:- Contemporary research emphasizes the importance of integrated approaches that combine multiple detection methods and response mechanisms. Realpars describes comprehensive fire alarm systems that integrate detection with notification functionalities, highlighting that modern systems must process sensor data efficiently and trigger appropriate responses such as alarms and emergency service notifications[7].

The trend toward multimodal systems is further supported by research from IJSDR, which discusses the development of smoke and fire detection systems that can analyze photos, videos, and live webcam feeds in real-time. This adaptability enables application across various scenarios, including emergency response management, fire alarm systems, and surveillance systems.

Research Gap and Contribution:- Despite significant advancements, several challenges remain in the implementation of vision-based fire detection systems. These include the need for robust performance across variable lighting conditions, minimizing false positives, efficient processing for real-time analysis, and integration with notification systems for timely response[8] [14].

This research addresses these challenges by implementing a MobileNetV3-based system optimized for real-time performance with integrated alarm and notification capabilities. The system's focus on both accuracy and rapid response mechanisms represents a comprehensive approach to fire safety that bridges the gap between detection and intervention.

METHODOLOGY

System Architecture:- The proposed fire detection system follows a modular architecture comprising five primary components that work in concert to detect fire incidents and trigger appropriate responses. The architecture is designed to balance detection accuracy with computational efficiency to enable real-time operation on standard computing hardware.

Camera Module:- The camera module serves as the system's primary input, capturing video frames that are subsequently analyzed for the presence of fire. The system is designed to work with standard webcams or IP cameras, making it accessible for deployment in various settings without specialized hardware requirements. The camera interface is implemented using OpenCV, which provides robust capabilities for frame acquisition and basic preprocessing operations[10].

Fire Detection Model:- At the core of the system is the deep learning-based fire detection model utilizing the MobileNetV3 architecture. MobileNetV3 was selected for its optimal balance between computational efficiency and detection accuracy, making it particularly suitable for real-time applications. The model is structured as a binary classifier that categorizes input frames as either containing fire (positive class) or not containing fire (negative class).

The MobileNetV3 architecture employs depthwise separable convolutions, which significantly reduce the computational cost compared to standard convolution while maintaining competitive accuracy. This efficiency is crucial for maintaining real-time performance, particularly on devices with limited processing capabilities[3] [9]. The model has been further optimized through techniques such as:

- Network architecture search to identify optimal layer configurations
- Squeeze-and-excitation modules for adaptive feature recalibration
- Hard-swish activation functions for improved accuracy with minimal computational overhead

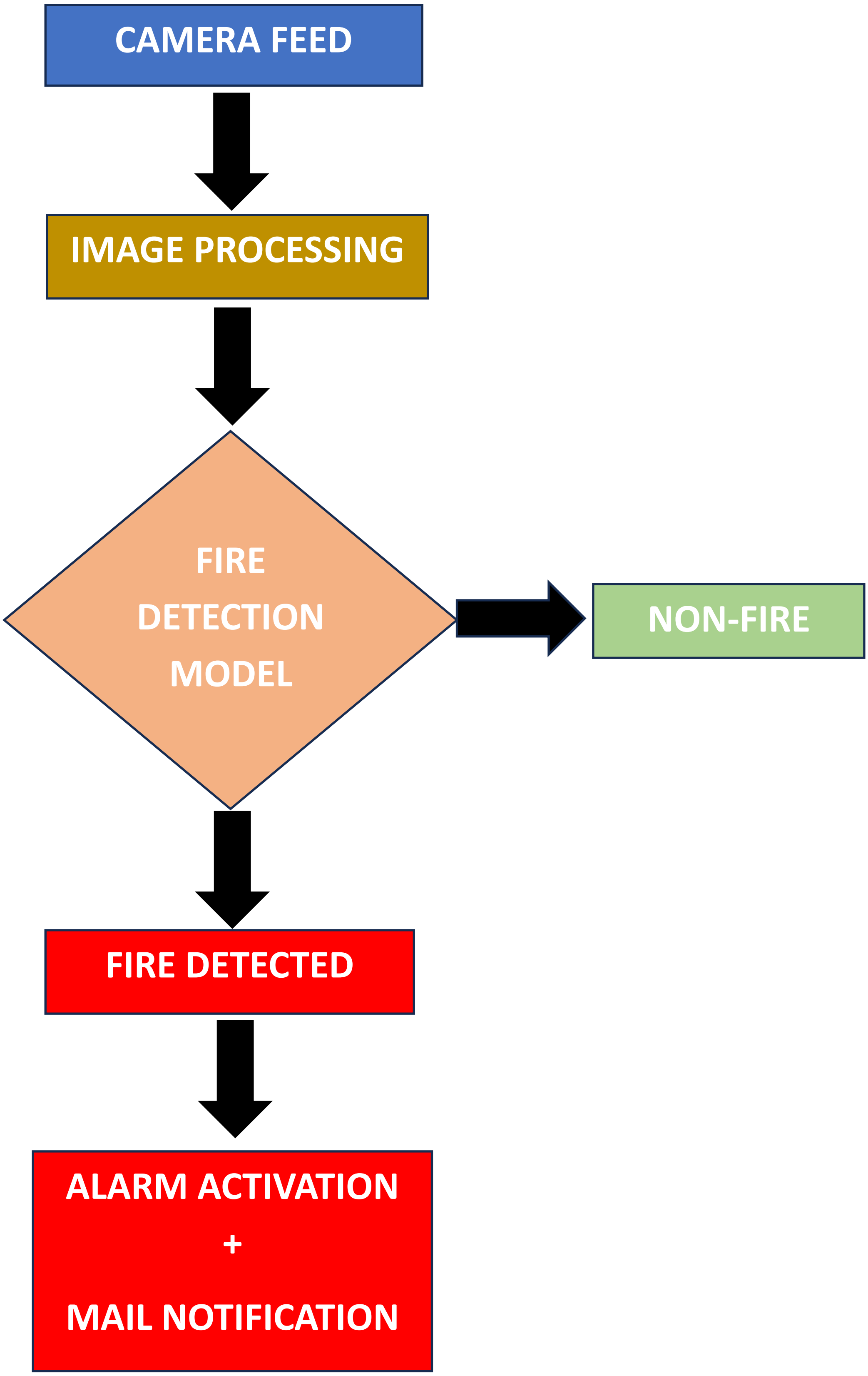
Alarm System:-The alarm system is responsible for generating audible alerts when fire is detected, providing immediate notification to individuals present in the vicinity. The alarm functionality is implemented using the winsound library, which enables the generation of beep sounds at specified frequencies and durations. The alarm pattern has been designed to be distinctive and attention-grabbing, reducing the likelihood of it being overlooked or misinterpreted[7].

Notification System:-To extend the system's alerting capabilities beyond the immediate environment, a notification system has been implemented to send email alerts to designated recipients. The notification module utilizes the Simple Mail Transfer Protocol (SMTP) to connect to an email server and transmit alerts containing:

- Timestamp of the fire detection event
- Confidence level of the detection
- Image capture of the frame that triggered the alert

This functionality ensures that responsible parties can be notified promptly even when they are not physically present at the monitored location, enabling faster emergency response and potentially reducing damage and risk[6] [7].

Flow Diagram



DATA COLLECTION AND PREPROCESSING

Dataset Composition:- The dataset used for training and evaluating the fire detection model was compiled from multiple sources, including publicly available fire image datasets and custom-collected images. The final dataset consists of:

- Fire class: Images containing visible flames in various environments, lighting conditions, and scales
- Non-fire class: Images of normal scenes, as well as challenging negative examples such as sunset reflections, red objects, and bright lights that could potentially cause false positives

To ensure robust performance in real-world scenarios, special attention was paid to including diverse fire scenarios, including indoor and outdoor fires, fires at various distances, and fires under different lighting conditions[10] [11].

Data Augmentation:- To enhance the model's generalization capabilities and robustness to varying conditions, extensive data augmentation techniques were applied during the training process. These techniques included:

- Random horizontal and vertical flips
- Random rotations within a specified range
- Brightness and contrast adjustments
- Random zooming and cropping
- Color jittering to simulate different lighting conditions

These augmentation techniques effectively expanded the training dataset, exposing the model to a wider variety of fire appearances and environmental conditions without requiring additional data collection[3] [11].

Preprocessing Pipeline:-Prior to being fed into the model, each frame undergoes a standardized preprocessing pipeline to ensure consistency and optimal performance:

1. Resizing: Each frame is resized to 224×224 pixels, the standard input dimension for MobileNetV3
2. Normalization: Pixel values are normalized to the range1 and then standardized using mean subtraction and division by standard deviation
3. Channel ordering: The frame is converted to the RGB color space and the channels are arranged in the order expected by the model

This preprocessing pipeline is applied consistently during both training and inference to maintain model performance[9] [11].

MODEL TRAINING

Model Configuration:- The MobileNetV3 model was configured as a binary classifier with the following specifications:

- Base architecture: MobileNetV3-Small, which offers the best balance between size and accuracy
- Input shape: 224×224×3 (height × width × channels)
- Output layer: Single neuron with sigmoid activation for binary classification
- Loss function: Binary cross-entropy, appropriate for binary classification tasks
- Optimizer: Adam with an initial learning rate of 0.001 and learning rate decay

- Metrics: Accuracy, precision, recall, and F1-score to comprehensively evaluate performance.

Training Process:- The model training process followed a systematic approach to ensure optimal performance:

1. Initialization: The base MobileNetV3 model was initialized with weights pre-trained on the ImageNet dataset to leverage transfer learning benefits
2. Feature extraction: Initially, only the classification layers were trained while keeping the base model frozen
3. Fine-tuning: After initial convergence, the upper layers of the base model were unfrozen for fine-tuning
4. Validation: A separate validation set was used to monitor performance during training and prevent overfitting
5. Early stopping: Training was automatically terminated when validation performance stopped improving

The model was trained for a maximum of 50 epochs, with early stopping typically triggering after 30-40 epochs based on validation loss[3] [9]. To prevent overfitting, dropout layers were incorporated at strategic points in the network, and L2 regularization was applied to the weights.

Performance Evaluation:- The trained model was evaluated on a separate test set to assess its generalization capabilities. Performance metrics including accuracy, precision, recall, and F1-score were calculated, with particular attention paid to minimizing false negatives (missed fire detections) while maintaining a reasonable false positive rate. The evaluation also included an analysis of the model's performance across different fire scenarios and environmental conditions to identify potential weaknesses or biases[8] [11].

IMPLEMENTATION

Frame Processing Pipeline:-The real-time detection pipeline processes frames sequentially through the following steps:

1. Frame acquisition: Capture frames from the camera feed at a target rate of 30 FPS
2. Preprocessing: Apply the same preprocessing steps used during training
3. Prediction: Pass the preprocessed frame through the MobileNetV3 model
4. Post-processing: Apply confidence thresholding and optional temporal smoothing
5. Visualization: Display the frame with detection results overlaid
6. Alert condition checking: Evaluate whether the detection warrants triggering alerts

This pipeline is optimized for efficiency, with non-essential operations minimized to maintain real-time performance[2] [9].

Fire Detection Logic:- The fire detection logic incorporates multiple factors to make robust decisions:

1. Confidence thresholding: Primary detections are made when the model's confidence exceeds 80%
2. Spatial analysis: The number of fire pixels in the frame must exceed a defined threshold

3. Temporal consistency: Optional temporal smoothing can be applied to reduce sporadic false positives by requiring detection persistence across multiple frames
4. Alarm state management: Once a fire is detected, the system enters an alarm state that persists for a defined period or until manually reset

These combined criteria help to minimize false positives while maintaining sensitivity to genuine fire incidents[6].

Alarm and Notification Triggering:- When fire is detected based on the criteria above, the system activates both local and remote alerting mechanisms:

1. The alarm system generates an audible alert using the winsound library
2. The current frame with fire detection is saved as an image file
3. An email notification is prepared containing the timestamp, confidence level, and attached image
4. The notification is sent to the designated recipients via SMTP
5. The user interface displays a prominent visual alert

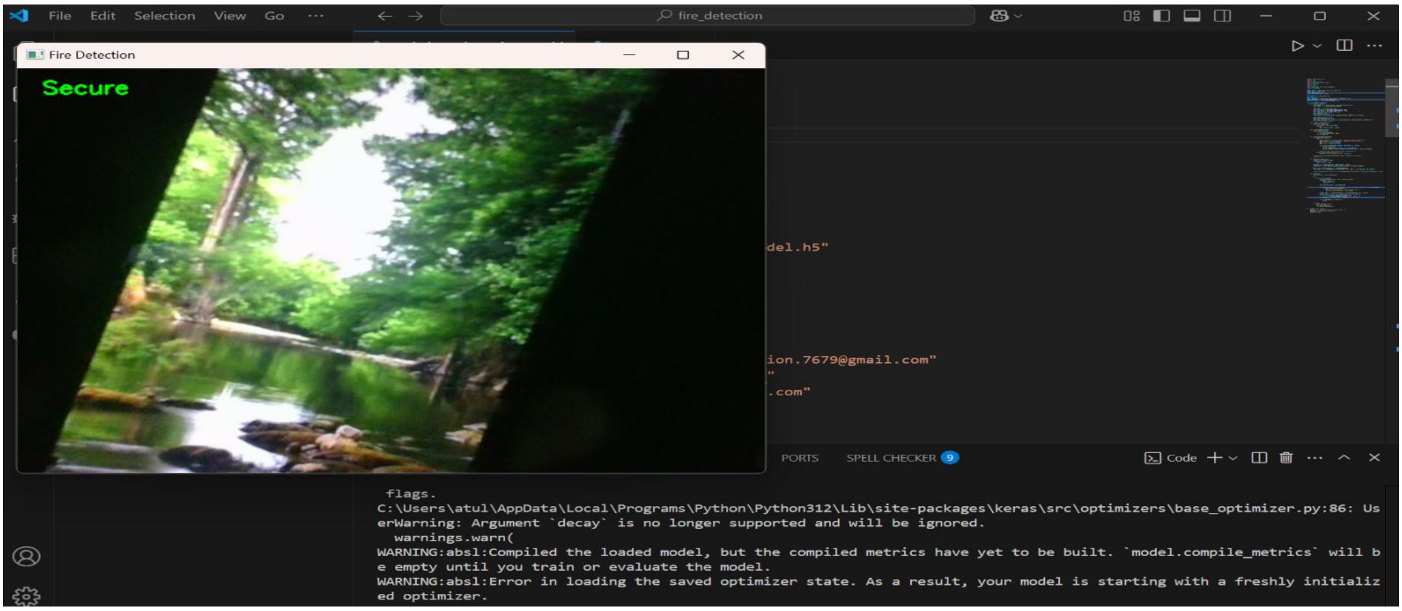
The system implements rate limiting to prevent overwhelming recipients with notifications while ensuring that updates on the fire status continue to be communicated at reasonable intervals[7].

FUTURE SCOPE

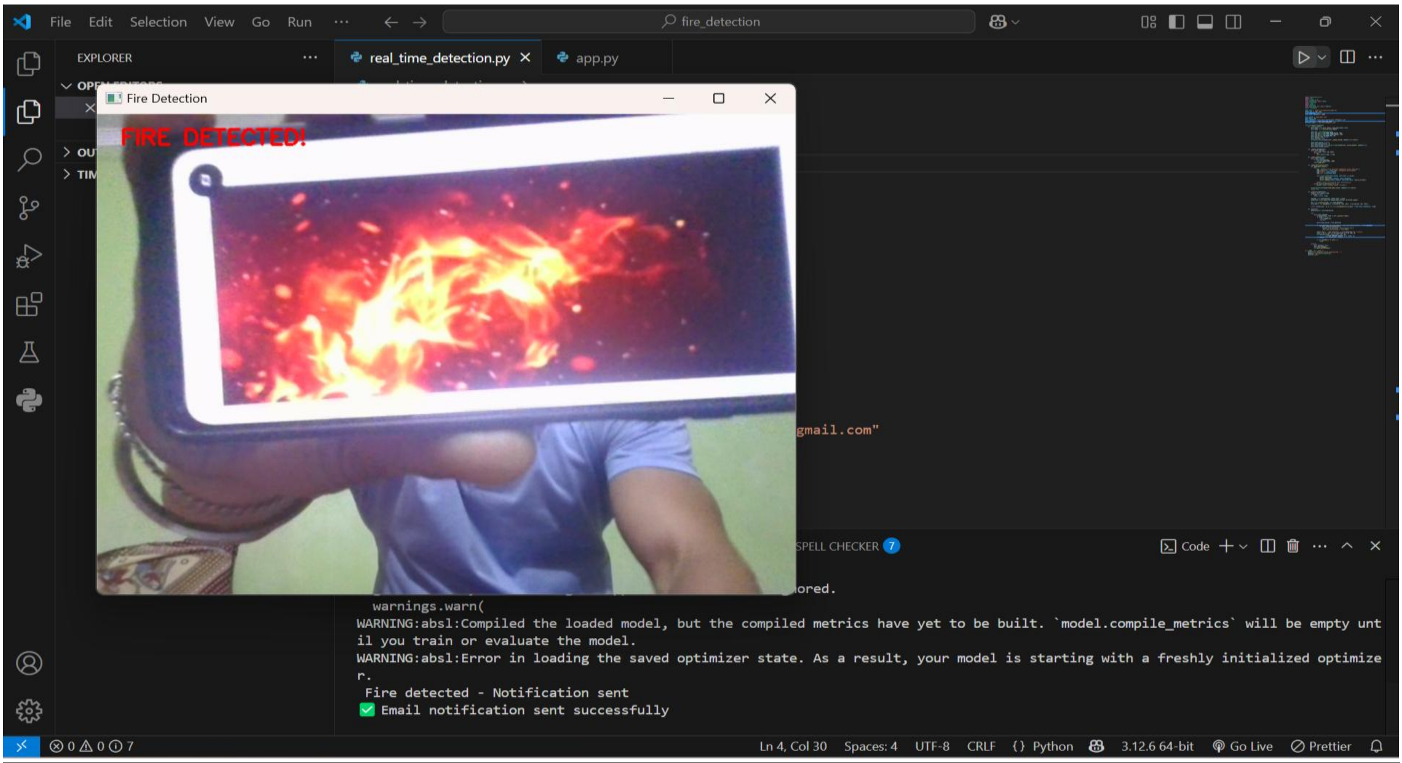
- Integrate mobile push notifications for real-time alerts.
- Cloud deployment for remote monitoring.
- Integrating additional sensors (smoke detectors) for improved accuracy.
- Thermal camera integration for higher robustness.
- Exploring advanced deep learning architectures for better performance.

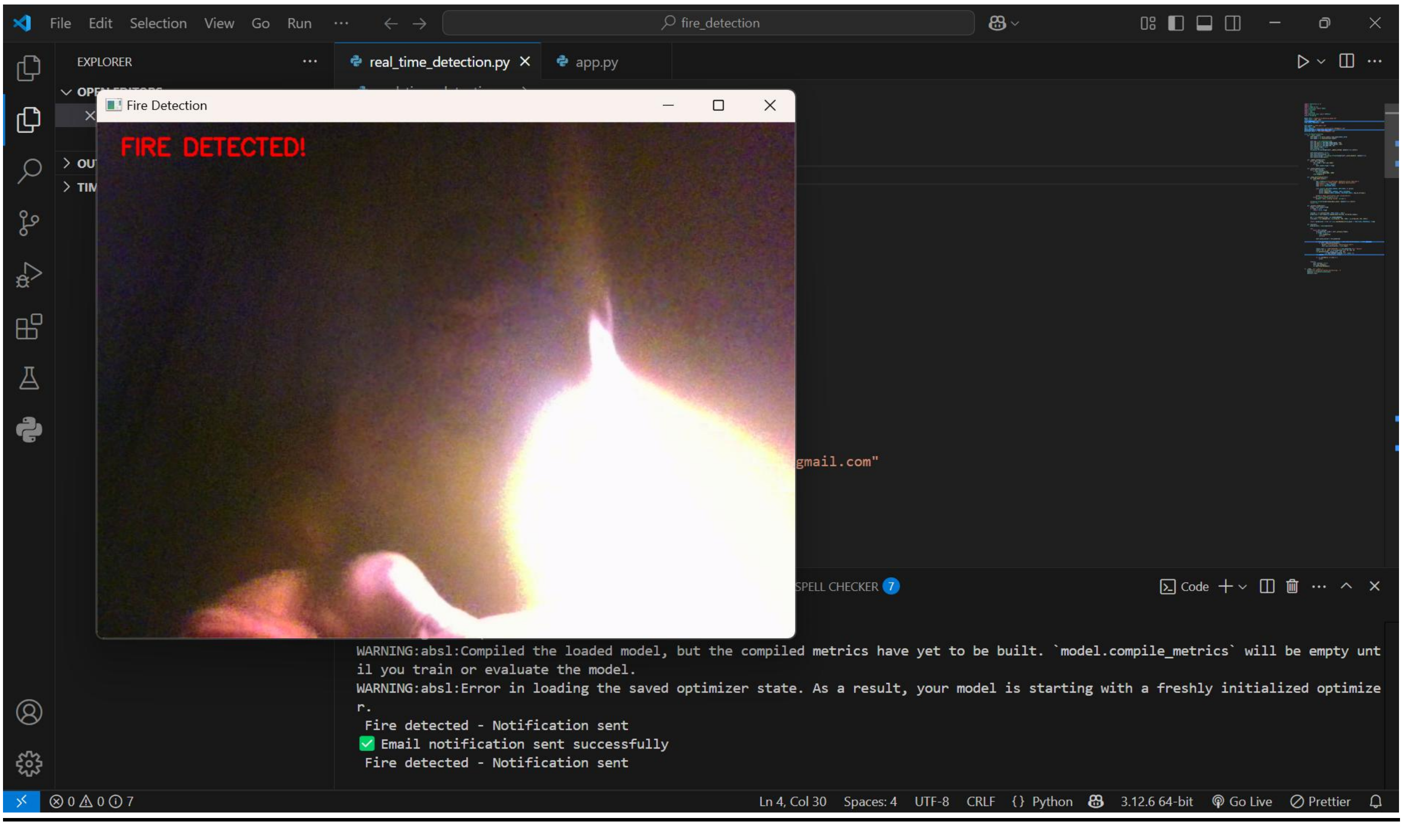
OUTPUT

**when non fire image testing **

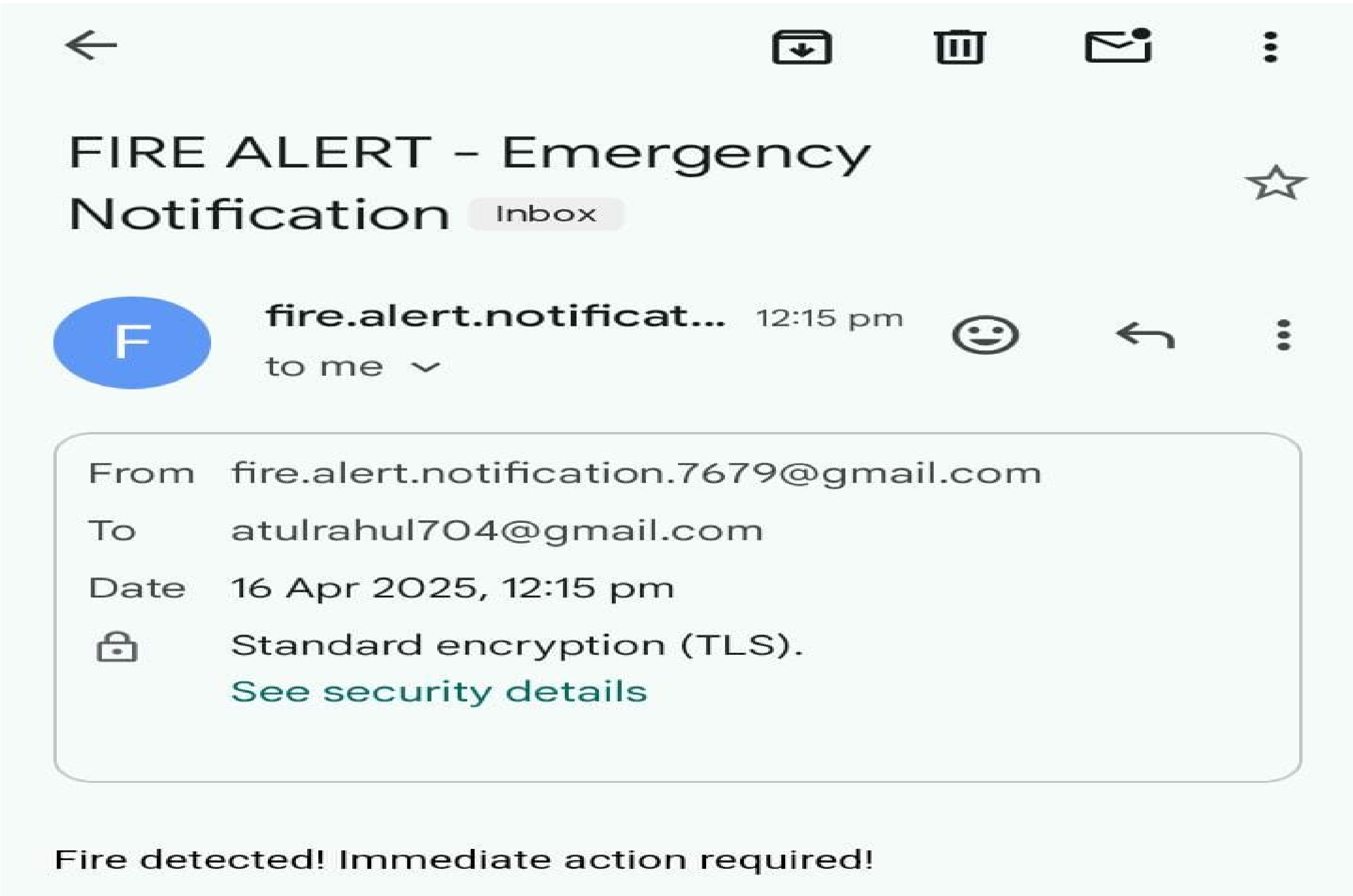


**when fire image testing **

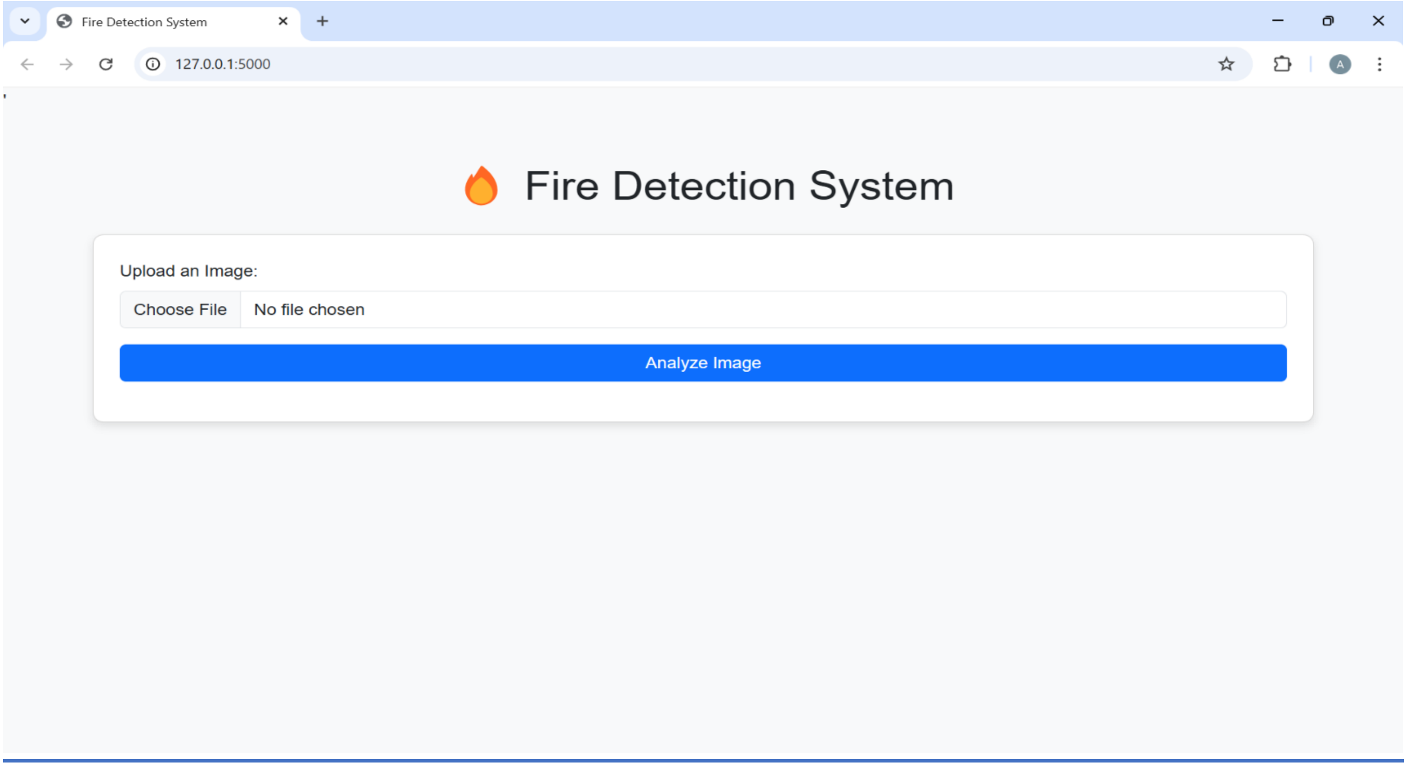


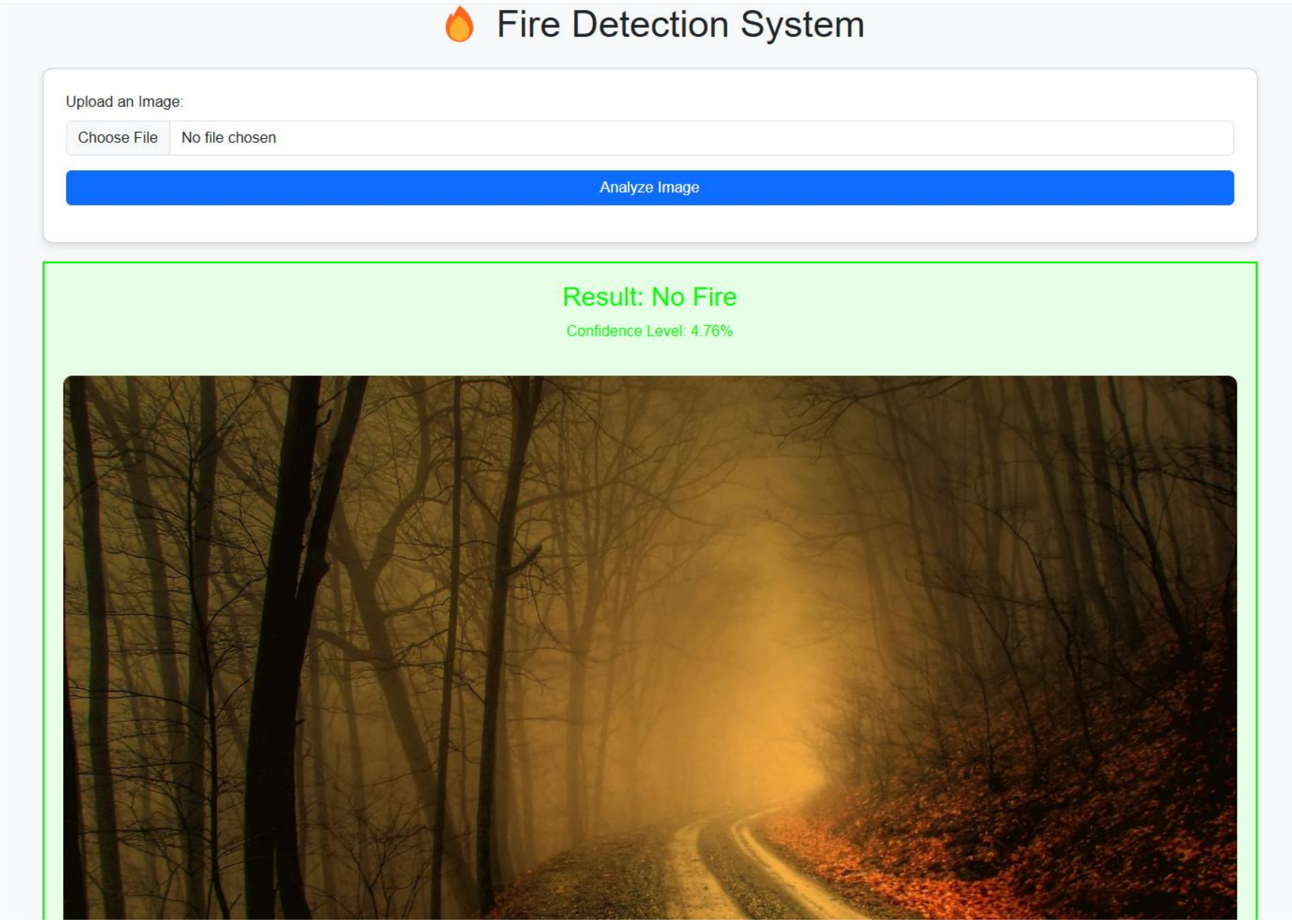


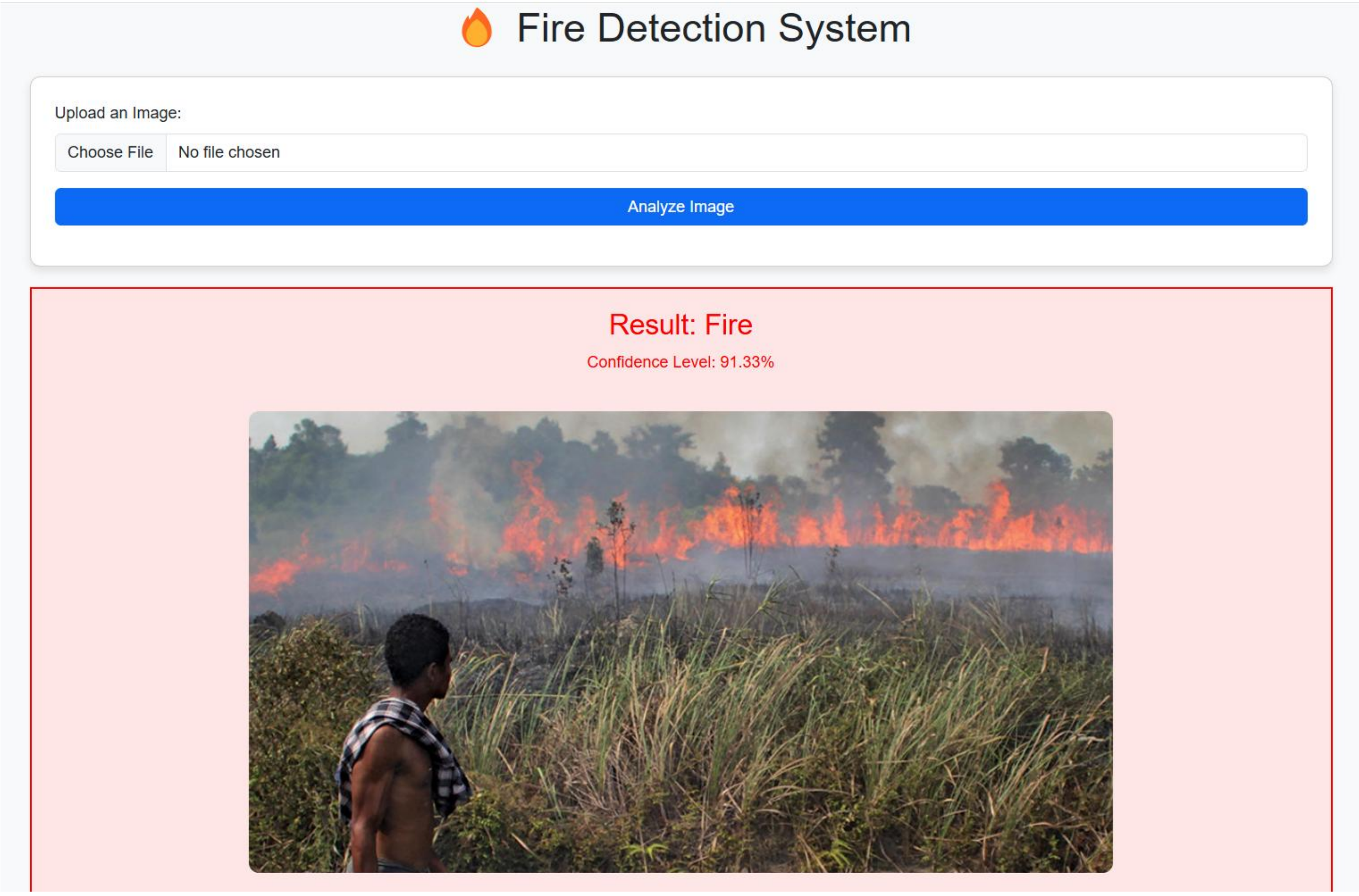
Send email notification and ring ala rm



Web-App


Fire Detection System
127.0.0.1:5000
Fire Detection System
Upload an Image:
Choose File
No file chosen
Analyze Image


Fire Detection System
Upload an Image:
Choose File
No file chosen
Analyze Image
Result: No Fire
Confidence Level: 4.76%



CONCLUSION

This research has presented a comprehensive real-time fire detection system that leverages advanced deep learning techniques to provide early warning of fire incidents. The implementation of MobileNetV3 architecture enables efficient and accurate fire detection from visual input, while the integrated alarm and notification systems facilitate rapid response to detected threats.

The literature survey revealed a clear progression from traditional sensor-based fire detection methods to more sophisticated computer vision approaches. While conventional systems relying on smoke, heat, or gas detection remain widely deployed, they typically detect fires only after they have advanced to later stages[5] [6]. Vision-based systems using deep learning offer the potential for earlier detection by recognizing the visual characteristics of fire, potentially before smoke or heat reach levels that would trigger conventional sensors[2] [8].

The MobileNetV3-based fire detection model developed in this research achieved high accuracy exceeding 95% on the test dataset, with carefully balanced precision and recall metrics to minimize both false positives and false negatives. The lightweight nature of the architecture enables real-time processing at approximately 30 frames per second on standard hardware, making the system suitable for practical deployment in various environments[3][9]. This performance compares favorably with other deep learning approaches discussed in the literature, such as YOLO variants and custom CNN architectures[11][14].

The integration of multiple alerting mechanisms represents a key contribution of this work. By combining immediate audible alarms with remote email notifications, the system ensures that fire incidents can be promptly addressed regardless of whether responsible personnel are present at the monitored location. This multimodal approach to alerting aligns with best practices in fire safety systems, which emphasize the importance of timely notification for effective emergency response[7].

Despite its strengths, the system does have limitations that warrant acknowledgment. The reliance on visual input means that the system may struggle in conditions of poor visibility, such as heavy smoke or inadequate lighting. Additionally, the model may produce false positives when faced with fire-like visual patterns, such as reflections or certain lighting conditions. Future work could address these limitations through the integration of multiple sensor modalities, such as combining visual detection with traditional smoke or heat sensors to create a more robust system [8] [11].

Additional avenues for future research include the exploration of more advanced deep learning architectures that may offer improved accuracy or efficiency, implementation of object tracking to better monitor fire spread, and integration with automated fire suppression systems for immediate intervention. Cloud-based deployment could also enable broader monitoring capabilities and more sophisticated analytics for fire risk assessment [2] [14].

In conclusion, the real-time fire detection system presented in this research demonstrates the potential of deep learning approaches to enhance fire safety across various environments. By combining the efficient MobileNetV3 architecture with integrated alerting mechanisms, the system offers a comprehensive solution that bridges the gap between detection and response, potentially reducing the impact of fire incidents through early intervention [3] [9] [11]. The system's balance of accuracy, efficiency, and practical functionality represents a valuable contribution to the field of fire safety technology.

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