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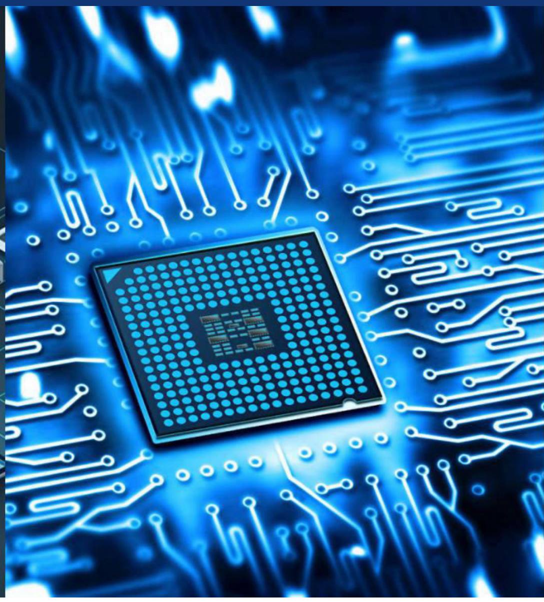

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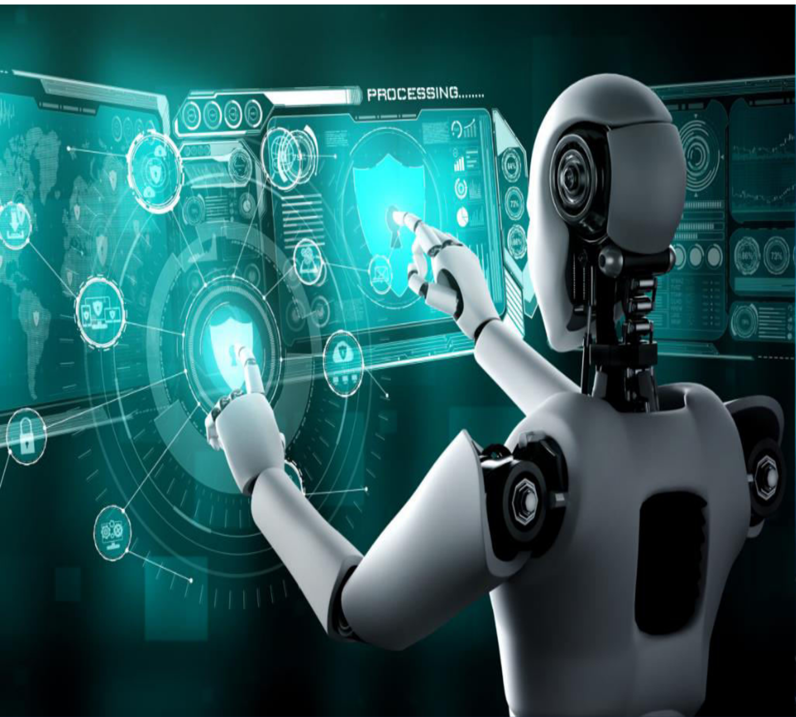

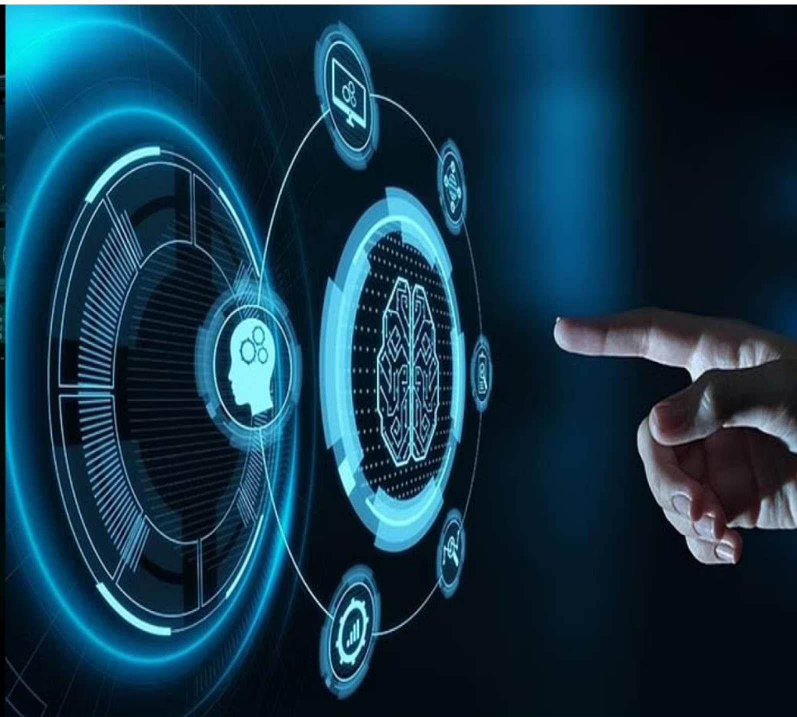

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QUAFIDE: Quantum – Assisted Fire Detection and Alert System

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ABSTRACT: QUAFIDE is a quantum-based fire detection and alert application designed to bridge the gap between fire accident victims and emergency services. It is an automated mobile and desktop application with a two-layered architecture. It takes 3-5 seconds to detect fire and another 5 seconds to inform the emergency contacts. The first layer captures real-time CCTV footage, divides it into 10-second video clips, and monitors them for visual cues of fire or smoke. These clips are processed through a Convolutional Neural Network (CNN), which analyzes the frames and identifies regions with a high probability of fire. The CNN serves as the initial detection mechanism that filters potential fire instances and forwards only the suspected regions to the next layer for deeper analysis. The second layer is the quantum layer, which employs a Variational Quantum Circuit (VQC) to analyze the highlighted regions and verify the possibility of fire. This hybrid approach ensures more accurate detection and minimizes false positives. Unlike traditional fire detection systems that depend on physical smoke or heat sensors, QUAFIDE leverages visual data and quantum enhanced computation to deliver faster and more precise results. Additionally, when fire is confirmed, the system automatically initiates emergency alerts via calls and emails, shares geolocation coordinates with responders, and triggers local alarms to warn nearby individuals. By combining classical deep learning with quantum intelligence, QUAFIDE offers a smarter, more reliable, and responsive fire detection solution.

KEYWORDS: Quantum Computing, Deep Learning, Variational Quantum Circuit (VQC), Convolutional Neural Network (CNN), Real-time Surveillance, Geolocation Fetching

I. INTRODUCTION

In recent years, the increasing number of fire accidents and the limitations of traditional fire detection systems have created a strong need for faster and more intelligent fire monitoring solutions. Conventional systems mainly rely on smoke or heat sensors, which may delay detection and sometimes generate false alarms, reducing their effectiveness in critical situations. Detecting fire accurately in real-time environments is a challenging task due to varying lighting conditions, smoke density, and complex visual backgrounds.

To address these challenges, this project proposes QUAFIDE, a quantum-based fire detection and alert application that combines deep learning and quantum computing techniques for improved fire identification. The system uses a two-layered architecture in which real-time CCTV footage is captured and divided into short video clips for continuous monitoring. In the first layer, a Convolutional Neural Network (CNN) analyzes the video frames to detect visual patterns related to fire and smoke and identifies suspicious regions with high probability of fire occurrence.

The detected regions are then forwarded to the second layer, where a Variational Quantum Circuit (VQC) performs deeper analysis and verifies the possibility of fire using quantum-enhanced computation. This hybrid approach improves detection accuracy while minimizing false positives. Once fire is confirmed, the system automatically sends emergency alerts through calls and emails, shares geolocation coordinates with emergency responders, and activates local alarms to warn nearby individuals. By integrating real-time surveillance, artificial intelligence, and quantum computing, QUAFIDE provides a smart, reliable, and highly responsive solution for modern fire safety management.

II. LITERATURE SURVEY

Fire detection using artificial intelligence and deep learning has gained significant research attention due to the increasing need for fast and reliable emergency response systems. S. M. Naveed Masroor et al. [1] proposed "FlameCure," an autonomous indoor fire detection and extinguishing surveillance car that uses image processing techniques for real-time fire identification and suppression. Although effective for indoor environments, the system is limited by hardware dependency and operational range. Jagruthi D. Waje et al. [2] developed a fire and smoke detection model using YOLOv8, achieving improved object detection speed and accuracy; however, the model requires large-scale training datasets and high computational resources. Van Nguyen Thanh et al. [3] introduced a CNN-LSTM based fire detection system for ships, combining spatial and temporal feature extraction for enhanced detection performance, but the approach increases model complexity and processing time. Ruoyun Ho et al. [4] proposed a forest fire detection framework based on the integration of Multi-Layer Perceptron (MLP) and Convolutional Neural Networks (CNN), which improved classification accuracy but faced challenges in handling real-time large-scale surveillance data. Balaji V. R. et al. [5] developed "Fireguard," a deep CNN-based video surveillance system for efficient fire detection, providing reliable monitoring but with limitations in reducing false positives under varying environmental conditions. T. Vigneshwaran et al. [6] presented a real-time fire detection system through surveillance video analysis, focusing on rapid detection, though the model performance depends heavily on video quality and lighting conditions.

III. PROBLEM DEFINITION

Traditional fire detection systems primarily rely on smoke, heat, or flame sensors, which often result in delayed response times, limited coverage, and a high rate of false alarms, especially in complex real-world environments. These systems may fail to detect fire at an early stage due to environmental factors such as lighting variations, smoke density, and sensor limitations, leading to severe damage to life and property. Additionally, most existing fire detection solutions lack intelligent verification mechanisms and automated emergency communication features, reducing their overall effectiveness during critical situations. Real-time surveillance-based fire detection using deep learning has improved detection capabilities, but challenges such as computational complexity, inaccurate predictions, and false positives still remain unresolved. Therefore, there is a need for an advanced, fast, and reliable fire detection system that can accurately identify fire from visual data, minimize false alarms, and provide immediate emergency alerts.

IV. EXISTING SYSTEM

Conventional fire detection systems primarily rely on smoke sensors, heat sensors, and vision-based CNN models for fire identification. Sensor-based systems are generally designed to detect smoke concentration or temperature rise; however, these parameters do not always indicate the occurrence of an actual fire, which can result in frequent false alarms. In addition, vision-based CNN models utilize CCTV footage to identify fire or smoke patterns, but they are often susceptible to misclassification, where bright light sources, sunlight reflections, or objects with fire-like colors are incorrectly detected as fire. Furthermore, most existing systems are limited to only detecting fire events and still depend on manual intervention to notify emergency services, causing delays in response time. Another major limitation is that CNN-based approaches, although computationally efficient, often lack the precision and robustness required to accurately confirm real fire incidents, thereby reducing their reliability in critical real-world applications.

V. PROPOSED SYSTEM

To overcome the limitations of traditional fire detection systems, QUAFIDE proposes a two-layer hybrid architecture that integrates the capabilities of deep learning and quantum computing for intelligent and accurate fire detection. In the first layer, real-time CCTV footage is continuously monitored and divided into short video clips for analysis. These video frames are processed using a Convolutional Neural Network (CNN), which identifies visual patterns related to fire and smoke while highlighting suspicious regions with a high probability of fire occurrence. This layer acts as the primary filtering mechanism by removing irrelevant regions and reducing noise, thereby improving the efficiency of the overall detection process. The use of CNN enables rapid analysis of surveillance data and supports real-time monitoring in complex environments.

The second layer of QUAFIDE employs a Variational Quantum Circuit (VQC) to perform deeper analysis on the suspicious regions identified by the CNN. This quantum-enhanced verification process helps in reducing false positives

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and improving detection accuracy by validating whether the detected region truly represents a fire incident. Once fire is confirmed, the system automatically initiates emergency response actions, including sending alerts through calls and emails, sharing Google Maps geolocation coordinates with emergency services and authorities, and activating local alarms to warn nearby individuals. By combining automation, deep learning, and quantum-assisted precision, QUAFIDE ensures faster fire detection, reliable confirmation, and immediate emergency communication, making it a highly responsive and advanced solution for modern fire safety management.

VI. DESIGN AND METHODOLOGY

The proposed QUAFIDE system follows a hybrid fire-detection approach using a Classical Deep-Learning Model integrated with a Variational Quantum Classifier (VQC) for accurate and reliable fire-risk evaluation. Initially, live CCTV video streams are captured and preprocessed using image enhancement techniques such as resizing, normalization, and noise reduction. The processed frames are then passed to the ShuffleNet model, which performs primary fire classification and extracts visual features. In cases where the confidence level of the classical model is uncertain, selected features are forwarded to the quantum processing module for enhanced verification. The Variational Quantum Classifier analyzes the encoded features and generates refined predictions. Finally, the outputs from both classical and quantum layers are combined through a decision fusion mechanism to produce an accurate fire-risk score and generate alerts in real time.

Algorithm Hybrid Classical–Quantum Fire Detection (QUAFIDE):

The QUAFIDE system combines classical deep-learning inference with quantum-assisted evaluation to improve the reliability of fire detection. The process begins with capturing live video frames from CCTV or IP cameras. Each frame undergoes preprocessing operations such as resizing, normalization, and noise reduction to improve image quality. The preprocessed frames are then passed to the ShuffleNet model, which performs lightweight real-time fire classification and produces a probability score with confidence values.

If the confidence level is sufficiently high, the prediction is directly forwarded to the decision module. However, when the model encounters ambiguous or uncertain cases, the extracted features are sent to the Variational Quantum Classifier (VQC). The quantum module encodes classical features into quantum states and executes quantum circuits on IBM Quantum simulators or QPU backends. The VQC returns quantum-enhanced classification outputs for improved discrimination between fire and non-fire scenarios.

The Decision Fusion Module combines the outputs of the classical and quantum models using weighted probability scoring to generate a final fire-risk value. Based on predefined threshold conditions, the system triggers alerts, stores logs, and updates the monitoring dashboard in real time. This hybrid approach significantly reduces false positives, improves detection accuracy, and ensures reliable fire-risk evaluation in critical real-world environments.

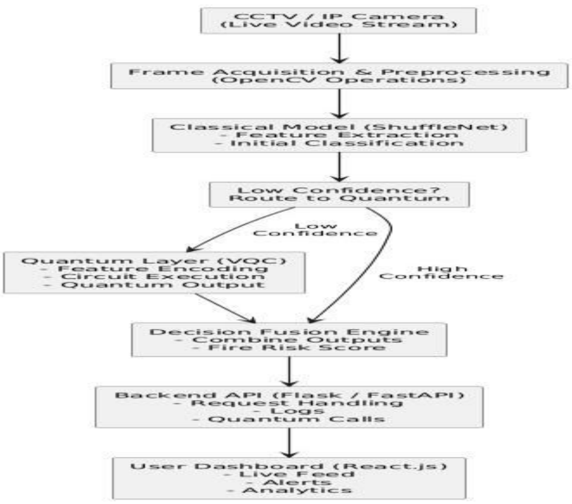

Figure 4.1: System Architecture Diagram of the QUAFIDE: Quantum - Assisted Fire Detection and Alert System

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The system architecture in Fig. 4.1 represents a modular hybrid fire-detection framework designed for real-time analysis of CCTV video streams using classical and quantum intelligence. The architecture is organized into multiple interconnected layers, each responsible for a specific stage of data processing and decision making.

The architecture begins with the **Image & Stream Input Layer**, where CCTV/IP cameras continuously provide live video feeds. Frames are extracted and forwarded to the preprocessing pipeline using OpenCV-based operations. This is followed by the **Preprocessing Layer**, where resizing, normalization, enhancement, and noise reduction are applied to improve image quality and prepare the frames for deep-learning analysis. Next, the **Classical Deep-Learning Layer** performs primary fire detection using the ShuffleNet model.

This lightweight CNN architecture extracts visual features and predicts fire probabilities optimized for real-time performance. Frames with uncertain confidence values are then forwarded to the **Quantum Processing Layer**, which contains the Variational Quantum Classifier (VQC). The VQC converts classical features into quantum-compatible representations and executes quantum circuits on IBM Quantum simulators or QPU backends for enhanced evaluation of ambiguous fire scenarios.

The **Decision Fusion Module** combines outputs from the classical ShuffleNet model and the quantum classifier to generate a reliable final fire-risk score. This fusion process improves detection accuracy and reduces false alarms caused by reflections, lighting variations, or fire-like objects. The **Backend Processing Layer** manages event logging, quantum execution tracking, API communication, and storage of detection results.

Finally, the **Frontend Dashboard Layer** presents live monitoring feeds, real-time alerts, fire-risk indicators, analytics, and system logs to security personnel and administrators. Supporting components such as alert systems, activity logs, and reporting modules ensure reliable monitoring, scalability, and efficient emergency response.

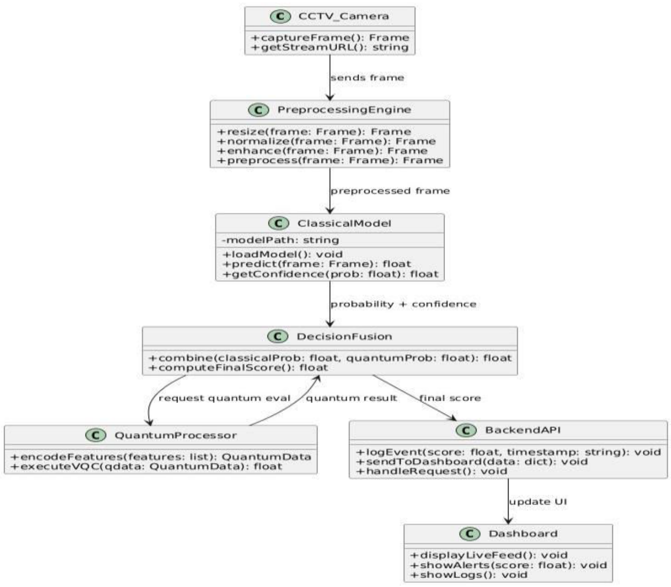

Figure 4.2: Class Diagram of the QUAFIDE: Quantum – Assisted Fire Detection and Alert System

Figure 4.2 illustrates the class structure and interaction between the major components of the QUAFIDE hybrid fire-detection system. The diagram represents how live CCTV frames are processed through preprocessing, classical deep-learning inference, quantum evaluation, decision fusion, backend communication, and dashboard visualization.

The **CCTV_Camera** class acts as the input source of the system. It captures live video frames using the captureFrame() method and provides stream access through getStreamURL(). The captured frames are continuously forwarded to the preprocessing module for further analysis. The **PreprocessingEngine** class is responsible for preparing the input frames before detection. It includes functions such as resize(), normalize(), enhance(), and preprocess(), which improve image quality by reducing noise, standardizing dimensions, and enhancing visibility. The processed frames are then sent to the classical deep-learning model.

The **ClassicalModel** class implements the ShuffleNet-based fire-detection engine. The loadModel() method loads the trained model, while predict() performs fire classification and generates probability scores. The getConfidence() method computes the confidence level of the prediction. If the confidence is low or uncertain, the system forwards the extracted features to the quantum processing module for enhanced verification. The **QuantumProcessor** class manages the quantum-assisted evaluation process. The encodeFeatures() method converts classical features into quantum-compatible representations, and executeVQC() executes the Variational Quantum Classifier (VQC) using IBM Quantum simulators or QPU backends. The generated quantum probability scores are returned to the decision module.

The **DecisionFusion** class acts as the core integration component of the system. It combines classical and quantum probabilities using combine() and computes the final fire-risk score through computeFinalScore(). This fusion mechanism improves reliability by reducing false alarms and improving classification accuracy in uncertain scenarios. The **BackendAPI** class manages communication between the processing modules and the user interface. It logs detection events through logEvent(), sends processed results to the dashboard using sendToDashboard(), and handles backend requests via handleRequest(). This layer ensures efficient data management, alert handling, and monitoring operations.

Finally, the **Dashboard** class provides the frontend visualization interface for users and security personnel. It displays the live video feed using displayLiveFeed(), shows fire alerts through showAlerts(), and presents activity logs using showLogs(). The dashboard enables real-time monitoring, alert tracking, and system analysis. The interaction flow of the class diagram begins from CCTV frame capture → preprocessing → classical ShuffleNet inference → optional quantum evaluation → decision fusion → backend processing → dashboard visualization. This structured workflow ensures scalable, accurate, and real-time hybrid fire detection with improved reliability and reduced false positives.

V. IMPLEMENTATION

5.1 System Execution Overview

The proposed system processes live CCTV frames using a hybrid classical–quantum pipeline. The workflow includes preprocessing, ShuffleNet-based classification, and quantum-assisted evaluation for uncertain cases. Frames are continuously analyzed in real time, and a final fire-risk score is generated using decision fusion. Alerts and logs are updated instantly on detection.

5.2 Development Environment

The system is developed using Python with a modular architecture for preprocessing, inference, quantum processing, and visualization. Flask/FastAPI is used for backend services, while React.js powers the dashboard interface. OpenCV handles video stream processing, and Qiskit is used for quantum execution. This structure ensures scalability and easy integration.

5.3 Data Processing

Fire and non-fire images are collected from datasets and CCTV frames and standardized into uniform formats. Preprocessing includes resizing, normalization, noise removal, and augmentation using OpenCV. Key features such as edges, intensity, and color patterns are extracted. Metadata like timestamp and frame ID is also attached.

5.4 Solution Representation and Evaluation

The system represents each input frame as a fire-risk prediction with probability and confidence scores. ShuffleNet generates initial classification results, while VQC refines uncertain predictions. Performance is evaluated using accuracy, precision, recall, and false-positive rate. Final scoring is computed using weighted fusion of classical and quantum outputs.

5.5 Hybrid Optimization using Classical and Quantum Inference

ShuffleNet performs fast real-time inference for clear cases, while uncertain frames are passed to the quantum module. The VQC processes encoded features using quantum circuits executed on IBM Quantum systems. Outputs from both models are combined using decision fusion. This hybrid approach improves accuracy and reduces false alarms.

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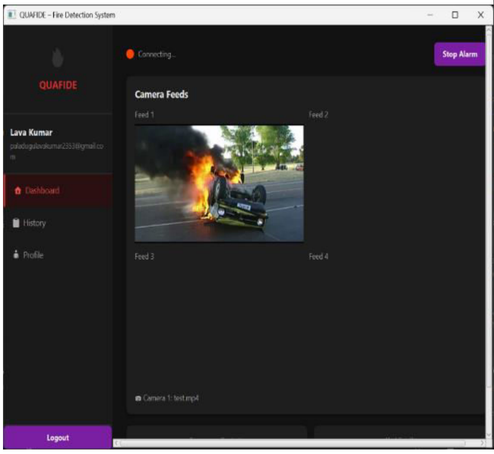
5.6 Comparison and Output

The final results are compared with traditional CNN-based fire detection models. Results show improved accuracy and better handling of complex scenarios like reflections and fog. Outputs include fire alerts, risk scores, logs, and real-time dashboard updates. The system ensures reliable monitoring and faster emergency response.

VI. TESTING AND RESULTS

The QUAFIDE Fire Detection System provides secure login and registration pages for users. It supports both desktop and mobile platforms for easy access.

A. Desktop Outputs



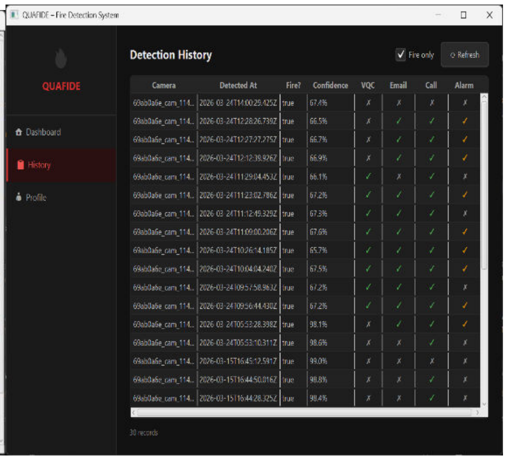
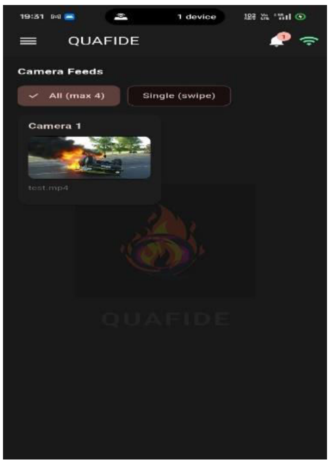


Figure 6A.1 Dashboard Page Figure 6A.2 Detection History

Figure 8A.1 Illustrates the Dashboard Page of the QUAFIDE Fire Detection System where multiple camera feeds are monitored in real time for fire incidents. It detects fire in the video feed, triggers alerts, and provides an option to stop the alarm when necessary. Figure 8A.2 Illustrates the Detection History Page of the QUAFIDE Fire Detection System where previously detected fire incidents are stored with details such as camera source, detection time, confidence level, and alert status. It helps users review past events and monitor system responses effectively.

B. Mobile Outputs



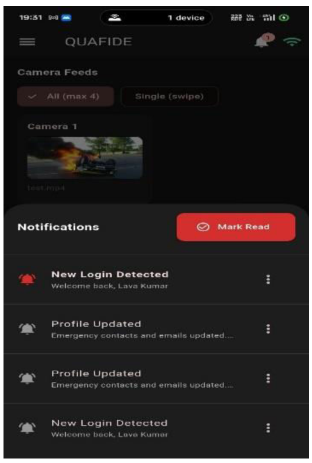


Figure 8B.1 Dashboard Page Figure 8B.2 Notification Page

Figure 8B.1 illustrates the Mobile Dashboard Page of the QUAFIDE Fire Detection System where users can monitor camera feeds through a mobile device. It provides options to view multiple cameras or swipe through single feeds for convenient real-time surveillance.

Figure 8B.2 illustrates the Notifications Page of the QUAFIDE Fire Detection System where users receive alerts related to login activity, profile updates, and system events. It allows users to review notifications and mark them as read for better management.

Figure 8B.3 Call Alert Page

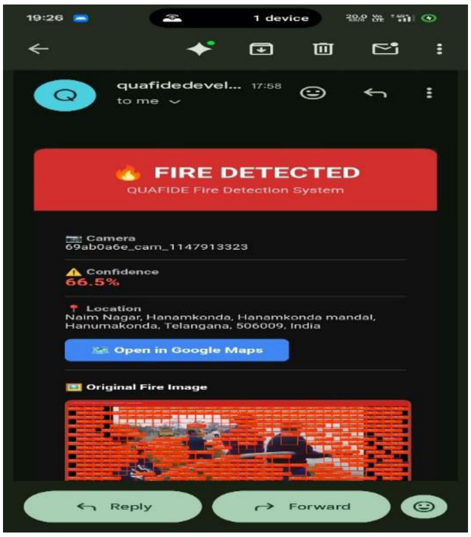


Figure 8B.4 Email Alert Page

Figure 8B.3 Illustrates the Emergency Call Alert of the QUAFIDE Fire Detection System where an automatic phone call is initiated to the registered emergency contact during a fire incident. It helps provide immediate notification and ensures quick response in critical situations.

Figure 8B.4 Illustrates the Email Alert Notification of the QUAFIDE Fire Detection System where an automated email is sent when fire is detected. It includes camera details, confidence percentage, location information, map access, and the captured fire image for immediate action.

IX. CONCLUSION AND FUTURE SCOPE

The QUAFIDE Fire Detection System is an intelligent and efficient solution developed for real-time fire monitoring and emergency alert management. It uses live camera feeds to detect fire incidents quickly and accurately, helping to reduce response time and prevent major damage. The system provides alerts through alarms, mobile notifications, emails, and emergency calls for immediate action. It also maintains detection history records for monitoring and analysis purposes. Overall, the system improves safety, reliability, and smart surveillance in fire-prone environments. The System is an intelligent and efficient solution developed for real-time fire monitoring and emergency alert management. It uses live camera feeds to detect fire incidents quickly and accurately, helping to reduce response time and prevent major damage. The system provides alerts through alarms, mobile notifications, emails, and emergency calls for immediate action. It also maintains detection history records for monitoring and analysis purposes. Overall, QUAFIDE improves safety, reliability, and smart surveillance in fire-prone environments.

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