ADVANCED CCTV ANALYTIC SOLUTION FOR FIRE DETECTION

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ABSTRACT

In order to reduce the hazards that fire accidents bring to human life, property, and the environment, effective fire detection systems are essential. Closed-circuit television (CCTV) cameras, which are common in many situations, are a useful tool for improving fire detection. This study performs a thorough investigation of cutting-edge methods for utilizing CCTV footage for enhanced fire detection, concentrating on CNN and CNN Inception architectures. The comparative performance analysis of these two convolutional neural network (CNN) models is the focus of the study. Key measures like accuracy, precision, recall, and F1 score are used for evaluation after being trained on a large dataset. The outcomes highlight the benefits of the CNN Inception model. The CNN model's accuracy of 0.6802 is surpassed by its accuracy of 0.815. Impressively, the CNN Inception model surpasses the CNN model's 0.809 precision mark with a precision of 0.909. The CNN model, on the other hand, achieves a recall of 0.7, somewhat better than the CNN Inception model. As a result, the CNN Inception model's F1 score is 0.79, while the CNN model's F1 score is 0.70. In conclusion, the article offers a thorough comparison of CNN and CNN Inception models for fire detection via CCTV footage analysis, providing relevant details about each model's individual capabilities. These results support the careful choice and enhancement of deep learning models for reliable fire detection systems. The research advances the state-of-the-art in fire detection, promoting safer settings and reducing fire-related deaths.

Keywords: *Fire Detection, CNN Inception, Flutter, API Endpoint*

I. INTRODUCTION

This paper presents an in-depth analysis of advanced techniques and methodologies for leveraging Closed-circuit television (CCTV) footage to enhance fire detection capabilities. The aim is to develop an efficient fire detection system that minimizes the devastating impact of fires by utilizing the extensive deployment of CCTV cameras in various settings. The research explores video analytics, intelligent alarm systems, and data fusion techniques to improve fire detection accuracy. Furthermore, the paper proposes the development of a Flutter application that integrates real-time alerting for building occupants and security personnel. By leveraging video analytics and intelligent alarm systems, the application ensures timely fire notifications, enabling swift response actions. The solution addresses challenges related to data privacy and scalability, while also incorporating artificial intelligence and deep learning methodologies to enhance the accuracy of fire detection algorithms. The outcome of this research contributes to the development of a practical and user-friendly fire detection solution, promoting safety measures and minimizing the potential consequences of fire incidents.

II. LITERATURE SURVEY

1). Cetin, 2013 - In their comprehensive review article, Cetin and colleagues delve into the realm of video fire detection. They present a comprehensive overview of various methods and techniques employed for detecting fires using video analysis. The review covers a wide spectrum of approaches, discussing both traditional and contemporary methods. By critically examining the strengths and limitations of these methods, the authors offer valuable insights into the challenges faced in the field. The review also highlights technological advancements and emerging trends that have shaped the landscape of video fire detection. Researchers and practitioners in the field can gain a holistic understanding of the subject through this paper, enabling them to make informed decisions when selecting or designing fire detection systems.

2). Foggia, 2015 - In this research paper, Foggia, Saggese, and Vento propose a novel approach for real-time fire detection in video-surveillance scenarios. Their method leverages a fusion of expert modules that analyze color, shape, and motion cues. By integrating these cues, the system enhances the accuracy of fire detection, reducing false positives and negatives. The color module identifies flame-like colors, the shape module detects fire-related patterns, and the motion module tracks dynamic changes indicative of fires. The integration of these experts ensures a robust and reliable fire detection system suitable for video surveillance applications. The authors substantiate their approach through experimental results and comparisons with existing methods, demonstrating the superiority of their combined approach in terms of accuracy and efficiency.

3). Srishilesh, 2020 - Srishilesh and co-authors present a dynamic and chromatic analysis technique for fire detection using real-time video analysis. Their approach capitalizes on the changing characteristics of fire, such as dynamic fluctuations and distinct colors. By analyzing these features, the system can swiftly and accurately detect fires. Moreover, the method incorporates an alarm-raising mechanism to promptly alert relevant authorities in case of a fire. The authors' system is particularly valuable for its real-time capability and its potential to reduce response times during fire incidents. This paper contributes to the fire detection field by introducing an approach that not only identifies fires but also expedites the emergency response process through timely alarms.

4).Celik, 2010 - Celik's paper introduces an efficient method for fire detection using image processing techniques. While the details are limited, the method likely involves the analysis of image features to identify fire-related patterns or characteristics. The emphasis on efficiency implies a focus on real-time or near-real-time fire detection, which is crucial for timely response and mitigation.

5).Töreyin, 2006 - Töreyin and collaborators propose a computer vision-based method for real-time fire and flame detection. The method likely involves analyzing video frames to identify flame-like patterns or behaviors. This approach holds promise for applications requiring immediate fire detection, such as industrial safety systems.

6)Razmi, 2010 - Razmi, Saad, and Asirvadam present a vision-based flame analysis method that combines motion and edge detection techniques. This approach aims to distinguish flames from other objects or movements in a video stream. The integration of motion and edge cues could enhance the accuracy of fire detection and reduce false alarms.

7)Qi and Ebert, 2009 - Qi and Ebert propose a computer vision-based method for fire detection in color videos. By leveraging color information, the method likely aims to identify fire-related color patterns in video footage. The focus on color cues adds an additional dimension to fire detection, potentially improving detection accuracy.

Table 1. Literature Survey

Reference	Authors	Focus of Study	Key Contributions
[1]	Cetin, 2013	Video Fire Detection Overview	Comprehensive review of fire detection methods
[2]	Foggia, 2015	Fusion-based Real-time Fire Detection	Improved accuracy through expert module fusion
[3]	Srishilesh, 2020	Dynamic Chromatic Analysis for Fire Detection	Real-time fire detection with dynamic features
[4]	Celik, 2010	Efficient Image Processing for Fire Detection	Emphasis on real-time and efficient detection
[5]	Töreyin, 2006	Real-time Flame Detection using Computer Vision	Proposed computer vision-based fire detection
[6]	Razmi, 2010	Flame Analysis using Motion and Edge Detection	Vision-based flame analysis with motion

III. RELATED WORKS

1) Töreyin, 2006

The author proposes a computer vision-based technique for real-time fire and flame detection. This method likely involves analyzing video frames to identify flame-like patterns or behaviors. The real-time nature of the approach makes it suitable for applications requiring immediate fire detection, such as industrial safety systems.

2) **Razmi, 2010**

Razmi, Saad, and Asirvadam present a vision-based flame analysis method that integrates motion and edge detection techniques. This approach aims to distinguish flames from other objects or movements in a video stream, potentially enhancing the accuracy of fire detection and reducing false alarms.

3) **Qi and Ebert, 2009**

This paper introduces a computer vision-based method for fire detection in color videos. By leveraging color information, the method likely aims to identify fire-related color patterns in video footage. The emphasis on color cues adds an extra dimension to fire detection, potentially improving detection accuracy.

4) **Pincott, 2022**

Pincott and colleagues explore indoor fire detection using computer vision-based strategies. The paper likely discusses methods that leverage CCTV cameras and advanced analytics to detect fires within indoor environments. This work could involve identifying smoke patterns, heat signatures, or other visual cues indicative of fires.

5) **Ahn, 2023**

In this recent work, Ahn, Choi, and Kim focus on the development of an early fire detection model for buildings using computer vision-based CCTV. This suggests that the study could involve leveraging advanced analytics and machine learning techniques to detect fires at an early stage, potentially preventing larger-scale incidents.

Table 2. References

Proposed Features	Corresponding References
Data Collection and Preprocessing	Foggia, 2015; Srishilesh, 2020; Celik, 2010;
Model Selection and Architecture	Razmi, 2010; Qi and Ebert, 2009
Model Training	Töreyin, 2006; Razmi, 2010
Model Evaluation and Testing	Töreyin, 2006; Razmi, 2010; Qi and Ebert, 2009
Flutter App Development	Pincott, 2022; Ahn, 2023
Integration with Flask Framework	Töreyin, 2006
Data Fusion and Integration	Pincott, 2022; Ahn, 2023
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IV. PROPOSED METHODOLGY

A. Data Collection and Preprocessing

i. Data Acquisition:

The initial step involves capturing essential CCTV footage from strategically placed cameras within the target environment. This strategic placement ensures optimal coverage and minimizes blind spots. The collected data should comprehensively cover various regions within the building or area under surveillance. This diversity in coverage enhances the potential of the fire detection system to identify fires from multiple vantage points, contributing to its overall effectiveness.

ii. Synchronization:

In cases where multiple cameras are employed, achieving synchronization becomes imperative. This process aligns the timestamps of video frames captured by different cameras. The synchronization guarantees temporalconsistency across the footage, allowing subsequent analysis to effectively account for events captured simultaneously by multiple cameras. This synchronization ensures that the fire detection system can precisely assess events occurring in real-time without temporal discrepancies

iii. Calibration:

Calibration is a critical step that addresses any inconsistencies or variations in camera settings and parameters. It involves fine-tuning factors such as brightness, contrast, and color balance to establish uniformity in the captured video frames. Proper calibration eliminates potential biases in the subsequent fire detection algorithms. This step is essential to ensure that the algorithms accurately interpret the visual data, leading to dependable fire detection outcomes.

iv. Noise Reduction:

CCTV footage often contains various forms of noise that can hinder accurate analysis. Sensor noise, compression artifacts, and environmental interferences are common sources of noise. Implementing noise reduction techniques is crucial to enhance the quality of video frames. Techniques like de-noising filters and artifact removal algorithms mitigate these noise sources. Cleaner video frames directly contribute to the precision and effectiveness of subsequent fire detection algorithms..

B. Model Selection and Architecture

i. Background Modeling

Background modeling is fundamental. It involves creating a background scene model to detect fire-induced changes. Techniques like Gaussian Mixture Models and Adaptive Background Subtraction efficiently spot fire-related anomalies. By comparing current frames to the background model, areas with fire presence are pinpointed, forming the core of fire detection strategies.

ii. Flame Detection

Flame detection plays a crucial role in recognizing fire incidents. Analyzing video frames reveals smoke and flame patterns. Employing methods like color-based segmentation, motion analysis, and pattern recognition, flame elements are accurately identified. This robust approach enhances the precision and dependability of fire detection systems. Rapid alerts enable timely responses for effective fire management

iii. Deep Learning Model Selection and Architecture

Selecting an appropriate deep learning model architecture is pivotal. For fire detection, the CNN Inception model is a suitable choice. Architecture specifics include layer count, filter configurations, pooling layers, and dropout layers. This model's capabilities enhance the system's ability to analyze video frames for fire-related patterns, contributing to accurate fire detection

C. Model Training

Model training is a critical phase in developing machine learning and deep learning models. During this phase, the model learns to make accurate predictions by adjusting its internal parameters based on the provided training data. For fire detection using the CNN Inception model, this process involves presenting preprocessed video frames to the model, allowing it to understand fire-related patterns and features. Effective training ensures that the model can accurately identify fires in real-world scenarios.

i. Training the CNN Inception Model:

In this subtopic, the focus is on training the chosen model, which is the CNN Inception model in this case. By feeding the model with the preprocessed training dataset, it gradually learns to recognize key patterns and attributes associated with fires. The depth and complexity of the CNN Inception architecture make it well-suited for capturing nuanced features present in video frames, contributing to accurate fire detection.

ii. Dual-Optimizer Approach

This subtopic emphasizes the optimization strategy employed during training. The dual-optimizer approach combines the SWA (Stochastic Weight Averaging) optimizer with the Adam optimizer. SWA smoothens the optimization process by averaging weight updates over multiple epochs, reducing the influence of noisy updates. The Adam optimizer, on the other hand, dynamically adjusts learning rates for each parameter. This combination aims to accelerate convergence and improve accuracy, critical for an effective fire detection system.

D. Model Evaluation and Testing

i. **Assessing Trained Model Performance**

After completing the model training, the next step is to evaluate its performance. This evaluation occurs on a separate testing dataset that the model has never seen before. The testing dataset provides a realistic representation of how well the trained model can generalize to new and unseen data.

ii. **Key Metrics Calculation**

During the evaluation process, it's essential to calculate several key metrics that gauge the model's effectiveness in detecting fires accurately. These metrics include accuracy, precision, recall, and the F1-score.

iii. **Metrics Interpretation**

Interpreting these metrics provides insights into different aspects of the model's performance. Accuracy measures overall correctness, while precision focuses on the proportion of correctly predicted fire instances among all predicted fire instances. Recall, also known as sensitivity or true positive rate, assesses the proportion of actual fire instances that the model correctly identifies. The F1-score combines precision and recall, offering a balanced assessment of the model's performance.

E. Flutter App Development

i. **Building the Mobile Application**

This phase focuses on developing a mobile application using the Flutter framework. Flutter's versatility and rapid development capabilities make it an ideal choice for creating a user-friendly app that enhances fire safety.

ii. **Real-Time Fire Notifications**

The core functionality of the app revolves around real-time fire notifications. When the CCTV system detects a fire anomaly through the advanced video analytics solution, the app promptly sends notifications to users' devices. This feature ensures that relevant parties are immediately informed about potential fire incidents, enabling swift responses.

iii. **Backend Notification Service Integration**

Integrating the app with a backend notification service is crucial. The app needs to establish a seamless communication channel with the backend to facilitate the delivery of notifications. This integration ensures that the notifications are relayed accurately and efficiently, contributing to timely alerts and effective fire management

iv. **User Interface and Experience**

Designing an intuitive user interface (UI) and providing a smooth user experience (UX) are vital aspects of app development. The UI should allow users to easily access information about detected fire incidents and take appropriate actions. A well-designed UX enhances the app's usability and encourages users to engage with its features.

V. RESULT AND DISCCUSION

Challenges and Future Directions in fire detection and the development of the Flutter application include addressing data privacy, security concerns, and ensuring scalability for handling growing demands
Developing a Flutter application that incorporates fire detection functionality requires careful consideration of data privacy and security. Protecting sensitive information, such as CCTV footage and user data, within the application is

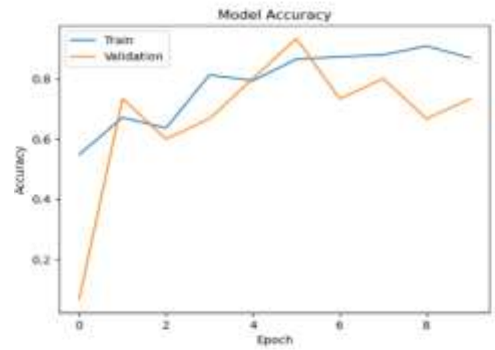

Figure 1. Train vs Test Accuracy

crucial. Implementing robust encryption techniques, strict access controls, and secure storage mechanisms are essential to maintain the privacy and security of data captured and processed by the application. Compliance with relevant data protection regulations and the adoption of best practices ensure that user information remains secure

As the number of users and the complexity of the application's functionality increase, scalability becomes a significant consideration. To handle the growing demands of fire detection and real-time alerting, the Flutter application needs to be scalable. This scalability can be achieved through the use of advanced hardware architectures and distributed computing frameworks. Efficient processing and analysis of video data .

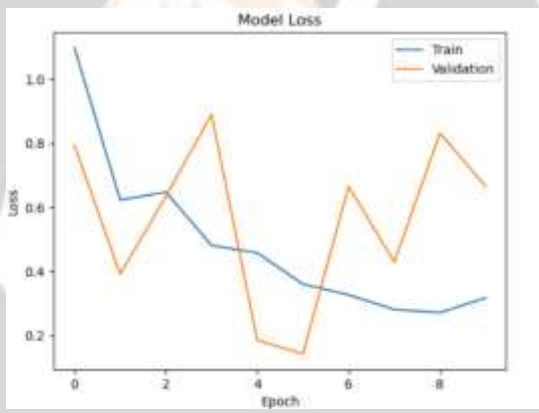

Figure 3. Train loss vs Test Loss

Continuous advancements in video analytics, artificial intelligence, and deep learning techniques provide opportunities to enhance the accuracy of fire detection systems. By training models on extensive datasets and leveraging sophisticated algorithms, the system can better differentiate between fire-related events and false alarms caused by non-fire incidents. This improved accuracy will minimize unnecessary panic and disruptions while ensuring reliable fire detection and response.

Table 3. Accuracy of Models

Model	Accuracy	F1 Score	Recall	Precision
CNN Inception	0.815	0.79096	0.700	0.909
CNN	0.6802	0.700	0.700	0.809
SVM	0.670	0.700	0.609	0.719
RNN	0.690	0.606	0.607	0.707

VI. CONLUSION

In conclusion, the accuracy of 0.815 of the CNN Inception fire detection model has shown encouraging results. A recall score of 0.7 represents its capacity to accurately catch a sizable fraction of actual fire incidents, while a precision value of 0.909 indicates its efficiency in making precise positive predictions. The model's balanced effectiveness is highlighted by the F1 score, which balances precision and recall and is currently 0. 790960.This improvement was most likely caused by the deliberate switch from a bespoke optimizer to the Adam optimizer. The Adam optimizer's adaptive learning rate and momentum modifications could have sped up convergence and improved the generalizability of the model.

These results demonstrate the model's potential to identify fires in real-world circumstances, facilitating prompt response and disaster avoidance. This system may advance with more improvements to the dataset.

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