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REAL-TIME COMBUSTION SURVEILLANCE SYSTEM USING CNN

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ABSTRACT: **The Real-Time Combustion Surveillance System leverages advanced technologies such as Convolutional Neural Networks (CNN) and machine learning to detect fire and smoke from images and video feeds in real-time. The system continuously monitors surveillance footage and video streams, analyzing patterns and signs of combustion with high accuracy. Utilizing a trained CNN model, the system can detect potential fire hazards swiftly and precisely, with detection accuracy reaching up to 99 to 100% . When a possible fire hazard is identified, the system triggers immediate alerts to relevant authorities, facilitating prompt response and mitigation efforts to prevent disasters. The system's quick detection and alert capabilities enhance fire surveillance and response efforts, thereby reducing the risk of property damage and safeguarding lives.**

The system is implemented using various methods and technologies, including the use of a Flask web application with help of mobile net architecture to enable real-time monitoring and control.The system also incorporates a cascade classifier for detecting fire in real-time video streams. Upon detecting a fire hazard, the system may play an alarm sound and send email notifications to specified recipients to alert them about the detected fire. Additionally, the system provides a web interface where users can upload images for analysis and receive predictions on whether the image contains signs of fire. The system also supports real-time video processing, allowing for continuous fire surveillance and timely alerts. Overall, the Real-Time Combustion Surveillance System is an innovative solution that combines state-of-the-art technologies to improve fire detection and prevention capabilities, ultimately enhancing public safety and disaster resilience.

Keyword : Real-Time,CNN,AI technology,Combustion Surveillance,Deep Learning,API integrated AI Alert System System and Triggers.

I. INTRODUCTION

In the realm of safety and security, the integration of cutting-edge technologies has become imperative, especially in scenarios like smoke or fire detection. Leveraging Convolutional Neural Networks (CNNs) for such detection systems has ushered in a new era of efficiency and accuracy.

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By employing deep learning techniques, CNN-based smoke or fire detection systems can discern patterns and anomalies in images or video feeds, enabling swift and precise identification of potential hazards. These systems are designed to analyze visual data, allowing for proactive measures to be taken in mitigating risks associated with fires . The integration of Application Programming Interfaces (APIs) further enhances the functionality of these detection systems. By linking to API-integrated bots, these systems can communicate alerts and notifications seamlessly across various platforms and devices. Whether it's sending alerts to smartphones, triggering alarms in buildings, or notifying emergency response teams, the APIintegrated bots ensure timely dissemination of critical information, thus facilitating prompt action in the event of a fire detection. The primary need for CNN-based smoke or fire detection systems lies in their ability to provide early warning and detection capabilities. Traditional methods often rely on human observation or rudimentary sensors, which may not always be reliable or timely. However, with CNNs at the helm, these systems can analyze vast amounts of visual data in real-time, significantly reducing the response time to potential threats. Moreover, the integration of API-driven bots addresses the need for efficient alert mechanisms, ensuring that relevant stakeholders are promptly informed, thereby minimizing the risk of casualties and property damage.The versatility of these systems extends beyond conventional applications.

Apart from safeguarding residential and commercial properties, CNN-based smoke or fire detection systems find utility in industrial settings, transportation infrastructure, and even forest fire monitoring. Their adaptability and accuracy make them indispensable assets in ensuring public safety and minimizing the impact of fire-related incidents.

In conclusion, the integration of CNNs fire detection systems, coupled with API-integrated bots for alert dissemination, represents a significant advancement in safety technology. By harnessing the power of deep learning and seamless communication channels, these systems offer unparalleled efficiency and reliability in detecting and responding to fire emergencies. With their ability to provide early warnings and facilitate swift action, they play a crucial role in safeguarding lives and property against the ravages of fire.

II. LITERATURE SURVEY

In this paper,**"** Near Real-Time Wildfire Management Using Distributed Satellite System" proposed by Kathiravan Thangavel , Dario Spiller , *Member, IEEE*, Roberto Sabatini,*Senior Member, IEEE* ,Pier Marzoccaan and d Marco Esposito in the year 2023 , The real-time wildfire management system proposed in this research leverages Distributed Space System (DSS) architectures to enhance Earth Observation (EO) and Space Domain Awareness (SDA) missions. By utilizing a constellation of Low Earth Orbit (LEO) satellites equipped with optical payloads, the system aims to detect and monitor wildfires with increased responsiveness and resilience.The system architecture consists of distributed satellites communicating via Intercommunication Satellite Links (ISL) and globally dispersed ground stations. Satellites are deployed in near-circular orbits, forming a Walker Delta constellation pattern to ensure effective coverage across the target area, such as the Australian continent.For wildfire detection, the system employs a one-dimensional Convolutional Neural Network (CNN) model trained on geocoded Level 2-D data from PRISMA hyperspectral imagery. The CNN model performs automatic segmentation of wildfire regions based on spectral information, enabling timely detection and management.To implement AI-on-the-edge capabilities, the trained CNN model is deployed on hardware accelerators such as the Intel Movidius and Jetson Nano, which offer low inference times and power consumption suitable for CubeSats or small satellites. This enables onboard processing of imagery data, allowing for near real-time wildfire detection and response. Overall, the proposed system demonstrates the potential of integrating advanced technologies like distributed satellite constellations and AI-driven wildfire detection algorithms to improve disaster resilience and emergency response capabilities. By harnessing the capabilities of DSS architectures and AI-powered edge computing, the system offers a scalable and efficient solution for monitoring and managing wildfires in real-time.

Algorithm 1: Pseudo code of the algorithm

```
# Set parameters
data_dir = 'dataset'
img_size = (224, 224)
batch_size = 32

# Create data generators
train_data_gen,
val_data_gen=create_data_generators(img_size,
batch_size)

# Load and preprocess data
x_train, x_val, y_train,
y_val=load_and_preprocess_data(data_dir,img_size,batch_
size)

# Define, compile, and train model
model=define_and_train_model(train_data_gen,val_data_g
en, x_train, y_train, x_val, y_val, epochs=15)

# Save and load model
save_and_load_model(model, 'fire_detection_model.keras')

# Real-time fire detection
detect_fire_real_time(model, 'fire.mp4', img_size)
```

III. PROPOSED SYSTEM

DATASET COLLECTION AND PROCESSING

The utilization of datasets containing fire and non-fire images, is instrumental in enhancing the accuracy of real-time combustion surveillance systems integrated with Alert system. By leveraging such datasets, these systems can train AI models to accurately distinguish between various scenarios and identify potential fire hazards with greater precision. The AI Alert System, integrated into the surveillance system, utilizes these trained models to analyze live video feeds in real-time, continuously monitoring for signs of combustion.

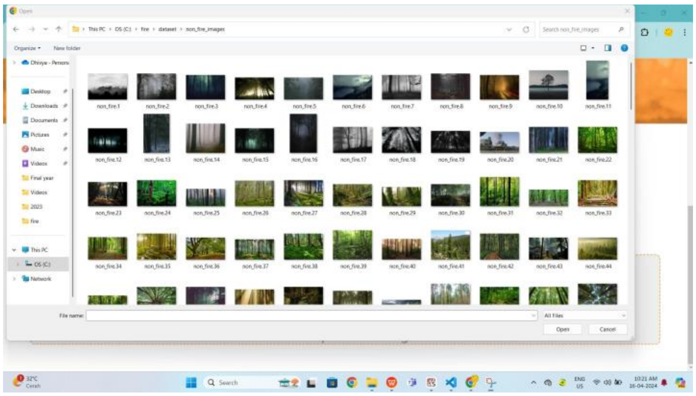


Figure 3.1 DATASET FOR NON FIRE IMAGES

Through the use of APIs, the AI Alert System interacts seamlessly with the surveillance system, providing alerts and notifications to relevant stakeholders and emergency responders as soon as potential fire hazards are detected. This integration ensures swift and effective response measures, minimizing the risk of property damage and loss of life.

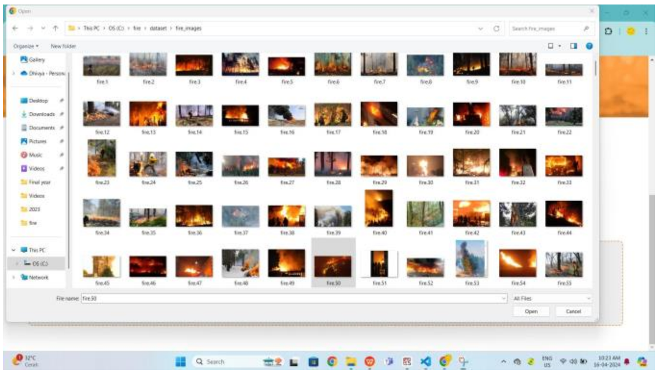


Figure 3.2 DATASET FOR FIRE IMAGES

Ultimately, the combination of dataset-driven AI models and real-time surveillance enhances the overall effectiveness and reliability of the combustion surveillance system.

```
25/25                          45s 2s/step -
accuracy: 0.6981 - loss: 0.7237 -
val_accuracy: 0.8450 - val_loss: 0.3168
Epoch 2/15
25/25                          41s 1s/step -
accuracy: 0.9133 - loss: 0.2358 -
val_accuracy: 0.9050 - val_loss: 0.1941
Epoch 3/15
 4/25                          28s 1s/step -
accuracy: 0.9329 - loss: 0.1847
```

Figure 3.3 THE PROCESSING OF DATASETS

The primary aim of implementing a deep learning system of fire detection using Convolutional Neural Networks (CNN) is to enhance safety measures by promptly identifying potential fire hazards. significantly improves overall safety and security, mitigating the risk of property damage, injuries, and loss of life associated with fire emergencies.

DISADVANTAGES OF EXISTING SYSTEM

- Data Synchronization:Ensuring consistent and timely data across distributed satellite systems poses a challenge.

- Communication Latency:Distributed systems often encounter communication delays between satellites and ground stations. Latency issues can impact the real-time nature of satellite data, affecting applications like Earth observation or disaster monitoring that require immediate response.
- Resource Management:Efficiently allocating resources such as power, bandwidth, and computational capacity across the distributed satellite network is a constant challenge. Balancing these resources is essential for optimal systemperformance.

IV RESULT AND DISCUSSION

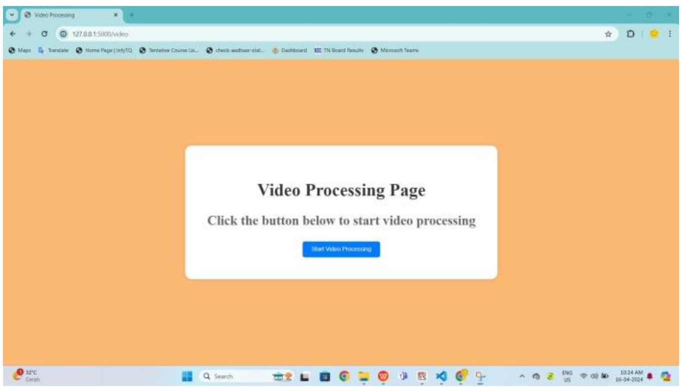
DETECTION OF FIRE ACCURACY FROM IMAGES

The system focus shifts to enhancing the accuracy of fire and smoke detection from images using advanced AI technologies. By leveraging API-integrated AI Alert System, the system can achieve improved accuracy in differentiating between fire and non-fire scenarios. Through continuous training and refinement of machine learning algorithms, the AI models can effectively analyze image data in real-time, identifying subtle patterns and features indicative of fire and smoke. This heightened accuracy enables the system to provide more reliable alerts and notifications to stakeholders, facilitating prompt response and mitigation actions. Additionally, the integration of AI Alert System enhances thesystem's capabilities by enabling automated decision-making and response mechanisms, thereby streamlining the overall surveillance process.

Figure 4.1 DETECTION FROM

IMAGE DETECTION OF FIRE FROM VIDEO FEED

The system focuses on enhancing the accuracy of fire and smoke detection from video feed by integrating advanced APIs and AI Alert System. By leveraging state-of-the-art machine learning algorithms and computer vision system



provides a proactive approach to fire safety, enabling early detection andmitigation of risks. As a result, it significantly reduces the likelihood of property damage, injuries, and loss of life, making it an invaluable asset in modern fire prevention and emergency response strategies. echniques, the system can accurately analyze video streams in real-time to identify signs of fire and smoke with high precision. The integration of APIs allows access to vast datasets and pre trained models, enabling continuous learning and adaptation to diverse environmental conditions.

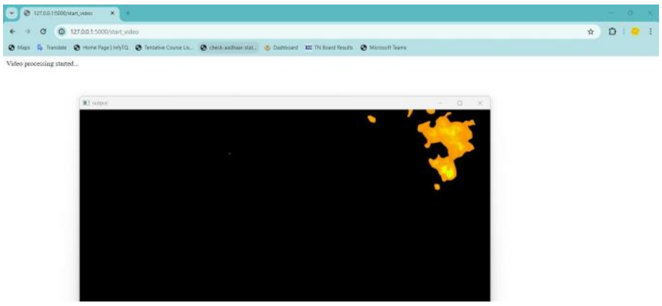


Figure 4.2 DETECTION FROM VIDEO FEED

DETECTION OF FIRE ACCURACY FROM CAMERA

Leveraging cutting-edge machine learning techniques, the system integrates API services to achieve superior accuracy and reliability. By continuously analyzing video streams from surveillance cameras, the AI Alert System swiftly identifies patterns indicative of fire presence with remarkable precision.

This advanced level of detection enables prompt and proactive response measures to be implemented, thereby minimizing the risk of property damage, injuries, and fatalities.Overall, this innovative approach significantly enhances the effectiveness and efficiency of real-time combustion surveillance, contributing to improved safety and security in diverse places.

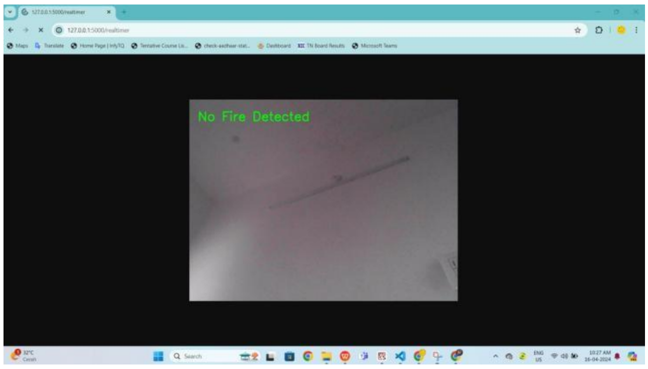


Figure 4.3 DETECTION WHEN NO FIRE OCCURS

The system's core objectives include developing a robust CNN architecture trained on diverse datasets to accurately detect smoke or fire patterns in various environments.

Integration of an API-linked bot facilitates real-time alerts to relevant stakeholders, ensuring swift response to potential threats. Additionally, the system aims to optimize computational efficiency to enable deployment across different platforms and environments seamlessly. Addressing scalability concerns, the objectives also encompass building a flexible framework capable of accommodating future enhancements and adaptations. Furthermore, emphasis is placed on the system's user-friendliness, ensuring ease of use for both administrators and end-users. Ultimately, the goal is to deploy a reliable and efficient smoke or fire detection system that contributes significantly to mitigating fire-related risks and enhancing overall safety standards.The incorporation of alert generation in SMS format through API integrated AI Alert System plays a pivotal role in enhancing the efficacy and responsiveness of real-time combustion surveillance systems.

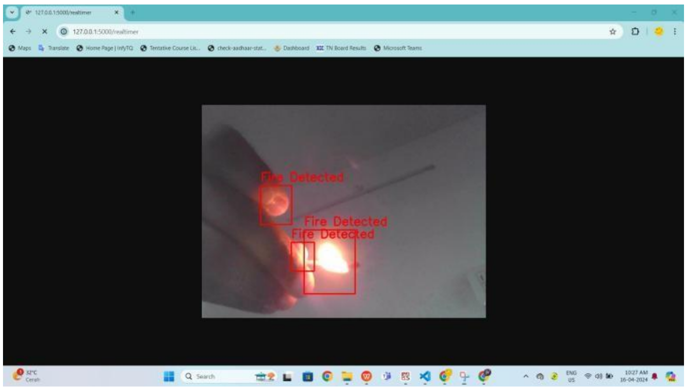


Figure 4.4 DETECTION WHEN FIRE OCCURS

By leveraging AI algorithms for fire detection and analysis, coupled with seamless integration of SMS alert generation via APIs, the system ensures swift and proactive notification of potential fire incidents to relevant stakeholders. This approach enables instantaneous dissemination of critical information, including location details and severity levels, to emergency responders, facility managers, and occupants, facilitating prompt and effective response measures. Moreover, the use of SMS format ensures widespread accessibility and reliability, reaching individuals across diverse demographics and geographic locations, even in areas with limited internet connectivity.

As a result, the integration of API-driven SMS alert generation with AI-based surveillance systems helps in order to avoid fire accidents in timely manner.

V. CONCLUSION

In conclusion, the integration of real-time combustion surveillance systems with AI-driven alert mechanisms presents a groundbreaking solution to the critical issue of fire detection and prevention. By leveraging advanced technologies such as artificial intelligence and machine learning, this system enables swift and accurate identification of potential fire hazards, allowing for immediate response and mitigation efforts with accuracy of 99 to 100 %. Moreover, the implementation of AI Alert System enhances the efficiency of alert dissemination, ensuring timely notifications to relevant stakeholders and emergency responders. As a result, this innovative approach not only enhances safety and security but also minimizes the risk of property damage and loss of life, making it a vital component of modern fire safety infrastructure.

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