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Forest Fire Detection using CNN

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Abstract : This paper introduces a novel fire detection system that uses Convolutional Neural Networks (CNNs) to address the inefficiencies of traditional smoke and heat sensors, which are often slow, costly, and limited in their detection capabilities. The proposed approach processes a custom dataset containing video frames from CCTV cameras to train a machine-learning model for fire detection. With extensive preprocessing to eliminate noise and irrelevant data, the system has a high detection accuracy of about 93%, hence a promising alternative for fire detection in many environments. The study highlights the need for timely fire detection, especially in scenarios such as forests where fires cause significant environmental damage and contribute to climate-related issues. The system demonstrates adaptability and scalability, capable of being implemented in homes, industries, and forests. It concludes that integrating this CNN-based framework with wireless sensors and CCTV networks could enhance detection accuracy and efficiency, potentially reducing fire-related losses and enabling quicker responses to emergencies.

Keywords: Fire detection, Convolutional neural networks, Machine learning, CCTV, Object detection.

1 1. Introduction

- Fire can make major hazards in this hectic world. All buildings and vehicles used in public transportation have fire prevention and fire protection systems due to the accelerated number in the fire incidents. Also, many of the firms conduct a mock fire drill in every occurrence of months to protect their employees from the fire. This would help them to understand what to do or what not to do when a fire situation happens. Forests are one of the main factors in balancing the ecology. It is very harmful when a fire occurs in a forest. But most of the time, the detection of forest fire happens when it spread over a wide region. Sometimes, it could not be possible to stop the fire. As a result, the damage of the environment is higher than predictable.
- The emission of large amount of carbon dioxide (CO2) from the forest fire damages the environment. As well as it would lead to complete disappearance of rare species in the world (Alkhatib, 2014). Also, it can make an impact on the weather, and this make major issues like earthquakes, heavy rains, floods and so on. The forest is a large surface of area filled with trees, lots of dried leaves, woods and so on. These elements encourage the fire when it starts. The fire can be ignited through many reasons such as high temperature in summer seasons, smoking, or some parties which having fireworks. Once fire starts, it will remain until it distinguished completely. The damage and the cost for distinguish fire because of forest fire can be reduced when the fire detected early as possible. So, the fire detection is important in this scenario. Finding of the exact location of the fire and sending notification to the fire authorities soon after the occurrence of fire can make a positive impact.
- There are different types of fire detection methods used by the Government authorities such as satellite monitoring, tower monitoring, using sensors, optical cameras and so on. There are some other techniques used for fire suppression. The major one is burning the dry areas or like in Canada; they are using flying water tanks for fire suppression. In middle east countries, these elements sweep away and burnt it in a certain unfuelled place. But, in Australia, they provide fire in these areas and wait until it dies itself without make any danger to the wildlife or humans. A research study shows an automatic fire detection can be divided into three groups: aerial, ground and borne detection. The ground-based systems use several staring black and white video cameras are used in fire detection which detect the smoke and compares it with the natural smoke.
- The main benefit of using this system is high temporal resolution and spatial resolution. So that, the detection is easier (Eric den breejen, 1998). But these mechanisms still have some drawbacks in detecting the early stage of the fire. So that, it is highly important to introduce a system to detect the fire early as possible.

2 Background

Fire detection technologies have been evolving over time, yet traditional systems remain constrained by key limitations when applied to large-scale or dynamic outdoor environments such as forests. These legacy systems include:

- **Smoke Sensors:** Commonly used in enclosed spaces like buildings, these sensors depend on the presence of particulate matter from smoke. In open or windy environments such as forests, smoke can disperse quickly, making detection unreliable or delayed.
- **Heat Sensors:** These devices trigger alarms when temperature thresholds are crossed. However, their sensitivity may result in false alarms, especially during hot seasons. Moreover, they only detect fires once a significant rise in temperature has occurred, making them reactive rather than proactive.

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- **Satellite-Based Monitoring:** Satellite imaging is used to detect thermal anomalies over vast areas. While effective in monitoring large geographical zones, this method suffers from low temporal resolution. Satellites may only pass over an area once every few hours or days, leading to delays in fire identification. In addition, cloud cover and weather conditions can obstruct image clarity.
- **Manual Surveillance:** Watch towers, patrolling personnel, and lookout stations are traditional but labor-intensive methods. These depend heavily on human observation, which introduces delays and risks due to fatigue or misjudgment, especially in low-visibility conditions such as night-time or dense foliage.

Due to these challenges, there has been a paradigm shift toward vision-based automated systems. The integration of artificial intelligence (AI), particularly deep learning models like Convolutional Neural Networks (CNNs), has transformed fire detection approaches. CNNs offer multiple advantages:

- **Automatic Feature Extraction:** CNNs eliminate the need for manual feature engineering. They learn and extract complex spatial hierarchies of features directly from raw image data.
- **High Accuracy in Visual Recognition:** Their layered architecture enables the recognition of intricate patterns like flame edges, flickering movements, and specific color profiles (e.g., reddish-orange hues typical of fire).
- **Scalability and Adaptability:** CNN models can be trained on a wide variety of data and deployed in different surveillance systems, including CCTV networks, UAVs, and mobile platforms.

Recent advancements have also explored multi-modal detection systems that combine visual data with environmental sensor readings (such as humidity, temperature, and gas concentration) to improve reliability. However, vision-based CNNs alone have already demonstrated high potential in reducing detection latency and improving accuracy in uncontrolled and wide-area settings such as forests.

By leveraging CNNs, this project seeks to create an early warning system that is both efficient and scalable, capable of operating in real time and adaptable to a variety of terrains and environmental conditions.

2.1 *Literature Review*

Several studies have shown the effectiveness of CNNs in fire detection:

- **YOLOv2:** Used for real-time fire/smoke detection in indoor/outdoor settings. Improved region proposal and localization.
- **UAV + CNN Integration:** CNNs trained on drone footage achieved over 92% accuracy for fire detection in inaccessible regions.
- **Data Fusion Systems:** Combined visual and environmental sensor data (e.g., humidity, temperature) to improve detection precision.
- **Color-Based CNNs:** Systems that segment frames by fire-color pixels and use CNNs for final classification.

These works show promising directions, particularly for real-time systems needing accuracy, low false positives, and adaptability.

3 Methodology

3.1 Dataset Description

The Forest Fire Dataset from Kaggle was used, consisting of 1000 RGB images (250x250 pixels). It includes 800 fire and 199 non-fire images. Irrelevant elements like people or tools were removed to ensure clean samples. Images were processed through CNN layers—Convolution, Global Average Pooling, Dense, Dropout—with augmentation techniques such as rescaling to boost feature learning. The final layer performs classification, returning 'Fire' or 'No Fire' based on the image content.

3.2 Architecture

CNN architecture includes convolutional layers that extract features using filters. Activation maps highlight patterns— white for strong fire features, gray for weak, and black for negative. AlexNet-style deep CNN was used for simplicity. The model processes input images, generates regions of interest, and uses fully connected layers to make the final decision, isolating fire areas effectively.

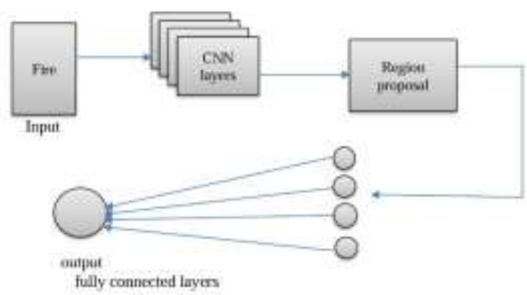

Figure 3.2 Architecture of CNN

3.3 CNN Framework

- **Input Layer:** Accepts 128x128x3 preprocessed frames from video or images.
- **Convolutional Layers:** Extract features like edges, color, texture using filters; ReLU introduces non-linearity.

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- **Pooling Layers:** Reduce spatial size using Max or Average pooling to retain key features and avoid overfitting.
- **ROI Generation:** Uses Region Proposal Networks (RPN) to identify potential fire zones.
- **Fully Connected Layers:** Flatten features and compute class probabilities using Softmax.
- **Feature Extraction:** CNN focuses on fire characteristics—color, shape, motion.
- **Training:** Optimized using loss functions (Cross- Entropy), Adam/SGD optimizer, and backpropagation.
- **Output Layer:** Returns binary result—Fire or No Fire—based on prediction probability.

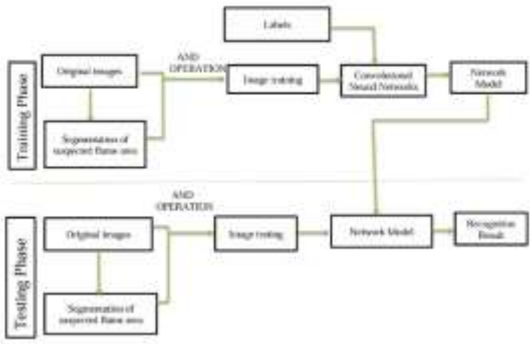

Figure 3.3 Work flow diagram

3.4 CNN Layers

- **Convolutional Layer:** Uses filters (3x3, 5x5) to detect visual patterns.
- **Activation Function (ReLU):** Introduces non- linearity to learn complex features.
- **Pooling Layer:** Reduces feature map size and emphasizes dominant patterns.
- **Fully Connected Layer:** Flattens data and performs final classification.

3.5 Work Flow

The methodology includes five stages:

- **A. Acquisition of Dataset:** Frames extracted from videos, manually labeled, balanced between fire/non-fire. Augmented using rotation, flipping, etc., to ensure diversity.
- **B. Data Preprocessing:** Images resized (250x250), normalized (0–1), and cleaned to remove noise.
- **C. Feature Extraction:** Fire features like reddish hue, shape, and flicker motion are extracted by the CNN during training.
- **D. Building Model:** Features passed through the CNN to build a predictive model using layers like Conv2D, Dense, Dropout, and ReLU.
- **E. Validation & Testing:** Model is evaluated on unseen data, achieving ~93% accuracy. Output includes a probability score and label ('Fire Detected' or 'No Fire Detected').

3.6 Model Training and Development

The model is built using InceptionV3 as a base, combined with layers like Conv2D, GlobalAveragePooling, Dense, and Dropout. It is trained using data generators and validated through accuracy/loss plots. Once trained, it classifies input images in real-time, displaying output and confidence.

Training Steps:

1. Load dataset and split into training/testing sets.
2. Apply data augmentation.
3. Define CNN architecture with specified layers.
4. Train using optimizer and loss function.
5. Validate and plot performance metrics.
6. Classify new input images with probability and alert output.

Output:

- If fire is detected → “Fire Detected!!”
- Else → “No Fire Detected!!”

4 Testing and Results

4.1 Performance Analysis

The performance graph of the model is shown below as in Figure.The accuracy and loss of training and validation for the model are shown in the figures below. The below shows us the performance of training and validation data and we can see that they meet at a point accurately which shows that our model is going to predict the output correctly.This shows us the performance of our model and how it will works when applied to an image.

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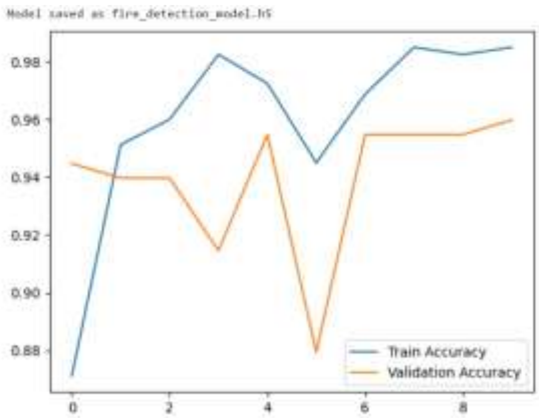

Figure 4.1 Performance graph of the model

When we show an image containing fire, if the picture shows evidence of fire. we will get the output as below showing the accuracy level as 53.62 and the text Fire!! is shown in Figure as below.

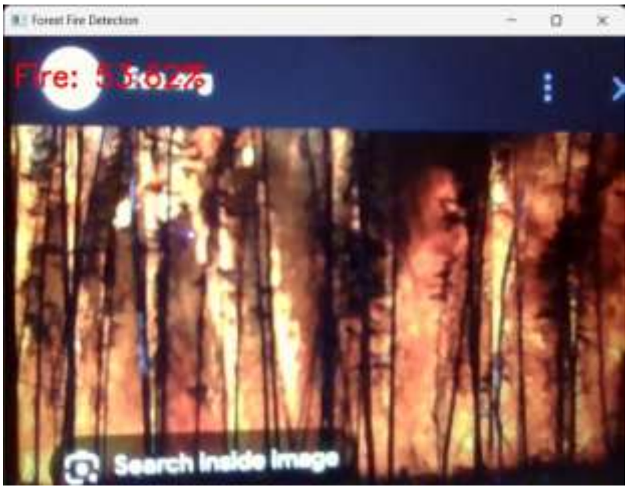

Figure 4.2 output when fire was detected

When we show an image containing no fire, if there is no sign of fire in the picture we will get the output as below showing the accuracy level as 87.98 and the text No Fire!! is shown in Figure as below.

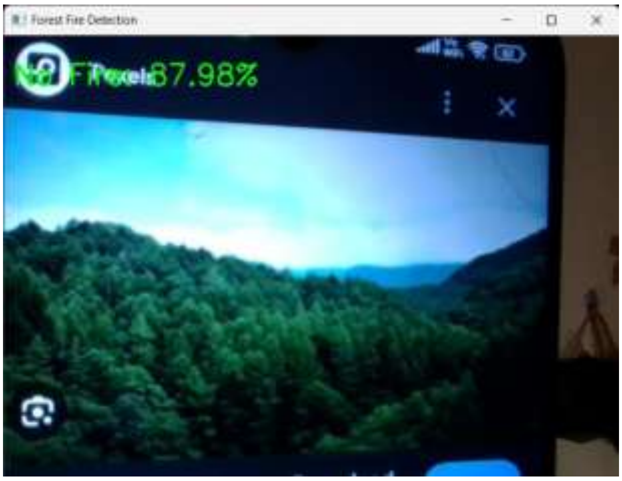

Figure 4.3 output when no fire was detected

When the fire is detected in the output then immediately we get the alret as beep sound and as well as email that was attached in the implementation process.If the fire is continuously detected then we get the beep sound continuously which makes the people alert.when the email alert was sent we get notified as Email alert sent !

Figure 4.4 output screen showing email alert sent!

The email template contains the subject as Fire Alert! Where it includes the body as Fire has been detected in the monitored area.please take immediate action! This email is received when the camera captures the fire.

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including residential, industrial, and forest environments. In addition, the project highlights the potential of integrating this detection system with existing infrastructure, such as CCTV cameras and wireless sensor networks, to enhance its real-world usability. The reduced response time and high accuracy can significantly minimize environmental damage, property loss, and the risk to human lives caused by uncontrolled fires. Future improvements could include expanding the dataset for greater generalization, incorporating advanced architectures like transformers for enhanced performance, and extending the system's functionality to provide predictive analytics for fire-prone areas. Overall, this study contributes meaningfully to the field of fire detection and establishes a robust foundation for future research and development in the domain.

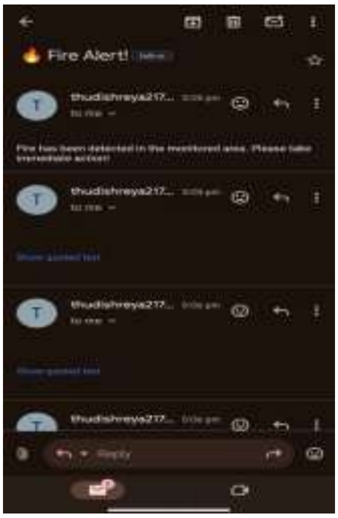

Figure 4.5 Fire Alert email that was sent

This project suggests a model that recognises the fire present in an image and as well as in real time. If fire is captured in the camera then we will get fire with percentage on the output frame otherwise we will get no fire with percentage on the output frame. We will also get the accuracy along with the detection.

5 Conclusion and Frame work

5.1 CONCLUSION

The project implements a Convolutional Neural Network (CNN)-based system for forest fire detection, addressing the limitations of traditional fire detection mechanisms like smoke and heat sensors. By leveraging the advanced capabilities of CNNs for image processing, the proposed model achieved an impressive accuracy rate of 93% in distinguishing fire scenarios from non-fire scenarios in real-time video frames. The framework effectively combines the strengths of visual data analysis and machine learning techniques to identify key fire attributes such as colour, shape, and motion. The methodology utilized includes dataset acquisition, preprocessing, feature extraction, and model validation, ensuring a comprehensive approach to problem-solving. Notably, the system demonstrated scalability and adaptability, making it suitable for various applications,

5.2 FUTURE WORK

Improve Model Accuracy
• Use more advanced CNN models (like YOLOv8 or EfficientNet) to reduce false positives and improve detection speed.

Expand Dataset
• Continuously gather real-time footage from different environments and conditions (nighttime, foggy, rainy) to enhance robustness.

Edge Deployment
• Deploy the system on edge devices (e.g., Jetson Nano, Raspberry Pi with GPU) to make it faster and more scalable in remote areas.

Alert System Enhancement
• Add GPS-tagged alerts and integrate with emergency services for automated dispatch.

Predictive Fire Risk Mapping
• Combine real-time detection with weather data and vegetation analysis to predict fire-prone zones.

Multi-Sensor Fusion
• Integrate with thermal or gas sensors to confirm fire presence and reduce false alarms.

Mobile Monitoring App
• Develop an app/dashboard to monitor live feeds, receive alerts, and view detection logs on the go.

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