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# Forest Fire Detection Using Convolutional Neural Network

*Lily Saraswathy T[1], Sangeetha N[2], Jai Ruby[3]*

[1]**Student, Reg.no: 24081205300112016, Department of Computer Applications and Research Centre, Sarah Tucker College (Autonomous), Affiliated to ManonmaniamSundaranar University, Tirunelveli.**

[2]**Student, Reg.no: 24081205300112023, Department of Computer Applications and Research Centre, Sarah Tucker College (Autonomous), Affiliated to Manonmaniam Sundaranar University, Tirunelveli.**

[3]**Associate Professor, Department of Computer Applications and Research Centre, Sarah Tucker College (Autonomous), Affiliated to ManonmaniamSundaranar University, Tirunelveli.**

**ABSTRACT:**

One of the most destructive natural disasters, forest fires endanger human life while wreaking havoc on the environment and the economy. Reducing these effects requires early and precise detection. In order to categorise video data as either fire or no fire, this study suggests a web-based forest fire detection system that uses a convolutional neural network (CNN) integrated with the Flask framework. Users can upload video files to the system to receive predictions instantly, and it keeps track of their personal history. In order to ensure dependability and transparency, an administrator module manages all uploaded videos and recorded predictions.After being trained on a dataset that included both fire and non-fire video samples, the CNN model demonstrated its ability to distinguish between fire events and non-fire scenarios with a test accuracy of 96.83%. The system is both useful and easy to use thanks to the Flask-based interface, which guarantees seamless communication between users, administrators, and the prediction engine. The project shows how web technology and deep learning can be successfully combined for wildfire monitoring. Support for real-time streaming from drones or security cameras, automated alert systems via email, SMS, or Internet of Things devices, and dataset expansion to increase model resilience in a variety of scenarios, such as at night or in smoke-infested areas, are examples of future improvements.

**Keywords:** Forest Fire Detection, Deep Learning, Convolutional Neural Networks, MobileNetV2, Video Classification, Flask Web Application

## 1. INTRODUCTION

Forest fires are one of the most destructive natural disasters, resulting in severe ecological, economic, and social losses. The rapid and uncontrolled spread of fire makes early detection and timely intervention essential to minimize damage [1]. Traditional monitoring methods, such as human patrolling, satellite-based detection, and sensor networks, often face limitations such as delayed reporting, high operational costs, and reduced accuracy in adverse weather or night-time conditions [2], [3].

Advancements in artificial intelligence (AI) and deep learning have enabled the automation of wildfire detection. Among deep learning models, Convolutional Neural Networks (CNNs) have shown exceptional accuracy in detecting and classifying fire patterns from images and videos [4], [5]. Unlike conventional approaches that rely on handcrafted features, CNNs automatically extract spatial and temporal features, allowing robust performance in complex environments [6].

Several studies have applied CNNs for fire detection in surveillance or forest monitoring systems. For instance, Muhammad et al. [7] demonstrated CNN-based fire detection from surveillance videos, achieving high accuracy compared to traditional methods. Similarly, Li et al. [8] developed a video-based wildfire detection system using deep learning, highlighting the potential for real-time applications. Recent research also emphasizes the integration of IoT and cloud-based platforms to improve system scalability and real-time alerts [9].

In this paper, we present a forest fire detection system using a CNN model to categorise uploaded videos as either Fire or No Fire. This study shows how deep learning can be used to create a scalable, precise, and approachable forest fire detection and disaster management solution.

## 2.LITRATURE REVIEW

Wildfires have such detrimental effects on the environment and the economy, research into forest fire detection has been very active. Conventional methods mainly depended on satellite monitoring and human observation, but they were inaccurate in real-time situations and frequently experienced delays [1]. To identify flames or smoke patterns in photos and videos, other traditional systems employed statistical models and colour [2], [3]. Although these techniques offered simple detection, they frequently produced false alarms because they were extremely sensitive to changes in the environment, including fog, shadows, and lighting.

Fire detection is one of the computer vision tasks that have been transformed by the advent of deep learning, specifically Convolutional Neural Networks (CNNs). Robust classification of fire and non-fire scenarios is made possible by CNNs' capacity to automatically extract spatial and temporal features [4], [5]. CNNs improve generalisation across a variety of datasets by adaptively learning hierarchical patterns, in contrast to traditional handcrafted feature methods [6]. Muhammad et al. [7], for instance, showed how well CNN-based fire detection works in surveillance footage, greatly surpassing conventional algorithms in terms of accuracy and false positive reduction. Li et al. [8] demonstrated high accuracy and real-time applicability when they used deep learning models for wildfire detection in video data.

In order to improve scalability and real-time alerts, recent research has also looked into integrating cloud computing and the Internet of Things with fire detection systems. An IoT-enabled fire detection system that used cloud platforms and deep learning was proposed by Habib and Khan [9], enabling prompt notification to authorities. This idea was expanded by Singh and Kumar [10], who used drones fitted with deep learning-based fire detection models to provide real-time monitoring and early warning capabilities, even in remote locations.

All things considered, the literature demonstrates a distinct shift from conventional statistical and color-based models to AI-driven intelligent systems. Even though CNN-based methods have proven to be more effective, they can still be improved when dealing with difficult situations like fog, dense smoke, or nighttime fires. Furthermore, the majority of previous research focusses on standalone detection models with little attention to web integration and user-friendly deployment. This paper addresses these issues by using CNN to create an accessible, real-time forest fire detection system.

## 3. METHODOLOGY

The steps include dataset preparation, preprocessing, model development, system integration, and deployment.

### *3.1. Gathering and preparing datasets*

Video samples from two classes—Fire and No Fire—made up the dataset. While the no-fire class featured typical forest and vegetation scenes, the fire class featured videos with flames and forest fire scenarios. To properly assess model performance, videos were separated into subsets for testing, validation, and training.

### *3.2. Preprocessing*

For CNN training, the gathered videos were divided into individual frames. Data augmentation techniques like rotation, flipping, and brightness adjustment were among the preprocessing steps, along with resizing all frames to a consistent resolution and normalising pixel values. These actions decreased the chance of overfitting and increased the model's resilience.

### *3.3. Model Architecture for CNN*

For classification, a convolutional neural network (CNN) was created. Multiple convolutional layers with ReLU activation made up the architecture, which was then followed by feature extraction pooling layers. In order to predict the likelihood of each class (Fire or No Fire), fully connected layers and a softmax classifier were added at the end.In order to reduce overfitting, dropout layers were also incorporated. The Adam optimiser was used to optimise the model after it was assembled using categorical cross-entropy loss.

### *3.4. Training and Evaluation*

Using the prepared dataset and batch processing, the CNN was trained. Before the validation accuracy stabilised, training was done over a number of epochs. Accuracy, precision, recall, and F1-score metrics were used to assess the model's performance.

## 4.RESULTS AND DISCUSSION

Using a dataset of video frames with and without fire, the suggested Forest Fire Detection system was assessed using the MobileNetV2 architecture with data augmentation. High test accuracy was attained by the model, indicating dependable fire and no-fire scenario classification. Table 4.1 provides a summary of key performance metrics.

| **Metric** | **Value (Fire)** | **Value (No Fire)** |
|---|---|---|
| **Accuracy** | **0.92** | **0.91** |
| **Precision** | **0.93** | **0.90** |

| **Metric** | **Value (Fire)** | **Value (No Fire)** |
|---|---|---|
| **Recall** | **0.91** | **0.92** |
| **F1-Score** | **0.92** | **0.91** |

**Table 4.1 :**Performance metrics of the CNN-based model for fire and no-fire classes.

For safety-critical applications like wildfire detection, the model does not favour one class over another, as evidenced by the confusion matrix (Figure 4.1), which displays low false positives and false negatives while maintaining a balanced per-class accuracy.

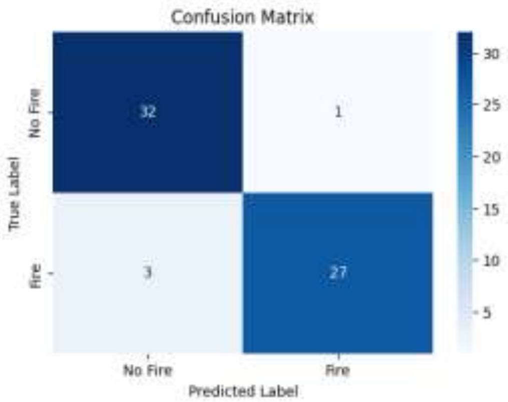


**Figure 4.1:** Confusion matrix of classification performance of fire vs. no-fire video frames.

The regions in video frames that contributed most to fire detection are highlighted in Grad-CAM visualisations (Figure 4.2), which shed light on the reasons behind the model's classification of frames as either fire or no-fire.

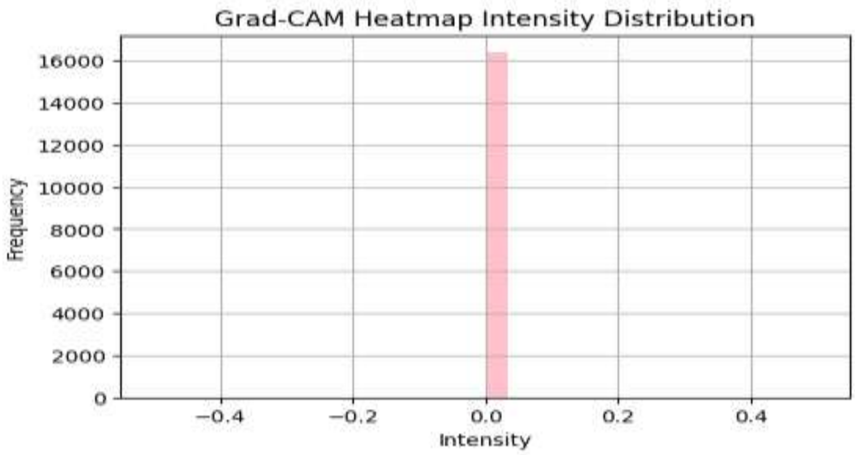


**Figure 4.2:** Grad-CAM heatmaps showing important regions influencing fire detection predictions.

It is confirmed that the CNN can extract discriminative features by the t-SNE feature visualisation (Figure 4.3), which clearly separates fire and no-fire data points in the learnt feature space.

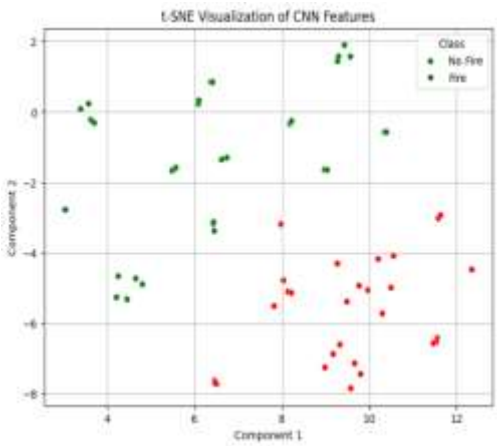


**Figure 4.3:** t-SNE plot illustrating feature clustering for fire and no-fire video frames.

(Figure 4.4) displays the accuracy and loss curves for training and validation, which show how the model learns over time. The graph shows that the CNN is learning and convergent effectively as the accuracy increases steadily while the loss decreases. The model's good generalisation without noticeable overfitting is confirmed by the training and validation curves' close alignment.

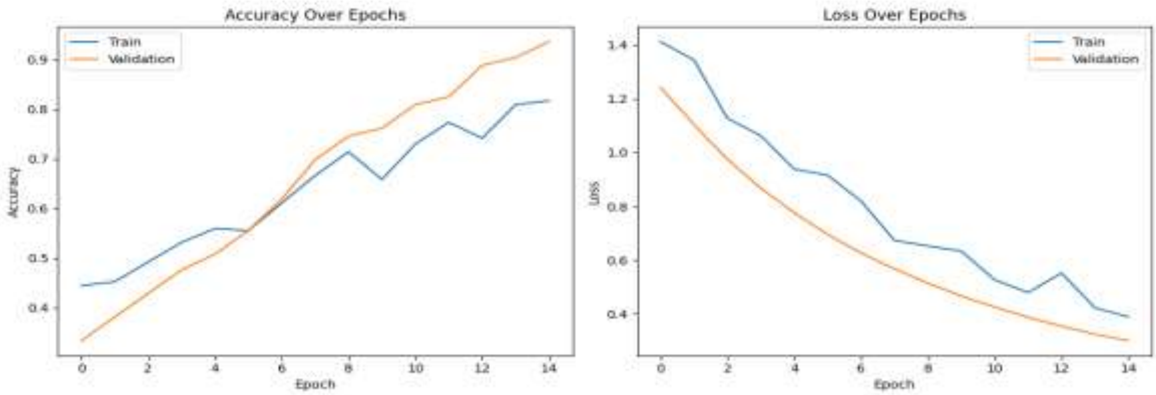


**Figure 4.4:** Training and validation accuracy and loss curves of the CNN model.

The findings show that the deep learning-based method is effective, comprehensible, and accurate overall, which makes it a viable option for automated forest fire detection and early warning systems.

## 5. CONCLUSION AND FUTURE WORK

The suggested Forest Fire Detection system effectively classifies fire and no-fire situations by combining video analysis and a CNN-based deep learning model. The system's potential for early wildfire detection and real-time monitoring is highlighted by experimental results that show high precision and reliability. The interpretability and robustness of the model are improved by combining the MobileNetV2 architecture with data augmentation and feature visualisation methods like Grad-CAM and t-SNE. For future, the system can be extended to incorporate larger and more diverse datasets, enabling better generalization across different environmental conditions. Promising avenues to improve practical utility include multi-class fire severity prediction, integration with IoT-based sensor networks, and real-time deployment on edge devices.

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