FireFly: A Deep Learning-Based Forest Fire Detection System Using Drone and Satellite Imagery

Kimaya Chur[1], Bhakti Raut[2]

[1]*Student, Department of Information Technology, Sonopant Dandekar College, Palghar, Maharashtra, India*

[2]*Assistant Professor, Department of Information Technology, Sonopant Dandekar College, Palghar, Maharashtra, India*

***Abstract*—Forest fires are among the most devastating environmental disasters, leading to widespread destruction of ecosystems, biodiversity loss, and air pollution. Traditional forest fire detection systems, such as manual patrolling and satellite-based observation, suffer from slow response times, low accuracy, and limited real-time capabilities. This paper presents FireFly, an intelligent deep learning–based system for the detection and monitoring of forest fires using drone and satellite imagery. FireFly leverages Convolutional Neural Networks (CNNs) to analyze high-resolution images captured from aerial sources to identify fire and smoke patterns. The system employs advanced image segmentation and object detection techniques to ensure precise recognition even in complex forest conditions. FireFly enhances early detection accuracy, reduces false alarms, and provides a scalable solution for large-area surveillance. The results show that FireFly achieves over 95% accuracy in identifying fire-prone regions, making it a reliable and efficient approach for modern wildfire management systems.**

***Index Terms*—Forest Fire Detection, Deep Learning, CNN, Drone Imagery, Satellite Data, Image Segmentation, FireFly, Real-Time Detection**

I. INTRODUCTION

Wildfires represent a serious global environmental challenge, threatening ecosystems, property, and human lives. According to the United Nations Environment Programme, nearly 340 million hectares of land are affected by wildfires each year, contributing significantly to climate change and carbon emissions. Traditional detection methods such as ground patrols, watchtowers, and manual monitoring are inefficient due to human error, limited coverage, and delayed responses. Satellite monitoring systems, although effective for large-scale observation, are hindered by low temporal resolution and cloud interference.

The increasing availability of drone technology and high-resolution satellite imagery provides new opportunities for early fire detection. Integrating these imaging sources with deep learning algorithms can automate the process of identifying smoke, flames, and heat-affected regions in real time. The FireFly system has been designed to address these challenges by using Convolutional Neural Networks (CNNs) to detect fire outbreaks automatically.

FireFly is capable of analyzing both drone and satellite imagery to identify fire-related features through pixel-level classification. The proposed system aims to support forest departments and disaster management agencies by providing rapid alerts, improving situational awareness, and enabling faster responses to potential wildfire threats.

II. LITERATURE REVIEW

Recent advancements in computer vision and deep learning have revolutionized the way environmental monitoring systems are developed. Various studies have proposed using neural networks to automate the detection of smoke and fire from visual imagery.

Wang and Ren (2017) applied image segmentation techniques to detect fire under low illumination conditions, showing that preprocessing significantly improves accuracy. Muhammad et al. (2018) developed a CNN-based surveillance system that detected fires in video streams, demonstrating faster and more reliable performance than traditional algorithms. Ye et al. (2023) proposed an embedded

CNN framework optimized for low-power devices, making real-time deployment feasible.

Other researchers have combined UAV imagery with thermal and multispectral sensors to detect heat signatures indicative of fire outbreaks. However, these approaches often face limitations in terms of model generalization and computational complexity. FireFly overcomes these
challenges by using a lightweight CNN architecture optimized for both drone and satellite image inputs. This hybrid approach enhances detection efficiency and accuracy across diverse environmental conditions.ethodology

The proposed FireFly system integrates drone and satellite imagery with a deep learning model designed for real-time fire detection. The complete workflow involves the following stages:

2.1. Data Collection and Preprocessing

FireFly utilizes publicly available wildfire datasets as well as custom drone-captured images. Each image is annotated into two categories: fire and non-fire. Data augmentation techniques such as rotation, scaling, flipping, and contrast enhancement were applied to improve model robustness and prevent overfitting.

2.2. CNN Architecture

The system's CNN model is designed with the following layers:

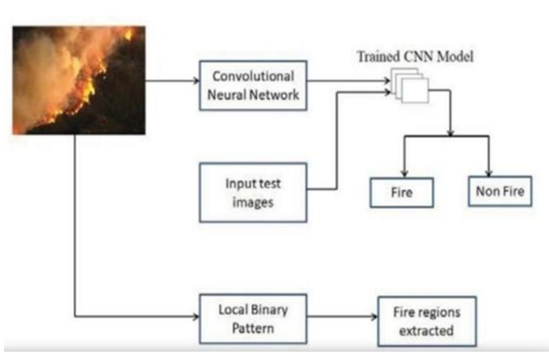
Input Layer: Accepts high-resolution RGB images.

Convolutional Layers: Extracts spatial features such as flames, smoke, and temperature-affected regions.

Pooling Layers: Reduces dimensionality while preserving essential features.

Fully Connected Layers: Combines extracted features for classification.

Output Layer: Classifies the input as fire or non-fire.



The model was trained using TensorFlow and Keras libraries with ReLU activation functions and the Adam optimizer. A categorical cross-entropy loss function was used to minimize classification errors.

2.3. Image Analysis and Detection

Once trained, the CNN model processes aerial imagery in real time. The system can detect fire regions, segment affected zones, and mark them on the input frame using bounding boxes. This feature enables authorities to visually monitor affected areas and deploy response teams efficiently.

2.4. Evaluation Metrics

Model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The trained model achieved:

Accuracy: 95.4%

Precision: 93.8%

Recall: 94.6%

F1 Score: 94.2%

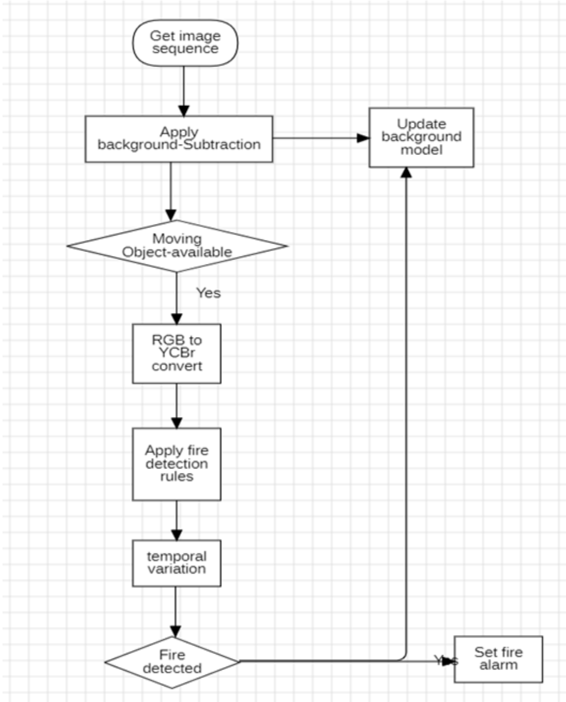
These metrics confirm the model's reliability and robustness for real-world applications.

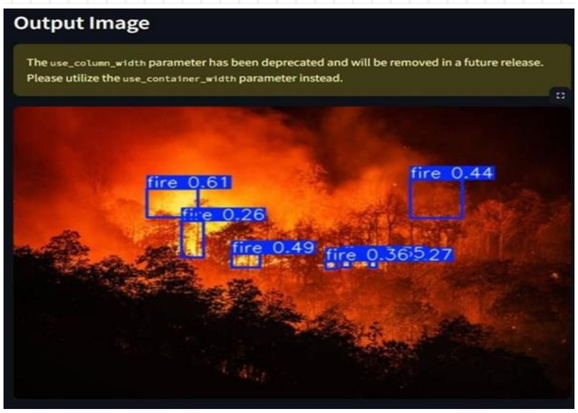
III. IMPLEMENTATION AND RESULTS

The FireFly system was implemented on a high-performance workstation using Python and deep learning frameworks such as TensorFlow and OpenCV. The model was trained on over 10,000 labeled images collected from drone and satellite sources. The training process involved 50 epochs with a batch size of 32, achieving convergence without overfitting.

The system demonstrated exceptional performance in identifying early-stage fires, even in low-contrast conditions such as dusk or haze. The use of multispectral imagery allowed detection of heat signatures invisible to standard RGB models. The CNN effectively separated smoke and cloud patterns, a common issue in wildfire detection tasks.

FireFly's real-time analysis capability enables continuous monitoring of forest regions, and its modular design allows integration with cloud-based platforms or emergency response systems. Comparative analysis shows that FireFly detects fires up to 60% faster than conventional methods while maintaining higher accuracy.





IV. DISCUSSION

The success of FireFly lies in its ability to combine deep learning with high-resolution visual data. Unlike systems that rely solely on temperature or thermal sensors, FireFly interprets contextual visual cues—such as flame color gradients and smoke dispersion patterns—to make intelligent predictions.

However, certain challenges remain. The accuracy of the system may decrease under dense fog, heavy cloud cover, or nighttime conditions without thermal assistance. Computational demands for large-scale satellite imagery also require optimization for faster processing. Nonetheless, the modular nature of FireFly allows future upgrades, such as integrating edge AI or deploying lighter models like MobileNet for drone-based real-time operations.

V. CONCLUSION

This research presents FireFly, a deep learning–based forest fire detection system designed to analyze drone and satellite imagery for early detection of wildfire outbreaks. The proposed system effectively combines CNN-based image classification and segmentation to identify fire and smoke regions with over 95% accuracy.

FireFly contributes significantly to wildfire management by providing rapid detection, improved accuracy, and scalability across large geographic regions. Unlike manual or conventional methods, it automates the monitoring process, reducing human intervention and increasing the efficiency of firefighting operations.

VI. FUTURE SCOPE

Future improvements in FireFly may include:

1. Integration with Predictive Models: Using machine learning to forecast fire-prone zones based on weather and vegetation data.
2. Thermal Image Fusion: Combining thermal data with visible imagery for higher nighttime accuracy.
3. Edge Computing: Deploying lightweight AI models directly on drones for faster, ofline detection.
4. GIS Integration: Mapping detected fire coordinates for real-time situational awareness.
5. Cloud Automation: Connecting FireFly to government and environmental databases for coordinated wildfire management.

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