



AI-Assisted Multi-Sensor Satellite Image Fusion For Early Fire Detection And Risk Mapping Of Forest Fires

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Abstract: Forest fires are becoming more frequent and intense worldwide due to climate change, human activity, and shifting environmental conditions. Rising temperatures, prolonged droughts, and land-use changes have significantly increased wildfire risks, causing severe ecological and economic losses. Early detection and reliable risk mapping are essential to minimize such impacts and enable timely response. However, conventional methods like ground observation or single-sensor monitoring often face limitations due to restricted coverage, delayed detection, and interference from clouds or smoke. This study proposes an artificial intelligence (AI)-based multi-sensor image fusion framework for early forest fire detection and risk assessment. The approach integrates thermal, optical, and radar satellite data from publicly available open-access sources to enhance spatial and temporal accuracy. Fusion is applied at pixel, feature, and decision levels, improving detection precision and minimizing false alarms.

Index Terms: Artificial Intelligence (AI), Forest Fire Detection Remote Sensing Satellite Imagery, Risk Mapping, Environmental Monitoring.

I. INTRODUCTION

1.1 Overview of Forest Fires

Forest fires are among the most destructive natural disasters, capable of transforming entire ecosystems in a short time. Their increasing frequency is linked to climate change, prolonged droughts, and human activities

such as deforestation and land expansion. As communities move closer to forest regions, even small ignitions can quickly grow into large-scale fires.

1.2 Environmental and Ecological Impacts

Wildfires severely affect vegetation, soil, and air quality. They release huge amounts of carbon dioxide and destroy habitats, reducing biodiversity. The resulting ash and smoke pollute rivers and air, threatening both humans and wildlife. These impacts also worsen global warming, creating a repeating cycle of fire and climate stress.

1.3 Socio-Economic Consequences and the Need for Early Detection

Beyond the environment, wildfires cause heavy social and economic losses. People face displacement, property loss, and health issues due to smoke exposure. Governments spend massive resources on emergency response and rehabilitation. Traditional monitoring methods such as ground patrols or single-satellite systems often fail due to limited coverage or delays. Hence, early detection using modern technology is essential.

1.4 Technological Approach and Project Scope

This study develops an AI-assisted framework that integrates thermal, optical, and radar satellite data for early wildfire detection and risk mapping. The system uses open-access datasets and environmental indicators to produce updated fire-risk maps. These maps help authorities identify vulnerable areas, improve response time, and support resource planning.

1.5 Global Significance

With climate change intensifying fire risks worldwide, adopting AI and remote sensing for fire management is becoming crucial. The proposed framework provides a cost-effective, scalable solution adaptable to different regions, promoting sustainable forest management and faster disaster response.

II. LITERATURE REVIEW

2.1 Traditional Wildfire Detection Methods

Early wildfire monitoring relied on lookout towers, ranger patrols, and public reporting. These manual methods worked in smaller or accessible regions but were ineffective for vast forest areas. Their success depended on human presence and clear weather conditions. As wildfire frequency and intensity grew, such systems became inadequate for large-scale or real-time observation.

2.2 Satellite-Based Detection Techniques

Remote sensing technology transformed wildfire detection by enabling wide-area, continuous monitoring. Different satellites provide complementary data:

- **Thermal Sensors (MODIS, VIIRS):** Detect heat anomalies and hotspots.
- **Optical Sensors (Sentinel-2, Landsat-8):** Capture detailed surface and vegetation information.
- **Radar Sensors (Sentinel-1 SAR):** Penetrate smoke and clouds for consistent monitoring.

While satellite data enhance accuracy, single-sensor systems still face issues like limited revisit time, cloud interference, and coarse resolution.

2.3 Multi-Sensor Fusion

Integrating optical, thermal, and radar data combines their strengths, improving detection accuracy and reducing false alarms. Multi-sensor fusion enables all-weather and day–night monitoring. Recent studies also use deep-learning methods to merge multiple data types, helping distinguish fire, smoke, and terrain more effectively.

2.4 Role of Artificial Intelligence in Detection

Artificial Intelligence (AI) plays a growing role in wildfire analysis. Machine learning models process large datasets to detect early fire signs and predict spread patterns. Tools like Google Teachable Machine simplify model training, while advanced algorithms such as Convolutional Neural Networks (CNNs) and YOLO provide accurate real-time detection. AI-based systems improve alert speed, accuracy, and response planning.

2.5 Challenges and Limitations

Despite technological progress, challenges remain. Cloud cover, sensor noise, and inconsistent data quality can affect detection reliability. AI models often need retraining for different ecosystems, and real-time satellite processing requires strong computational power. Further advancements in data fusion and cloud-based systems are essential for achieving fast and dependable wildfire monitoring.

III. METHODOLOGY

3.1 Overview

This study presents an AI-based framework for early wildfire detection using multi-sensor satellite data. The approach combines thermal, optical, and radar imagery with environmental factors to improve accuracy and reduce false alarms.

The workflow includes:

- **Data Acquisition:** Collecting multi-sensor satellite and environmental datasets.
- **Preprocessing:** Cleaning, aligning, and standardizing data for uniform analysis.
- **Multi-Image Fusion:** Integrating complementary data from different sensors.
- **AI Model Development:** Training and validating models for fire detection.
- **Fire Detection and Risk Mapping:** Generating spatial risk maps for decision support.

3.2 Data Acquisition

Open-source satellite data were obtained from reliable repositories to ensure accuracy and consistency:

- **NASA Earthdata (MODIS, VIIRS):** thermal and optical data for hotspot identification.
- **Copernicus Sentinel Hub (Sentinel-1, Sentinel-2):** radar and high-resolution optical imagery for fire progression under cloud or smoke.
- **USGS EarthExplorer (Landsat):** long-term multispectral data for historical analysis.
- **Google Earth Engine (GEE):** cloud-based access and visualization of datasets.

This multi-source approach enables continuous, day–night, all-weather fire monitoring.

3.3 Optical Imagery

Optical data from Sentinel-2 and Landsat-8 provided vegetation and surface details. Healthy vegetation shows strong near-infrared reflectance, while burned areas appear darker. Images were atmospherically corrected,

calibrated, and clipped to the study area. Since optical sensors are limited by smoke and cloud, the analysis was strengthened with thermal and radar data.



Figure 1: Optical Map Accuracy and Pixel Resolution

3.4 Thermal Imagery

Thermal data from MODIS and VIIRS detect heat anomalies and active fire zones. They provide continuous coverage and are effective under low visibility. Key steps included conversion to brightness temperature, atmospheric correction, spatial alignment, and thresholding to identify hotspots.

3.5 Radar Imagery

Sentinel-1 radar data supply surface texture and moisture information, penetrating smoke and cloud layers. Preprocessing involved calibration, speckle filtering, and terrain correction using DEM data. Radar imagery complements optical and thermal datasets for consistent detection.

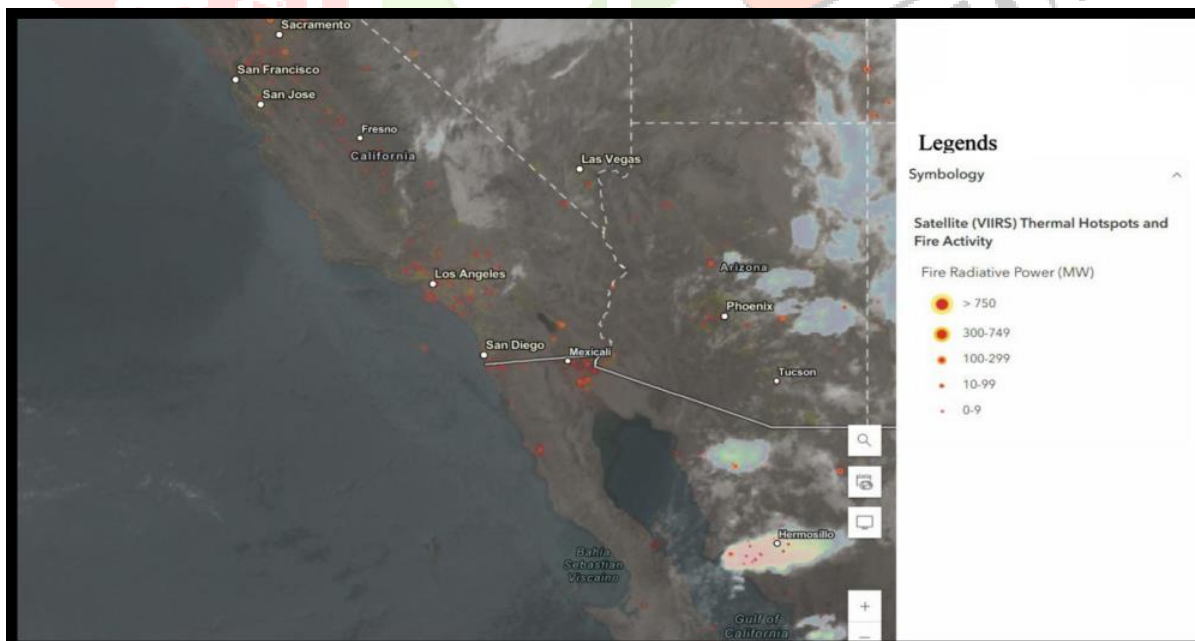


Figure 2: Thermal Image Highlighting Hotspots

3.6 Preprocessing

Preprocessing ensures clean and consistent data before AI analysis. Steps included radiometric and geometric correction, cloud and smoke masking, and normalization to maintain uniform resolution. Features such as NDVI, temperature gradients, and radar backscatter were extracted to train the model effectively.

3.7 Data Fusion

Multi-sensor fusion integrates the strengths of each imagery type into a unified dataset.

- **Pixel-Level Fusion:** merges image pixels across sensors.
- **Feature-Level Fusion:** combines temperature, vegetation, and surface indicators.
- **Decision-Level Fusion:** consolidates AI outputs for final detection and risk mapping.

This integration enhances detection accuracy, reduces false alarms, and supports faster emergency response.

IV. WORKING PRINCIPLE

4.1 Overview

This chapter explains the working process of an AI-assisted wildfire detection and risk mapping system. The method integrates fused multi-sensor satellite data—optical, radar, and thermal—within a Google Teachable Machine (GTM) model to detect fire activity early. This approach enhances accuracy, minimizes false alarms, and remains reliable even under smoke, cloud, or low-light conditions.

4.2 Data Collection and Fusion

Satellite imagery from various sensors was acquired to provide a complete view of terrain and vegetation. Optical data captured surface conditions, radar detected structural and moisture changes, and thermal imagery revealed heat signatures. All datasets were preprocessed using radiometric correction, normalization, and cloud masking for uniformity. The refined data were then fused into a composite layer, enabling the AI model to extract complementary information and improve detection performance.

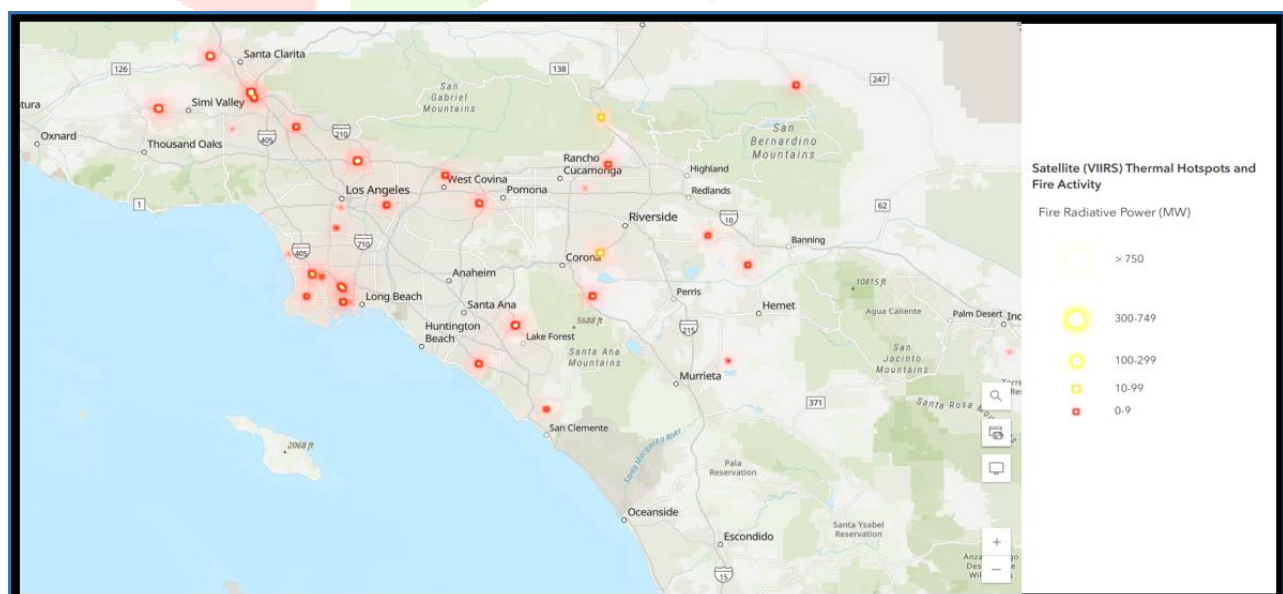


Figure 3: Thermal Hotspot Map (VIIRS) showing active fire regions across the study area based on fire radiative power (MW). The intensity of red and yellow zones indicates varying heat emission levels.

4.3 Model Development Using Google Teachable Machine

The AI model was trained using GTM due to its simplicity and effective learning capability. Fused images were categorized into two classes Normal and Fire Activity to help the model learn key visual and thermal patterns. After training, test images were used to validate accuracy. The system outputs a probability score that indicates the likelihood of fire presence, allowing for clearer interpretation than a simple binary result.

4.4 Detection and Evaluation

During operation, the AI analyzes new fused images to detect potential fire zones. It assigns a probability score showing confidence in its prediction higher values represent active fire regions. Evaluation results showed that using fused datasets increased accuracy and reduced false detections compared to single-sensor models. The system proved reliable for early wildfire identification even under complex environmental conditions.

4.5 Fire Risk Mapping

Fire risk mapping visualizes vulnerable areas and supports proactive management. The AI-generated detection outputs are integrated with factors such as vegetation cover, temperature, humidity, and wind to create risk layers. These maps categorize regions into Low, Moderate, High, or Extreme risk zones. The process includes data acquisition, AI classification, environmental integration, and risk scoring.

4.6 Summary

The fusion-driven, probability-based mapping approach provides early warning, supports decision-making, and promotes sustainable forest and fire management practices.

V. RESULTS AND DISCUSSION

5.1 Overview

This chapter presents the outcomes of the AI-assisted multi-sensor fusion model for early forest fire detection and risk mapping. The system effectively identifies fire-affected areas by integrating optical, radar, and thermal data, improving detection reliability and reducing false alarms.

5.2 Model Performance

The AI model trained using Google Teachable Machine achieved an overall accuracy of around **95%**. The fusion of multiple data types provided better consistency than using a single sensor, maintaining high accuracy even under smoke or cloud cover. False detections caused by shadows or soil were notably reduced.

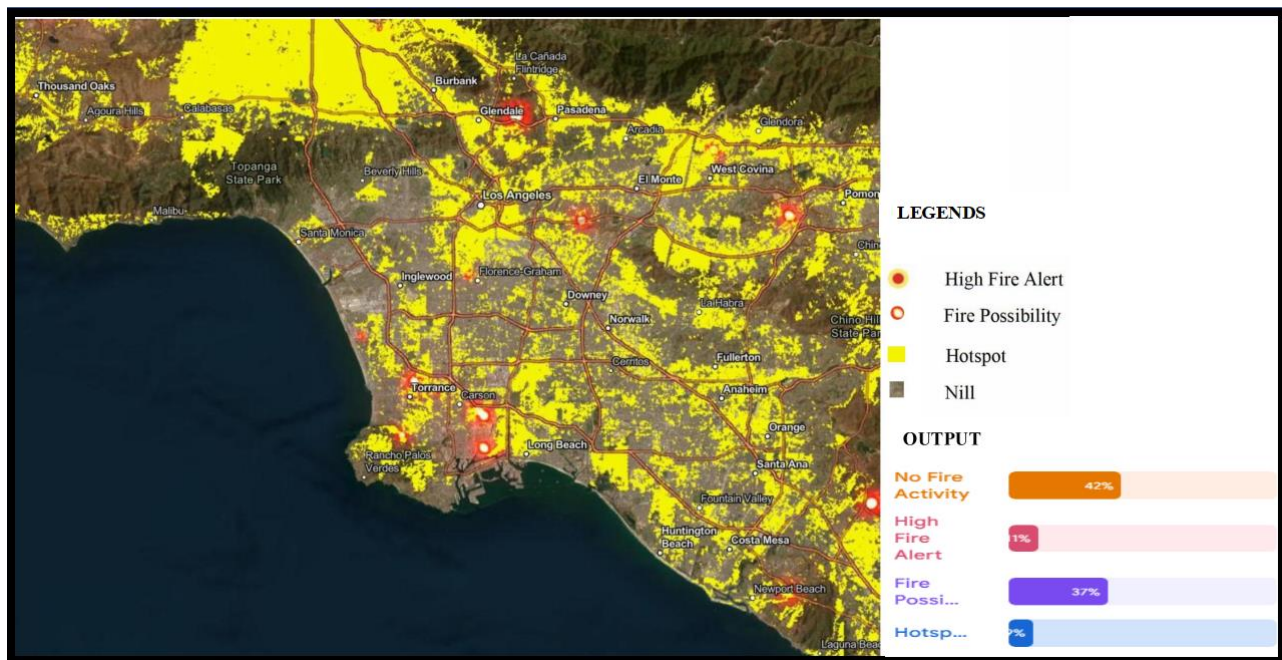


Figure 4: Final fire activity map generated by the AI model using fused multi-sensor satellite imagery. The red and orange zones indicate detected fire-prone or active regions.

5.3 Output Interpretation

The system generates probability-based maps showing different fire risk levels:

- **High Risk** – Active or confirmed fire zones
- **Moderate Risk** – Possible heat build-up or residual activity
- **Low Risk** – Normal vegetation conditions

These classified maps allow faster identification of vulnerable areas and improve decision-making for fire management.

VI. CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This study developed an AI-assisted multi-sensor satellite image fusion system for early detection and risk mapping of forest fires. By combining optical, thermal, and radar datasets from open-access satellite platforms and integrating them with AI-based classification, the framework demonstrated strong potential for near real-time wildfire monitoring. The results confirmed that multi-sensor fusion significantly improves accuracy, reduces false detections, and ensures consistent performance under cloud or smoke interference. The AI model trained on fused datasets effectively identified active fire regions and generated detailed risk maps that classified areas into different vulnerability levels.

Overall, the proposed approach provides a cost-effective, scalable, and sustainable solution for wildfire detection and forest risk management. It bridges the gap between traditional manual monitoring and automated, data-driven surveillance systems — supporting rapid response, resource planning, and long-term environmental protection.

6.2 Future Scope

While the system achieved promising results, there are several opportunities for future improvement:

- **Integration with IoT and Drone Sensors:** Combining satellite data with ground-based IoT or UAV systems can enhance local detection precision.
- **Real-Time Implementation:** Linking the model to a live data stream through cloud computing platforms (e.g., Google Earth Engine) can enable automated early warning systems.
- **Model Optimization:** Expanding the training dataset and including diverse forest ecosystems can improve generalization across regions.
- **Predictive Fire Spread Modeling:** Future studies can integrate wind, fuel load, and humidity parameters to forecast fire spread dynamics.
- **Mobile or Web Application:** A simplified visualization interface can make the system accessible to forest departments and emergency response teams.

6.3 SUMMARY

In conclusion, this research establishes a foundation for AI-driven wildfire detection and fire risk assessment through multi-sensor data fusion. With further optimization and automation, this framework can evolve into a fully operational early warning system, contributing significantly to global forest conservation and disaster management efforts.

VII. REFERENCES

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