Toward Intelligent Forest Fire Management: Hybrid Tree- Neural Models for Extreme Forest Fire Spread Prediction

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Abstract: The frequency and intensity of forest fires are escalating owing to climate change, requiring sophisticated and prompt management techniques. This study proposes an integrated framework that integrates **forest fire detection** with **fire spread prediction** through **hybrid tree-neural models**. Deep learning architectures, including **CNN, EfficientNet, and ConvLSTM**, are utilized for precise fire detection, whilst a **hybrid XGBoost–LSTM model** is implemented to forecast burned area and extreme fire spread. The framework integrates spatial, temporal, and meteorological features, alongside preprocessing and exploratory analysis, to address issues including **data imbalance and heavy-tailed distributions**. Experimental findings indicate that **EfficientNet-B0** attains a detection accuracy of **96.9%,** whilst the hybrid model surpasses others with a **R^2 = 0.93** and reduced prediction errors. The suggested methodology facilitates early detection, enhanced decision-making, and optimal resource distribution, thereby enhancing intelligent forest fire management and scalable disaster response frameworks.

Keywords: Hybrid Tree–Neural Models; Deep Learning; Extreme Fire Events; XGBoost–LSTM; ConvLSTM

Introduction

Forest fires are becoming more prevalent and intense as a result of climate change and harsh weather conditions, leading to substantial ecological, economic, and human losses. Recent advancements in deep learning have facilitated precise fire detection with CNNs, UAV imagery, and satellite data (Zhang et al., 2020; Yuan et al., 2023) [1,2]. Nonetheless, forecasting fire spread and affected areas appears to be challenging due to **non-linearity, spatio-temporal interdependence, data imbalance, and heavy-tailed distributions** (Zhao et al., 2023; Lin et al., 2023) [3,4]. Furthermore, current methodologies generally treat fire detection and spread prediction as distinct processes, so constraining their efficacy for real-time decision-making and early warning systems.

To address these limitations, this study presents an integrated **hybrid tree-neural framework** that amalgamates deep learning-based fire detection with machine learning and temporal models to enhance the accuracy of extreme fire spread predictions.

Related work

The literature survey for this present study is 2-manifold. First, it emphasizes the key works on **forest fire detection,** and secondly, the study presents works related to **fire spread and burned area prediction**.

A. Forest Fire Detection

Prior studies have employed **CNNs, YOLO-based object detection, attention mechanisms, UAV imagery, and satellite data**. While these approaches achieved **high detection accuracy**, most of them focused solely on **fire presence**, without addressing **fire severity or spread**. The table 1 highlights the key works on forest fire detection.

Table 1. Forest Fire Detection Related Works

Authors	Dataset Used	Methodology	Accuracy/Results	Key Findings
Zhang et al. (2020)	UAV-based forest fire images	Deep CNN with feature fusion	Accuracy ≈ 95%	Aerial imagery combined with deep learning improves early fire detection
Frizzi et al. (2021)	Video surveillance fire dataset	CNN + temporal filtering	Precision ≈ 94%	Incorporating temporal consistency reduces false alarms in video-based fire detection
Li et al. (2022)	Forest fire image & video datasets	YOLO-based object detection	mAP ≈ 90–93%	Object detection frameworks enable fast and localized fire detection
Yuan et al. (2023)	Satellite-based fire imagery	CNN + attention mechanism	Accuracy ≈ 95%	Attention mechanisms improve focus on fire-prone regions in large-scale imagery
Pang et al. (2023)	Forest fire images under foggy conditions	FuF-Det: CNN-based fire with fog-robust detection	Accuracy ≈ 94%	Fog-aware preprocessing and robust CNN design improve early forest fire detection in low-visibility environments.

B. Fire Spread and Burned Area Prediction

Traditional machine learning models, ensemble techniques, and deep learning models such as **LSTM and CNN-based architectures** have been explored. However, modeling **extreme fire events** remains challenging due to **heavy-tailed distributions and temporal complexity**. Table 2 presents works related to **fire spread and burned area prediction**.

Table 2. Forest Fire Spread Prediction Related Works

Authors	Dataset Used	Methodology	Accuracy/Results	Key Findings
Amatulli et al. (2013)	Mediterranean forest fire data	Statistical regression models	Moderate predictive performance	Meteorological variables significantly influence fire spread, but linear models are limited
Oliveira et al. (2020)	Forest fire weather datasets	Gradient Boosting Regression	Improved RMSE by ~15% over RF	Boosting models better capture non-linear interactions affecting fire spread
Jain et al. (2021)	Forest fire datasets (weather-based)	Support Vector Regression (RBF)	RMSE ≈ 0.55	SVR effectively models non-linear fire spread patterns in small datasets
Zhao et al. (2023)	Multi-year fire & weather data	Deep Neural Network Regression	$R^2 \approx 0.75–0.80$	Deep learning improves generalization for complex fire spread dynamics
Khennou & Akhloufi (2023)	Satellite imagery, DEM, weather data	Deep U-Net (FU-NetCastV2)	Accuracy ≈ 94.6%	Deep CNNs effectively model spatial fire spread and high-risk regions

Key Contribution

The key contribution of this research are:

- To design an **intelligent end-to-end framework** for forest fire management
- To develop **deep learning models** for accurate fire detection
- To design a **hybrid XGBoost–LSTM model** for fire spread prediction

- To address challenges of **non-linearity, data imbalance, and temporal dependency**
- To perform a **comparative analysis** of classical ML and deep learning models

Method, Experiments and Results

The proposed methodology is depicted in Figure 1.

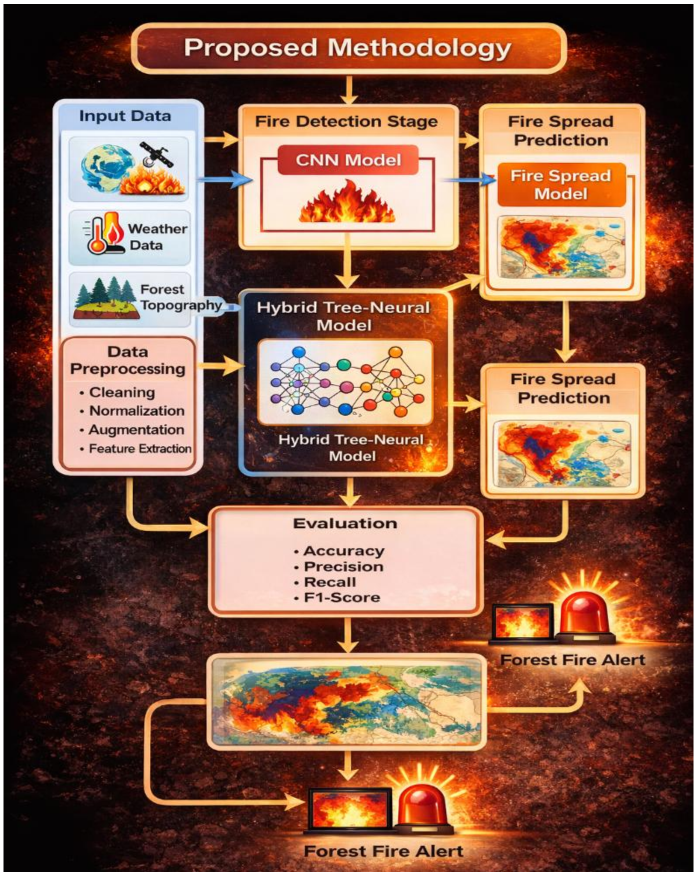

Figure 1. Proposed Methodology

Method:

This study proposes a unified framework integrating **forest fire detection and fire spread prediction**. Fire detection is performed using deep learning models, including **CNN, EfficientNet-B0, and ConvLSTM**, on image-based datasets. For fire spread prediction, a hybrid **XGBoost–LSTM model** is developed to capture both **non-linear feature interactions** and **temporal dependencies**. The framework incorporates spatial, meteorological, and fire index features, along with preprocessing steps such as normalization, encoding, and data augmentation.

Experiments:

Experiments are conducted on publicly available **Kaggle forest fire datasets.** Performance is measured using **Accuracy, Precision, Recall, F1-score** for detection and **RMSE, MAE, and R^2** for spread prediction.

Results:

The results are presented in Tables 3 and 4 as follows:

Table 3. Forest Fire Detection Accuracy Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	91.8	92.1	90.6	91.3
RCNN	93.2	93.5	92.4	92.9
LSTM	90.6	89.9	91.2	90.5
ConvLSTM	94.7	95.1	94.0	94.5
DenseNet-121	96.1	96.4	95.7	96.0
EfficientNet-B0	96.9	97.2	96.5	96.8

The **EfficientNet-B0** model achieves the highest detection accuracy of **96.9%,** outperforming other deep learning models for **fire detection.**

Table 4. Forest Fire Spread Prediction Accuracy Metrics

Model	RMSE ↓	MAE ↓	R^2 ↑
Random Forest	0.61	0.38	0.71
SVR (RBF)	0.55	0.34	0.77

For fire spread prediction, the **Hybrid XGBoost–LSTM** model achieves the best performance with

KNN Regression	**0.57**	**0.37**	**0.73**
XGBoost	**0.48**	**0.29**	**0.83**
LightGBM	**0.46**	**0.27**	**0.85**
LSTM	**0.41**	**0.24**	**0.88**
GRU	**0.39**	**0.23**	**0.89**
CNN-LSTM	**0.38**	**0.22**	**0.90**
Hybrid XGBoost + LSTM	**0.35**	**0.20**	**0.93**

R^2 = 0.93, lowest RMSE (0.35), and MAE (0.20). The accuracy-loss curves of **EfficientNet-B0** and **Hybrid XGBoost–LSTM** models are presented in Figures 2 and 3.

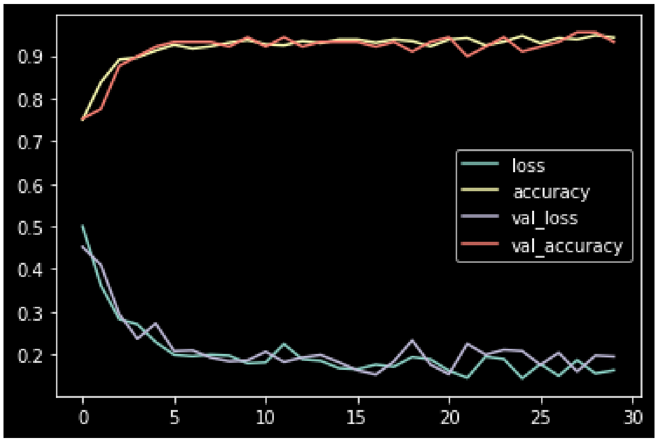

Figure 2. EfficientNet-B0 Accuracy-Loss Curves

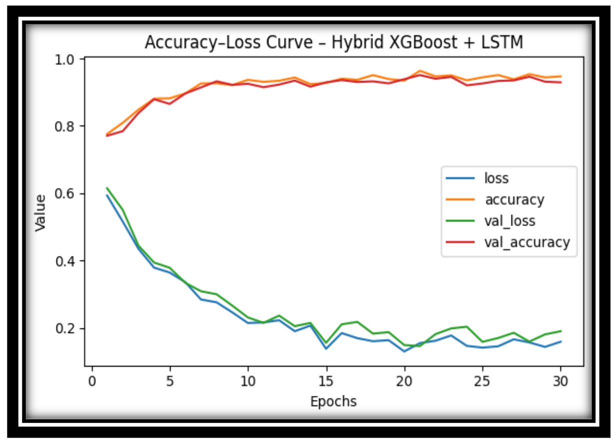

Figure 3. Hybrid XGBoost–LSTM Accuracy-Loss Curves

Conclusion

This paper introduces a comprehensive framework that integrates deep learning-based fire detection with a **hybrid XGBoost–LSTM model** for precise prediction of forest fire spread. Experimental findings indicate that the suggested methodology markedly surpasses independent models, especially in managing non-linear dynamics and severe fire incidents. The framework facilitates enhanced **early warning and decision support**, aiding in the development of **intelligent and scalable forest fire management systems**.

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