DEEP LEARNING-DRIVEN WILDFIRE DETECTION: A HYBRID FRAMEWORK INTEGRATING MULTI-SOURCE DATA AND ENSEMBLE LEARNING

M. U. Iqbal, S. Akhtar, E. A. Ansari, M. N. Rafiq, M. Farooq-i-Azam and M Ahmad

COMSATS University Islamabad (CUI), Lahore Campus, Lahore- 54000, Pakistan
Corresponding author's email: usmaniqbal@cuilahore.edu.pk

ABSTRACT: This paper presents a state-of-the-art framework for detection and prediction of forest fires with the use of advanced ensemble learning techniques in combination with CNNs. Traditional systems of forest-fire detection suffer from problems of poor accuracy, slow speeds, and scalability issues. On the contrary, this paper uses a hybrid approach which integrates DL and DIP specifically for handling multi-source datasets comprising satellite imagery, drone videos, and environmental variables like temperature, wind velocity, and humidity. The data preprocessing techniques that will be included for improving feature extraction effectiveness will involve color space conversion, image enhancement, and spatial segmentation. The CNN architecture had a number of convolutional and pooling layers that were set up to extract high-dimensional features pertinent to fire detection. Transfer learning using pre-trained models significantly improved performance even with limited labeled data. This was complemented by ensemble learning where the outputs of CNN models were combined with probabilistic models such as Random Forests and Gradient Boosting for enhancement of classification robustness and avoidance of overfitting. The system was trained on different datasets collected from the Kaggle repositories, satellite feeds, and field observations of the Margalla Hills. A k-fold cross-validation technique ensured the generalization of the model, and it achieved 92% detection accuracy with a precision of 89% and an F1-score of 90%. Complex scenarios such as smoke fog differentiation and small-scale fire hotspots in dense vegetation were successfully addressed. Experimental results show that the model has better adaptability in a variety of environmental conditions, and its real-world evaluation proves its validity. Predictive capabilities further enabled identification of fire-prone zones before ignition while triggering its utility in early intervention systems.

Keywords: Convolutional Neural Networks (CNNs), Deep Learning (DL), Ensemble Learning

INTRODUCTION

The world's ecosystems, economy, and human livelihoods are all seriously threatened by forest fires. According to recent research, human activity and climate change are mostly to blame for the sharp rise in wildfire frequency and intensity. Massive carbon dioxide emissions and biodiversity loss are caused by forest fires, which calls for immediate action using cutting-edge technology solutions [1], [2], [3]. Due to their limits in terms of scalability, data integration, and environmental adaptation, traditional techniques like satellite imagery, watchtowers, and ground-based sensors sometimes fall short of providing precise and timely alerts [4], [5].

Image-based detection systems have been completely transformed by recent developments in Deep Learning (DL), especially in the form of Convolutional Neural Networks (CNNs). With significant gains in accuracy and detection speed, CNNs are very good at finding intricate patterns in high-dimensional datasets, like satellite and drone photography [6], [7]. CNN models such as ResNet and VGG16, for instance, have been effectively used in environmental monitoring, with accuracy rates in wildfire detection tasks that surpass 90% [8], [9].

An improved framework for managing wildfires is offered by integrating CNNs with data from several sources, such as satellite imaging and meteorological characteristics (such as temperature, humidity, and wind speed) [10], [11]. Predictive analytics is made possible by this multi-modal method, which identifies fire-prone locations prior to ignition by comparing environmental factors with past fire events [12]. Furthermore, transfer learning overcomes the problem of insufficient labeled data by enabling the adaption of previously trained CNN models to datasets particular to wildfires [13], [14].

The necessity of hybrid techniques has been underlined by researchers more and more. For example, CNN outputs combined with probabilistic models like Random Forests enhance classification resilience and reduce false alarms, as shown by Xu et al. (2023) [15]. Similarly, to improve forecast accuracy, Sharma et al. (2022) suggested a framework that combines real-time imaging with environmental data through the use of ensemble learning techniques [16].

A common preprocessing technique for images is color space modifications, like YCbCr, which make it possible to divide fire and smoke areas effectively. Enhancing feature extraction by preprocessing is essential for CNN model training on high-dimensional datasets [16] [17]. Additionally, the model's adaptability to a variety of situations, such as changing light, vegetation, and atmospheric interference, is improved by augmentation techniques including rotation, scaling, and cropping [17].

By combining environmental data with a CNN-based wildfire detection system, this study expands on previous developments and offers real-time monitoring and prediction. The system achieves excellent accuracy, resilience, and scalability by utilizing ensemble learning, transfer learning, and multi-source datasets. This strategy solves the drawbacks of conventional approaches and provides a revolutionary way to lessen the negative effects of wildfires on the environment and the economy.

METHODOLOGY

This section outlines the methodology employed for the development and evaluation of a CNN-based framework for forest fire detection. The process involves multi-source data acquisition, preprocessing, model development, training, and validation. The proposed methodology integrates DL algorithms, color space transformation, and ensemble learning to achieve high accuracy and robustness.

1) Data Acquisition: Data was collected from several sources, such as:

i). Satellite Imagery: Resources like Landsat 8 and Sentinel-2 are known for their improved spatial resolution *[18]*.

ii). Multicopter footage: Hi-resolution images taken of aerial shots of drone overflights across the fire-prone Margalla Hills.

iii). Environmental Data: Accessing meteorological parameters such as temperature, wind speed, and humidity from publicly available weather APIs [19].

Table 1 provides an overview of the data sets used in the study.

2. Data Preprocessing: Preprocessing is crucial for optimizing the performance of DL models. The following steps were performed:

i). Resizing and Normalization: The images were resized to 224x224 pixels, and pixel values were normalized to a [0,1] range to make the datasets consistent [6].

ii). Color Space Transformation: Colour-space YCbCr was implemented for region of interest. In particular, fire, smoke were defined using their efficacy in distinguishing luminance from chrominance, the basis of segmentation processes as presented in [13]

iii). Data Augmentation: Rotation, flipping, cropping, and scaling were applied to improve model generalization over diverse conditions [14].

3. Model Architecture: The core of the proposed system is a Convolutional Neural Network (CNN) augmented with ensemble learning for improved classification. The CNN was designed with the following layers:

i). Input Layer: Handles 224x224x3 input images.

ii). Convolutional Layers: Extract spatial features using filters of size 3x3.

iii). Pooling Layers: Downsample feature maps via max pooling.

iv). Fully Connected Layers: Integrate extracted features for classification.

v). Output Layer: Utilizes a softmax activation function for binary classification (fire/no fire).

Pre-trained models, including ResNet50 and VGG16, were fine-tuned on the wildfire dataset. This approach leveraged existing feature hierarchies, reducing training time and improving accuracy [15]

To enhance robustness, predictions from multiple CNN models were combined using a majority voting strategy, mitigating biases from individual models [20].

4)Training and Validation: The dataset was divided into three subsets to facilitate the model development process. The training set, comprising 70% of the data, was used for training the CNN model. A validation set, accounting for 20% of the data, was utilized for hyperparameter tuning and to monitor the model's performance during training. Finally, the remaining 10% was allocated to the test set, which was employed for evaluating the model's performance on unseen data. The binary cross-entropy loss function was employed to evaluate the model's performance during training. For optimization, the Adam optimizer was utilized with a learning rate of 0.001. Adam is an efficient gradient-based optimization algorithm that combines the benefits of both adaptive learning rate methods and momentum, ensuring faster convergence and

Table 1:

Source	Type	Resolution	Purpose
Landsat 8	Satellite Imagery	30m	Fire-prone region detection
Sentinel-2	Satellite Imagery	10m	Enhanced spatial analysis
Drone Footage	Aerial Imagery	HD (1920x1080)	Close-range fire detection
Meteorological API	Environmental Metrics	-	Correlation with fire events

improved performance during training [11]. The binary cross-entropy loss function was employed to evaluate the model's performance during training. For optimization, the Adam optimizer was utilized with a learning rate of 0.001. Adam is an efficient gradient-based optimization algorithm that combines the benefits of both adaptive learning rate methods and momentum, ensuring faster convergence and improved performance during training [11].

RESULTS AND DISCUSSION

The results acquired using the suggested CNN-based forest fire detection framework are described in this section, after which the results are analyzed in light of existing research. To determine the robustness and generalizability of the suggested approach, its performance was assessed using a large dataset that included environmental and photographic data collected in a variety of settings.

The model's output is shown in Table 1 along with its key performance indicators, including accuracy, precision, recall, and F1-score. The system's 92% accuracy rate indicates how well it separates fire incidents from non-fire occurrences. Overall, it has a good ability to separate true positives while minimizing false negatives, as evidenced by the precision value of 89% and recall value of 90%. An F1-score of 89.5% indicates that recall and precision are balanced.

Test samples were used to verify the framework's visual detection capabilities. Examples of successful detections are shown in Figure 1, where the CNN correctly located locations that were prone to fire despite difficult circumstances like smoke obscuring and poor sight. When compared to conventional wildfire detection techniques, the suggested system showed several noteworthy advantages. Its performance measures outperform those of comparable studies. The combination of ensemble approaches and transfer learning, which increase model resilience by pooling predictions from several classifiers, is responsible for this gain.

One of the critical challenges in wildfire detection is the variability of environmental conditions, such as changes in light, vegetation density, and smoke interference. The proposed model addressed these challenges effectively. The use of YCbCr color space

Table 1: Performance Metrics of the Proposed Model

Metric	Value (%)
Accuracy	92.0
Precision	89.0
Recall	90.0
F1-Score	89.5

Figure 2: Fire detection in an aerial image

segmentation played a pivotal role in isolating fire and smoke features, ensuring reliable performance even under suboptimal conditions. Integrating satellite imagery with environmental parameters enhanced the system's predictive capabilities. The proposed framework, providing a holistic understanding of fire-prone zones, by incorporating meteorological data, allowed for preemptive action before ignition.

Despite these strengths, however, the system does come with its weaknesses. As one example, its dependency on high-resolution imagery puts its scalability to areas without much access to high satellite data. Furthermore, being built on top of pre-trained CNN architecture is one disadvantage-it enhances the precision and thus restricts its pliability in cases involving data distribution completely new to it. Going into the future, integration into real-time acquisition with the use of IoT sensor networks will also help model refinement.

CONCLUSION

This research articulated a whole framework for the detection and prediction of forest fires based on the capabilities of CNNs and the integration of diverse data sources. This system, by combining satellite images, drone recordings, and environmental factors such as temperature and humidity, can overcome the significant shortcomings of conventional wildfire detection techniques, such as low accuracy and slow response times. The combination of complex preprocessing techniques, including conversion to YCbCr color space, and transfer learning and ensemble approaches improved the system's robustness and accuracy to a considerable extent, and ultimately, the total detection accuracy was 92%. The results are a testimony to the deep learning technology revolutionizing the field of wildfire management. The system proved to be quite robust for various environmental conditions, successfully detecting fire-prone areas even under challenging scenarios such as smoke interference and poor visibility. Furthermore, the addition of weather data enhanced the predictive models, thus allowing advance areas of high risk to be identified, which further helped in early intervention strategies. However, the framework has some downsides, for example, reliance on high-resolution data and difficulties with scaling to areas that are not infrastructure-developed. The future work will be aimed at the solution of these issues through IoT-based sensor networks that enable real-time data acquisition and a model architecture that could better flex and adapt.

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