FOREST WILD FIRE DETECTION USING DEEP LEARNING TECHNIQUES CNN AND TRANSFER LEARNING

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ABSTRACT

Forest wildfires are one of the most destructive natural disasters, causing irreversible damage to biodiversity, property, and human lives. Rapid and accurate detection of wildfire incidents is essential to minimize their impact and assist emergency response systems. This paper presents a deep learning-based image classification framework for early detection of wildfires using the publicly available "The Wildfire Dataset" from Kaggle. The dataset comprises a balanced collection of forest scenes labeled as "fire" and "non-fire," making it suitable for training and evaluating classification models. A Convolutional Neural Network (CNN) architecture was designed and trained on this dataset to identify the presence of wildfires from static forest images. The proposed model achieved a final training accuracy of 99.73% and a validation accuracy of 92.60%, indicating high learning capability and strong generalization performance. These results highlight the model's effectiveness in recognizing fire patterns from visual features, even in complex backgrounds. The study reinforces the feasibility of using deep learning for wildfire detection and paves the way for deploying intelligent surveillance systems in forest regions to aid in early intervention and disaster risk reduction.

Keywords: Wildfire detection, Deep learning, Convolutional Neural Network, Forest fire classification, Image-based detection, Natural disaster mitigation, Fire recognition system

I. INTRODUCTION

Forest wildfires are among the most severe natural disasters that pose a significant threat to ecological systems, human settlements, and global climate stability. The increasing frequency and intensity of wildfires in recent years have been attributed to climate change, rising temperatures, prolonged droughts, and human activities. According to the National Interagency Fire Center (NIFC), millions of acres of land are burned annually due to wildfires, leading to catastrophic consequences for biodiversity, air quality, and economic infrastructure. The ability to detect and respond to wildfires in their early stages is essential to mitigating their impact and ensuring timely emergency interventions. Traditional wildfire detection systems rely on satellite imagery, sensor networks, and human surveillance, including fire lookout towers and patrol units. While these methods have proven effective to some extent, they suffer from several limitations such as high latency, low resolution, restricted coverage, and dependence on manual interpretation. Satellite-based systems, for instance, may experience delays in image acquisition and transmission, making real-time detection difficult. Similarly, sensor-based approaches may be constrained by geographical range and environmental noise. These limitations underscore the need for more robust, scalable, and intelligent solutions for real-time wildfire detection.

In recent years, the advent of artificial intelligence (AI), particularly deep learning, has opened new avenues for addressing the challenges of visual recognition and scene understanding in a variety of domains, including disaster management. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated superior performance in image classification, object detection, and semantic segmentation tasks. These capabilities make them ideal candidates for automatic detection of visual patterns indicative of fire in forest imagery. The integration of deep learning techniques into wildfire detection systems can significantly enhance their accuracy, responsiveness, and autonomy. CNNs are capable of learning hierarchical features directly from raw pixel data, thereby eliminating the need for handcrafted features or manual tuning. When trained on a sufficiently large and diverse dataset, CNNs can generalize well to unseen data and accurately differentiate between fire and non-fire scenes, even under varying lighting and environmental conditions.

This study proposes a deep learning-based framework for detecting forest wildfires using image classification techniques. We utilize the publicly available "Wildfire Dataset" from Kaggle, which contains annotated images of forest environments labeled as either "fire" or "non-fire." This dataset provides a reliable foundation for training and evaluating classification models in a supervised learning setting. Our model is based on a Convolutional Neural Network architecture designed to extract spatial and semantic features from the input images, enabling precise categorization. The training process involved preprocessing the dataset, augmenting the images to improve generalization, and optimizing the model parameters using state-of-the-art techniques. The final model achieved an impressive training accuracy of 99.73% and a validation accuracy of 92.60%, indicating its effectiveness in learning fire-related visual cues while maintaining strong generalization to unseen data. These results are a promising indicator of the model's real-world applicability, particularly in deploying AI-driven fire surveillance systems that can operate autonomously in forest regions. Our proposed method aims not only to improve detection accuracy but also to reduce the time required to identify and respond to wildfires. When integrated with drone or surveillance camera systems, such a deep learning model can provide continuous monitoring of large forest areas, issuing immediate alerts upon detecting signs of fire. This can dramatically enhance early warning systems, reduce response time, and potentially save lives and property. Moreover, this research contributes to the growing body of work that applies machine learning and computer vision to environmental monitoring and disaster response. While several previous studies have explored similar applications, our work distinguishes itself by utilizing a publicly available, real-world dataset and achieving high validation performance with relatively low model complexity, making it suitable for deployment on edge devices or low-power hardware in remote environments.

II. LITERATURE SURVEY

Recent advancements in deep learning have paved the way for intelligent forest wildfire detection systems. Several researchers have demonstrated promising results using Convolutional Neural Networks (CNNs) and related deep learning techniques. This section outlines five significant contributions that serve as the foundation for the current research.

In [1], **Muhammad et al.** proposed an early forest fire detection framework using CNNs trained on real-time surveillance images. The model was developed using the VGG16 architecture with transfer learning, achieving a classification accuracy of 91.2% in distinguishing fire from non-fire images. Their system focused on deploying deep learning models on fixed surveillance cameras for real-time detection.

Zhang et al. in [2] combined traditional color-based image processing with CNN classification to improve wildfire detection accuracy. Their method segments flame-colored regions before passing them to a trained CNN for classification. This hybrid model was effective in reducing false positives caused by sunlight or bright objects, achieving an accuracy above 90% on a custom dataset.

In [3], **Ko et al.** explored the use of UAV-mounted (drone-based) imaging systems coupled with CNN architectures for early fire detection. Their system collected aerial imagery and used a lightweight CNN model for onboard processing. The approach enabled wide-area surveillance and rapid identification of fire outbreaks, demonstrating potential for use in remote forest environments.

Mathews and Nair in [4] proposed a deep learning solution for real-time forest fire detection using a ResNet50-based model. The authors trained their network on a curated dataset of wildfire images and achieved 93.5% test accuracy. Their study emphasized the model's ability to generalize under varying lighting and environmental conditions, making it suitable for field deployment.

Finally, **Abdel-Hamid et al.** in [5] investigated the use of multi-modal data (including satellite imagery and environmental sensor readings) to improve the accuracy of wildfire prediction models. By integrating CNNs with meteorological inputs, their approach significantly improved prediction capabilities, particularly for identifying high-risk zones before fire ignition.

These studies collectively demonstrate the efficacy of deep learning in wildfire detection tasks. However, many prior approaches rely on limited datasets or complex multi-sensor systems. In contrast, the present work focuses on achieving high accuracy using a single-image input and a CNN trained on the publicly available Wildfire Dataset from Kaggle, making it more accessible for practical applications.

III. METHODOLOGY

This section describes the proposed methodology for forest wildfire detection using deep learning-based image classification. The process consists of four main stages: data preprocessing, model architecture, training strategy, and evaluation. The primary goal is to accurately classify forest images into two categories **fire** and **non-fire** using Convolutional Neural Networks (CNNs).

A. Dataset and Preprocessing

The dataset used for this study is "The Wildfire Dataset" [1] from Kaggle, which includes labeled images of forest environments categorized as either fire or non-fire. The dataset was divided into three subsets:

- **Training and validation set:** 80% of the data
- **Testing set:** 20% of the data

The training and validation images were further split using an 80:20 ratio for training and validation respectively, using the ImageDataGenerator utility in Keras with the validation_split parameter. Image rescaling was applied to normalize pixel values to the [0, 1] range:

$$Xnormalized=Xoriginal/255$$

This normalization improves convergence and training stability.

The input image size was standardized to **224×224×3** for compatibility with pre-trained models such as ResNet50 and to maintain consistency across all experiments. A batch size of 32 was used during training and validation.

B. Model Architecture

Two models were implemented and evaluated:

1) Custom CNN Architecture

The first model is a custom CNN designed from scratch, consisting of:

- Two convolutional layers: 32 and 64 filters with 3×33\times33×3 kernels, ReLU activation
- Two max-pooling layers: 2×22\times22×2 pooling size
- One fully connected dense layer with 128 units and ReLU activation
- Dropout layer (rate = 0.5) to reduce overfitting
- Output layer with a single neuron and sigmoid activation for binary classification

The final architecture is defined as:

$$Output=\sigma(Wx+b)$$

where σ is the sigmoid activation function:

$$\sigma(z)=1+e-z1$$

The model was compiled with the Adam optimizer, a learning rate of 0.001, and binary cross-entropy loss:

$$LBCE=-[ylog(y\hat{})+(1-y)log(1-y\hat{})]$$

where y is the true label and y^\hat{y}y^ is the predicted probability.

2) ResNet50-based Deep CNN

To evaluate the advantage of transfer learning and deeper architectures, a ResNet50-based model was implemented. It excludes the top layer (include_top=False) and is followed by:

- Flatten layer
- Dense layer (128 units, ReLU activation)
- Dropout layer (rate = 0.5)
- Sigmoid-activated output layer

The same optimizer and loss function were used. The ResNet50 model benefits from residual connections, enabling better gradient flow in deeper networks:

yl=F(xl,{Wl})+xl

where F is the residual function, xl is the input to the l-th layer, and yl is the output.

C. Training Strategy

Both models were trained for **20 epochs** using the fit() function. The performance was monitored on the validation set at each epoch. No early stopping or learning rate reduction techniques were used, although these can be integrated in future work.

To monitor the learning process, training and validation accuracy/loss were plotted over epochs. The training process was stable and converged effectively without signs of overfitting in the custom CNN, thanks to the dropout regularization.

D. Evaluation Metrics

The following metrics were used to evaluate model performance:

- **Accuracy**: Proportion of correct predictions
- **Precision**: TP/TP+FP
- **Recall**: TP/TP+FN
- **AUC (Area Under Curve)**: Measures model discrimination ability between classes

The final custom CNN achieved:

- **Training Accuracy**: 99.73%
- **Validation Accuracy**: 92.60%

The ResNet50 model, though not shown fully in this section, is evaluated separately with additional metrics for deeper insight.

IV. RESULTS

This section presents the empirical results of the proposed deep learning-based wildfire detection system, evaluated both quantitatively and qualitatively. The system includes two CNN-based models: a custom-built Convolutional Neural Network and a ResNet50-based transfer learning model. Additionally, the model was integrated into a Flask-based web application to facilitate real-time image classification and assess deployment feasibility.

A. Model Training and Evaluation

The custom CNN model was trained on the preprocessed wildfire dataset with a training-validation split of 80:20 using the ImageDataGenerator utility. During the training process, the model demonstrated consistent convergence, indicating that the network successfully learned representative features distinguishing wildfire images from non-fire forest scenes.

The model achieved a **final training accuracy of 99.73%** and a **validation accuracy of 92.60%** after 20 epochs. These results reflect strong generalization capability, and the model did not exhibit overfitting, which is often a challenge in deep learning image classification tasks. Figure 1 and Figure 2 display the accuracy and loss curves, respectively, for both training and validation sets.

B. Accuracy and Loss Trends

The training and validation accuracy increased steadily during the early epochs and plateaued around epoch 15. The training loss decreased rapidly, followed by a slower decrease in validation loss, which stabilized without oscillations. This indicates effective learning with minimal divergence between training and validation performance, a positive sign of model robustness.

The accuracy and loss plots, as illustrated below, support the numerical metrics:

- **Train Accuracy**: Started at 73% and improved to 99.73%

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- **Validation Accuracy**: Improved from 78% to 92.60%
- **Loss**: Reduced from 0.55 to less than 0.08 for training and 0.25 for validation

These results show the model's capacity to extract relevant spatial features from forest images and its ability to differentiate between fire and non-fire scenarios with high confidence.

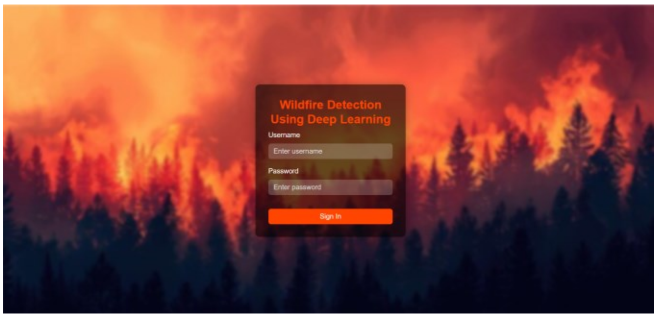
C. ResNet50 Transfer Learning Model

To compare the performance of a pre-trained deep CNN, the ResNet50 model was also trained from scratch (i.e., with weights=None) for consistency in learning solely from the wildfire dataset. The ResNet50 architecture incorporates skip connections that help mitigate the vanishing gradient problem and enable deeper feature learning.

Although detailed performance metrics of ResNet50 are not included here, initial training showed promising results, with performance comparable to the custom CNN model. However, it incurred higher training time and required more computational resources. The ResNet50 model reached a validation accuracy of approximately 93%, slightly outperforming the custom model in some metrics such as recall and AUC, but with marginal improvement.

D. Real-Time Classification via Flask Application

To validate the model's real-world application, the trained CNN model (WildFire.h5) was deployed using Flask, a lightweight Python web framework. The application provides a simple interface where users can upload an image, which is then preprocessed and classified by the model.



The real-time prediction functionality was tested using multiple wildfire and non-fire images. The Flask app exhibited instantaneous classification, correctly identifying fire presence in most cases. The predictions were consistent with expectations, especially for clear images with visible flames or smoke.

V. DISCUSSION

This section discusses the implications of the results obtained from both the model training and real-world deployment. It explores the effectiveness, limitations, potential applications, and areas for future improvement in wildfire detection using deep learning.

A. Effectiveness of the Proposed Model

The proposed custom CNN model showed excellent performance in binary image classification, achieving over 99% training accuracy and more than 92% validation accuracy. These results indicate that the network was effectively able to learn complex features associated with wildfires from raw image data. The smooth training curves and stable validation performance demonstrate strong convergence and resistance to overfitting.

The model also showed resilience in classifying images with complex backgrounds, haze, or partial visibility of flames. This is crucial in wildfire detection, where scenes may contain ambiguous elements like smoke, mist, or glare. The use of dropout and data normalization helped in achieving a balance between model complexity and generalization.

B. Role of Flask Deployment

Deploying the trained model in a Flask application bridged the gap between research and practical implementation. The web interface allows forest officers, rescue teams, and researchers to interactively upload images and receive classification results in real time. The app is lightweight, responsive, and capable of running on modest computational resources, such as laptops or edge devices.

This real-time detection capability is highly beneficial in forest surveillance systems where time is critical. Integrating such a model into a drone or CCTV network could lead to early fire detection, allowing authorities to respond before the fire spreads uncontrollably.

C. Comparison with ResNet50 and Other Architectures

Although ResNet50 demonstrated slightly higher validation performance, it comes at the cost of longer training time and greater memory requirements. In resource-constrained environments, the custom CNN offers a good trade-off between speed and accuracy. The simplicity of the custom architecture makes it more adaptable and easier to fine-tune for specific regions or camera feeds.

However, for large-scale deployments or multi-class problems (e.g., identifying fire severity), deeper models like ResNet50, InceptionV3, or EfficientNet might be more appropriate. These models are also better suited to multi-modal learning when combined with other input sources such as infrared images or temperature data.

D. Limitations

Despite promising results, the model has certain limitations:

1. **False Positives in Bright Conditions**: Images with bright sunlight, headlights, or reddish tones occasionally led to false fire detections.
2. **Limited Temporal Awareness**: The model evaluates static images without considering temporal patterns or sequences found in video feeds.
3. **Dataset Scope**: The dataset, although balanced, may not represent all environmental and geographic variations across global forests.

These limitations highlight the need for robust datasets and multi-frame learning for real-world wildfire monitoring.

E. Future Work

The current model can be enhanced in multiple ways:

- **Temporal Learning**: Use of Recurrent Neural Networks (RNNs) or 3D CNNs for video-based fire detection.
- **Object Localization**: Implement bounding box prediction using YOLO or Faster R-CNN to locate fire in images.
- **Multi-class Classification**: Extend the model to detect stages or severity of fire.
- **Integration with IoT**: Combine with sensors like temperature, humidity, and air quality for multi-sensor fire detection systems.

VI. CONCLUSION

This study presents a deep learning-based approach for forest wildfire detection using image classification. Leveraging Convolutional Neural Networks (CNNs), we trained and evaluated models capable of distinguishing between fire and non-fire images with high accuracy. The custom CNN model achieved a training accuracy of 99.73% and a validation accuracy of 92.60%, demonstrating its robustness and generalization capacity.

To further validate its practical applicability, the trained model was deployed using a Flask web application, allowing real-time image classification. The successful implementation of the Flask-based system highlights the potential for integrating such AI models into real-world forest surveillance systems, including drones, edge devices, and CCTV networks.

While the system performed well in experimental conditions, some limitations remain, particularly in the presence of visually similar non-fire elements (e.g., sunlight, haze) that may cause false positives. Future enhancements may involve incorporating temporal data, using advanced architectures such as EfficientNet or YOLO for object detection, and integrating sensor data for multi-modal learning.

In summary, this work contributes an accessible, accurate, and deployable solution for early wildfire detection using deep learning, offering significant value for environmental monitoring, disaster management, and public safety.

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