FireXplainer: An Interpretable Approach for Detection of Wildfires.

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Abstract

Several reports from prominent national centers monitoring wildfires and emergencies indicate that the impact of wildfire devastation increased by 2.96 folds compared to a decade ago. Various deep-learning solutions have been proposed to tackle this problem, yet there is a lack of interpretability in their classification. To address these shortcomings, we present FireXplainer, an efficient model that leverages transfer learning, fine-tuning techniques, and the Learning without Forgetting (LwF) methodology. This model incorporates convolution blocks and image pre-processing techniques to enhance classification precision. Additionally, we utilize multiple datasets (Kaggle & Mendeley) and apply Explainable AI (XAI) (Grad-CAM) methodology for result interpretation. Our experimental results demonstrate that FireXplainer outperforms state-of-the-art methods and is well-suited for wildfire interpretable image classification.

1. INTRODUCTION

Despite a decrease in wildfires in the USA, the impact and devastation caused by wildfires are increasing, with a significant rise in the total burned land area [1-3]. Considering the challenge of wildfires, recent advancements in deep learning-based systems for detection and classification have emerged as a promising solution [4-9]. Unmanned Aerial Vehicles (UAVs) equipped with cutting-edge computer vision technology hold significant potential for detecting and monitoring wildfires, thereby providing valuable support to wildlife preservation, forestry management, and wildfire research efforts.

This paper presents a transfer-learning-based approach that utilizes a pre-trained [12] MobileNet model fine-tuned with additional Convolution Blocks for interpretable wildfire image classification. The proposed method is rigorously evaluated on publicly available datasets to overcome the issue of model dependency on large datasets when training with limited data.

This paper presents several significant contributions as follows:

1- We utilized diverse data sources and applied preprocessing techniques, such as ellipse morphing, image sharpening, and ROI segmentation.

2- We leverage the pre-trained MobileNet model as a baseline and enhance the model's performance by introducing convolution blocks and fine-tuning the model, resulting in significant improvements in accuracy, efficiency, and outperforming among state-of-art pre-trained models and previously proposed methodologies.

3- We employ the GRAD-CAM [11] explainable AI (XAI) methodology to enhance model interpretability in fire detection, providing transparent insights into model decision-making and classification explanations.

The rest of the paper is organized as follows: In Section 2, we describe dataset, preprocessing techniques, and the proposed methodology. In Section 3, we present results, comparison and conclude in Section 4.

2. METHODOLOGY

This section provides an overview of the dataset formulation and preprocessing, the proposed model, and its workflow.

2.1 DATASETS

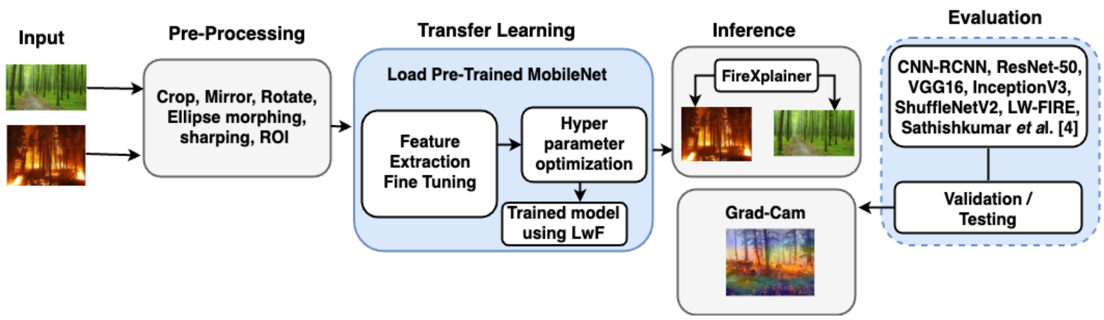

Figure 1: A High-level Overview of FireXplainer and a Comprehensive Evaluation.

The dataset consists of 2,216 fire images and 1,304 non-fire images accumulated from multiple data sources, including Kaggle and Mendeley [10]. We employ various OpenCV image pre-processing techniques, such as ellipse morphing, rotation, mirroring, sharpening, blurring, and noise elimination, to enhance the quality of the images. The data divide into the standard 80:10:10 ratio for training, validation, and testing purposes.

2.2 FIREXPLAINER

In our FireXplainer architecture, we utilize transfer learning and employ pre-trained models to adapt to diverse tasks by leveraging source domain knowledge and customizing them as feature extractors and fine-tuners. Initially, we reuse pre-trained model for features extraction, retraining only specific layers for target dataset classes. Subsequently, we fine-tune the MobileNet model by training select top layers, including the newly added classification layers, while keeping early layers frozen, resulting in improved accuracy. Finally, we utilize Learning without Forgetting (LwF) methodology [4] to prevent the loss of original task-specific parameters and ensure performance on the original tasks, we add convolution layers and train the MobileNet on our dataset. Figure 1 presents an overview of our methodology and a comprehensive comparison of our approach with state-of-the-art and previously proposed models.

2.3 XAI

We employ the XAI method, Gradient-weighted Class Activation Mapping (Grad-CAM), to enhance the explainability/interpretability of our model. Using Grad-CAM, we generate heatmaps highlighting the specific regions in the images that contribute the most to the fire detection. The interpretability is crucial in enhancing the transparency and trustworthiness of the model. Figure 2 highlights the most critical regions which are contributing to fire detection and classification.

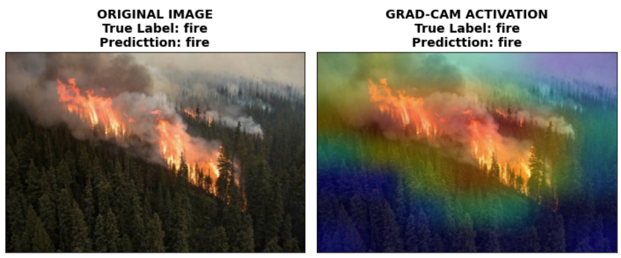

Figure 2: Grad-Cam visualization to highlight key features to identify fire detection and classification.

3. RESULTS AND DISCUSSION

We consider multiple evaluation parameters to comprehensively evaluate state-of-the-art models and previously proposed methodologies. The evaluation metrics consist of training parameters, classification evaluation metrics (precision, recall, F1 score), and interpretable classification, providing a comprehensive assessment of model performance.

3.1. RESULTS

Our study evaluated the performance of pre-trained models using feature extraction, fine-tuning, and learning without forgetting techniques. We used GPU-enabled kernels to train deeper models in TensorFlow and Keras frameworks. We fine-tuned the hyperparameters to obtain the best results during training and stopped the models early using early stopping functions. Finally, we compared the models' performance with our classifier using F1 score, precision, and recall metrics and presented the results in Table 1. Our model outperformed recent deep learning models and the latest proposed models regarding evaluation metrics while we continue improving hyperparameters to reduce model weight.

Table 1: Comparison of the state of art models based on evaluation metrics.

		Evaluation Metrics		
Models	**No. Parameters**	**Precision**	**Recall**	**F1**
CNN - RCNN	1.4 M	81.3	84.4	83.2
ResNet - 50	111.6 M	83.6	85.7	87.2
VGG - 16	15.4 M	92.1	88.3	91.3
InceptionV3	23.9 M	90.4	92.7	94.6
ShuffleNetV2-OnFire [7]	0.15 M	94.0	94.0	95.0
LW-FIRE [6]	1.1 M	-	-	97.2
Sathishkumar *et al.* [4]	-	96.4	96.5	98.7
Proposed Model	5.3 M	**99.1**	**99.3**	**99.0**

Furthermore, we provide models' classification interpretability, which helps identify the specific regions in an image the model uses to make its decision for detection and classification, potentially providing valuable insights that can assist in improving the model's performance.

4. CONCLUSION

Increasing wildfire incidents demand efficient detection and monitoring systems. This paper proposes a transfer-learning-based approach for the efficient detection and monitoring of wildfires using a pre-trained MobileNet model with additional convolution blocks and fine-tuning. The methodology is rigorously evaluated on publicly available datasets, showcasing significant improvements in accuracy and efficiency compared to state-of-the-art pre-trained models. In addition, the proposed method employs the GRAD-CAM methodology for XAI, providing insights into the model's decision-making explanations.

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