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Fire and Smoke detection using AI

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ABSTRACT:

Woodlands represent a vital natural asset to humanity, furnishing a diverse range of direct and indirect advantages. Catastrophic events like woodland blazes exert a significant influence on global climate change and the ongoing sustenance of life on our planet. The automated identification of woodland fires emerges as a crucial area of investigation aimed at mitigating such disasters. Timely detection of fires can aid decision-makers in devising effective strategies for prevention and suppression. This study delves into the detection of fire and smoke from images utilizing AI-driven computer vision methodologies. Convolutional Neural Networks (CNNs) stand out as a type of Artificial Intelligence (AI) approach that surpasses traditional methods in image classification and various other computer vision tasks, notwithstanding the time-intensive nature of their training. Additionally, a pre-trained CNN might falter in the absence of a sufficiently large dataset. To tackle this challenge, transfer learning is applied to pre-existing models. Nonetheless, these models may lose their proficiency in classification when subjected to transfer learning. To circumvent this issue, we employ learning without forgetting (LwF), which updates the network with a new task while preserving its existing capabilities.

Outcomes:

In this investigation, transfer learning is implemented on pre-trained models like VGG16, InceptionV3, and Xception, enabling us to operate with a reduced dataset and diminish computational complexity without compromising accuracy. Among all models, Xception demonstrates superior performance with an accuracy of 98.72%. We evaluate the efficacy of the proposed models with and without LwF. Without LwF, Xception achieves an accuracy of 79.23% on a novel task (BowFire dataset). However, with LwF, Xception achieves accuracies of 91.41% and 96.89% for the BowFire dataset and the original dataset, respectively. Our findings indicate that fine-tuning the new task with LwF yields commendable results on the original dataset.

Conclusion:

Based on the empirical evidence, it is evident that the proposed models outstrip current state-of-the-art methods. Furthermore, we demonstrate that LwF effectively categorizes novel and previously unseen datasets.

Keywords woodlands, fires, detection, AI-driven, computer vision, Convolutional Neural Networks, transfer learning, outcomes, Xception, LwF

INTRODUCTION:

Forest fires are a prevalent occurrence worldwide due to shifts in climate patterns, resulting in substantial economic and environmental devastation (Bot 2022; Castelli et al. 2015). These fires can arise from both natural phenomena and human activities, such as summer wildfires ignited by debris and other biomass materials, as well as instances of human negligence. While wildfires can offer ecological benefits to local flora, fauna, and ecosystems, they also pose significant threats to property and human lives. In recent times, the frequency of forest fire incidents has been on a steady rise. Consequently, there has been a growing interest in the development of automated systems for detecting and monitoring forest fires as a means of safeguarding forested areas from destruction.

A variety of traditional and state-of-the-art techniques for fire and smoke detection have been proposed to mitigate the impact of fire disasters. Among these techniques, sensor-based and vision-based smoke detection systems have garnered considerable attention within the research community. These fire detection methods can be categorized into five primary groups based on sensor types and applications: smoke-sensitive, light-sensitive, gas-sensitive, temperature-sensitive, and composite (Saeed et al. 2018). Temperature and smoke sensors are commonly employed for this purpose (Kizilkaya 2022). However, sensor-based approaches suffer from limitations in terms of detection range and speed, particularly as fire propagation can occur rapidly, necessitating minimal detection delays. As advancements in video surveillance technology have emerged, researchers have turned to analyzing fire images based on their color characteristics to identify fires effectively. Typically, flames are visualized as orange or yellow hues moving horizontally, while smoke appears as a mixture of white, gray, and black plumes. Nonetheless, smoke detection in images and videos presents its own set of challenges, including distinguishing between genuine fire instances and false positives. To address these challenges, image processing-based methods have been developed, leveraging various color spaces such as RGB, YUV, YCbCr, and CIELab (Yang 2022; Al-Duryi 2022; Fang 2022; Seydi 2022) to capture fire properties such as color, shape, flickering, frequency, and dynamic textures.

In addition to color information, motion data has been incorporated into fire detection methodologies, enhancing the reliability and accuracy of detection systems (Anh et al. 2022). The utilization of surveillance camera images, however, introduces new challenges in image processing, particularly regarding storage and processing costs associated with continuous image streams. Consequently, numerous approaches and systems for fire detection have been devised to optimize precision and autonomy. The advent of video surveillance technology has also propelled advancements in machine vision-based fire and smoke detection technology, enabling the development of diverse detection approaches by extracting features from fire and smoke images. Traditional machine learning and deep learning-based computer vision techniques have been advocated for assessing fire and smoke presence in images, leveraging video surveillance data to train detection models effectively.

Machine learning techniques have been widely employed in various applications, including forest fire prediction and detection (Abid 2021; Arif et al. 2021; Ko et al. 2009; Kong et al. 2016; Bouguettaya et al. 2022; Friggens 2021). These techniques often involve manual feature extraction from images, focusing solely on superficial flame characteristics, potentially leading to information loss. In contrast, deep learning approaches, particularly Convolutional Neural Networks (CNNs), offer automated feature extraction capabilities, enabling the learning of complex feature representations from images (Schmidhuber 2015). CNN-based methods have demonstrated promising results in fire detection tasks, utilizing frames from surveillance systems as input for predictive analysis. Various CNN architectures, such as Inception (Szegedy 2015), VGG-Net (Simonyan 2014), and Xception (Chollet 2017), have been applied to fire detection tasks.

However, classifying fire and smoke images remains challenging due to the extensive parameter space utilized by deep architectures like VGG16, DenseNet, Inception, and Xception. Transfer learning presents a viable solution in scenarios involving large parameter spaces, allowing knowledge learned in one domain to be transferred to another with limited data. Despite the effectiveness of pre-trained CNN classifiers, they may underperform when tasked with recognizing new, albeit similar, tasks, a phenomenon known as "catastrophic forgetting." To address this issue, we explore the concept of Learning without Forgetting (LwF) for detecting forest fire/smoke images from new datasets. The proposed research aims to tackle the aforementioned challenges while enhancing the efficacy of fire and smoke detection systems.

LITRATURE SURVEY:

This section highlights various research endeavors aimed at constructing models for fire and smoke detection systems. The proliferation of AI has spurred numerous endeavors to identify fire/smoke presence in images utilizing machine learning and deep learning models. Specifically, we explored CNN-based models for fire/smoke detection. CNNs have significantly improved performance in visual recognition and image classification tasks. Notably, CNN variations have

shown exceptional performance in image categorization. While prior efforts have delved into CNNs for smoke and fire detection, gaps persist, including faster training, parameter efficiency, hyperparameter tuning, and transfer learning over new datasets. While some studies have utilized transfer learning to expedite training, hyperparameter tuning remains largely unexplored. We propose combining deep learning and transfer learning with hyperparameter tuning to develop classification models distinguishing fire and smoke in images, reducing time and ensuring early detection. Additionally, we employ Learning without Forgetting (LwF) to retain original network capabilities while training on new data. Thus, CNNs hold significant potential for fire detection, promising to mitigate human and financial losses due to fires. However, addressing existing gaps can further enhance their efficacy in real-world applications.

Further exploration into the application of CNNs for fire and smoke detection reveals untapped potential and areas for improvement. While existing research has made significant strides, additional efforts are warranted to address emerging challenges. These include the need for faster training methodologies to enhance efficiency, optimization of model parameters for improved performance, and robust hyperparameter tuning strategies to enhance model adaptability. Moreover, incorporating transfer learning techniques over novel datasets can facilitate broader applicability and enhance model generalization capabilities. By leveraging these advancements alongside Learning without Forgetting (LwF), we can fortify CNN-based fire detection systems, ensuring they remain effective in dynamically changing environments and contribute to timely fire mitigation efforts.

Materials and Methodology:

Validation	200	200	200	200	800
Test	200	200	200	200	800

Description of Dataset and Augmentation Techniques

The dataset utilized in this study was constructed using geostationary weather satellites, including MODIS, VIIRS, Copernicus Sentinel-2, and Landsat-8, as outlined by Kaulage

(2022). These satellites offer exceptional temporal precision and the capability to detect fires in remote areas worldwide, making them ideal for fire detection purposes. Additionally, satellite imagery sourced from Google and Kaggle repositories, along with manually compiled forest fire satellite imagery, was incorporated into the dataset. Each image was meticulously labeled as Fire, No Fire, Smoke, or Smoke Fire. Initially comprising 4800 images, the dataset was expanded using image augmentation techniques such as shifting, flipping, rotating, scaling, blurring, padding, cropping, translation, and affine modification. Post-augmentation, the dataset encompassed 6,911 images. Subsequently, the dataset was partitioned into training, validation, and testing sets, with 80% allocated for training the classifier and 10% each for testing and validation. The distribution of images across the training, testing, and validation sets is delineated in Table 1. Sample images extracted from the dataset are depicted

Table 1 Dataset description

Dataset	Fire	No Fire	Smoke	Smoke Fire	Total
Train	2161	2150	490	510	5311
Validation	200	200	200	200	800
Test	200	200	200	200	800

Additionally, alongside the assembled dataset, we have incorporated the BoWFire dataset to evaluate the transferability of knowledge acquired from classifying forest fire and smoke images. The BoWFire dataset, accessible at http://bitbucket.org/gbdi/bowfire-dataset/downloads/, comprises 240 images categorized into fire images, no-fire images, smoke fire, and smoke images. Despite its small size, this dataset poses significant challenges due to the inclusion of fire-like scenarios such as sunset and sunrise, fire-colored objects, and diverse architectural lighting conditions. A representation from each category is showcased i

Variants of CNNs

Various fundamental architectures of CNNs have effectively addressed complex vision tasks. Convolution and pooling are the core operations in CNNs. Convolution operation enables the extraction of features from images using diverse filters, preserving spatial information. Pooling, a technique for dimensionality reduction, is employed to downsample feature maps produced by convolution. Max pooling and average pooling are the two predominant methods utilized in CNNs. CNNs serve as both feature extractors and classifiers in resolving intricate vision challenges.

Learning without Forgetting

The inadequacy of shared parameters in effectively capturing discriminative features for new tasks often leads to subpar performance in feature extraction when applied to novel tasks. Fine-tuning typically diminishes performance on previous tasks as it alters shared parameters without adjusting task-specific parameters. Retraining a model on a fresh dataset may result in the loss of original task-specific parameters, rendering the model ineffective for its initial tasks. To address this issue, we implemented the LwF concept as proposed by (source: https://www.kaggle.com/datasets/phylake1337/fire-dataset). LwF facilitates training the network on new images while retaining its prior capabilities. Through this approach, the network's original capabilities remain intact, while the new task's samples are utilized to enhance accuracy. Notably, the inclusion of images and labels from the previous task is unnecessary. For testing this method, we utilized 240 images from the BoWFire dataset. The LwF procedure employed for the present study is outlined as follows:

Variables

(a) Fire (b) No Fire

(c) Smoke (d) Smoke Fire

Shared parameters → SP (network parameters updated for the original forest fire dataset)
Task-specific parameters for original forest fire data-set → P_O
Task-specific parameters for BowFire dataset → P_n
(X_n, Y_n) ◊ training data and class label for tfle Bow-Fire dataset

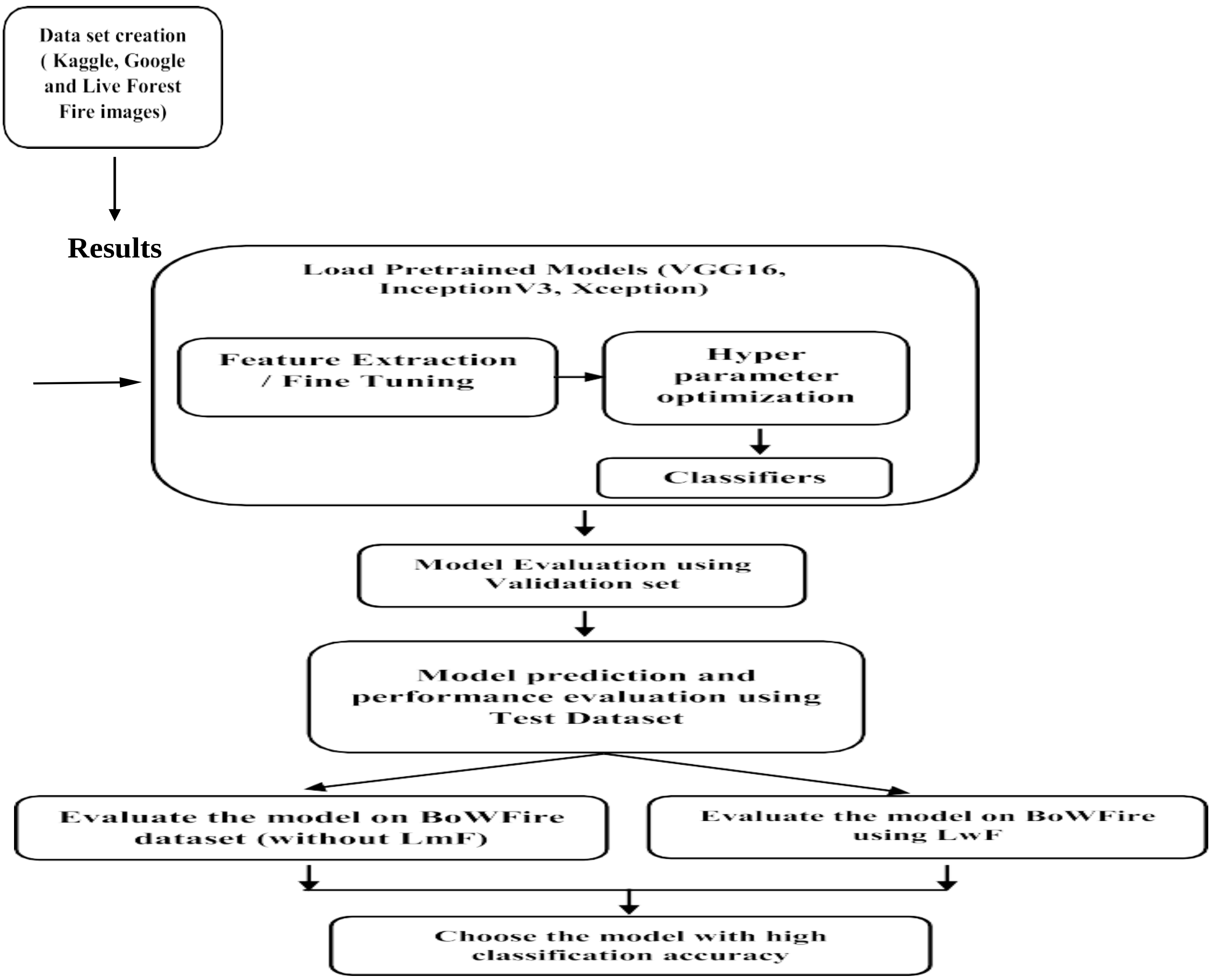
Procedure

1. Y_o = Pre-trained CNN(X_n, P_S, P_O) → find Y_o foreacfl image in tfle BowFire dataset.
2. Add nodes in tfle output layer for eacfl class intfle BowFire dataset.
3. Initialize P_n witfl random weigflts.

Train the network with BowFire dataset images.

1. Compute $\widehat{Yo}$ = Pre-trainedCNN(X_n, $\widehat{Ps}$, $\widehat{Po}$)
2. Compute $\widehat{Yn}$ = Pre-trainedCNN(X_n, $\widehat{Ps}$, $\widehat{Pn}$)
3. Compute loss functions for images in tfle originaland BowFire dataset and update P_S, P_O, and P_n.
4. Repeat from step 4 till convergence

From the above steps, it can be seen that goal of LwFis to make a model learn new capabilities while keepingits old capabilities working well, without using training data from the old tasks. Figure 3 shows how the proposed models would be used



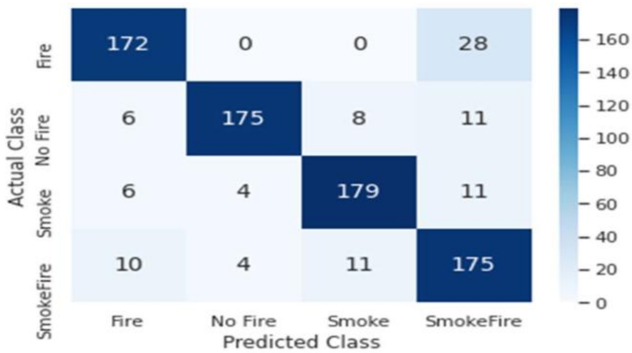
- To assess the performance of the pre-trained models based on feature extraction, experiments were devised, wherein the model was trained for a variable number of epochs until no further improvement in validation accuracy or reduction in validation loss was observed. As previously stated, two distinct sets of experiments were conducted. The classifier was removed from these models, and our own classifier was incorporated for experimentation purposes. VGG16 was augmented with two fully connected layers and a softmax layer, while InceptionV3 and Xception were enhanced with one fully connected layer and one softmax layer each. During the fine-tuning

- process, the top 5, 8, and 7 layers of VGG16, InceptionV3, and Xception, respectively, were retrained. Subsequently, the models were evaluated against the test data to gauge their effectiveness. Table 4 provides an overview of the performance evaluation results for all proposed models, encompassing testing and validation metrics.

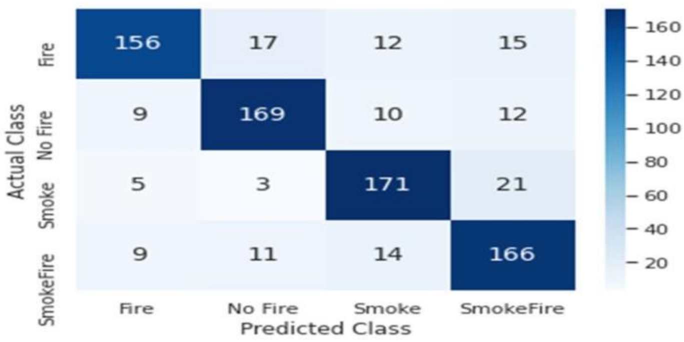
- Since each image in the dataset necessitates classification into one of four classes, the performance of each model was assessed against these classes using metrics such as accuracy, precision, recall, and F1-score. TP, FP, TP, and TN were computed using Eqs. (1) to (4).

- For fine-tuning and learning without forgetting procedures, GPU-accelerated kernels from Kaggle were employed due to the deeper nature of the proposed models. Training was conducted using the Tensorflow and Keras frameworks. The hyperparameters outlined in Table 2 were utilized during training, with Table 3 presenting the optimized hyperparameter values yielding the best results. Although the models were initially configured to run for 100 epochs, early stopping was implemented to halt training prematurely if no further improvement was observed. Early stopping is a technique

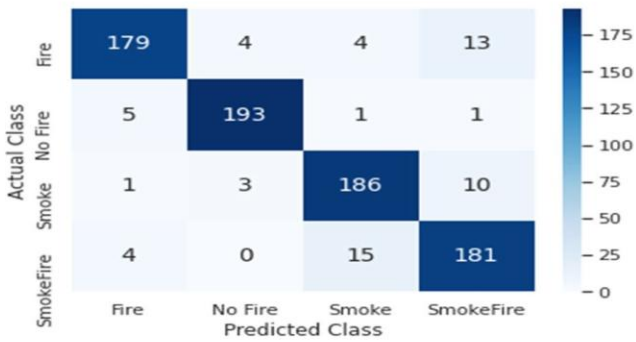
(a) VGG16 (Feature Extractor)



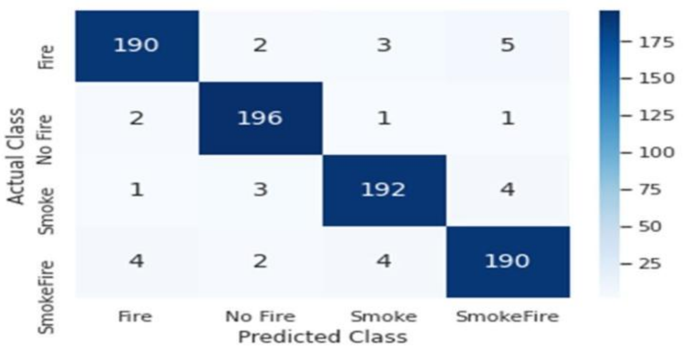
(b) VGG16 (Fine Tuner)

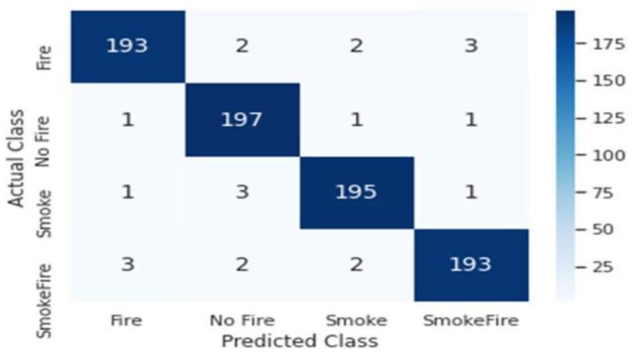


(c) InceptionV3 (Feature Extractor)



(d) InceptionV3 (Fine-tuner)





Conclusion:

Our study underscores the importance of promptly and accurately detecting wildfires to mitigate their catastrophic impact. By investigating transfer learning of pre-trained models for forest fire/smoke detection, we found that the Xception-based model exhibited superior performance, achieving 98.72% accuracy. Leveraging Learning without Forgetting (LwF) further enhanced model performance, particularly in preserving dataset characteristics. Moving forward, our focus remains on advancing fire detection capabilities using the latest CNN models to swiftly identify fires with minimal false positives. Additionally, we aim to delve deeper into LwF and multitask learning to refine our methodologies for enhanced fire detection accuracy.

References	**Models**	**Accuracy (%)**
(Li and Zhao 2020)	YOLO v3	83.7
(Mahmoud 2022)	Deep ANN and AlexNet	95 and 98
(Cheng 2021)	VGG16 with TL	97.83
(Guede-Fernández et al. 2021)	Faster R-CNN	80
(Luo et al. 2018)	CNN	90
(Muhammad et al. 2018)	CNN	94.39
(Jeon et al. 2021)	CNN with feature-squeeze block	97.89
Proposed models	VGG16 - Feature Extractor	94.38
	VGG16 - Fine Tuner	95.46
	InceptionV3 - Feature Extractor	92.04
	InceptionV3 - Fine Tuner	97.01
	Xception - Feature Extractor	97.77
	Xception - Fine Tuner	**98.72**

(a) No Fire Image

(b) Fire Image

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