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Enhancing Forest Fire Detection: Utilizing VGG16 for High-Accuracy Image Classification and Machine Learning Integration

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Abstract

Forest fires cause significant problems for nature, communities. They damage forests, animals' homes, and places where people live. The bad effects of forest fires go beyond just hurting the air, water, and animals. They also make climate change worse and mess up the balance of nature for a long time. In our efforts to address this significant issue, we utilize trained Convolutional Neural Networks (CNNs) algorithm VGG16 model to classify images containing fire and smoke versus non fire images. To enhance the training performance and the model's ability to generalize to unseen data, we curated a dataset comprising approximately 12,000 images from each category. We proposed using the features extracted the VGG16 model for training a simple neural network and multiple machine learning algorithms. Following the training process of the neural network model, our model achieved a training accuracy of 98.4231% and a validation accuracy of 99.0717%. Subsequently, to assess the robustness of our model, we subjected the output layer of our trained model to 13 different machine learning algorithms. Remarkably, all 6 models surpassed a performance threshold of 99% across all metrics.

Keywords: Forest Fires, Image Classification, Deep Learning, Convolutional Neural Network

I. Introduction

Wildfires pose significant threats to both property and human life, with increasing contributions from human activities. In response, researchers are turning to deep learning models as a pivotal tool for early wildfire detection and rapid response, aiming to mitigate the profound environmental, economic, and societal impacts caused by these disasters. Traditional sensor-based methods, while effective in many scenarios, often struggle to provide comprehensive coverage over expansive landscapes, necessitating more sophisticated and scalable detection solutions. According to the UNEP report [1] the escalation of wildfire frequency and intensity is primarily driven by climate change and alterations in land-use patterns. The report forecasts a potential surge of up to 50% in extreme fire events globally by the year 2100, underscoring the urgent need for strategic investments in wildfire prevention, preparedness, and ecosystem restoration. These proactive measures are essential not only for safeguarding biodiversity and habitats but also for curbing the release of significant greenhouse gas emissions that exacerbate climate change. Accurate prediction of fire behavior is critical for enabling firefighters to strategize effectively, allocate resources efficiently, and minimize damages in fire-prone areas. Neural networks excel in tasks like smoke detection, distinguishing it from natural phenomena such as clouds, terrain features, dust, and ocean patterns. Researchers are exploring a variety of technologies to enhance early detection capabilities, including unmanned aerial vehicles (UAVs) and advanced models like YOLO (You Only Look Once) for real-time analysis of imagery. Furthermore, the integration of convolutional neural networks (CNNs) and vision transformer architectures represents a significant advancement in wildfire detection methodologies. Hybrid models combining CNNs and transformers leverage the strengths of both approaches to achieve more robust performance in detecting and predicting fire

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outbreaks. Ensuring these models generalize well across diverse environmental conditions and datasets is crucial to avoid false alarms and enhance operational reliability. In the realm of deep learning algorithms, the selection of appropriate technologies and model architectures is as crucial as the quality and breadth of the datasets used for training. Insufficient data or overfitting issues can undermine the model's ability to generalize effectively, potentially leading to inaccurate predictions during real-world fire events. Researchers leverage datasets such as BowFire, The Corsican Fire Database, CCTV surveillance feeds, and NASA datasets to train and validate their models. Additionally, techniques like generative adversarial networks (GANs) are employed to augment datasets and enhance model robustness. In summary, ongoing advancements in deep learning technologies and methodologies are pivotal in enhancing early wildfire detection capabilities and mitigating the devastating impacts of wildfires on ecosystems, communities, and global climate stability.

II.Related Works

Many researchers have explored various deep learning techniques for fire detection. Here is a summary of the relevant studies:

In [2], it was demonstrated that deep CNNs can achieve high classification accuracy even with limited data. They addressed the issue of overfitting, which often results from the scarcity of image data for training, by expanding their training datasets through various data augmentation techniques. To enhance early forest fire detection and improve response times, [3]developed a YOLO-based model trained with over 5,000 images, achieving an accuracy of 90%. Their system demonstrated a sensitivity of 92% and specificity of 90%. In their study, [4]applied numerous tests to measure the success of popular image processing and classification algorithms such as CNN, AlexNet, YOLO, R-CNN, and U-Net. They utilized multiple datasets including CCTV surveillance systems, Kaggle datasets, and General Advanced Networks for early forest fire detection. This work emphasizes the importance of addressing dataset availability and computational requirements to advance wildfire detection methods. [5] conducted experiments comparing CNNs and Vision Transformers, which belong to the transformer architecture. They found that hybrid architectures combining Vision Transformers with CNNs consistently yield superior accuracy compared to standalone CNN networks. Vision Transformers were particularly resilient in handling noisy or augmented images, while CNNs demonstrated better generalization with smaller datasets. In their research, [6] worked on classifying overhead images using FLAME, NASA, and GitHub datasets. They trained models on the FLAME and NASA datasets and evaluated them on the GitHub and FLAME datasets. Their findings highlighted that model performance heavily depends on the characteristics of the training dataset, emphasizing the need for selecting appropriate datasets to develop robust models. [7] utilized the CNN-based VGG16 model with the NASA dataset, which included "fire images" and "non-fire images". Due to the small number of examples, the model was prone to overfitting, achieving high accuracy on both training and testing datasets but raising concerns about overfitting and generalization. [8] employed active learning methods for fire and smoke classification using a small number of labeled data. They optimized their deep learning algorithm for best results with minimal samples, focusing on increasing the number of active learning rounds to select the most informative samples. [9] studied the performance of pre-trained CNN models like VGG16, InceptionV3, and Xception for fire and smoke detection. They used Bayesian Optimization for hyperparameter selection and achieved the highest accuracy with the Xception-based model at 98.72%. Their study emphasized the importance of fast and accurate fire detection to prevent escalation. [10] proposed a novel convolutional neural network (CNN) named FireCNN, trained on a dataset containing fire and non-fire classes. They combined color feature extraction with CNN training to identify flame regions and used Faster R-CNN to detect fire regions, projecting them onto a Grassmannian space for aggregation. Their study introduced three distinct approaches for fire detection: using the VGG-16 pre-trained model for image classification, employing Faster R-CNN for detection, and integrating the YOLO algorithm for real-time detection. Comprehensive performance testing was conducted in both virtual and real-world settings, highlighting the suitability of CNN for image classification and the accuracy and speed of YOLO and Faster R-CNN for real-time detection. In their study, [11] noted that transformers, unlike CNNs, struggle with nearby pixel correlations but excel at learning global dependencies. They proposed a hybrid model combining CNNs and transformers, which outperformed pure transformer models and top CNNs in image classification tasks. [12] highlighted that deep learning-based fire detection algorithms capture more abstract fire and smoke attributes than traditional methods. They trained a YOLOv8-CBAM model using PyTorch, integrating the Convolutional Block Attention Module (CBAM) to improve detection of flame and smoke characteristics. Their enhanced algorithm showed significant improvement in average precision, although further validation is needed for more complex scenarios.

In image classification, many studies traditionally focus on training and testing models using a single dataset. However, this approach can limit the model's exposure to diverse information types. In our project, we aimed to enhance the generalization capability of our model for real-world applications by combining three different datasets. Rather than employing conventional machine learning methods directly, we adopted transfer learning. Specifically, we utilized the pre-trained CNN model VGG16, which has been trained on extensive image datasets and optimized parameters. Integrating VGG16 with our combined datasets enabled us to develop a robust model. To mitigate overfitting during testing, we implemented early stopping, which halted unnecessary model iterations. We evaluated our model's performance and classification accuracy using metrics such as the confusion matrix, F1-score, recall, and precision, in addition to accuracy alone. Furthermore, to validate our model's performance, we transferred the final dense layer output to the input layer of classical machine learning models. After training, twelve machine learning models demonstrated performance exceeding 92%, with eight models achieving accuracy levels surpassing 98%, underscoring their exceptional precision.

III. Materials and Methods

A. Artificial Intelligence (AI)

Artificial intelligence (AI) is changing many areas of technology today. It affects different industries like healthcare, finance, transportation, and communication[13], [14], [15], [16], [17]. In healthcare, AI helps with diagnoses, treatment plans, and finding new drugs. This improves patient care. In finance, AI helps with trading, risk assessment, and spotting fraud. This makes decision-making better and markets work well. AI also helps with transportation by making self-driving cars, making roads safer, and managing traffic. In communication, AI helps with talking to machines, translating languages, and understanding feelings. Overall, AI is very important for making new technology and ideas happen.

B. Machine Learning

Machine learning, a prominent subfield of artificial intelligence, encompasses a diverse set of algorithms and methodologies aimed at enabling computer systems to learn from data and make predictions or decisions without being explicitly programmed. At its core, machine learning algorithms leverage statistical techniques to identify patterns and relationships within data, thereby extracting insights and facilitating autonomous decision-making. These algorithms are typically categorized into supervised learning, unsupervised learning, and reinforcement learning paradigms, each tailored to different learning scenarios. Supervised learning involves training algorithms on labeled datasets, where input-output pairs are provided, enabling the algorithm to learn mappings between inputs and corresponding outputs. In contrast, unsupervised learning tasks involve extracting patterns and structures from unlabeled data, facilitating tasks such as clustering and anomaly detection. Reinforcement learning, on the other hand, focuses on training agents to interact with an environment in pursuit of maximizing cumulative rewards, often employed in dynamic decision-making scenarios. Across these paradigms, machine learning continues to drive innovations across various domains, from healthcare and finance to natural language processing and computer vision, ushering in transformative advancements in automation, prediction, and decision support systems.

C. Deep Learning

Deep learning, a subset of machine learning, encompasses a class of algorithms inspired by the structure and function of the human brain's neural networks. These algorithms are characterized by the use of multiple layers of interconnected artificial neurons to extract high-level features from raw data. Deep learning models excel at automatically learning intricate patterns and representations from large volumes of unlabeled data, enabling tasks such as image and speech recognition, natural language processing, and autonomous decision-making. The success of deep learning can be attributed to its ability to leverage hierarchical representations of data, progressively abstracting and refining features at each layer of the network. Through techniques like backpropagation and stochastic gradient descent, deep learning models are trained to minimize errors and optimize performance on specific tasks. Deep learning has revolutionized various fields, from healthcare and finance to transportation and entertainment, driving innovations and breakthroughs in artificial intelligence research and applications.

D. Convolutional neural network (CNN)

Convolutional Neural Networks (CNNs) belong to a category of sophisticated neural networks crafted specifically for the analysis and interpretation of visual data like images and videos. They play a pivotal role in numerous computer vision endeavors, encompassing tasks such as image categorization, object identification, and image partitioning. Inspired by the workings of the human visual system, CNNs are composed of diverse layers, including convolutional layers, pooling layers, and fully connected layers.

E. VGG16

The VGG16 model is a convolutional neural network (CNN) architecture that characterized by its simplicity and uniformity. It consists of 16 layers, hence the name "VGG16," including 13 convolutional layers and 3 fully connected layers. The convolutional layers are primarily comprised of 3x3 convolutional filters with a stride of 1 and same padding, followed by max-pooling layers of 2x2 size with a stride of 2. The fully connected layers serve as classifiers at the end of the network.

Additionally, we chose the VGG16 model for its simplicity and proven effectiveness in image classification tasks. The architecture's uniform design, consisting of 13 convolutional layers, allows it to capture complex visual features while maintaining computational efficiency. Its use of small 3x3 filters with same padding enables precise feature extraction, which is essential for identifying subtle patterns in the input data. Moreover, VGG16 has consistently demonstrated strong performance across a variety of computer vision benchmarks, making it a reliable choice for our specific classification problem.

F. Dataset Collection

In this study, we created a new dataset with a larger number of samples by combining three different fire datasets[18], [19],[20]available on Kaggle repository. These three datasets have been merged as illustrated in figure 1. This merged dataset provided us with a more comprehensive set of examples for our model training and evaluation. The constructed dataset contains 12.657 fire and 11.044 non-fire images. Table 1 illustrates the distribution of samples in the datasets used for constructing our dataset.

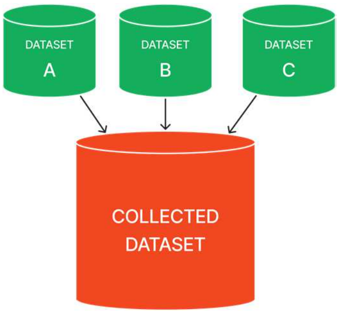

Figure 1. Dataset construction process

TABLE 1. distribution of samples in the datasets used for constructing the proposed dataset

DATASETS	Fire and Smoke Image Count	Non Fire Image Count
A	755	244
B	1102	-
C	10800	10800

G. Transfer Learning

Transfer learning involves adapting a pre-trained CNN model, initially trained on a large dataset, for a different but related task. In image classification, models like VGG16, ResNet, or MobileNet, which are trained on extensive datasets such as ImageNet, are fine-tuned on a new, smaller dataset. This approach achieves high performance with less training time and computational resources. Without transfer learning, it would take years to gather the hundreds of thousands or even millions of data points required for training. Even if we managed to collect this data, our personal computers lack the necessary hardware to process it efficiently. However, by leveraging pre-trained models with millions of parameters, we can easily apply these models to our tasks. This allows us to achieve high performance in our projects, even with limited data. Figure 2 illustrates a block diagram for the transfer learning process.

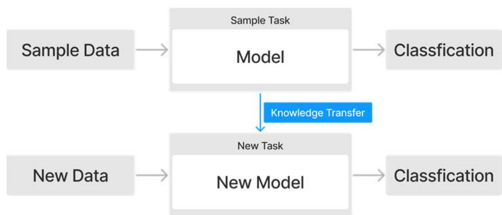

Figure 2. Transfer learning process.

IV. Proposed Model

In this work, we aim to maximize the efficiency of trained models by employing a transfer learning approach on a balanced dataset. To ensure the reliability of the results and assess the robustness of the model, we subjected our dataset to training with 12 different machine learning models. In doing so, we set the outputs of our VGG16 model as the input for the respective machine learning models, observing the contributions of our model to the performance of the machine learning models. Through this hybrid approach, we have developed a model capable of achieving successful results across different datasets and real-life scenarios. The proposed method has been applied in two different scenarios. In the first scenario we proposed using the features extracted using the VGG16 pretrained model for training a neural network composed of two dense layers, one dropout layer, and one Sigmoid classification layer. Table 2 illustrates the model proposed for the first scenario. In the second scenario we proposed feeding the features extracted using the VGG16 model to a different machine learning algorithms to enhance the performance of them. Figure 3 illustrates the proposed model.

TABLE 2. The model proposed for the first scenario

Layer (type)	Output Shape	Number Of Params
VGG16	(None, 4, 4, 512)	14714688
Dense(512)	(None, 4, 4, 512)	262656
Dense(256)	(None, 4, 4, 256)	131328
Flatten	(None, 4096)	0
Dropout	(None, 4096)	0
Dense (Sigmoid Activation)	(None, 1)	4097

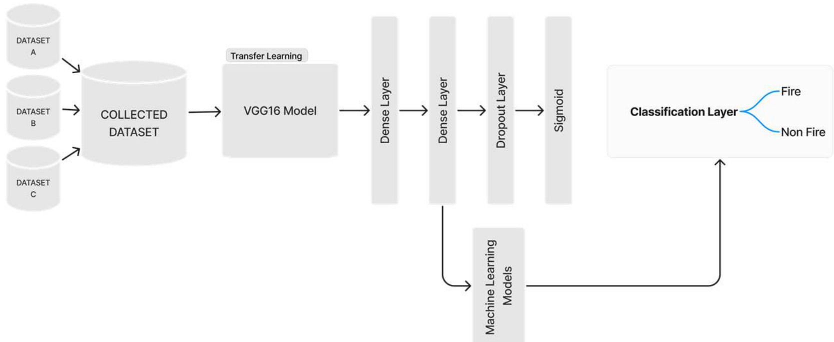

Figure 3. Proposed Model

V. Experimental Results

A. Hardware And Software

The experiments in this study were performed on a computer with an i7 12th generation processor. A GTX 3060 video card was used as a GPU accelerator. All experiments were carried out using the TensorFlow library.

B. Evaluation Metrices

The experiments aim to test how well the proposed model classifies fire and non-fire images. The measures we use to evaluate something include precision, recall, F-score, and accuracy. Precision is the number of right decisions divided by the total number of decisions in a specific category. It is figured out as:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

True Positive refers to correctly identifying images that contain wildfires, while False Positive refers to incorrectly classifying images as containing wildfires when they do not. Recall measures the number of correct classifications made by the model for wildfire images relative to all actual wildfire images in the dataset. It is calculated as:

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

False Negative occurs when an image that does not contain a wildfire is incorrectly labeled as containing one. Accuracy indicates how correct the model's classifications are compared to the true labels. The model's decision is only considered correct if it matches the actual wildfire classification in the dataset. It is figured out as:

$$\frac{TruePositive + TrueNegative}{TrueNegative + FalsePositive + FalseNegative}$$

Where True Negative is the correct non-fire decision. Finally, the F1-score is the harmonic mean of precision and recall. It is calculated as:

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

C. Obtained Results

Deep Learning Results

In our training process using a pre-trained CNN model, specifically the VGG16 model, we set the learning rate parameter to 1e-5 to achieve more precise learning performance. To prevent unnecessary iterations and overfitting, we utilized the early stopping callback mechanism with the patience parameter set to 3. Using the Adam optimizer, we ensured the updating of the model's weights. We opted to run the training for 20 epochs. As a result of our training, we observed that both the accuracy and validation accuracy metrics increased with each iteration, while the loss value consistently decreased.

As shown in Table 4 and Figure 4, the accuracy values increased with each iteration, while the loss values decreased consistently.

TABLE 3. The values of accuracy and loss during each step in the training process

	Loss	**Accuracy**	**Validation Loss**	**Validation Accuracy**
1	1.865838	0.788250	0.710843	0.895148
2	0.769519	0.895892	0.452262	0.926582
3	0.544278	0.919888	0.340571	0.943671
4	0.409371	0.934075	0.266065	0.951266
5	0.340830	0.942250	0.210364	0.958228
6	0.281285	0.948842	0.179415	0.963713
7	0.235881	0.956173	0.152218	0.966456
8	0.215102	0.957544	0.128818	0.969409
9	0.182320	0.962133	0.111643	0.974684
10	0.154921	0.964823	0.097153	0.977215
11	0.147141	0.966774	0.086114	0.977426
12	0.117957	0.971204	0.081624	0.981224
13	0.118765	0.971837	0.066726	0.982911
14	0.102813	0.974105	0.057274	0.984599
15	0.092791	0.975898	0.051746	0.985021
16	0.083480	0.979379	0.044340	0.987764
17	0.073304	0.980381	0.043120	0.987764
18	0.066184	0.981910	0.038695	0.989662
19	0.066251	0.981488	0.036891	0.990928
20	0.059573	0.983492	0.032908	0.991772

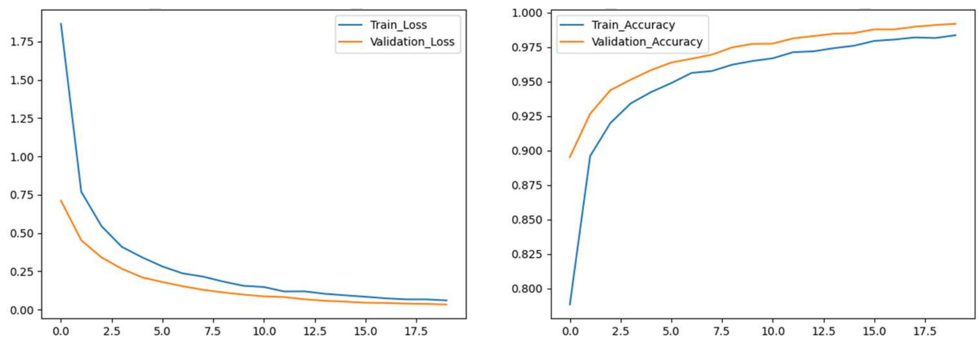

Figure 4. The accuracy and loss values during the training process

As shown in Figure 5, the confusion matrix indicates that our model has a high classification sensitivity. Out of 2520 non-fire images, the model misclassified only 13. Similarly, for 2181 fire images, it made only 26 incorrect classifications.

Furthermore, in Table 5, our model demonstrated exceptional performance not only in terms of accuracy but also in precision, recall, and F1-score, achieving 99% success in each metric.

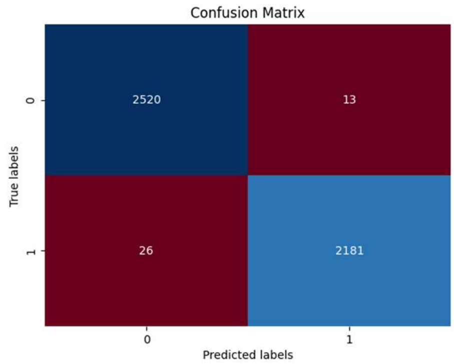

Figure 5. The confusion matrix of the proposed deep learning model.

TABLE 4. The results of the proposed deep learning model.

Precision	Recall	F1-score	Support
0	0.99	0.99	2533
1	0.99	0.99	2207
accuracy	0.99	0.99	4740
macro avg	0.99	0.99	4740
weighted avg	0.99	0.99	4740

Machine Learning Results

We used the features extracted using VGG16 for training 12 machine learning models (XGB Classifier, AdaBoost Classifier, Decision Tree Classifier, Random Forest Classifier, Extra Trees Classifier, Gradient Boosting Classifier, Extra Tree Classifier, SVC, Bagging Classifier, XGBRF Classifier, Logistic Regression, SGD Classifier) in order to deal with forest fire detection issue. The results obtained in this scenario are shown in Table 6. According to results, the first 6 models based on VGG19 CNN architecture showed significant performance over 99%.

TABLE 5. The results obtained using VGG16 and Machine learning algorithms.

Model Name	Accuracy	ROC_AUC	F1_Score	Precision	Recall
XGB Classifier	99.683544	0.996777	0.996599	0.997278	0.995922
Extra Trees Classifier	99.620253	0.996155	0.995920	0.996372	0.995469
SGD Classifier	99.599156	0.995929	0.995693	0.996370	0.995016
Random Forest Classifier	99.599156	0.995870	0.995689	0.997273	0.994110
Logistic Regression	99.578059	0.995673	0.995463	0.996820	0.994110
SVC	99.409283	0.994181	0.993668	0.991874	0.995469
Bagging Classifier	98.649789	0.985880	0.985375	0.994006	0.976892
Decision Tree Classifier	98.143460	0.981259	0.980036	0.981372	0.978704
Extra Tree Classifier	97.426160	0.974139	0.972361	0.972361	0.972361
Gradient Boosting Classifier	97.130802	0.970997	0.969105	0.971754	0.966470
XGBRF Classifier	93.227848	0.930863	0.926020	0.942308	0.910285
Ada Boost Classifier	92.974684	0.929573	0.924746	0.922453	0.927050

VI. CONCLUSION AND FUTURE WORKS

Through our training sessions with the pre-trained CNN model VGG16, we have made significant progress in classification performance. The results indicate that our model demonstrates high classification capability on previously unseen images, achieving a 99% validation accuracy without overfitting. This claim is further supported by our machine learning model training and results. We tested the performance of our VGG16 model by using the outputs from its dense layer as inputs for 12 different machine learning models. Notably, 6 out of these 12 models achieved accuracy values exceeding 99%.

In our future work, we plan to build a more robust model by combining pre-trained models such as VGG19, ResNet, ConvNeXtLarge, MobileNet, EfficientNetB1, and Xception. To enhance the performance of these combined models, we aim to utilize an Auto Encoder structure to maximize classification capabilities. Additionally, we will conduct performance tests on multiple datasets to compare and evaluate the effectiveness of our integrated model. This approach aims to enable more effective responses to environmental issues such as forest fires, which threaten both nature and living beings. By facilitating earlier action from authorities and the public, we hope to mitigate the impact of natural or human-caused environmental problems.

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