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Fine Tuned Deep Transfer Learning Framework for Forest Fire Image Detection

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Fire is one of the major disasters faced by humanity, with an increasing number of incidents each year. Forest fires disrupt the ecological balance, put lives at risk and cause widespread property damage. Early fire detection is critical for effective firefighting and mitigation efforts during forest fires. Present-time fire detection systems use numerous mechanisms such as sensor networks, image analysis and satellite surveillance. This article presents a robust and fine-tuned methodology for correctly identifying forest fires using both deep transfer learning models and image analysis. The proposed framework comprises a comprehensive database of fire and no-fire images. The technique presented in this paper utilizes Forest Fire Image Database. The Forest Fire dataset is an imbalanced and diverse dataset comprising binary classes: fire and no fire. These images are fed as inputs to the detection algorithm. Three prominent deep transfer learning models, VGG-19, AlexNet, and Inception-V3, are fed with fire and no fire image samples, and these framework employs the ability to capture intricate patterns in image data and effective feature extraction and classification of forest fire. To allow faster training of these networks, a few initial layer weights are frozen. When the dataset is limited in size, freezing the earlier layers of the network can also safeguard against overfitting those layers to the new dataset. The performance of each model is rigorously evaluated based on critical metrics, including sensitivity, specificity, precision, F-measure, and accuracy. The proposed deep transfer learning framework demonstrates significant potential in enhancing early fire detection systems, thereby contributing to timely intervention and mitigation of forest fire disasters.
Keywords: Forest fire detection, Deep learning model, Convolutional neural network, Forest Fire database, Inception-V3, AlexNet

1. Introduction

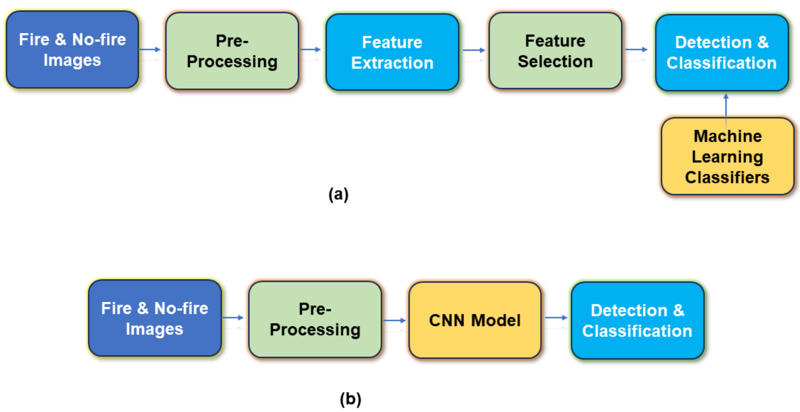
Fire is one of the major disasters faced by humanity, with an increasing number of incidents each year. The rise in building developments and crowded spaces has exacerbated the problem to treacherous levels. Due to the rapid spread of fire, the primary challenge is to explore ways to extinguish it in its initial stages, rather than spending extensive hours battling an uncontrollable blaze, which poses increasing risks to firefighters and human lives. Fire detection is an area where both existing and emerging technologies can be leveraged to address this urgent issue (Woodford, 2020).

Conventional approaches for fire detection include smoke and fire sensors with alarm systems. These sensors usually contain additional temperature and humidity sensors. The sensors then turn on the fire alarms, thereby starting up the suppression systems. While this method is robust, it inherently delays until the smoke reaches the sensor, which can allow the fire to spread beyond control. Reducing this time delay is extremely important; hence, one primary method is to use image and video data from standard surveillance systems (Enis et al., 2013).

In images and videos, fire is typically identified by yellow or orange flames that flicker back and forth. The smoke is seen as grey, white, or black plumes made up of burnt particles known as soot. Fires are usually caused by arson, electrical sparks, chemical reactions, and can spread rapidly depending on their intensity. Detecting fire or smoke in visual media poses challenges, as the system must accurately differentiate between actual fire and similar colors, as well as distinguish between real smoke and foggy conditions (Gaur et al., 2020). Therefore, the system needs to be reliable, precise, and have a very low rate of false detections. Moreover, manually processing the large amounts of video data from surveillance cameras is impractical, leading to the need for the development of autonomous and accurate detection systems (Geetha et al., 2021).

In volatility detection of fire and smoke, both traditional image processing and convolution neural networks (CNNs) of deep learning are being used (Pan et al., 2020). However, legacy methods require processing and extracting features in multiple steps utilizing simple image processing techniques and machine learning algorithms for classifying them. Figure 1 shows the workflow of two broad types of fire and smoke detection techniques.

Figure 1 Interaction Between Main Actors of the Integration Process.



Ensuring the welfare and protection of human makes sensing fire in rustic environments a critical and challenging task. Fires pose significant hazards to industries, busy streets, and crowded areas globally. Such incidents can devastate property, damage the earth, and endanger living beings. Disasters due to fire results in severe financial and environmental damage. However, taking immediate action can greatly reduce the losses caused by these incidents. Vision-based automated systems have the potential to be highly effective in detecting fires.

Inspired by this, in the present work we propose an efficient fire detection framework, which is based on convolutional neural networks. Conventional image-based techniques require manual selection of features, while deep neural networks can automatically identify relevant features with adequate training data (Geetha et al., 2021). This research introduces a rapid and efficient technique for accurately sensing forest fires based on image analysis and deep transfer learning models. The approach utilizes a diverse database containing fire and non-fire images as inputs to the detection and sensing algorithm. Three well-known deep transfer learning models - VGG-19, AlexNet, and Inception-V3 are trained on samples of fire and non-fire images, enabling them to capture intricate patterns in image data and effectively extract and classify features related to forest fires. The performance of each model is thoroughly assessed using key parameters namely: sensitivity, specificity, precision and accuracy, F-measure, utilizing a publicly available Forest Fire database.

In summary, key contributions of this study are:

1. Efficient and fast forest fire detection algorithm is developed using fine tuned deep transfer learning based features. To allow faster training of these networks, a few initial layer weights are frozen.

2. Intricate patterns in image data are effectively extracted and employed for the classification of forest fires.

3. The proposed algorithm demonstrated improved forest fire detection performance compared to state-of-the-art methods.

This article is divided into four main sections to provide a detailed overview of an efficient and rapid deep transfer learning framework for detection and sensing forest fire. Section 2 reviews different frameworks of various deep learning techniques for forest fire detection, providing the theoretical background necessary to understand the proposed framework. Section 3 details the architecture of the novel deep transfer learning framework designed for forest fire detection, including the selection and detailed discussion of pre-trained models. Section 4 consists of experimental results that are presented to showcase the performance of the framework through various metrics like sensitivity, accuracy, and precision followed by Conclusion in Section 5.

2. Literature Survey

The recent rise of image-based fire detection, a cutting-edge technology, is proving essential in minimizing fire losses. This is achieved by enabling swift action through early fire warnings. However, conventional detection algorithms, which include both manual and automated image feature extraction, suffer from lower accuracy, delayed detection, and high computational demands. To address these issues, authors in (Li & Zhao, 2020) proposed an image fire detection algorithm using object detection CNN models such as Faster-RCNN, YOLO and R-FCN. A comparison between these proposed algorithms and existing ones showed that fire detection algorithms utilizing object detection CNNs are more accurate. Notably, the YOLO v3 algorithm achieved greater robustness in performance and a speed of 28 FPS for the detection and an average precision of 83.7%, outperforming the other proposed algorithms.

The work in (Zheng et al., 2024) proposes a new method for forest fire detection using deep learning that tackles challenges caused by limited and uneven data. To address this issue, high-quality fire image samples using a technique called Generative Adversarial Networks (GANs) are generated. EfficientNet with segmentation stage is presented in (Khan et al., 2021) for the smoke detection. This method, unlike previous ones, demonstrated improved detection accuracy. The study used DeepLabv3+, a deep learning model, to segment smoke regions in images. This method breaks down images into key parts (encoding) and builds them back up (decoding) while employing a special classifier to pinpoint each pixel belonging to smoke. This resulted in a 3% improvement in smoke detection accuracy and a 0. 46% reduction in false alarms.

RGB and CIELAB color models based forest fire detection technique is illustrated with fire object tracking to minimize false alarms and evaluate risk (Khalil et al., 2021). By excluding stationary regions and analyzing the fire's growth rate, the method aimed to reduce false positives with fewer parameters compared to existing techniques. Experimental findings illustrated the effectiveness of this method in reducing false alarms while maintaining precision. In another study (Wu et al., 2021), researchers aimed to boost forest fire detection accuracy by employing a novel approach: a graph neural network (GNN) model. This model leverages the similarities between features extracted from multiple images (multi-view) to establish connections between them. Essentially, it transforms the original features into "correlation features" that capture the relationships between the images. The system then identifies potential fire areas by applying a threshold to the hue-saturation-value (HSV) color space of the images.

A study addressed the challenges of manual feature extraction in fire detection by proposing a new algorithm in (Qian & Lin, 2022). This method relies on combining two different models, YOLOv5 and EfficientDet, to achieve better accuracy in identifying fire sources under various conditions. This essentially combines the strengths of each model's predictions to create a more accurate "fusion frame". The proposed method's performance was evaluated using the Microsoft COCO standard, and experimental findings showed that the Y4SED model proposed in the study improved detection accuracy by 2.5% to 4.5% compared to Yolov5 and EfficientDet.

Researchers in (Majid et al., 2022), proposed a new system for fire detection using powerful image recognition techniques based on CNN. This system leverages pre-trained state-of-the-art CNNs fine-tuned with real-world fire images. To pinpoint fire more precisely within the images, the system incorporates a method called Grad-CAM for visualization and localization. Interestingly, the Grad-CAM results showed that this focus on specific image regions enhanced the model's ability to locate fire accurately.

The algorithm in (Dogan, et al., 2022) described a study using a Residual Network (ResNet) to identify important features in the images. They used four different versions of ResNets (ResNet18, ResNet50, ResNet101, and InceptionResNetV2) and combined them to achieve very high accuracy (98.91% and 99.15%) in detecting fire obtained using SVM classification technique. In (El Madafri et al., 2023), researchers introduced a new approach called multi-task learning. This method considers multiple types of confusing elements besides fire in the training process. This innovative strategy aims to make the model better at distinguishing fire from other things and reduce false alarms. When tested, this multi-task approach significantly improved detection accuracy compared to traditional methods.

An enhanced forest fire detection method that classifies fires using deep learning is presented in (Abdusalomov et al., 2023). They showcase an improved method that uses a new version of a deep learning platform called Detectron2 to classify fires in images. Experimental findings showed that this method of forest fire detection effectively identified fires with an improved precision rate of 99.3%. In another study, a specialized deep learning model called "FireXnet" was introduced to enhance efficiency and accuracy in wildfire detection (Ahmad et al., 2023). FireXnet is a new fire detection model designed to be fast and accurate, even on devices with limited computing power. Unlike other models, FireXnet is lightweight, meaning it requires less training time and runs faster. When tested against other five popular models, FireXnet achieved the highest accuracy (98.42%) at detecting fires.

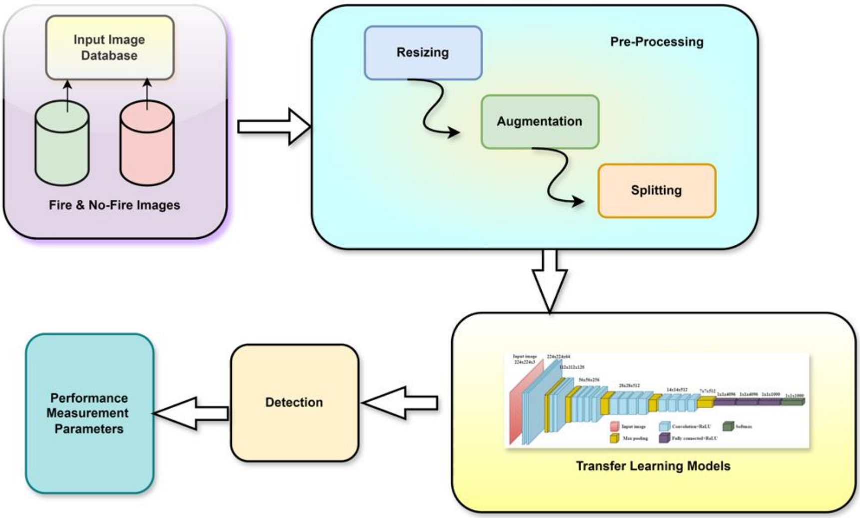
Researchers explored using pre-trained models (VGG16, InceptionV3, Xception) for fire detection with smaller datasets (Sathishkumar et al., 2023). Xception performed best, reaching 98.72% accuracy. They also investigated a technique called Learning without Forgetting (LwF) to prevent the models from forgetting what they learned previously. Overall, using pre-trained models with LwF attained good fire detection accuracy even with limited data. The study in (Idroes et al., 2023) presented TeutongNet, an adapted ResNet50V2 model tailored for precise forest fire detection. Trained on a meticulously curated dataset and assessed through diverse metrics, TeutongNet exhibited exceptional performance, achieving a high accuracy rate of 98.68% with minimal false positive and false negative rates. They utilized ResNet-18 for image semantic segmentation to detect elements related to energy infrastructures. The results showed a classification accuracy of 96%, demonstrating promising outcomes in cross-dataset scenarios.

A new method to improve wildfire detection in various forest settings is investigated in (El Madafri et al., 2024). This method addresses shortcomings of traditional convolutional neural networks that struggle to perform well in different environments. This framework utilized a dual-dataset approach to train a model proficient in handling various wildfire scenarios, initially demonstrated with EfficientNetB0. Comparative analysis against conventional methods revealed the superior performance of this approach in accuracy and precision. A prototype fire detection system called a Video Surveillance Unit (VSU) is developed in (Peruzzi et al., 2023). This compact device uses two machine learning algorithms to analyze sights and sounds in its environment. Running on low power, the VSU can detect forest fires quickly and trigger alerts.

3. Proposed Forest Fire Detection Approach

The flow of convolutional neural network-based forest fire detection algorithms is developed in Figure 2. The CNN offers various functions for feature extraction, classification, and region suggestions. First, utilizing convolution, pooling, and other techniques, the CNN generates region suggestions from an image input. As shown in Figure 2, input image database collected contains both fire and without fire images. These input images were acquired from the database as in paper (Forest Fire Dataset, 2024).

Figure 2 The algorithm for detecting forest fires using convolutional neural networks.



The algorithm starts by inputting a detailed forest fire database containing images of both fires and non-fires. This dataset is essential for training and validating the models to effectively differentiate between these two categories. The images in the database undergo preprocessing to ensure they meet the necessary specifications for various convolutional neural networks utilized in the classification task. This preprocessing typically involves resizing the images and enhancing the image database to enhance model resilience. Additionally, the forest fire image database is segmented into training, validation, and testing sets.

Three advanced CNN architectures are utilized for forest fire classification: VGG-19, AlexNet, and Inception-V3. VGG-19 is recognized for its deep 19-layer network, capable of capturing intricate image features. AlexNet, a pioneering deep learning model, offers a relatively simpler yet powerful architecture that performs well with limited computational resources. Inception-V3, with its intricate inception modules, enables more efficient computation and improved performance by handling multi-scale image features.

To assess the forest fire detection performance of these models, various key metrics are calculated: sensitivity, specificity, precision, F-measure, and accuracy. Sensitivity evaluates the CNN framework ability to identify fire images correctly, while specificity gauges its accuracy in identifying non-fire images. These performance metrics offer a comprehensive insight into how well each model detects forest fires, aiding in further enhancements and optimizations.

Transfer learning architectures

This study examines three distinct CNN models for detecting forest fires: VGG-19, AlexNet, and Inception-V3. Brief descriptions of these architectures are provided in this section.

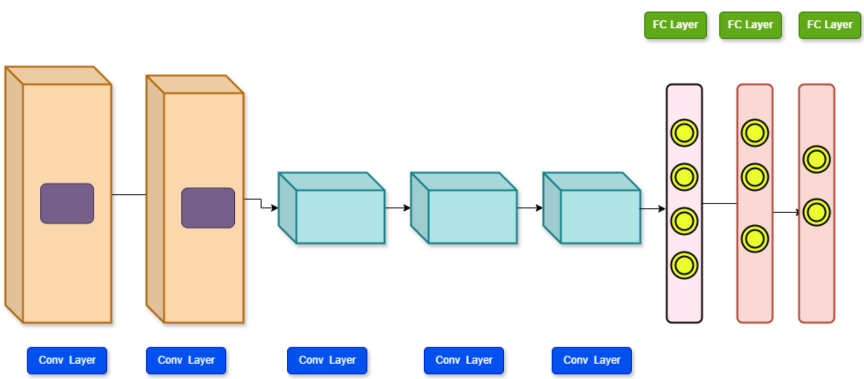
VGG-19

The VGG-19 network, created by the Oxford University, is a sophisticated convolutional neural network known for its straightforward yet powerful design. Unveiled in the VGGNet paper in 2014, this network comprises 19 layers, with 16 being convolutional layers with three fully-connected layering framework, along with a softmax layer for classification (Simonyan et al., 2015). Notably, it utilizes small 3x3 convolutional filters to excel at capturing intricate image details. Each convolutional layer is paired with a ReLU transfer function and interspersed with reduced spatial dimensions utilizing max-pooling (Bansal et al. 2023). The VGG-19 CNN model's architecture, as depicted in Figure 3, is deep and uniform, enabling it to effectively discern hidden patterns in large datasets for tasks like classification, object detection under various environment, and style transfer (Nguyen et al., 2022). Despite its effectiveness, VGG-19 is computationally demanding, necessitating significant processing power and memory, which can be a drawback in resource-limited settings. Nevertheless, its achievements in competitions such as ImageNet have cemented its position as a fundamental model in the realm of deep learning research and practical applications.

AlexNet

AlexNet, created by Alex Krizhevsky and authors in 2012, is a well-known convolutional neural network model in the fields of computer vision application development. It consists total of eight layering architecture, that includes 5 convolutional and three fully-connected layers (Eldem et al., 2023). AlexNet introduced novel methods like ReLU activation functions, dropout for regularization, and overlapping max-pooling to decrease spatial dimensions while retaining important information. Its success showcased the potential of deep CNNs and influenced future architectures by demonstrating superior performance in image recognition tasks (Raveendran et al., 2023} and other applications (Kollem et al., 2023).

Figure 3 Typical architecture of VGG-19 model.



Inception-V3

Inception-V3, developed by Google in 2015, is part of the Inception network family designed to improve computational efficiency while maintaining high accuracy. It consists of 48 layers with different convolution types like randing from 1×1 to 5×5, along with parallel max-pooling layers within Inception modules to effectively capture multi-scale features (Anand et al., 2024). The network incorporates innovative techniques like factorized convolutions to reduce computation and auxiliary classifiers to aid in training by adding extra gradients. Batch normalization is extensively used to stabilize and fasten the training process (Kaushal et al., 2024).

Inception-V3 has been widely adopted in various application areas including image classification, object detection, and scene recognition. Its robust performance has made it suitable for tasks in medical imaging for diagnosing diseases from medical scans, in autonomous driving for identifying objects and pedestrians (Kim et al., 2024). To allow faster training of these networks, few initial layer weights are froze. When the dataset is limited in size, freezing the earlier layers of the network can also serve to safeguard against overfitting those layers to the new dataset. This process results is faster training of these three CNN networks reducing the time complexity in a significant manner.

4. Experimental Results and Discussions

Detection algorithm for forest fire based on transfer learning frameworks is proposed in the article. The primary goal of this study is to detect the presence of fire using the image. Over the last ten years, numerous studies have concentrated on conventional methods of feature extraction for forest fire detection. However, these methods are limitations like lengthy development process and poor fire detection performance. These techniques generate numerous false alarms, particularly when dealing with poor lighting environment, shadows, and captured objects with bright illumination. To resolve these challenges, we investigated fire detection methods inspired by recent deep learning models.

Database

The technique presented in this paper utilizes Forest Fire Image Database. The Forest Fire dataset, collected from (Forest Fire Dataset, 2024), is an imbalanced and diverse dataset comprising binary classes: fire and no fire. The fire category includes 3,895 images, while the no fire contains 7,139 images. These images are divided into 80\% training set, 10\% of validation and test set. Pre-processing operations including image resizing and augmentation are performed on these datasets.

Parameter settings

The parameter settings of deep kearning framework is important to attain better detection accuracy rate. Table 1 shows parameter settings employed during the implementation of various transfer learning parameters. Image resizing is applied on the database images based on the input layer CNN size. Moreover, reflection and translation operations are applied during the image augmentation.

Table 1 Parameter settings of various transfer learning architectures.

Parameter	Value
Batch size	128
Optimization	SGDM and Adams
Maximum epochs	6
Initital learning rate	0.001
Shuffle	Every epoch

Experimental Results

This study investigates three distinct transfer learning models for detecting forest fires. The forest fire image database is divided as training data, validation dataset, and testing data sets, and the training set is utilized to train the VGG-19, AlexNet, and Inception-V3 networks. Figure 4, 5 and 6, depict training plots for these three transfer learning models with Adams optimization technique. As it is seen that, overall, the training accuracy is higher than 98\%. Additionally, training time of VGG-19, AlexNet and Inception-V3 models for Adams and SGDM optimization algorithms are depicted in Figure 7. Inception-V3 and AlexNet frameworks are faster as compared to VGG-19 model. Table 2, 3 and 4 show the performance evaluation of VGG-19, AlexNet and Inception-V3 architectures using different training, validation and test sets.

The development of forest fire detection algorithms using deep learning networks like VGG-19, AlexNet, and Inception-V3 reveals significant insights into the performance differences based on network architecture, optimization algorithms, and dataset partitioning. This comprehensive analysis covers the effectiveness of these networks using Adam and SGDM optimizations with various splits for training, validation, and testing sets.

Figure 4 Training accuracy and error rate plot for VGG-19.

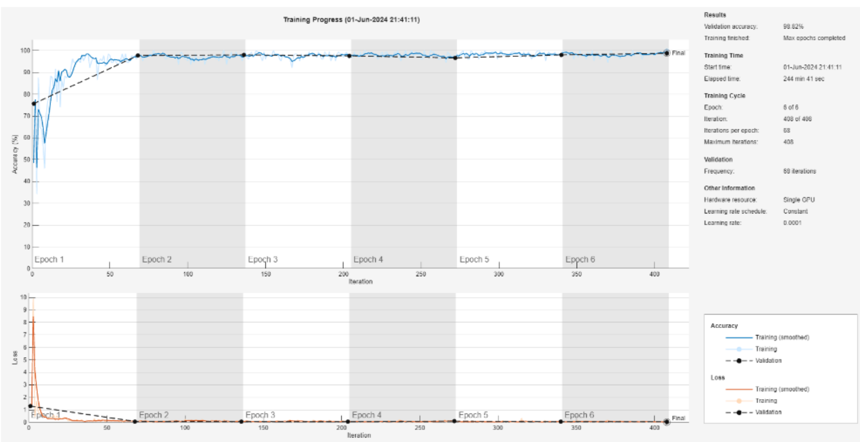


Figure 5 Training accuracy and error rate plot for AlexNet.

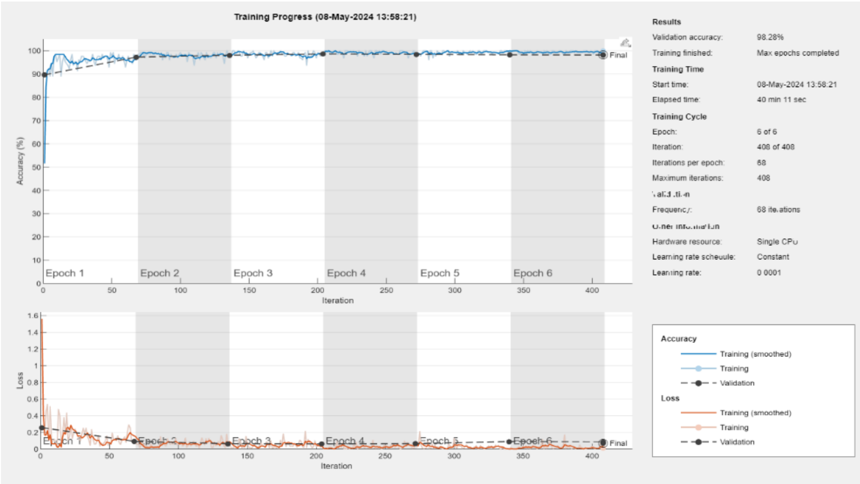


Figure 6 Training plots for Inception-V3 network.

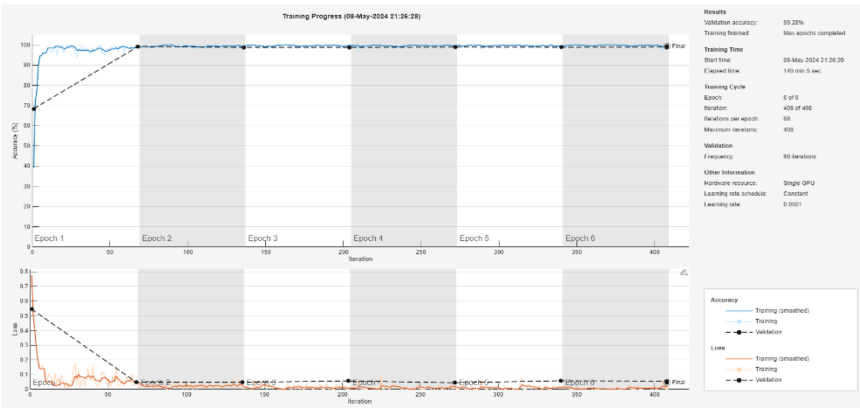


Figure 7 Training time for VGG-19, AlexNet and Inception-V3 models for different optimization algorithms.

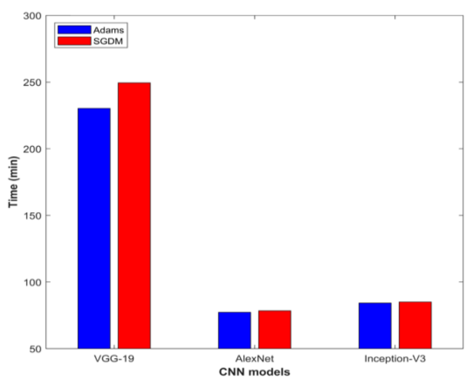


Table 2 Performance evaluation of VGG-19 architecture using different training, validation and test sets.

Train:Val:Test	Sensitivity	Specificity	Precision	F-score	Accuracy
Adams					
60:20:20	0.9367	0.9689	0.9617	0.9431	0.9537
70:15:15	0.9523	0.9857	0.9837	0.9676	0.9728
80:10:10	0.9640	0.9972	0.9947	0.9791	0.9855
SGDM					
60:20:20	0.9336	0.9621	0.9552	0.9402	0.9468
70:15:15	0.9464	0.9782	0.9782	0.9612	0.9659
80:10:10	0.9613	0.9892	0.98468	0.9723	0.9778

Table 3 Performance metric evaluation of AlexNet architecture using different training, validation and test sets.

Train:Val:Test	Sensitivity	Specificity	Precision	F-score	Accuracy
Adams					
60:20:20	0.9584	0.9663	0.95762	0.9564	0.9675
70:15:15	0.9727	0.9862	0.9782	0.9774	0.9841
80:10:10	0.9871	0.9944	0.9897	0.9884	0.9912
SGDM					
60:20:20	0.9514	0.9606	0.9515	0.9509	0.9612
70:15:15	0.9689	0.9804	0.9716	0.9707	0.9796
80:10:10	0.9826	0.9893	0.9831	0.9821	0.9849

Table 4 Performance metric evaluation of Inception-V3 architecture using different training, validation and test sets.

Train:Val:Test	Sensitivity	Specificity	Precision	F-score	Accuracy
Adams					
60:20:20	0.9737	0.9713	0.9761	0.9763	0.9747
70:15:15	0.9864	0.9875	0.9847	0.9856	0.9888
80:10:10	0.9923	0.9958	0.9923	0.9923	0.9946
SGDM					
60:20:20	0.9705	0.9687	0.9715	0.9732	0.9708
70:15:15	0.9835	0.9798	0.9769	0.9788	0.9815
80:10:10	0.9868	0.9847	0.9845	0.9862	0.9901

VGG-19 Network

With an 80%-10%-10% split, VGG-19 using Adam optimization achieved sensitivity, specificity, precision, F-score, and accuracy of 0.9640, 0.9972, 0.9947, 0.9791, and 0.9855, respectively. These metrics indicate a high degree of accuracy and a low false-positive rate, demonstrating the network's robustness. Using SGDM optimization, the performance metrics were slightly lower, with sensitivity at 0.9613, specificity at 0.9892, precision at 0.98468, F-score at 0.9723, and accuracy at 0.9778. Although these values are lower than those achieved with Adam, they still represent strong performance.

With a 70%-15%-15% split, the performance of VGG-19 showed a slight decline. Adam optimization yielded sensitivity, specificity, precision, F-score, and accuracy of 0.9523, 0.9857, 0.9837, 0.9676, and 0.9728. SGDM optimization resulted in metrics of 0.9464, 0.9782, 0.9782, 0.9612, and 0.9659. The decrease in performance with a smaller training set suggests that VGG-19's accuracy benefits from a larger training dataset, reflecting its need for extensive data to generalize effectively.

The 60%-20%-20% split further reduced VGG-19's performance, particularly with Adam optimization, where sensitivity, specificity, precision, F-score, and accuracy were 0.9367, 0.9689, 0.9617, 0.9431, and 0.9537. SGDM optimization showed metrics of 0.9336, 0.9621, 0.9552, 0.9402, and 0.9468. These results indicate that reducing the training data significantly impacts the model's ability to accurately detect forest fires, highlighting the necessity of ample training data for maintaining high performance.

AlexNet Network

AlexNet with an 80%-10%-10% split and Adam optimization achieved better metrics: sensitivity of 0.9871, specificity of 0.9944, precision of 0.9897, F-score of 0.9884, and accuracy of 0.9912. This suggests AlexNet's superior ability to detect forest fires accurately. Using SGDM optimization, the sensitivity was 0.9826, specificity 0.9893, precision 0.9831, F-score 0.9821, and accuracy 0.9849, slightly lower but still indicating robust performance.

With a 70%-15%-15% split, Adam optimization in AlexNet resulted in sensitivity, specificity, precision, F-score, and accuracy of 0.9727, 0.9862, 0.9782, 0.9774, and 0.9841, respectively. SGDM optimization achieved metrics of 0.9689, 0.9804, 0.9716, 0.9707, and 0.9796. While there is a slight decrease in performance, AlexNet remains highly effective, demonstrating better generalization capabilities with less training data compared to VGG-19.

With the 60%-20%-20% split, AlexNet's performance using Adam optimization was 0.9584 for sensitivity, 0.9663 for specificity, 0.95762 for precision, 0.9564 for F-score, and 0.9675 for accuracy. SGDM optimization showed slightly lower metrics at 0.9514, 0.9606, 0.9515, 0.9509, and 0.9612. Despite the reduced training data, AlexNet maintains strong detection capabilities, albeit with a noticeable decline compared to the higher training data splits.

Inception-V3 Network

Inception-V3 with an 80%-10%-10% split and Adam optimization achieved exceptional results with sensitivity, specificity, precision, F-score, and accuracy of 0.9923, 0.9958, 0.9923, 0.9923, and 0.9946, respectively. SGDM optimization also performed well with metrics of 0.9868, 0.9847, 0.9845, 0.9862, and 0.9901. These results highlight Inception-V3's capacity for high accuracy and reliability in detecting forest fires, making it highly suitable for this task.

For a 70%-15%-15% split, Inception-V3 with Adam optimization achieved sensitivity, specificity, precision, F-score, and accuracy of 0.9864, 0.9875, 0.9847, 0.9856, and 0.9888, respectively. SGDM optimization showed metrics of 0.9835, 0.9798, 0.9769, 0.9788, and

0.9815. These values reflect a slight decrease from the 80%-10%-10% split but still maintain a high performance level, indicating the network's robustness even with reduced training data.

With a 60%-20%-20% split, Inception-V3 using Adam optimization resulted in sensitivity, specificity, precision, F-score, and accuracy of 0.9737, 0.9713, 0.9761, 0.9763, and 0.9747, respectively. SGDM optimization yielded slightly lower metrics at 0.9705, 0.9687, 0.9715, 0.9732, and 0.9708. The results suggest that while Inception-V3's performance diminishes with less training data, it still outperforms VGG-19 and maintains competitive performance with AlexNet.

The experimental results clearly indicate that the Inception-V3 network generally outperforms VGG-19 and AlexNet in forest fire detection across all dataset splits and optimization algorithms. Inception-V3's highest sensitivity, specificity, precision, F-score, and accuracy demonstrate its exceptional capability in distinguishing fire from non-fire conditions. AlexNet also performs remarkably well, especially with Adam optimization, showcasing its robustness and reliability even with smaller training sets. VGG-19, while effective, tends to perform lower than the other two networks, particularly when the training data is reduced.

Adam optimization consistently outperforms SGDM optimization across all networks, suggesting that Adam's adaptive learning rate significantly enhances model performance. The variation in metrics with different dataset splits underscores the importance of a substantial training dataset for achieving high accuracy in forest fire detection. Even though there is an imbalcned database, still the proposed algorithm perfomed well. Overall, the study highlights the effectiveness of deep learning networks, particularly Inception-V3 and AlexNet, in developing reliable and accurate forest fire detection systems.

Figure 8, 9 and 10 show the confusion matrix plots for VGG-19, AlexNet and Inception-V3 models respectively. The confusion matrices obtained for the VGG-19, AlexNet, and Inception-V3 networks for forest fire detection provide detailed insights into their classification performance. For VGG-19, the confusion matrix typically showed higher true positives and true negatives but with slightly more false positives and false negatives compared to AlexNet and Inception-V3, reflecting its relatively lower sensitivity and precision. AlexNet's confusion matrix displayed a more balanced and higher count of true positives and true negatives, indicating its robustness and high accuracy, especially with Adam optimization. Inception-V3's confusion matrix further highlighted its superior performance with higher TP rate and the lower FP and FN rates, resulting in the highest overall accuracy among the three networks. These matrices underscore the comparative effectiveness of each network in minimizing classification errors and enhancing forest fire detection reliability.

Figure 8 Confusion matrix of VGG-19 model using Adams optimization.

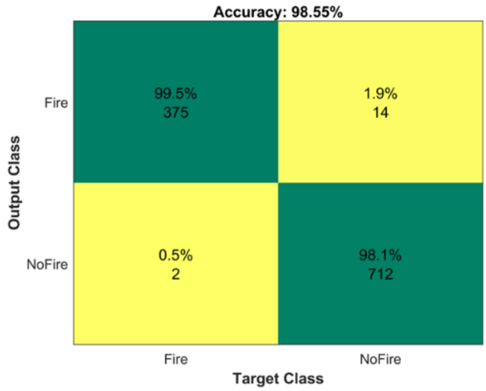


Figure 9 Confusion matrix obtained using AlexNet framework and Adams optimization.

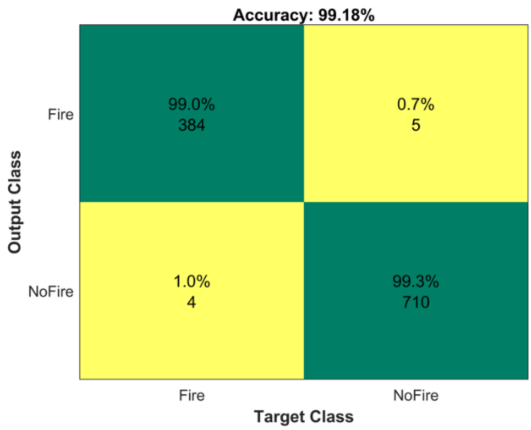


Figure 10 Confusion matrix of Inception-V3 model using Adams optimization.

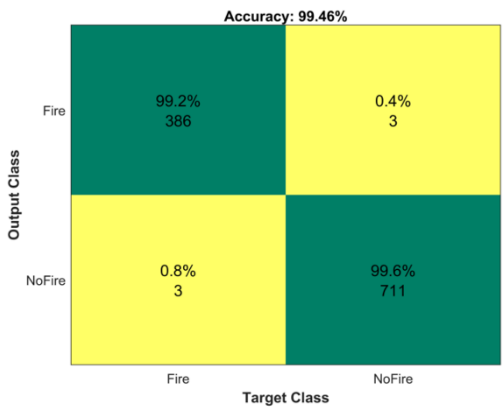


Figure 11, 12 and 13 illustrate receiver operating characteristics (ROC) plots for VGG-19, AlexNet and Inception-V3 deep learning networks respectively. The receiver operating characteristic plots for VGG-19, AlexNet, and Inception-V3 networks illustrate their ability to distinguish between fire and no-fire categories across various threshold settings. For VGG-19, the ROC curve, while demonstrating good performance, typically showed a slightly lower area under the curve (AUC), indicating less optimal balance between sensitivity and specificity. AlexNet's ROC plot exhibited a higher AUC, reflecting its superior capacity for accurate classification with fewer false positives and false negatives. Inception-V3's ROC plot displayed the highest AUC, approaching near-perfect classification capability, underscoring its exceptional performance in forest fire detection. These ROC plots visually confirm that Inception-V3 outperforms both AlexNet and VGG-19, offering the most reliable detection capability across different threshold values.

Figure 11 Receiver operating characteristics obtained using VGG-19 model and Adams optimization.

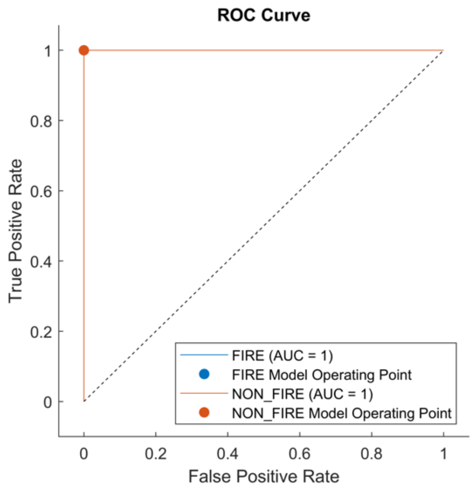


Figure 12 ROC plot of AlexNet framework using Adams optimization.

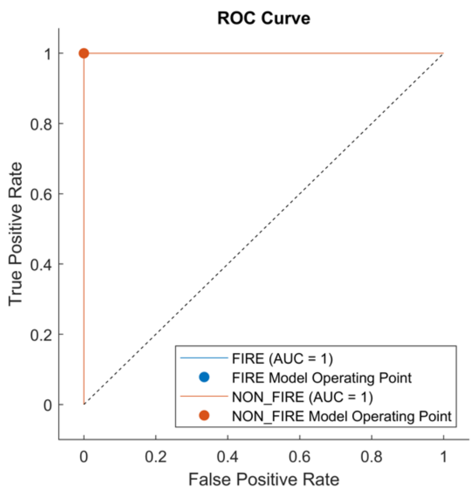
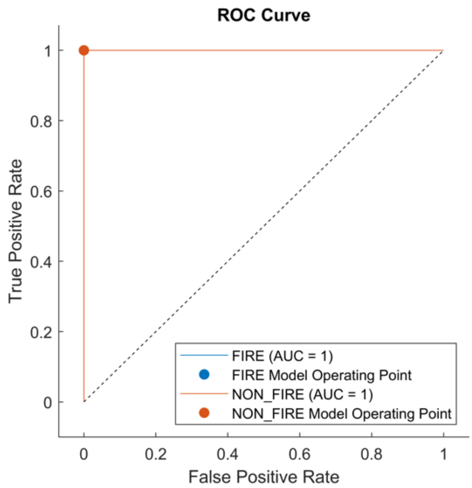


Figure 13 Receiver operating characteristics Inception-V3 framework using Adams optimization.



5. Conclusion

This work successfully demonstrates VGG-19, AlexNet, and Inception-V3 transfer learning models in fire and no-fire image detection. By utilizing a publicaly available image database as input, CNN models are trained and thoroughly evaluated their performance based on sensitivity, specificity, precision, F-measure, and accuracy. Experimental results indicate that each CNN model possesses distinct advantages, with specific models excelling in various performance metrics. Inception-V3 showcased superior precision and accuracy, making it a promising candidate for high detection scenarios. AlexNet and Vgg-19 also delivered notable performance, with Inception-V3 demonstrating a notable balance across all metrics. This comprehensive evaluation underscores the usefulness of deep learning frameworks in enhancing the efficacy of forest fire detection systems. By providing fast and accurate identification, these models can significantly improve early warning systems, facilitating prompt intervention and reducing the detrimental impact of forest fires. Future research should explore the integration of learning frameworks in real-time image feeds and consider the deployment of these frameworks in diverse environmental conditions to further validate and extend their applicability.

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