Journal of Artificial Intelligence and Data Mining (JAIDM), Vol. 13, No. 4, 2025, 479-488.

Shahrood University of Technology

Journal of Artificial Intelligence and Data Mining (JAIDM)
Journal homepage: http://jad.shahroodut.ac.ir

Research paper

Enhanced Deep Learning Approaches for Wildfire Detection Using Satellite Imagery

Sekineh Asadi Amiri* and Zahra Davoudi

Department of Computer Engineering, Faculty of Engineering and Technology, University of Mazandaran, Babolsar, Iran.

Article Info

Article History:
Received 28 February 2025
Revised 13 May 2025
Accepted 07 July 2025

DOI:10.22044/jadm.2025.15837.2699

Keywords:
Wildfire Detection, Deep Learning, ResNet50, ResNet101, EfficientNetB0.

*Corresponding author: s.asadi@umz.ac.ir (S. Asadi Amiri).

Abstract

Wildfires are among the most serious environmental and socio-economic threats worldwide, significantly impacting ecosystems and climate patterns. In recent years, deep learning-based methods, particularly convolutional neural networks (CNNs), have played a crucial role in improving wildfire detection accuracy. This study presents an enhanced approach for identifying wildfire-affected areas using deep learning models. Specifically, three models—ResNet50, ResNet101, and EfficientNetB0—were examined. To improve accuracy and reduce model complexity, the Flatten layer in all three architectures was replaced with a Global Average Pooling (GAP) layer. This modification reduces the number of features and enhances the extraction of meaningful patterns from images. Additionally, a Dense layer with 128 neurons was added after the GAP layer to enhance the learning and integration of extracted features. To prevent overfitting, a Dropout layer with a rate of 0.5 was incorporated. Finally, a Dense layer with 2 neurons serves as the output layer, responsible for the final classification. These optimizations led to improved model accuracy and enhanced performance in wildfire detection. The dataset consisted of 42,850 satellite images, categorized into wildfire and nowildfire areas. Experimental results indicate that the Modified ResNet101 model achieved the highest accuracy of 99.60%, while Modified ResNet50 and Modified EfficientNetB0 achieved accuracies of 99.35% and 99.10%, respectively. These results highlight the high potential of deep learning-based methods in improving wildfire detection accuracy and their role in environmental crisis management.

1. Introduction

Wildfires, as a major environmental challenge, occur year-round and worldwide [1]. This phenomenon causes significant damage to human communities and plays a decisive role in ecosystem changes [2]. Approximately 2.3% of the Earth's surface burns annually, significantly impacting human life and ecosystems [3]. Wildfires destroy vast areas, as reported in the European Commission's 20th annual wildfire report [4-6]. This report, pertaining to 2019, recorded a total burned area of 789,730 hectares across 40 countries in Europe, the Middle East, and North Africa. This figure is nearly four times larger than that of 2018. Wildfires significantly impact climate change, estimated to contribute to 10% of global CO_2 emissions annually [7]. Furthermore, wildfires cause severe societal damage, leading to fatalities, accidents, injuries, health issues, and destruction of human infrastructure. These damages have a substantial economic impact, due to both fire-related losses and the massive investments required for prevention, preparedness, firefighting, and recovery efforts [8]. Additionally, predictions indicate that future climate change will exacerbate wildfires [9]. Figure 1 displays samples of images from the dataset related to wildfires and areas without wildfires [10].

a) wildfire b) nowildfire

Figure 1. Images sample from dataset.

In recent years, deep learning methods have proven efficient for detecting and predicting wildfires. CNNs are powerful and well-known deep learning models that have revolutionized image interpretation by machines. CNNs enable computers to learn patterns from large datasets of two-dimensional images using processing filters, backpropagation algorithms, and various techniques aimed at accurate predictions, similar to human pattern recognition [11].

Due to CNNs' high capability in recognizing and extracting complex patterns from images, these models have become one of the most effective methods for analyzing image data. This study utilized ResNet50, ResNet101, and EfficientNetB0 to extract features from satellite images for wildfire detection. A Global Average Pooling layer was added to reduce feature dimensionality while preserving essential spatial information. A Dense layer with 128 neurons and ReLU activation enhanced feature representation, followed by a Dropout layer (rate = 0.5) to mitigate overfitting. Finally, a Dense output layer with two neurons and SoftMax activation classified fire-affected and unaffected areas. This method effectively improves wildfire detection accuracy and contributes to optimizing satellite image processing for fire prediction.

The following sections review related works on wildfire detection, introduce the proposed method, including deep learning models for fire identification, discuss the dataset, experimental results, and model evaluation.

2. Related Work

In recent years, numerous studies have investigated forest fire detection, employing various models and techniques. This section reviews related work, highlighting significant advancements in the use of deep learning models and neural networks for fire detection.

Spiros Maggioros and Nikos Tsalkitzis [12] utilized various pre-trained models, including VGG16, VGG19, ResNet50, ResNetV2, Xception, EfficientNetB7, and EfficientNetV2L, to identify fire-affected areas. Their results indicated that VGG19 achieved the highest accuracy (95%). However, a key limitation of this study is the minimal structural optimization of the pre-trained models. VGG19, for example, was primarily used in its original form, with only the addition of a Flatten layer and a final Dense layer. This lack of adaptation to the specific characteristics of fire-related data may hinder the model's accuracy and generalizability.

Yunfei Liu and colleagues [13] developed a hybrid image classifier comprising EfficientNet, YOLOv5, and EfficientDet. They employed an integrated dataset of 10,581 images, including 2,976 fire images and 7,605 non-fire images. However, the study did not address the potential issue of class imbalance. After training, the proposed classifier achieved an accuracy of 99.6% on 476 fire images and 99.7% on 676 non-fire images.

Z. Jiao and colleagues [14] extensively utilized the YOLOv3 algorithm for real-time processing of images captured by unmanned aerial vehicles (UAVs). Leveraging a high-performance computer at the ground station, the method achieved 91% accuracy in fire detection. However, the paper solely evaluated YOLOv3's performance without comparing it to other methods or newer models, such as YOLOv4 or EfficientDet, thus limiting a comprehensive assessment of its effectiveness. Notably, the authors used YOLOv3 despite its publication date in 2016, without justifying the omission of more recent versions.

M. Rahul and colleagues [15] fine-tuned the ResNet50 network by adding convolutional layers with ReLU activation functions and designed the output layer for binary classification. The model achieved 92.27% accuracy on the training set and 89.57% on the testing set. However, the study primarily relied on a public dataset with unspecified characteristics. Furthermore, the evaluation solely focused on accuracy metrics, neglecting standard performance measures such as Precision, Recall, and F1-Score.

Anupama Namburu and colleagues [16] proposed a method for early forest fire detection using UAVs and the X-MobileNet model, achieving an accuracy of 97.26%. However, the approach exhibits several limitations, including a lack of evaluation on diverse datasets, limited comparison with advanced architectures, insufficient explanation of hyperparameter selection, and an overlooking of computational efficiency and real-world deployment feasibility.

Shoukat Alam Sifat and colleagues [17] introduced the PyroVision model, which combines a Convolutional Neural Network with attention mechanisms, achieving a notable accuracy of 95.51%. They utilized the dataset from our study. However, this work lacks sufficient details regarding execution time, hardware requirements, and energy consumption.

Despite significant advancements, previous studies on wildfire detection exhibit certain limitations. These include minimal structural optimization of pre-trained models, a lack of comprehensive evaluation using metrics such as Precision, Recall, and F1-Score, insufficient attention to data imbalance, and neglect of computational considerations. Moreover, some studies lack comparisons with more advanced architectures.

This study addresses these shortcomings by proposing an enhanced method based on deep networks such as ResNet50, ResNet101, and EfficientNetB0. By modifying their internal structures and applying precise configurations, our approach achieves improved performance in detecting wildfires from satellite imagery. The details of this method are presented in the following section.

3. Proposed Method

This study employed advanced deep learning models, including ResNet50, ResNet101, and EfficientNetB0, to extract features from satellite images of forested areas. These models were chosen for their deep architectures and ability to identify complex patterns. To enhance their performance in wildfire detection, we modified their structures by introducing a Global Average Pooling layer, which reduces feature dimensionality while retaining essential spatial information. This transformation ensures a more compact representation, making the extracted features more suitable for subsequent processing. Following the GAP layer, a Dense layer with 128 neurons and ReLU activation was added to improve feature interactions. To mitigate overfitting and enhance generalization, a Dropout layer with a rate of 0.5 was incorporated, randomly deactivating neurons during training. The final classification stage consisted of a Dense output layer with two units and SoftMax activation, enabling the model to distinguish between wildfire and nowildfire regions. Prior to training, we preprocessed the images by normalizing pixel values between zero and one and resizing them to 224×224×3 to ensure compatibility with the deep learning models. Through fine-tuning and structural modifications, our proposed method significantly improved classification performance. Figure 2 presents the final architecture of the fine-tuned models. The following sections provide a detailed explanation of each network's configuration and its role in wildfire detection.

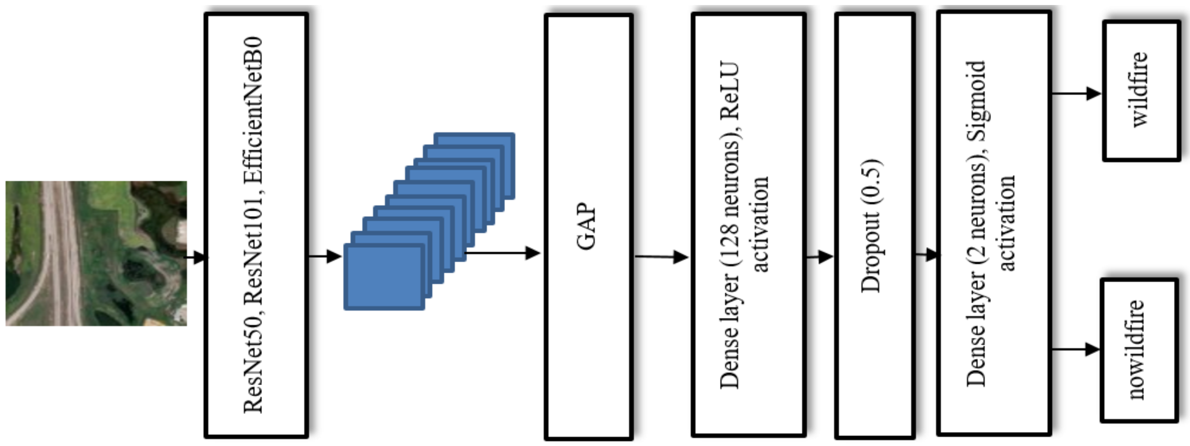


Figure 2. Proposed architecture of the final layers for model fine-tuning.

3.1. ResNet50

ResNet is an advanced CNN architecture that addresses performance degradation in deep networks by introducing shortcut connections and using Bottleneck blocks to accelerate training [18]. The shortcut connection bypasses one or more layers, effectively ignoring them; in other words, it connects one layer to a more distant layer. [19]

ResNet50 is a 50-layer model trained on ImageNet-1k with 224×224 resolution; it uses 3×3 filters, doubling filter numbers when output size is reduced, and ends with an Average Pooling and SoftMax layer for 1000 classes [20–21]. Figure 3 illustrates the ResNet50 block diagram, showing block repetitions and output sizes [22].

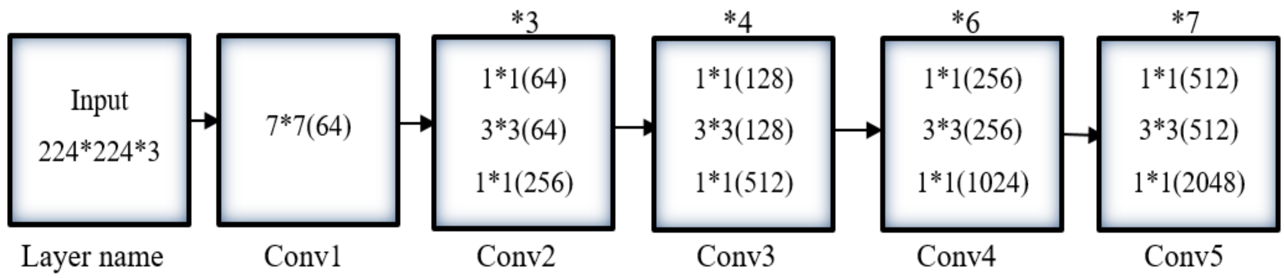


Figure 3. Block diagram of ResNet50 architecture.

3.2. EfficientNetB0

The EfficientNetB0 architecture, part of the EfficientNet family [23], is built on MBConv and Squeeze-and-Excitation blocks. By utilizing depthwise separable convolution layers, it significantly reduces computational complexity. Additionally, the inclusion of inverted residual blocks help decrease the number of trainable parameters and enhances model efficiency [2٤]. Figure 4 illustrates the overall structure of this architecture.

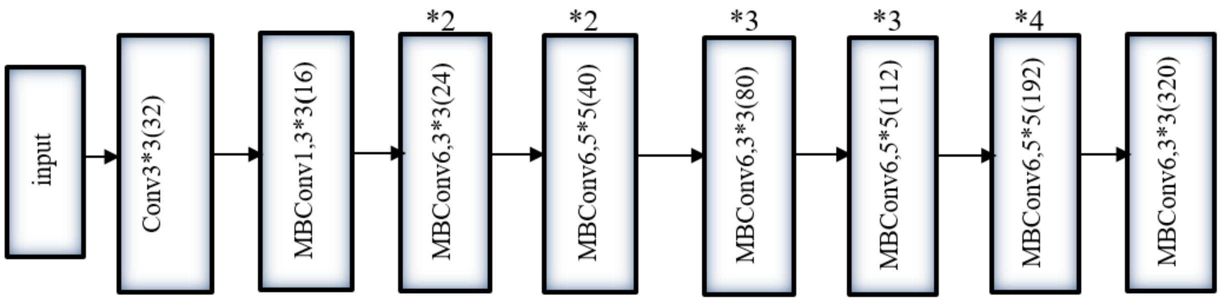


Figure 4. EfficientNetB0 baseline model architecture.

3.3. ResNet101

The ResNet101 architecture is a deep CNN that facilitates the training of deep networks through the use of residual blocks. This network includes convolutional layers to extract low-level features from images, residual blocks that use shortcut connections to skip layers, and stacked blocks to create a deep hierarchy. Subsequently, a GAP layer is used to extract global information from the feature map. Finally, a fully connected layer maps the extracted features to the output classes, and a softmax activation function is applied for accurate prediction [25]. In Figure 5**,** the original architecture of the ResNet101 deep learning model is shown.

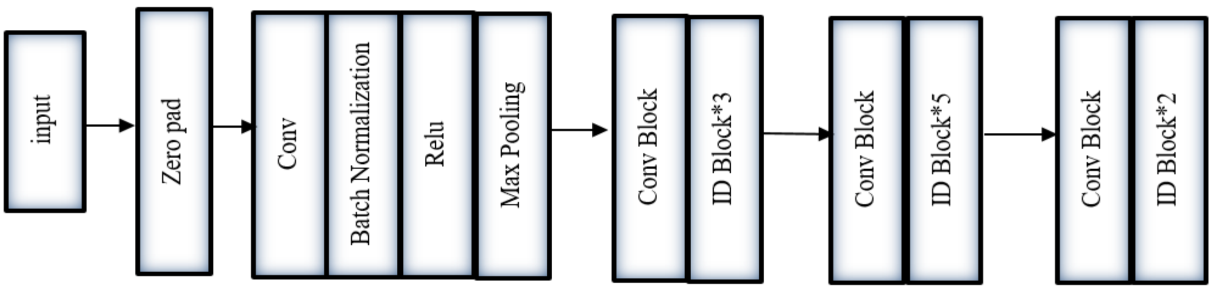


Figure 5. Original architecture of ResNet101 deep learning model [26].

4. Dataset

The dataset used in this study is the wildfire Prediction Dataset (Satellite Images), which consists of satellite images captured from regions in Canada that have previously experienced wildfires. This dataset contains a total of 42,850 images, each with a resolution of 350x350 pixels. The images are categorized into two classes: wildfire and nowildfire, representing areas affected by fire and those unaffected, respectively. The dataset is divided into three subsets: training, testing, and validation, which were created based on the distribution shown in Table 1. The distribution ensures a balanced approach to training, evaluating, and validating the deep learning models. The training set consists of 30,250 images (70% of the total), with 14,500 images labeled as nowildfire and 15,750 images as wildfire. The testing and validation sets each contain 6,300 images (15% each), with an equal number of wildfire and nowildfire images in both sets. This division allows for an effective assessment of model performance.

To provide a visual representation of the dataset, samples of images from both the wildfire and nowildfire categories are shown in Figure 6. These images offer a glimpse into the types of satellite imagery that will be processed and analyzed to predict wildfire occurrence.

Table 1. Distribution of images across dataset subsets and classes.

Folder	Wildfire	Nowildfire	Percentage	Total Images
Train	15,750	14,500	70%	30,250
Test	3,480	2,820	15%	6,300
Validation	3,480	2,820	15%	6,300
Total	22,710	20,140	100%	42,850

Figure 6. Sample images from the dataset: the top row shows wildfire-affected forests, and the bottom row shows unaffected forests.

5. Result and Discussion

In this section, we first introduce the performance metrics, then examine the simulation results, and finally present the results of the optimized models on the datasets, comparing them with other references.

5.1. Performance Metrics

The evaluation metrics used to assess model's performance include Accuracy, Precision, Recall, and F1-Score. These metrics help determine how effectively the model detects wildfires.

- Accuracy measures the proportion of correct predictions made by the model, calculated as the number of correct predictions divided by the total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

- Precision evaluates the model's accuracy in positive predictions. It measures the percentage of instances correctly identified as positive (e.g., fire) out of all instances the model labeled as positive.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- Recall indicates the proportion of actual positive instances (e.g., fire images) correctly identified by the model.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1-Score is a combined metric that considers both precision and recall. It is useful when balancing precision and recall is crucial, providing an overall evaluation of the model's predictive performance.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

In these equations, TP, FP, TN, and FN denote the number of True Positives, False Positives, True Negatives, and False Negatives, respectively.

5.2. Simulation Results

The proposed method was implemented in Python and executed on the Kaggle platform using an NVIDIA Tesla P100 GPU with 16 GB of RAM to accelerate training and enhance computational efficiency. Training durations for 10 epochs were as follows: modified EfficientNetB0 – 22 minutes and 6 seconds, modified ResNet50 – 25 minutes and 18 seconds, and modified ResNet101 – 41 minutes and 29 seconds.

The hyperparameters used for training the models are summarized in Table 2. All models were trained for 10 epochs with a batch size of 32. However, different learning rates and optimizers were selected based on the architecture to achieve optimal performance. For modified EfficientNetB0, the Adam optimizer with a learning rate of 0.001 was used.

In contrast, modified ResNet50 and modified ResNet101 were trained using the SGD optimizer with a momentum of 0.9 but with different learning rates of 0.001 and 0.01, respectively. Additionally, the Categorical Cross-Entropy (CCE) loss function was applied to all models to optimize classification performance.

5.3. Model Evaluation

To assess the effectiveness of the proposed approach, the performance of different models was analyzed in terms of Precision, Recall, and F1-score. The results highlight how well each model distinguishes between wildfire and nowildfire areas, ensuring reliable detection for real-world applications. Table 3 presents the performance of Modified ResNet101, Modified ResNet50, and Modified EfficientNetB0 in detecting wildfire and nowildfire areas. Based on these results, Modified ResNet101 achieved the highest Precision, Recall, and F1-score among the models. This model successfully identified the wildfire class with 99.16% precision and 99.96% recall, demonstrating excellent performance in detecting wildfire-related images. Additionally, for the nowildfire class, it achieved 99.97% precision and 99.31% recall. Modified ResNet50 also performed well, identifying the wildfire class with 98.87% precision and 99.68% recall, while for the nowildfire class, it obtained 99.74% precision and 99.08% recall. Modified EfficientNetB0, compared to the other two models, showed slightly lower performance but still maintained high precision and recall.

This model classified the wildfire class with 98.56% precision and 99.43% recall, while for the nowildfire class, it achieved 99.54% precision and 98.82% recall. Overall, these results indicate that Modified ResNet101 outperforms the other models and can be considered the optimal choice for wildfire detection.

Figure 7 presents the confusion matrices of the models, illustrating their performance in classifying wildfire and nowildfire images. Modified ResNet101 achieves the highest accuracy with minimal error, while Modified EfficientNetB0 has the highest error rate. These results confirm Modified ResNet101 as the optimal choice for wildfire detection.

Figure 8 illustrates the accuracy and loss curves of the three modified models—EfficientNetB0, ResNet50, and ResNet101—during training and evaluation. The modified EfficientNetB0 model shows a gradual improvement in both training and test accuracy.

Although the evaluation loss curve demonstrates noticeable fluctuations, this behavior is common in lightweight models with limited capacity when exposed to complex data. Nevertheless, the model continues to learn progressively, indicating a general upward trend in accuracy despite minor instability.

The modified ResNet50 model achieves high accuracy in the early epochs and maintains stable performance throughout training. The sharp decline in both training and test loss, followed by a consistent plateau, suggests fast and stable convergence, making this model a strong candidate in terms of reliability and learning efficiency.

The modified ResNet101 model also reaches high levels of accuracy, with relatively stable accuracy curves. However, its loss curve exhibits some fluctuations, which can be attributed to the model's greater depth and capacity. Such models often require more careful tuning and longer training periods to stabilize, yet the overall trend confirms effective learning.

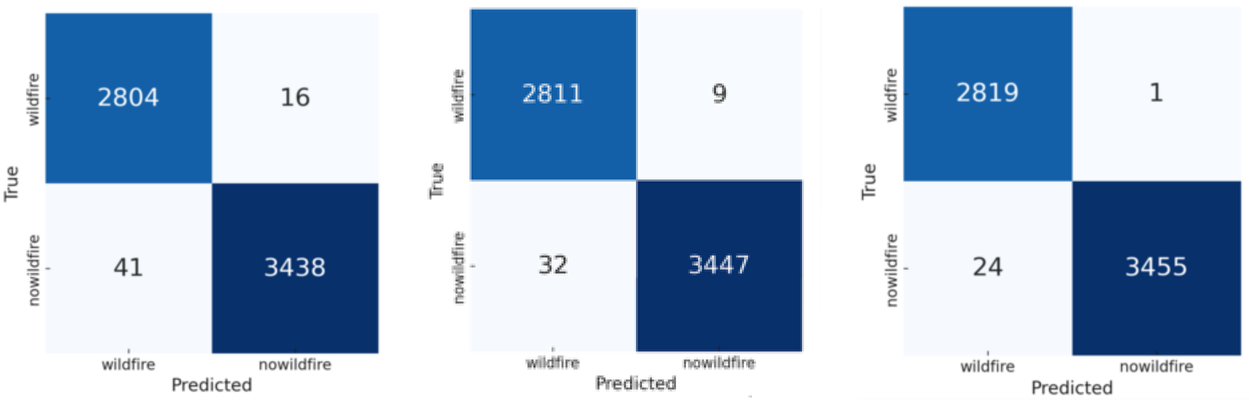
In summary, all three models successfully reach high accuracy, but the ResNet-based architectures—particularly modified ResNet50—demonstrate smoother and more stable convergence behavior.

The fluctuations observed in modified EfficientNetB0 and modified ResNet101 are consistent with expectations given their respective architecture sizes and complexities.

These observations affirm that the training processes were effective overall, and the minor instabilities are not indicative of convergence failure but rather model-specific learning characteristics.

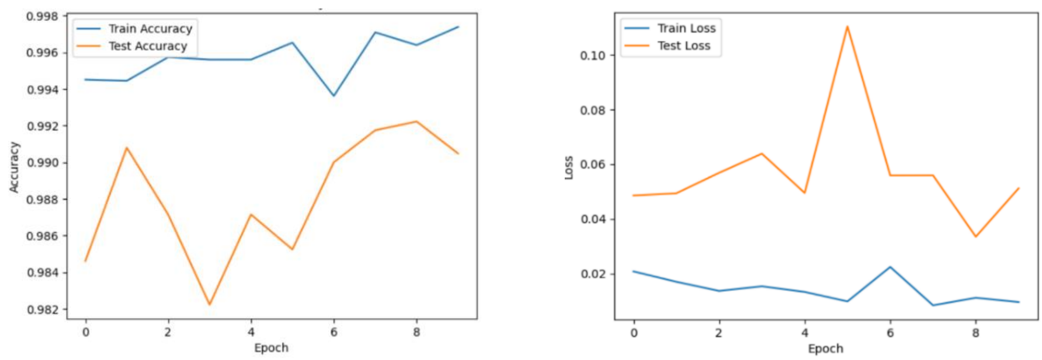
Table 2. The hyper-parameters used for training different models in our experiments.

Model	Epoch	Batch Size	Learning Rate	Loss Function	Momentum	Optimizer
EfficientNetB0	10	32	0.001	CCE	-	Adam
ResNet50	10	32	0.001	CCE	0.9	SGD
ResNet101	10	32	0.01	CCE	0.9	SGD

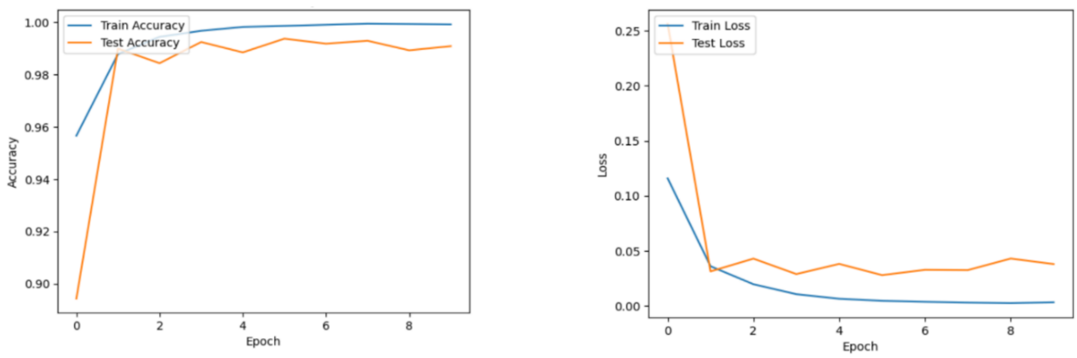


a) Modified EfficientNetB0 b) Modified ResNet50 c) Modified ResNet101

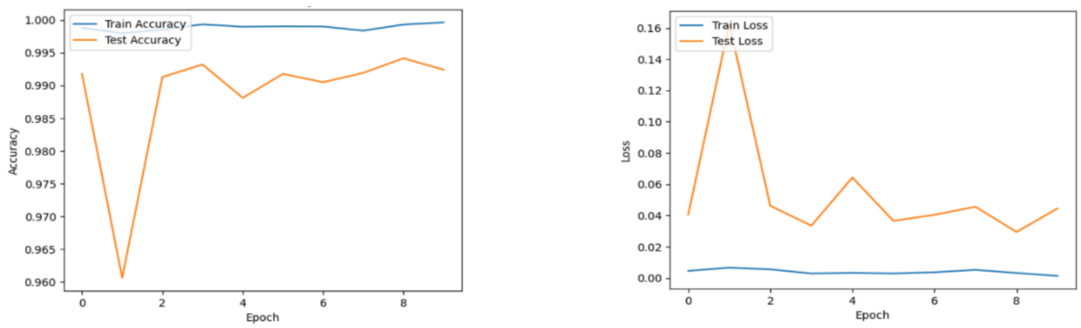
Figure 7. Confusion matrices of the models.



a) Accuracy and Loss curves of the Modified EfficientNetB0.



b) Accuracy and Loss curves of the Modified ResNet50.



c) Accuracy and Loss curves of the Modified ResNet101.

Figure 8. Accuracy and Loss curves of the models during training and evaluation phases.

Table 4 presents the experimental results of various models using four main metrics: Accuracy, Precision, Recall, and F1-score, providing a comprehensive comparison of their performance.
According to the results, the modified ResNet101 achieved the best performance among all models, with 99.60% accuracy, 99.56% precision, 99.64% recall, and an F1-score of 99.60%. The modified ResNet50 ranked second with an accuracy of 99.35%, followed by the modified EfficientNetB0, which also showed strong performance with 99.10% accuracy.
In contrast, baseline models such as VGG19, VGG16, ResNet50, and Xception, previously used in earlier studies, achieved accuracies in the range of 94% to 95%, which is noticeably lower than the modified architectures. This significant gap in performance highlights the critical role of architectural optimization and depth enhancement in improving model effectiveness.

Additionally, the three models referenced in [17]—PyroVision, 2D CNN, and MobileNetV2—also demonstrated weaker performance compared to our proposed models. Specifically, PyroVision achieved 95.51% accuracy, 2D CNN 88.40%, and MobileNetV2 only 83.57%.
These results clearly demonstrate that our modified models not only outperform traditional baseline models such as VGG, ResNet50, and Xception, but also show superior accuracy compared to more recent approaches like PyroVision and 2D CNN. This superiority underscores the importance of optimizing deep learning architectures to enhance accuracy and reliability in wildfire detection.
Overall, Table 4 emphasizes the effectiveness of structural modifications and architectural optimizations applied to deep networks such as ResNet and EfficientNet, showing that such enhancements can lead to highly accurate, robust, and reliable performance in automatic wildfire detection system.

Table 3. Performance comparison of Modified ResNet101, ResNet50, and EfficientNetB0 in wildfire detection.

Model	Class	Precision (%)	Recall (%)	F1-score (%)
Modified ResNet101	wildfire	99.16	99.96	99.56
	nowildfire	99.97	99.31	99.64
Modified ResNet50	wildfire	98.87	99.68	99.28
	nowildfire	99.74	99.08	99.14
Modified EfficientNetB0	wildfire	98.56	99.43	98.99
	nowildfire	99.54	98.82	99.18

6. Conclusion

This study investigated the potential of deep learning models for identifying wildfire-affected areas using satellite imagery. We modified and optimized ResNet50, ResNet101, and EfficientNetB0, all of which achieved strong classification performance, with ResNet101 outperforming the others. The integration of feature extraction with advanced CNN architectures, as well as the use of GAP and Dropout layers, significantly contributed to improved model accuracy.
Our findings confirm that deep learning techniques are highly effective for wildfire detection and can

support early warning systems and risk management efforts. However, we recognize that real-world deployment introduces additional challenges not fully captured in our experimental setup. As such, future research should explore the operational implementation of these models using real-time satellite data or imagery captured by Unmanned Aerial Vehicles (UAVs). Moreover, efforts should be made to integrate multiple remote sensing data sources and to enhance model robustness under dynamic and diverse environmental conditions.

Table 4. Comparison of the proposed method with previous methods on the same dataset.

Models/Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Modified EfficientNetB0	99.10	99.5	99.13	99.09
Modified ResNet50	99.35	99.31	99.38	99.34
Modified ResNet101	**99.60**	**99.56**	99.64	**99.60**
VGG19[12]	≈95	-	-	-
VGG16[12]	≈94	-	-	-
ResNet50[12]	≈95	-	-	-
Xception[12]	≈94	-	-	-
PyroVision [17]	95.51	95.53	**94.80**	95.16
2D CNN[17]	88.40	99.35	76.07	86.16
MobileNetV2[17]	83.57	81.75	83.34	82.54

References

[1] P. Jain, S. C. P. Coogan, S. G. Subramanian, M. Crowley, S. Taylor, and M. D. Flannigan, "A review of machine learning applications in wildfire science and management", *Environmental Reviews*, vol. 28, no. 4, pp. 478-505, 2020. [Online]. Available: https://doi.org/10.1139/er-2020-0019. [Accessed: Feb. 22, 2025].

[2] T. Schoennagel, J. K. Balch, H. Brenkert-Smith, P. E. Dennison, B. J. Harvey, M. A. Krawchuk, N. Mietkiewicz, P. Morgan, M. A. Moritz, R. Rasker, M. G. Turner, and C. Whitlock, "Adapt to more wildfire in western North American forests as climate changes", *Proceedings of the National Academy of Sciences*, vol. 114, no. 18, pp. 4582-4590, 2017. [Online]. Available: https://doi.org/10.1073/pnas.1617464114. [Accessed: Feb. 22, 2025].

[3] G. Shi, H. Yan, W. Zhang, J. Dodson, H. Heijnis, and M. Burrows, "Rapid warming has resulted in more wildfires in northeastern Australia", *Science of The Total Environment*, vol. 771, p. 144888, 2021. [Online]. Available: https://doi.org/10.1016/j.scitotenv.2020.144888.[Accessed: Feb. 22, 2025].

[4] J. San-Miguel-Ayanz, T. Durrant, R. Boca, P. Maianti, G. Libertà, T. A. Vivancos, D. J. F. Oom, A. Branco, D. D. De Rigo, D. Ferrari, H. Pfeiffer, R. Grecchi, D. Nuijten, T. Leray, "Forest Fires in Europe, Middle East and North Africa 2019", Publications Office of the European Union, Luxembourg, Rep. KJ-NA-30402-EN-N, 2020.

[5] J. S. S. Júnior, J. Pãulo, J. Mendes, D. Alves, and L. M. Ribeiro, "Automatic Calibration of Forest Fire Weather Index For Independent Customizable Regions Based on Historical Records", in *Proceedings of the 2020 IEEE Third International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)*,1-8, 2020, Laguna Hills, CA, USA. Available: IEEE Xplore, https://doi.org/10.1109/AIKE48582.2020.00011. [Accessed: Feb. 22, 2025].

[6] J. S. S. Júnior, J. R. Paulo, J. Mendes, D. Alves, L. M. Ribeiro, and C. Viegas, "Automatic forest fire danger rating calibration: Exploring clustering techniques for regionally customizable fire danger classification", *Expert Systems with Applications*, vol. 193, p. 116380, 2022. [Online]. Available: https://doi.org/10.1016/j.eswa.2021.116380.[Accessed: Feb. 22, 2025].

[7] G. R. van der Werf, J. T. Randerson, L. Giglio, T. T. van Leeuwen, Y. Chen, B. M. Rogers, M. Mu, M. J. E. van Marle, D. C. Morton, G. J. Collatz, R. J. Yokelson, and P. S. Kasibhatla, " Global fire emissions estimates during 1997–2016", *Earth System Science Data*, vol. 9, no. 2, pp. 697-720, 2017. [Online]. Available: https://essd.copernicus.org/articles/9/697/2017/.[Accessed: Feb. 22, 2025].

[8] F. N. Robinne and F. Secretariat, "Impacts of disasters on forests, in particular forest fires," UNFFS, 2021.

[9] L. Vilà-Vilardell, W. S. Keeton, D. Thom, C. Gyeltshen, K. Tshering, and G. Gratzer, "Climate change effects on wildfire hazards in the wildland-urban-interface – Blue pine forests of Bhutan", *Forest Ecology and Management*, vol. 461, p. 117927, 2020. [Online]. Available:

https://www.sciencedirect.com/science/article/pii/S0378112719319024. [Accessed: Feb. 22, 2025].

[10] Aaba, A. “Wildfire Prediction Dataset (Satellite Images).

[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning", Nature, vol. 521, pp. 436–444, 2015. [Online]. Available: https://doi.org/10.1038/nature14539. [Accessed: Feb. 22, 2025].

[12] S. Maggioros and N. Tsalkitzis, "Wildfire danger prediction optimization with transfer learning," arXiv, 2024, [online]. Available: https://arxiv.org/abs/2403.12871. [Accessed: Feb. 22, 2025].

[13] R. Xu, H. Lin, K. Lu, L. Cao, and Y. Liu, "A forest fire detection system based on ensemble learning", *Forests*, vol. 12, no. 2, p. 217, 2021. [Online]. Available: https://doi.org/10.3390/f12020217. [Accessed: Feb. 22, 2025].

[14] Z. Jiao, Y. Zhang, L. Mu, J. Xin, S. Jiao, H. Liu, and D. Liu, "A YOLOv3-based Learning Strategy for Real-time UAV-based Forest Fire Detection", *in Proceedings of the 2020 Chinese Control and Decision Conference (CCDC)*, 4963-4967, 2020, Hefei, China. Available: IEEE Xplore, https://doi.org/10.1109/CCDC49329.2020.9163816. [Accessed: Feb. 22, 2025].

[15] M. Rahul, S. S. Karnekanti, S. Attili, and S. N. Nenavath, "Early Detection of Forest Fire using Deep Learning", in *Proceedings of the 2020 IEEE REGION 10 CONFERENCE (TENCON)*, 1136-1140, 2020, Osaka, Japan. Available: IEEE Xplore, https://doi.org/10.1109/TENCON50793.2020.9293722. [Accessed: 22 Feb. 2025].

[16] A. Namburu, P. Selvaraj, S. Mohan, S. Ragavanantham, and E. Tag Eldin, "Forest Fire Identification in UAV Imagery Using X-MobileNet," *Electronics*, vol. 12, no. 3, art. no. 733, Feb. 2023.[Online].Available: https://doi.org/10.3390/electronics12030733[Accessed: Feb. 22, 2025].

[17] S. A. Sifat, S. A. Shoukat, *et al.*, "PyroVision: A deep learning based model for wildfire detection in satellite imagery," in Proc. 6th Int. Conf. Electr. Eng. Inf. Commun. Technol. *(ICEEICT)*, IEEE, 2024, pp. 705–710. [Online]. Available: https://doi.org/10.1109/ICEEICT62016.2024.10534576. [Accessed: Feb. 22, 2025].

[18] Z. Wu, C. Shen, and A. van den Hengel, "Wider or deeper: Revisiting the ResNet model for visual recognition", *Pattern Recognition*, vol. 90, pp. 119-133, 2019. [Online]. Available: https://doi.org/10.1016/j.patcog.2019.01.006.[Accessed: Feb. 22, 2025].

[19] F. Salimian Najafabadi and M. T. Sadeghi, "AgriNet: a New Classifying Convolutional Neural Network for Detecting Agricultural Products’ Diseases," *Journal of Artificial Intelligence and Data Mining (JAIDM)*, vol. 10, no. 2, pp. 285–302, 2022. [Online]. Available: http://jad.shahroodut.ac.ir/article_2431_10ea85357f4b93525c9f43aa020d424a.pdf. [Accessed: Aug. 18, 2025].

[20] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks", *Pattern Analysis and Applications*, vol. 24, no. 3, pp. 1207-1220, 2021. [Online]. Available: https://doi.org/10.1007/s10044-021-00984-y. [Accessed: Feb. 22, 2025].

[21] A. A. Farhat, M. M. Darwish, and T. M. El-Gindy, "Resnet50 and logistic Gaussian map-based zero-watermarking algorithm for medical color images", *Neural Computing and Applications*, vol. 36, no. 31, pp. 19707–19727, 2024. [Online]. Available: https://doi.org/10.1007/s00521-024-101215. [Accessed: Feb. 22, 2025].

[22] A. Manzoor, W. Ahmad, M. Ehatisham-ul-Haq, A. Hannan, M. A. Khan, M. U. Ashraf, A. M. Alghamdi, and A. S. Alfakeeh, "Inferring emotion tags from object images using convolutional neural network", *Applied Sciences*, vol. 10, no. 15, p. 5333, 2020. [Online]. Available: https://doi.org/10.3390/app10155333. [Accessed: Feb. 22, 2025].

[23] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", in *Proceedings of the 36th International Conference on Machine Learning (ICML 2019)*, 6105-6114, 2019, Long Beach, CA, USA. [Online]. Available: PMLR http://proceedings.mlr.press/v97/tan19a.html.[Accessed: 22 Feb. 2025].

[24] A. Iqbal, M. A. Jaffar, and R. Jahangir, "Enhancing brain tumour multi-classification using Efficient-Net B0-based intelligent diagnosis for Internet of Medical Things (IoMT) applications", *Information*, vol. 15, no. 8, p. 489, 2024. [Online]. Available: https://doi.org/10.3390/info15080489. [Accessed: Feb. 22, 2025].

[25] R. Sonavane, P. Ghonge, S. U. Patil, K. S. Sagale, and A. A. Maha, "Exploring ResNet101, InceptionV3, and Xception for Modi Script Character Classification", *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 17, pp. 117–124, 2024. [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/4841. [Accessed: Feb. 22, 2025].

[26] A. Khan, M. A. Khan, M. Y. Javed, M. Alhaisoni, U. Tariq, S. Kadry, J.-I. Choi, and Y. Nam, "Human Gait Recognition Using Deep Learning and Improved Ant Colony Optimization", *Computers, Materials & Continua*, vol. 70, no. 2, pp. 2113–2130, 2022. [Online]. Available: https://doi.org/10.32604/cmc.2022.018270. [Accessed: Feb. 22, 2025].

بهبود روش‌های یادگیری عمیق برای تشخیص آتش‌سوزی‌های جنگلی با بهره‌گیری از تصاویر ماهواره‌ای

سکینه اسدی امیری* و زهرا داودی

گروه مهندسی کامپیوتر، دانشکده مهندسی و فناوری، دانشگاه مازندران، بابلسر، مازندران،ایران

ارسال ۲۰۲۵/۰۲/۲۸؛ بازنگری ۲۰۲۵/۰۵/۱۳؛ پذیرش ۲۰۲۵/۰۷/۰۷

چکیده:

آتش‌ســـوزی‌های جنگلی از جدی‌ترین تهدیدهای زیســـت‌محیطی و اجتماعی-اقتصـــادی در ســـراســـر جهان به‌شـــمار می‌روند که تأثیر قابل‌توجهی بر اکوسـیستم‌ها و الگوهای اقلیمی دارند. در سال‌های اخیر، روش‌های مبتنی‌بر یادگیری عمیق، به‌ویژه شبکه‌های عصبی پیچشی(CNN) ، نقش کلیدی در بهبود دقت تشـخیص آتش‌سـوزی‌های جنگلی ایفا کرده‌اند. این مطالعه رویکردی بهبودیافته برای شـناسـایی مناطق تحت‌تأثیر آتش‌ســوزی جنگلی با استفاده از مدل‌های یادگیری عمیق ارائه می‌دهد. به‌طور خاص، سه مدلResNet101 ، ResNet50و EfficientNetB0 مورد بررسی قرار گرفتند. برای افزایش دقت و کاهش پیچیدگی مدل، لایه Flatten در هر ســه معماری با یک لایه تجمیع میانگین ســراســری (GAP) جایگزین شــد. این تغییر باعث کاهش تعداد ویژگی‌ها و بهبود اســتخراج الگوهای معنادار از تصــاویر می‌شــود. علاوه‌بر این، یک لایه Dense با ۱۲۸ نورون پس از لایه GAP اضافه شد تا فرایند یادگیری و یکپارچه‌سـازی ویژگی‌های استخراج‌شده تقویت شود. برای جلوگیری از بیش‌پردازش، از یک لایه Dropout با نرخ ۰٫۵ استفاده شد. در نهایت، یک لایه Dense با ۲ نورون به‌عنوان لایه خروجی عمل می‌کند که مســئول دســته‌بندی نهایی است. این بهینه‌سازی‌ها منجر به افزایش دقت مدل و بهبود عملکرد در تشـخیص آتش‌سـوزی جنگلی شـد. مجموعه‌داده مورد اسـتفاده شـامل ۴۲،۸۵۰ تصویر ماهواره‌ای بود که به دو دسته مناطق دارای آتش‌سـوزی و بدون آتش‌سـوزی تقسـیم شـده بودند. نتایج آزمایش‌ها نشان داد که مدل ResNet101 اصلاح‌شده به بالاترین دقت یعنی ۹۹٫۶۰٪ دست یافته، در حالی‌که مدل‌های ResNet50 و EfficientNetB0 اصلاح‌شده به‌ترتیب دقت‌های ۹۹٫۳۵٪ و ۹۹٫۱۰٪ را به‌دست آوردند. این نتایج نشان‌دهنده پتانسیل بالای روش‌های مبتنی‌بر یادگیری عمیق در بهبود دقت تشخیص آتش‌سوزی جنگلی و نقش آن‌ها در مدیریت بحران‌های زیست‌محیطی است.

کلمات کلیدی: تشخیص آتش سوزی‌های جنگلی، یادگیری عمیق، ResNet50، ResNet101، EfficientNetB0.