Yalvaç Akademi Dergisi

https://dergipark.org.tr/tr/pub/yalvac

# PERFORMANCE EVALUATION OF DEEP NEURAL NETWORKS FOR FOREST FIRE CLASSIFICATION

**Oğuzhan KİLİM*[1], Şerafettin ATMACA[1], Tuncay YİĞİT[2], Hamit ARMAĞAN[3]**

[1]Süleyman Demirel University, Graduate School of Natural and Applied Sciences, Computer Engineering, Isparta, Türkiye

[2]Süleyman Demirel University, Faculty of Engineering and Natural Sciences, Computer Engineering, Isparta, Türkiye

[3]Süleyman Demirel University, Rectorate, Isparta, Türkiye

**E-posta :** d2240138002@ogr.sdu.edu.tr, d2240139803@ogr.sdu.edu.tr, tuncayyigit@sdu.edu.tr, hamitarmagan@sdu.edu.tr

***Abstract:*** Forest fires are destructive natural disasters that not only destroy vast forested areas but also threaten biodiversity, degrade air quality, damage agricultural land, and accelerate climate change. Due to rising global temperatures, prolonged droughts, and human-induced factors, the frequency and intensity of forest fires are increasing year by year. Consequently, the early detection and rapid classification of forest fires are critical for preventing loss of life and property and ensuring the effective management of disaster response processes. This study aims to present a deep learning-based approach for the early detection and classification of forest fires. In this context, four advanced convolutional neural network (CNN) architectures (Xception, InceptionV3, DenseNet121, and EfficientNetV2), which have shown outstanding success in image classification tasks in recent years, were comparatively evaluated for the classification of forest fire images. Training and testing procedures were performed using the Forest Fire Images dataset, consisting of fire and non-fire classes. The experimental results revealed that all models performed well in forest fire classification; however, the Xception model demonstrated superior performance, exhibiting higher accuracy than the others. These results emphasize that deep learning architectures are effective tools for the rapid and accurate classification of forest fires, thereby making significant contributions to forest fire monitoring and management strategies.

**Keyword:** Deep Learning, Forest Fire, Convolutional Neural Network

## 1. INTRODUCTION

Fires are a high-impact disaster that can cause serious harm to human health both directly (death, burns, injuries) and indirectly (respiratory disorders due to smoke exposure, psychosocial effects, etc.). These disasters, which deepen environmental damage through biodiversity losses in ecosystems, changes in soil and atmospheric chemistry, and large-scale carbon emissions, also have multifaceted consequences on a global scale [1]. Forest fires are natural disasters that can have a significant impact on large ecosystems. Predicting and monitoring fires is crucial for preventing environmental damage and protecting human life and property. The causes of forest fires are multifactorial; human factors, climate change, and natural climatic conditions are among the most prominent causes [2]. According to CTIF's 2024 World Fire Statistics, a total of 3.7 million fires were recorded in 55 countries in 2022; 19,600 people lost their lives and 55,600 were injured in these fires. 30.7% of fires occurred in buildings (23.1% in residential buildings, 7.5% in other facilities), 12.4% in transportation vehicles, 1.4% in forests, 26.5% in grass/shrub cover, 13.5% in waste/storage areas, and 15.5% in other categories [3].

Forest fires have devastating effects on ecological integrity, biodiversity, the carbon cycle, and human safety. The most critical step in mitigating these effects is early detection and rapid response. Deep learning techniques represent a significant area of development in this field. Deep learning offers algorithms optimized for visual data analysis, holding great potential for detecting forest fires. The integration of multi-scale data from fixed tower cameras, unmanned aerial vehicles (UAVs), and satellite sensors using image-based deep learning methods aims to capture smoke and flame data with minute-by-minute accuracy to provide an alarm before the fire grows. Recent comprehensive reviews indicate that optical remote sensing, digital image processing, and advanced classification methods have gained significant momentum in early warning systems [4], [5].

Data sources can be grouped into three main categories: ground-based camera networks (observation towers and panoramic cameras), unmanned aerial vehicles (UAVs), and satellites. Models operating on real-time images from ground-based camera networks have been shown to be able to detect smoke within minutes of a fire starting; however, they carry the risk of false alarms due to similar textures such as clouds or fog. UAVs are effective at detecting small smoke signatures thanks to their low altitude and high resolution advantages; satellite systems, on the other hand, provide continuous monitoring with their wide area coverage and report high thermal anomalies through active fire products [6], [7], [8].

The detection of forests and the identification of related events such as fires using deep learning techniques have attracted significant attention in recent years. This increase stems primarily from the need to address the rising incidence of forest fires, which pose significant threats to ecological systems and human life. Advanced algorithms, including Convolutional Neural Networks (CNNs), proved themselves to be highly qualified for activities like pattern recognition, image division, and object identification, becoming a highly valuable tool for this field of work [9], [10].

In this study, forest fires were classified based on images by comparing four different advanced convolutional neural network (CNN) architectures (Xception, InceptionV3, DenseNet121, and EfficientNetV2). The models were analyzed using various performance metrics. The next section of the study summarizes the literature in the second chapter. The third chapter details the dataset used, the deep learning models, and the metrics employed. The fourth chapter presents the experimental results and evaluates the models comparatively. Finally, the fifth chapter summarizes the study's findings and offers recommendations for future work.

## 2. RELATED WORKS

On September 30, 2025, a search conducted under the heading “All Fields” using the keywords “fire,” “Densenet121,” “Xception,” “Inceptionv3,” “EfficientNetV2,” and “deep learning” yielded 712 records. These sources, compiled from different disciplines by year, include 562 articles, 122 conference papers, 30 review articles, 6 early access articles, 2 data documents, 2 retracted publications, and 1 book chapter. Publication dates range from 2001 to 2025, with the highest production year being 2024. The data was compiled based on author, journal, country, institution, keywords, and content abstracts. Analyses were performed on publications indexed in the Web of Science database. The distribution of keywords showing popularity over the years related to the topic is presented in Figure 1.

The deep learning framework called Fire-Net was presented by Seydi and colleagues for the detection of active fires and burned areas. In their study, they achieved 97.35% accuracy by combining both optical and thermal data from Landsat-8 images taken from various regions, and they also reliably detected small active fires. [11].

Xu et al. developed an effective forest fire detection model called CNTCB-YOLOv7. The aim of the study is to increase the effectiveness and accuracy of forest fire detection by combining the YOLOv7 algorithm with the ConvNeXtV2 and Conv2Former methods. According to the experiments conducted, the CNTCB-YOLOv7 model demonstrates better performance than the YOLOv7 algorithm, with a 1.39% increase in accuracy, 1.14% average precision and a 0.73% recall rate. [12].

Wang et al. propose a convolutional neural network (CNN)-based image recognition approach to automatically detect forest fires. By combining traditional image processing techniques with CNN technology, they aim to eliminate blindness and randomness issues in the learning process. The results obtained show that the convolutional neural network technique based on adaptive pooling has a higher recognition rate. [13].

In the study conducted by YÜKSEL, the remote sensing indices dNDVI, dSAVI, and dNBR were evaluated in order to identify the areas burned in the 2022 Mersin (Gülnar) forest fire. The research demonstrated that dNBR exhibited optimal performance among the various indices, with an accuracy rate of 88.89%, thereby providing an effective method for the rapid detection of areas damaged by forest fires. The study revealed that satellite images and remote sensing techniques can be used to identify areas damaged by fires. The identification of areas damaged by forest fires can be accomplished expeditiously and with a high degree of precision by means of satellite imagery and remote sensing techniques [14].

The study conducted by Kumari and colleagues developed the FireGuard model, a lightweight CNN architecture optimized for use in resource-limited environments such as manned or unmanned aerial vehicles. Experimental results show that the model outperforms traditional methods and existing deep learning models in detecting forest fires with high accuracy and recall rates. FireGuard enables firefighting agencies to intervene in a timely manner by providing early fire warnings [15].

Aksoy et al. propose a system that uses UAV-based image processing and deep learning technology known as SqueezeNet to detect fires in their early stages. The model was trained on the FIRE-Dataset (consisting of 999 images: 755 fires and 244 non-fires) on Kaggle using preprocessing steps such as Gaussian filtering and thresholding. When evaluating the performance of the architecture used in the study based on the confusion matrix, it achieved 96% accuracy, 98% sensitivity, 89% specificity, and 96% precision. This study could facilitate the early detection of fires and rapid intervention. [16].

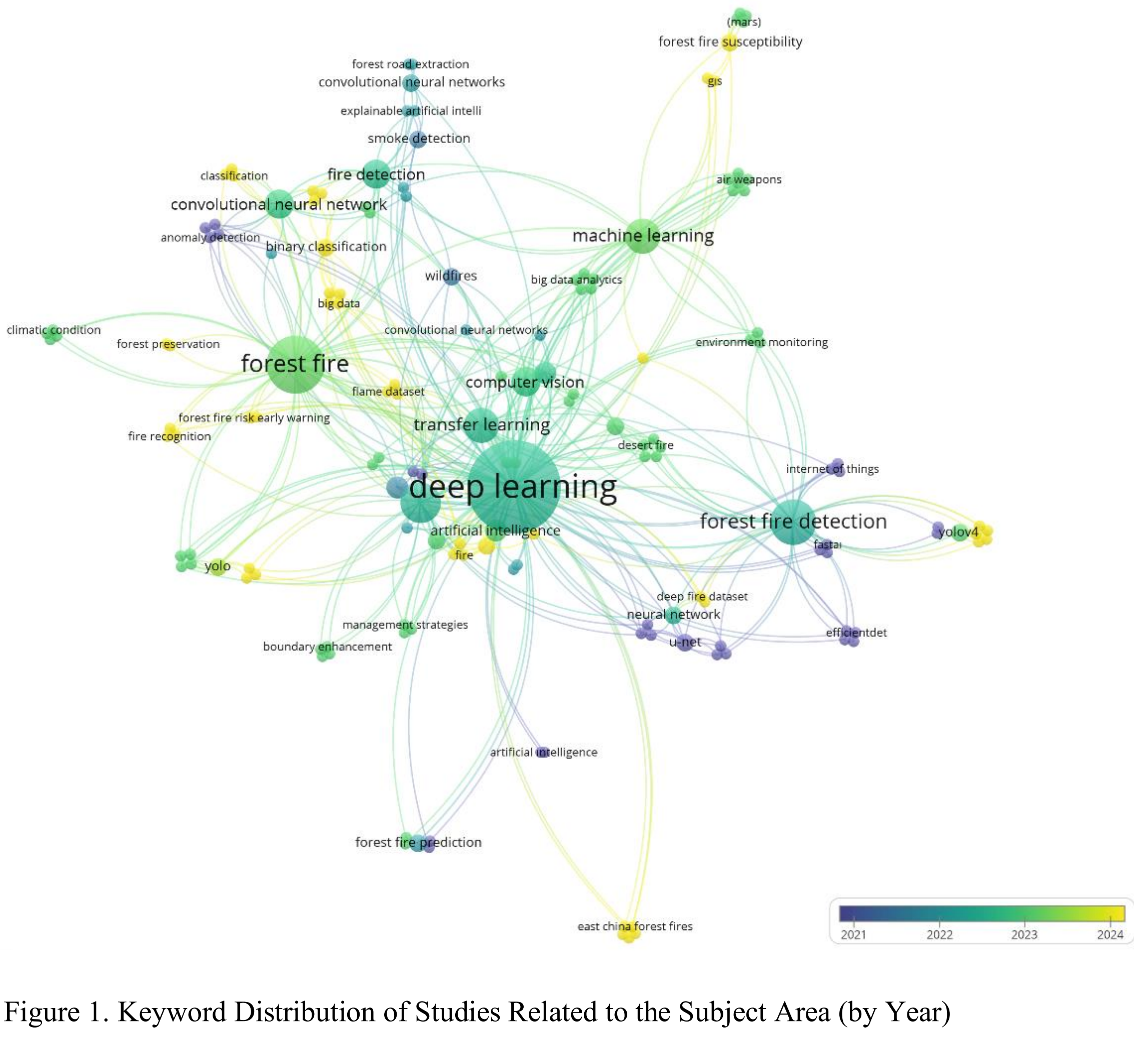



Figure 1. Keyword Distribution of Studies Related to the Subject Area (by Year)

## 3. MATERIALS AND METHODS

The image-based detection of forest fires was compared using four CNN architectures (Xception, InceptionV3, DenseNet121 and EfficientNetV2). Experiments were conducted using the 'Forest Fire

Images' open dataset, consisting of real-world images containing both fire and non-fire visual classes. This section provides information about the dataset and the CNN architectures employed.

### 3.1. Dataset

This study utilized Kaggle's "Forest Fire Images" dataset. The dataset under examination was created by combining numerous small datasets found on the internet. The dataset consists of two classes named "Fire" and "Not Fire" and is presented in two folders. The training set consists of 5,000 images divided into two subfolders, one containing fire images and the other containing non-fire images. Each of these subfolders contains 2,500 images. The test dataset folder consists of a total of 50 images, which are divided into two subfolders: 'fire' and 'not fire'. Each of these subfolders contains 25 images. Sample images from the dataset are shown in Figure 2 [17].

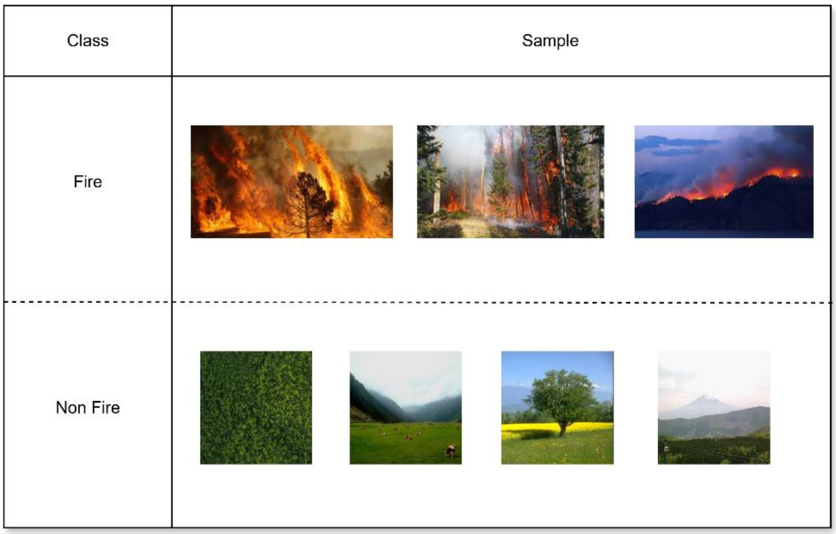



Figure 2. Dataset examples

### 3.2. Convolutional Neural Network Models

Convolutional Neural Networks (CNNs) are feedforward networks with a structure where information flows in only one direction, from input to output. Similarly, while artificial neural networks (ANNs) are inspired by biological neural processes, CNNs are directly inspired by the visual processing mechanisms of the human brain. Neurons located in the visual cortex, in particular, are arranged in a hierarchy, starting with the first layers that detect simple features (e.g., edges, lines) and progressing to higher-level cells that recognize increasingly complex structures (e.g., faces, object parts) [18], [19] .This hierarchical structure forms the basic principle of the CNN architecture.

CNNs are one of the fundamental building blocks of the deep learning field and have achieved significant success, particularly in image recognition, object detection, and computer vision applications. Their basic architecture consists of convolutional layers, pooling layers, and fully connected layers. Convolution layers significantly reduce the number of parameters based on local connection structures and weight sharing; they also enable the hierarchical learning of spatial features within the data. This feature enables CNNs to effectively identify and represent complex patterns in image data [20]. Pooling layers reduce computational load and model complexity, particularly by reducing the size of feature maps. Furthermore, these layers increase the model's generalization ability by providing a higher degree of robustness against transformational variations (e.g., translation, rotation). Thus, CNNs can automatically extract hierarchical representations (features) from low to high levels on high-dimensional visual data, largely eliminating the need for manual feature engineering. This feature enables CNNs to perform strongly on natural image data [21].

In this study, the Xception, InceptionV3, DenseNet121, and EfficientNetV2 convolutional neural network models were preferred. These architectures are widely preferred in forest fire detection due to their strong feature extraction capabilities and computational efficiency. Xception can capture small smoke and flame traces at low cost with its depth-separable convolution structure; InceptionV3 can detect fire areas of different sizes simultaneously thanks to its multi-scale filtering feature. DenseNet121 prevents small fire foci from being overlooked by preserving the information learned from previous layers with dense connections. EfficientNetV2, on the other hand, provides an optimal balance between accuracy and speed, delivering high performance in drone or satellite-based real-time monitoring systems [21], [22], [23], [24]. The basic characteristics of the models used are provided in Table 1.

**Table 1.** Comparison of key characteristics

| ***Model*** | ***Architecture Overview*** | ***Features*** | ***Complexity*** |
|---|---|---|---|
| Xception | The generalized form of the Inception architecture; all convolutions have been converted to depthwise separable convolutions. | High efficiency, strong feature extraction, transfer learning capability | Reduced computational complexity |
| Inceptionv3 | Factorization of large-core convolutions. | Better generalization via batch normalization, label smoothing, and regularization | Balanced accuracy–efficiency trade-off |
| Densenet121 | Dense connections where each layer feeds into all subsequent layers | Feature reuse, mitigated vanishing gradients, parameter efficiency | Lower parameter count, competitive accuracy |
| Efficientnetv2 | Fused-MBConv blocks with progressive learning strategy | Faster training, advanced data augmentation, scalable performance | Higher accuracy with fewer resources |

**3.2.1. Xception**

The Xception model proposed by François Chollet is an innovative architecture considered an advanced extension of the traditional Inception architecture in the field of deep learning. The model's key contribution lies in the systematic incorporation of depthwise separable convolutions, a technique distinct from the standard convolutions used in Inception modules. In this approach, spatial and channel-based features are processed separately; each channel is filtered independently and then combined using pointwise convolution. This approach leads to a significant reduction in the number of parameters and computational complexity while preserving or even increasing the model's representational power. The author's proposed hypothesis is presented as a more advanced and powerful version of the assumption underlying the Inception architecture. Therefore, the architecture has been named Xception, short for "Extreme Inception." Experimental results on the ImageNet and JFT datasets show that Xception achieves higher accuracy compared to Inception-V3 with a similar parameter size and demonstrates superior performance, particularly in transfer learning scenarios [25].

**3.2.2. InceptionV3**

The Inception-v3 model, proposed by Szegedy et al., is a deep convolutional neural network that represents a significant evolutionary step in the Inception architecture. Its most notable contribution is the factorised convolutions approach, which increases learning capacity while reducing computational cost. Large convolutions (e.g. 5x5) are specifically decomposed into smaller convolutions (e.g. two 3x3) or asymmetric convolutions (e.g. 1xN and Nx1) to improve parameter efficiency. Including batch normalization, label correction and auxiliary classifier methods has been shown to increase the model's generalization capacity. Furthermore, various optimization strategies were employed during the design process to mitigate the gradient vanishing issue. Experimental findings on the ImageNet dataset demonstrate that Inception-v3 achieves greater accuracy and lower error rates than previous versions [26].

**3.2.3. DenseNet121**

DenseNet121, a dense-connection-based convolutional neural network architecture aimed at improving parameter efficiency and reducing learning issues such as gradient vanishing, was developed by Huang and colleagues in 2017. In this architecture, each layer is directly connected to the outputs of all preceding layers. This provides significant advantages, particularly in terms of feature reuse and information flow efficiency, as each layer takes the feature maps produced by all previous layers as input. DenseNet121 consists of a softmax output layer, 121 convolutional layers, three pass-through layers, and four dense blocks. This architecture, with input images of size 224 × 224 × 3, facilitates the creation of high-performance deep network models using fewer parameters. The more effective and robust backpropagation of gradients throughout the network, particularly due to the dense connection structures, accelerates the learning process and increases the model's stability. Experiments conducted on the ImageNet dataset show that DenseNet121 performs comparably to ResNet in terms of both classification accuracy and computational cost. The results demonstrate that DenseNets are effective and efficient among deep learning models [27].

#### 3.2.4. EfficientNetV2

EfficientNetV2, designed to reduce model complexity and training time, is an enhanced version of the EfficientNet architecture developed by Tan and Le. The model has a structure based on the principle of progressive learning. In the initial stage, the model is trained with low-resolution images and simple data augmentation methods, while input sizes and transformation complexity increase over time. This gradual approach allows the model to start learning more stably and reduces the risk of overfitting. Fused-MBConv optimized convolution blocks have significantly improved training time by reducing the computational intensity of depth-separable convolutions. Experimental studies have shown that EfficientNetV2 exhibits higher accuracy rates and lower computational costs on the ImageNet dataset compared to previous models [28].

### 3.3. Evaluation Metrics

The following evaluation metrics were used in this study:

- **Accuracy:** Indicates the proportion of examples correctly classified by the model across all examples. This metric is used to evaluate overall performance; however, its interpretation may be misleading in imbalanced datasets.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

- **Precision:** This value indicates the ratio of examples predicted to be positive that are actually positive.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

- **Recall:** This metric measures the number of true positive examples that can be correctly identified.

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

- **F1-score:** The harmonic mean of Precision and Recall.

$$\text{F1} - \text{score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

The total numbers of negative and positive class examples are represented by the symbols N and P, respectively. In the proposed classification, the P value represents fire events, while N represents non-fire events. In this context, the concepts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) correspond to true positive, true negative, false positive, and false negative examples, respectively.

In this study, the applications were performed using a forest fire dataset. To implement the research, a Collab GPU with an A100 GPU hardware accelerator, offering 167 GB of RAM and 80 GB of GPU, was used.

## 4. EXPERIMENTAL RESULTS

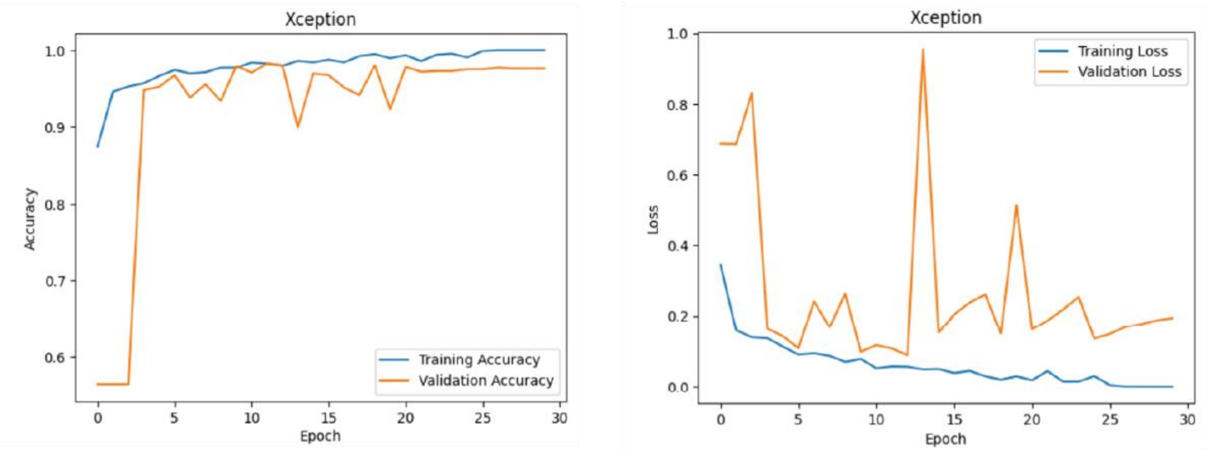
This section analyses the metrics and performance values used by four different deep learning architectures (Xception, InceptionV3, DenseNet121 and EfficientNetV2) to classify forest fire images. The models were tested using the Kaggle 'Forest Fire Images' dataset. The evaluation metrics used were training and validation accuracy, training and validation loss, and precision, recall and F1-score.

The models were trained using the same training and test datasets and hyperparameters (learning rate, number of epochs and batch size). Accuracy, precision, recall and F1-score were used as evaluation metrics. Table 2 shows the performance comparison of the proposed models. As can be seen in Table 1, Xception achieved the highest accuracy rate and performance. Additionally, its precision, recall and F1-score values are superior to those of other models.

**Table 2.** Performance comparison of the proposed models

| *Model* | *Acc* | *Val_Acc* | *Loss* | *Val_Loss* | *Precision* | *Recall* | *F1-Score* |
|---|---|---|---|---|---|---|---|
| *Xception* | 1.0000 | 0.9761 | 0.0001 | 0.1938 | 0.9760 | 0.9758 | 0.9761 |
| *InceptionV3* | 0.9667 | 0.9685 | 0.1041 | 0.1028 | 0.9692 | 0.9675 | 0.9685 |
| *DenseNet121* | 0.9805 | 0.9664 | 0.0565 | 0.1569 | 0.9658 | 0.9671 | 0.9664 |
| *EfficientNetV2* | 0.9959 | 0.9620 | 0.0098 | 0.2422 | 0.9620 | 0.9613 | 0.9620 |

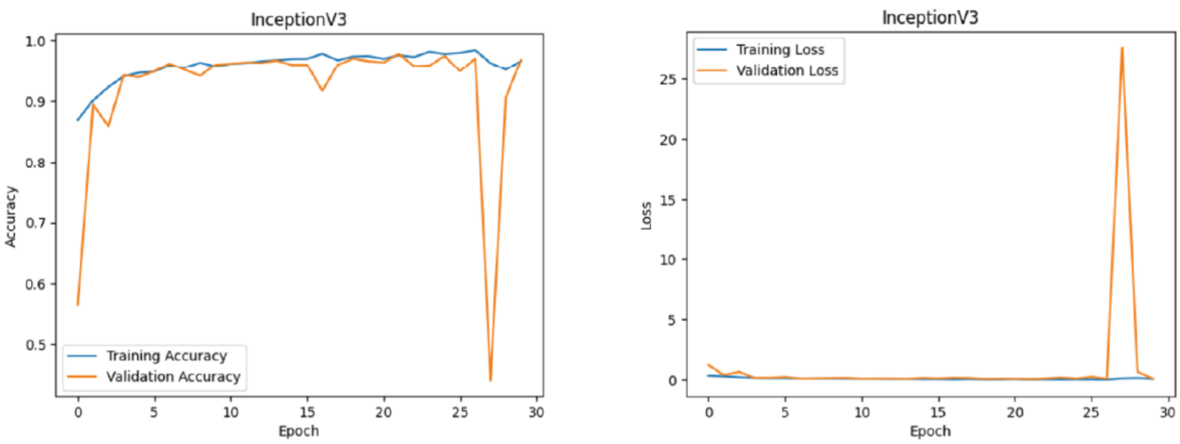
Table 2 shows that the Xception model outperformed all other models in all metrics, achieving 100% accuracy, 97.61% precision, 97.58% recall, and an F1-score of 97.61 on the test data. Figure 3.a shows that the training accuracy reached 100% and the validation accuracy reached 97.61%. Figure 3.b shows the change in training and validation loss depending on the number of epochs. Examining the graph, it can be seen that the final training loss in the Xception model reached 0.0001 and the validation loss reached 0.1938.




(a) (b)

Figure 3. Xception Performance

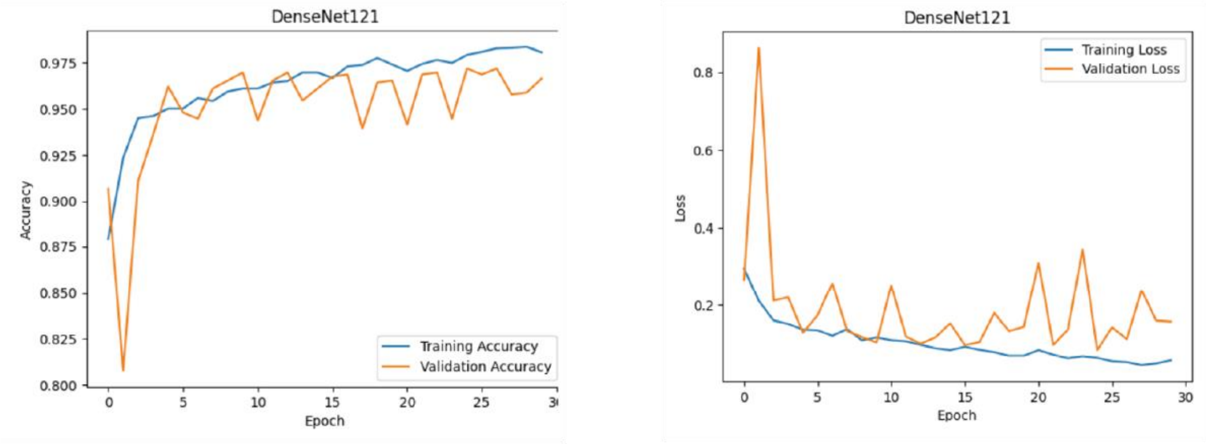
As shown in Table 1, the InceptionV3 model achieved 96.67% accuracy, 96.92% precision, 96.75% recall, and 96.85% F1-score. Figure 4.a illustrates that the training accuracy reached 96.67%, while the validation accuracy attained 96.85%. Figure 4.b shows that the training loss was recorded at 0.1041, whereas the validation loss was observed at 0.1028.




(a) (b)

Figure 4. InceptionV3 Performance

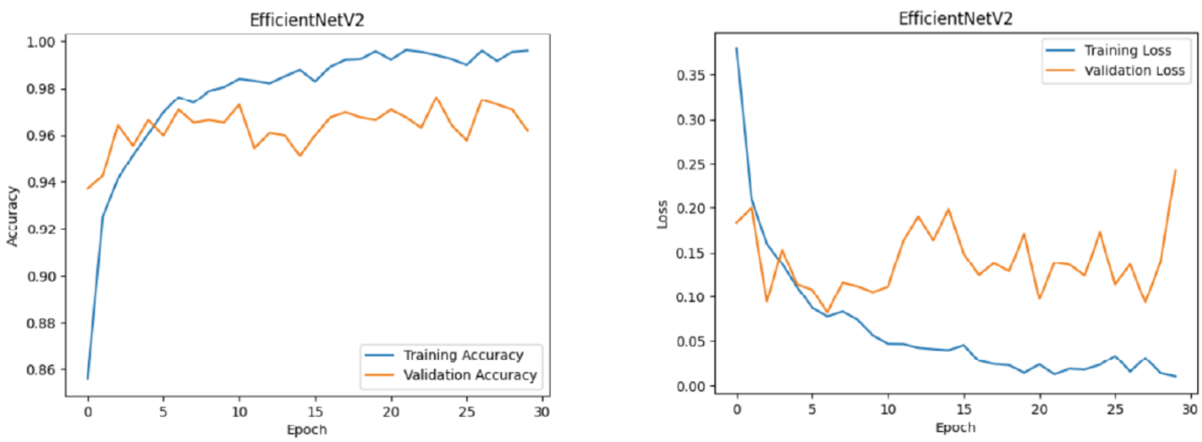
According to Table 1, the DenseNet121 model demonstrated strong performance, achieving 98.05% accuracy, 96.58% precision, 96.71% recall, and 96.64% F1-score. As illustrated in Figure 5.a, the training accuracy reached 98.05%, while the validation accuracy attained 96.64%. Figure 5.b shows that the training loss was 0.0565, whereas the validation loss was observed at 0.1569.




(a) (b)

Figure 5. DenseNet121 Performance

According to Table 1, the EfficientNetV2 model exhibited strong performance, achieving 99.59% accuracy, 96.20% precision, 96.13% recall, and 96.20% F1-score. As illustrated in Figure 6.a, the training accuracy reached 99.59%, while the validation accuracy attained 96.20%. Figure 6.b shows that the training loss was recorded at 0.0098, whereas the validation loss was observed at 0.2422.




(a) (b)

Figure 6. EfficientNetV2 Performance

Examining the confusion matrices in Figure 7 reveals that all models can accurately distinguish between fire and non-fire classes. The Xception model produced the most balanced results, achieving 390 correct fire classifications and 510 correct non-fire classifications while misclassifying only 22 examples. The InceptionV3 model was also successful, achieving 382 correct fire classifications and 511 correct non-fire classifications; however, it produced more errors in the fire class. DenseNet121 also performed well, with 393 correct fire examples and 498 correct non-fire examples; however, relatively more false positives were observed in the non-fire class. Similarly, the EfficientNetV2 model showed high performance with 382 correct fire examples and 505 correct non-fire examples. Overall, the Xception model demonstrated superior fire detection results compared to the other models, achieving the lowest error rate.

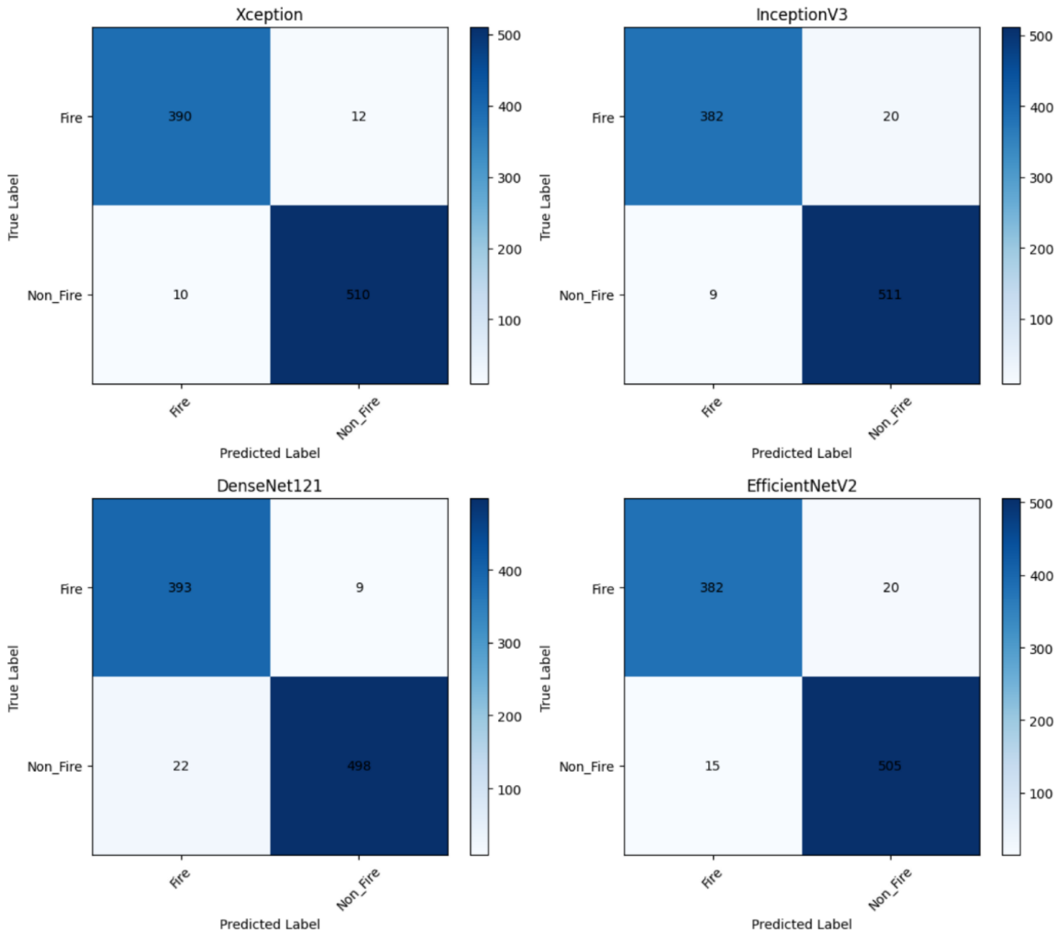



Figure 7. Confusion Matrix of the Models

## 5. CONCLUSIONS

In this study, four different deep neural network architectures were compared for classifying forest fires. All models used for training and validation yielded high accuracy rates and successful results. However, performance differences revealed important issues related to learning capacity, generalization ability, and overfitting tendencies among the architectures.

The Xception model performed better than the others, achieving 100% training accuracy and 97.61% validation accuracy, making it the best-performing model. Precision, recall, and F1 score values also showed that the Xception architecture was more advanced. Although the performance of the InceptionV3, DenseNet121, and EfficientNetV2 models lagged behind the Xception model, they still achieved high accuracy in forest fire classification. Confusion matrices showed that all models effectively distinguished between fire and non-fire classes. However, the Xception model produced more balanced results by minimizing misclassifications. This indicates that the Xception architecture is an excellent candidate for fire early detection systems.

Graphical analyses revealed that the Xception and EfficientNetV2 models showed a steady increase in validation accuracy throughout training and did not exhibit overfitting tendencies. These models can provide stable classification performance under the critical conditions caused by forest fires. Visual analyses confirmed that the Xception and EfficientNetV2 models steadily increased validation accuracy throughout training without showing significant signs of overfitting.

The findings of this study demonstrate that deep learning models are effective tools for forest fire detection and classification. However, broader integration is needed for real-world applications. Future studies will integrate deep neural networks with unmanned aerial vehicle (UAV) and satellite imagery to develop real-time fire detection systems. Additionally, we plan to integrate trained models with mobile devices and cloud systems. This will allow field teams to perform real-time data analysis and provide more detailed classifications, such as the degree of fire spread, intensity, and risk level.

In summary, this paper validates that deep learning architectures can classify forest fires with high accuracy. Therefore, disaster management systems should fully integrate real-time, autonomous, and multi-source data systems to become more effective. Studies in this area will promote environmental sustainability and save lives.

## REFERENCES

[1] D. Bowman *et al.*, "Fire in the Earth System," *Science*, vol. 324, pp. 481–484, May 2009, doi: 10.1126/science.1163886.

[2] B. Calda, N. An, M. T. Turp, and L. Kurnaz, "İklim Değişikliğinin Akdeniz Havzasındaki Orman Yangınlarına Etkisi," *International Journal of Advances in Engineering and Pure Sciences*, vol. 32, no. 1, pp. 15–32, 2020, doi: 10.7240/jeps.571001.

[3] CTIF, "World Fire Statistics | CTIF - International Association of Fire Services for Safer Citizens through Skilled Firefighters." Accessed: Aug. 14, 2025. [Online]. Available: https://www.ctif.org/world-fire-statistics

[4] R. N. Vasconcelos *et al.*, "Fire Detection with Deep Learning: A Comprehensive Review," *Land (Basel)*, vol. 13, no. 10, 2024, doi: 10.3390/land13101696.

[5] A. Saleh, M. A. Zulkifley, H. H. Harun, F. Gaudreault, I. Davison, and M. Spraggon, "Forest fire surveillance systems: A review of deep learning methods," *Heliyon*, vol. 10, no. 1, p. e23127, 2024, doi: https://doi.org/10.1016/j.heliyon.2023.e23127.

[6] NASA VIIRS Land Team, "NASA VIIRS Active Fire Product," 2025. [Online]. Available: https://viirsland.gsfc.nasa.gov/Products/NASA/FireESDR.html

[7] K. Govil, M. L. Welch, J. T. Ball, and C. R. Pennypacker, "Preliminary Results from a Wildfire Detection System Using Deep Learning on Remote Camera Images," *Remote Sens (Basel)*, vol. 12, no. 1, 2020, doi: 10.3390/rs12010166.

[8] M. Mukhiddinov, A. B. Abdusalomov, and J. Cho, "A Wildfire Smoke Detection System Using Unmanned Aerial Vehicle Images Based on the Optimized YOLOv5," *Sensors*, vol. 22, no. 23, 2022, doi: 10.3390/s22239384.

[9] J. Feng, D. Zhu, and + L., "A Novel Method for Forest Fire Detection Based on Convolutional Neural Network," 2018. doi: 10.18178/wcse.2018.06.047.

[10] S. B. KUKUK and Z. H. Kilimci, "Comprehensive Analysis of Forest Fire Detection Using Deep Learning Models and Conventional Machine Learning Algorithms," 2021. doi: 10.22399/ijcesen.950045.

[11] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, "Fire-Net: A Deep Learning Framework for Active Forest Fire Detection," 2022. doi: 10.1155/2022/8044390.

[12] Y. Xu, J. Li, L. Zhang, H. Liu, and F. Zhang, "CNTCB-YOLOv7: An Effective Forest Fire Detection Model Based on ConvNeXtV2 and CBAM," 2024. doi: 10.3390/fire7020054.

[13] Y. Wang, L. M. Dang, and J. Ren, "Forest Fire Image Recognition Based on Convolutional Neural Network," 2019. doi: 10.1177/1748302619887689.

[14] K. YÜKSEL, "Yanan Orman Alani Tespitinde Farkli Uzaktan Algilama İndislerinin Değerlendirilmesi: 2022 Yili Mersin (Gülnar) Orman Yangini Örneği," 2022. doi: 10.57165/artgrid.1179074.

[15] P. L. Kumari, Z. Abid, A. Abid, and G. D. Saxena, "Robust Forest Fire Detection Using Deep Convolutional Neural Networks," vol. 01, no. 01, pp. 49–57, 2024, doi: 10.58599/ijsmcse.2024.1111.

[16] B. Aksoy, K. Korucu, Ö. Çalışkan, Ş. Osmanbey, and H. D. Halis, "İnsansız Hava Aracı ile Görüntü İşleme ve Yapay Zekâ Teknikleri Kullanılarak Yangın Tespiti: Örnek Bir Uygulama," *Duzce University Journal of Science and Technology*, vol. 9, no. 6, pp. 112–122, 2021, doi: 10.29130/dubited.1016195.

[17] Prasad Mohnish Sai, "Forest Fire Images," 2022, *Kaggle*. [Online]. Available: https://www.kaggle.com/datasets/mohnishsaiprasad/forest-fire-images

[18] D. H. Hubel and T. N. Wiesel, "Receptive fields, binocular interaction and functional architecture in the cat's visual cortex," *J Physiol*, vol. 160, no. 1, pp. 106–154, Jan. 1962, doi: https://doi.org/10.1113/jphysiol.1962.sp006837.

[19] D. H. Hubel and T. N. Wiesel, "Receptive fields of single neurones in the cat's striate cortex," *J Physiol*, vol. 148, no. 3, pp. 574–591, Oct. 1959, doi: https://doi.org/10.1113/jphysiol.1959.sp006308.

[20] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[21] W. Rawat and Z. Wang, "Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review," *Neural Comput*, vol. 29, pp. 2352–2449, Sep. 2017, doi: 10.1162/NECO_a_00990.

[22] A. Biswas, S. K. Ghosh, and A. Ghosh, "Early Fire Detection and Alert System using Modified Inception-v3 under Deep Learning Framework," *Procedia Comput Sci*, vol. 218, pp. 2243–2252, 2023, doi: https://doi.org/10.1016/j.procs.2023.01.200.

[23] H. C. Reis and V. Turk, "Detection of forest fire using deep convolutional neural networks with transfer learning approach," *Appl Soft Comput*, vol. 143, p. 110362, 2023, doi: https://doi.org/10.1016/j.asoc.2023.110362.

[24] V. E. Sathishkumar, J. Cho, M. Subramanian, and O. S. Naren, "Forest fire and smoke detection using deep learning-based learning without forgetting," *Fire Ecology*, vol. 19, no. 1, p. 9, 2023, doi: 10.1186/s42408-022-00165-0.

[25] F. Chollet, "Xception: Deep Learning With Depthwise Separable Convolutions," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jul. 2017.

[26] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," 2015. [Online]. Available: https://arxiv.org/abs/1512.00567

[27] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 2261–2269. doi: 10.1109/CVPR.2017.243.

[28] B. Wang, G. Huang, H. Li, X. Chen, L. Zhang, and X. Gao, "Hybrid CBAM-EfficientNetV2 Fire Image Recognition Method with Label Smoothing in Detecting Tiny Targets," *Machine Intelligence Research*, vol. 21, no. 6, pp. 1145–1161, 2024, doi: 10.1007/s11633-023-1445-5.