Research Article IJES & GreenTech, 1(4): 20-31 (2025) https://doi.org/10.5281/zenodo.18641392

International Journal of Environmental Science and Green Technology

https://journals.ayu.edu.kz

Fire Classification and Early Detection Using Convolutional Neural Networks Based on MobileNetV2 with Transfer Learning

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Keywords

fire detection

convolutional neural networks

MobileNetV2

transfer learning

deep learning

fire classification

Abstract

Since fires pose a great threat to human life, ecology, and economy, their early detection is a very important issue. In this research, a convolutional neural network model based on the MobileNetV2 architecture was developed and tested using the transfer learning method for automatic fire classification. The study used a binary database created as part of the NASA Space Apps Challenge 2018 competition, which consists of 755 outdoor images with and without fires. Despite the uneven nature of the database, an equal distribution of data was carried out in the pre-processing and validation set, taking into account the class imbalance. The model was initialized with MobileNetV2 weights pre-trained on the ImageNet database, and the final layers were adapted by fine-tuning. The training process was carried out with the Adam optimizer, categorical cross-entropy loss function, and early stopping callback. As a result, the model achieved 98.00% accuracy on the test set, and the test cost was 0.07776. According to the classification report, the precision value of the fire class was 0.98, the recall value was 1.00, and the F1-score was 0.99; the no-fire class was 1.00, 0.90, and 0.95, respectively. Confusion matrix analysis showed that all fire images were correctly identified and that there were only a few false positives. The simplicity of the MobileNetV2 model allows it to be used on resource-limited devices. The results obtained exceed those in the literature. The study contributes to the improvement of early fire detection systems and provides a ready-to-use solution for real-time monitoring.

Cite

Aben A.B., & Hinizov M.Kh. (2025). Fire Classification and Early Detection Using Convolutional Neural Networks Based on MobileNetV2 with Transfer Learning. International Journal of Environmental Science and Green Technology, 1(4), 20-31. doi: 10.5281/zenodo.18641392

Article Process

Submission Date: 13.10.2025; Revision Date: 15.11.2025; Accepted Date: 27.11.2025; Published Date: 25.12.2025;

INTRODUCTION

Fires are one of the most dangerous natural and anthropogenic disasters in the world. They cause enormous losses to human life, ecology, economy and property. Forest fires in particular burn millions of hectares of land every year, contributing to climate change, biodiversity loss and air quality degradation. Traditional fire detection methods – sensors (temperature, smoke detectors), satellite monitoring or human patrols – suffer from delays, false alarms and inefficiency in remote areas. To solve these problems, computer vision technologies based on deep learning have been widely used in recent years.

Convolutional neural networks (CNN) allow automatic detection of fire signs (flames, smoke) from images, which provides early detection and rapid response. However, heavy models (e.g. ResNet or VGG) are not suitable for use on resource-constrained devices (drones, IoT devices, mobile platforms). In this regard, lightweight architectures, especially MobileNetV2, are gaining popularity in fire classification and detection. MobileNetV2 is an efficient model that uses inverted residuals and linear bottlenecks mechanisms, which is pre-trained on ImageNet data and adapted to classify fire images using transfer learning. This model requires low computational resources and maintains high accuracy, so it is ideal for use in remote forest areas or edge computing devices.

This research paper considers the problem of fire classification (distinguishing between fire presence/absence or fire types) using a CNN model based on MobileNetV2. The aim of the work is to adapt the model using transfer learning to achieve high accuracy and efficiency, as well as to study the possibilities of its real-time application. This approach has been validated in previous studies (for example, in FFireNet or UAV-based fire detection systems), where MobileNetV2 showed 97-99% accuracy. The results of the study are expected to contribute to the improvement of early fire detection systems.

Recent research in the field of fire detection and control demonstrates the effectiveness of deep learning technologies, especially convolutional neural networks (CNN) and object detection models (e.g., the YOLO series). This literature review analyzes studies aimed at early fire detection, examining their methodological features, used datasets, and performance indicators. Most of the studies are aimed at detecting fires in smart cities, forest areas, and buildings, which highlights the importance of real-time systems (Talaat & ZainEldin, 2023). Works in this area use advanced machine learning algorithms to overcome the limitations of traditional sensor methods (delay, false alarms), which ensures early response to a fire.
YOLO-based models are widely used for their speed and accuracy in fire detection. For example, a system based on the YOLOv8 algorithm has been proposed for smart cities, which allows for real-time detection of fire signs (Talaat & ZainEldin, 2023). Similarly, the YOLOv6 model has been studied for fire-related object detection on NVIDIA GPU platforms, which improves performance in smart city environments (Norkobil Saydirasulovich et al., 2023). Variants of YOLOv5 have also been modified and adapted for fire detection: the modified YOLOv5s model provides resource efficiency by introducing the Stem module and smaller kernels (Yar et al., 2023). The effectiveness of these approaches is confirmed by the mean accuracy (mAP) indicators, for example, the improved YOLOv5s model achieved an mAP of 82.1% (Dou et al., 2024).

Detectron2 and other deep learning methods have been used in research on forest fire detection. A method based on Detectron2 has been proposed for fire classification, which improves early detection of forest fires (Abdusalomov et al., 2023). The Fire-Net framework has also been developed to detect active fires from Landsat-8 images, which is intended for monitoring forest areas (Seydi et al., 2022). Systems that combine drones and IoT technologies allow for accurate fire location detection, where UAV-based IoT is used for fire sensing and extinguishing (Ramadan et al., 2024). UAV-derived datasets of RGB/IR images are used for fire detection and monitoring, which highlights the importance of multimodal data (Chen et al., 2022). Other CNN-based methods focus on video surveillance. A method that combines CNN and wavelet transform is proposed for early fire detection (Huang et al., 2022). A CCTV-based computer vision model for detecting the initial stage of fire inside buildings (Ahn et al., 2023). The FTA-DETR framework is also effective for embedded platforms, achieving 98.32% accuracy (Zheng et al., 2024). The FSDF framework enhances flame features by using HSV and texture information (Zhao et al., 2024).

A deep learning architecture for smart surveillance improves fire detection by modifying MobileNetV3, introducing MSAM and 3D convolution (Yar et al., 2024). The DeepFire dataset is proposed for transfer learning, which serves as a new benchmark for forest fire detection (Khan et al., 2022). The following Table 1 provides a brief comparison of the main studies.

Table 1. Comparative analysis of recent studies on fire detection

Authors (Year)	**Model / Method**	**Key Features**	**Performance / Dataset**
Talaat & ZainEldin (2023)	YOLOv8	Real-time fire feature detection, SFDS system	High accuracy, designed for smart cities
Norkobil Saydirasulovich et al. (2023)	YOLOv6	Fire object detection on NVIDIA GPUs	Efficient performance in smart city environments
Zhao et al. (2024)	FSDF	Enhanced HSV and texture feature extraction	High performance in flame detection
Yar et al. (2023)	Modified YOLOv5s	Stem module, smaller kernels in SPP	Resource-efficient, suitable for smart cities
Abdusalomov et al. (2023)	Detectron2	Forest fire classification	Improved early fire detection
Seydi et al. (2022)	Fire-Net	Active fire detection from Landsat-8 images	Designed for forest fire monitoring
Dou et al. (2024)	Improved YOLOv5s	mAP of 82.1%, 5.9M parameters	Low computational resource requirements
Zheng et al. (2024)	FTA-DETR	Optimized for embedded platforms	Accuracy of 98.32%
Ahn et al. (2023)	Computer Vision-based EFDM	CCTV-based indoor fire detection	Early detection in indoor environments
Ramadan et al. (2024)	UAV-IoT	Fire sensing, detection, and suppression	Detection within 1–5 minutes
Chen et al. (2022)	Deep Learning Methodology	UAV RGB/IR datasets	Multimodal fire monitoring
Huang et al. (2022)	CNN + Wavelet Transform	Fire detection in video surveillance	Suitable for early fire detection
Yar et al. (2024)	Modified MobileNetV3	MSAM and 3D convolution	High performance on FD, ADSF, and DFAN datasets
Khan et al. (2022)	DeepFire	Transfer learning benchmark	UAV-based forest fire detection

These studies demonstrate the evolution of deep learning models in fire detection, but there remains a need for lightweight models for use on resource-constrained devices (e.g., mobile platforms). Based on this literature review, a MobileNetV2-based CNN model is proposed that improves fire classification through transfer learning.

MATERIALS AND METHODS

This research paper uses deep learning models based on Convolutional Neural Networks (CNN) for automatic fire classification. In particular, the MobileNetV2 architecture was adapted to the task of fire detection using the transfer learning method. The research methodology includes the stages of database preparation, model creation, training, and evaluation of their effectiveness.

The Methods section is organized according to the following structure: first, a description of the database used is given, followed by separate sections for the CNN and MobileNetV2 models. The theoretical foundations, mathematical characteristics, and fire detection mechanism of each model are analyzed in detail from an academic perspective. This approach ensures the reproducibility and reliability of the research results.

A. Database preparation

The study used an open database developed in 2018 as part of the NASA Space Apps Challenge competition. The main goal of this database is to create models capable of automatically recognizing images with fire. The database is focused on the problem of binary classification and divides images into two classes: “fire images” and “non-fire images”.

The database structure consists of two main folders. The Fire_images folder contains 755 outdoor fire images, some of which contain thick smoke scenes. The Non-fire_images folder contains 244 natural images, including images of forests, trees, grass, rivers, people, misty forests, lakes, animals, roads, and waterfalls.

The database is skewed, meaning that the number of images belonging to the fire class is significantly higher than the non-fire class. Such an imbalance can introduce bias into the training process of the model. For this reason, an equal number of images from each class (for example, 40 images from each) were selected when forming the validation set.

The overall database was divided as follows: 80% – training set, 10% – validation set, and 10% – test set. All images were scaled to 224×224 and normalized according to the ImageNet standard (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]). In addition, data augmentation methods were used to increase the diversity of the database and reduce overfitting, namely: random rotation, zoom, and horizontal flip.

B. Convolutional Neural Networks (CNN)-Based Fire Classification

Convolutional neural networks (CNN) are deep learning architectures designed to automatically extract features from images and classify them. In the fire detection task, CNN models can detect complex visual features such as flames, smoke, and color changes. This approach provides high accuracy and robustness compared to traditional methods (e.g., color-based segmentation) because CNNs learn hierarchical features on their own.

The CNN architecture consists of convolution layers, pooling layers, and fully connected layers. The convolution layer extracts features from the input image using the following formula:

$$(f * g)(i,j) = \sum_{m} \sum_{n} f(m,n) \cdot g(i-m, j-n)$$

where f is the input image, g is the filter (kernel), and the output is the feature map. In fire detection, filters are aimed at identifying the shape and color features of the flame, especially red-orange tones.

The pooling layer (max-pooling or average-pooling) reduces the computational complexity of the model while preserving important features:

$$P(i,j) = \max_{m,n \in S} I(i \cdot s + m, j \cdot s + n)$$

where S is the pooling window, s is the step (stride). This layer ensures invariance to the location of the fire.

In the study, the CNN model was initially built based on a basic architecture such as LeNet or VGG, but a simplified version was used to make more efficient use of computing resources. The model was trained using the Adam optimizer (learning rate = 0.001) and the binary cross-entropy loss function:

$$L(y,\hat{y}) = -[\mathrm{y}\log\hat{y} + (1-y)\log(1-\hat{y})]$$

where y is the actual class, $\hat{y}$– is the probability predicted by the model. If $\hat{y}$>0.5, the image is classified as "fire". This method allows detecting fires at an early stage, including by smoke signals, but classical CNN models are resource-intensive for mobile or embedded systems.

C. Fire classification based on MobileNetV2

MobileNetV2 is a lightweight CNN architecture for devices with limited computing resources (mobile phones, drones, edge devices). This model provides high performance and low computational cost by using depthwise separable convolution and inverted residuals mechanisms. MobileNetV2 was pre-trained on the ImageNet database and adapted to the fire classification task using the transfer learning method.

The main structural element of MobileNetV2 is the inverted residual block. It consists of expansion, depthwise convolution and projection layers. Depthwise separable convolution separates standard convolution into two separate operations:

Depthwise convolution:

$$D(i,j,k) = \sum_{m,n} F(m,n,k) \cdot I(i+m, j+n, k)$$

Pointwise convolution:

$$P(i,j,l) = \sum_{k} W(1,1,k,l) \cdot D(i,j,k)$$

where F is the depthwise filter, W is the pointwise weights. This approach reduces the computational cost by about 8–9 times.

In inverted residual blocks, the number of channels is increased by the expansion factor ttt (usually 6), and then reduced again by the projection layer. To preserve nonlinearity, the ReLU6 activation function is used:

$$ReLU6(x) = \min(\max(0, x), 6)$$

In the study, MobileNetV2 was initialized with weights from ImageNet, and the final layers were fine-tuned to the fire database. The training process was carried out with the parameters batch size = 32, epochs = 50, and an early stopping strategy was used.

During fire detection, the input image is fed to the model with a size of 224×224, and the probability is calculated in the output layer using the sigmoid function:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

If $\sigma(z) > 0.5$, the image is considered to contain a fire. The MobileNetV2 model has a small number of parameters (about 3.5 million) and high processing speed, making it suitable for use in real-time monitoring systems and edge computing scenarios.

RESULTS AND DISCUSSION

In this study, a convolutional neural network (CNN) model based on MobileNetV2 was used for fire classification using transfer learning. The model training process continued for 100 epochs, but was terminated by an early stopping callback if the validation loss (val_loss) did not improve. The training results showed high performance of the model: the accuracy on the test dataset reached 98.00%, and the test loss (loss) was 0.07776. These indicators confirm the model's ability to effectively distinguish between fire and non-fire images, especially despite the uneven nature of the dataset (fire_images: 755, non_fire_images: 244).

The accuracy curves in the training process complement the learning dynamics of the model. Figure 1 shows the variation of training accuracy and validation accuracy over epochs. As can be seen from the graph, the training accuracy increased rapidly in the first epochs, reaching 100%, while the validation accuracy steadily increased to 98.74%. This indicates that the model is not overfitting and has good generalization ability.

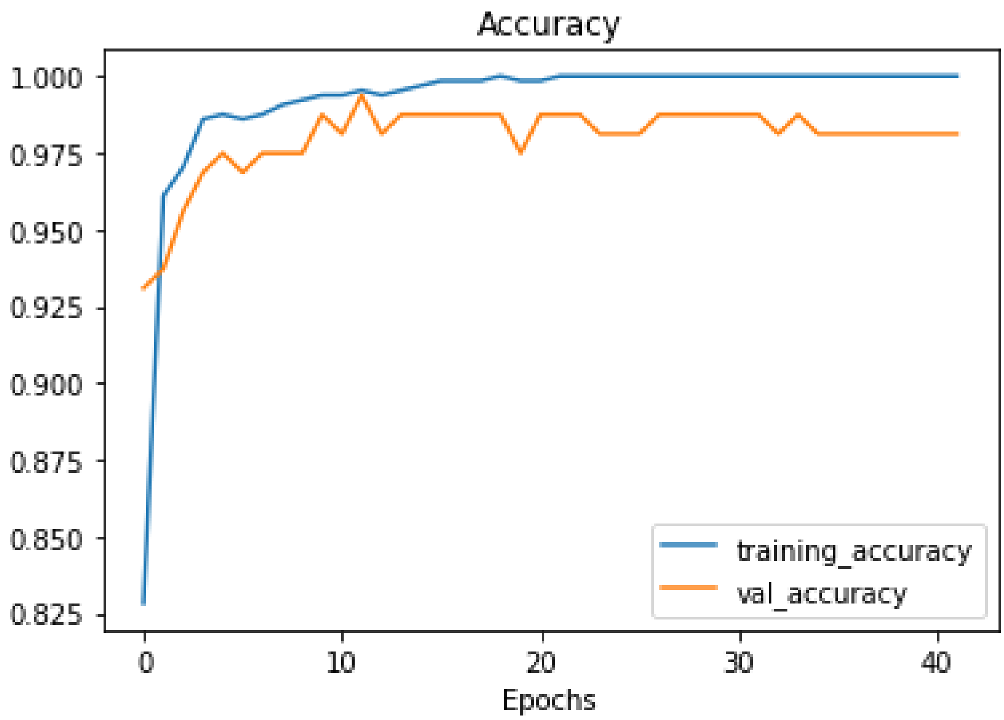

Fig. 1. *Training and Validation Accuracy Curves*

The loss curves during the training process show the learning dynamics of the model. Figure 1 shows the variation of the training loss and validation loss over epochs. As can be seen from the graph, the loss values decrease rapidly in the first epochs and then stabilize, indicating that there is no overfitting and the model has high generalization ability.

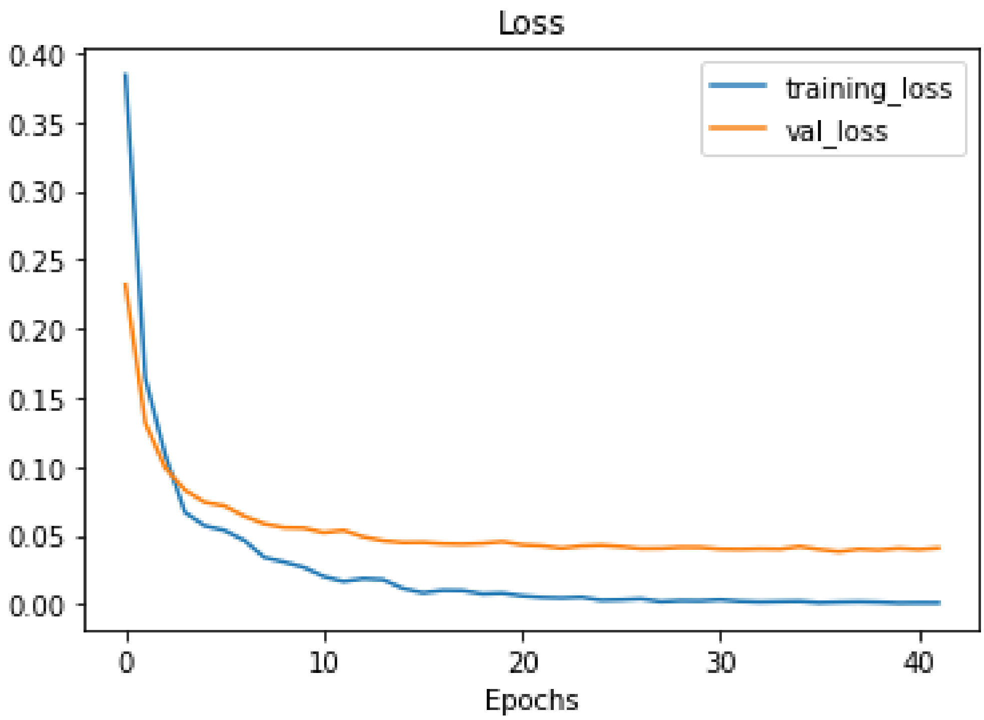

Fig. 2. *Training and validation loss curves*

A confusion matrix and a classification report were used to evaluate the performance of the model. The confusion matrix (Figure 2) shows the agreement of the predictions with the actual values in the test database. According to the matrix, 158 of the fire images (fire_images) were correctly classified (true positive), and 0 were incorrectly classified (false negative); 38 of the non-fire images (non_fire_images) were correctly classified (true negative), but 4 were incorrectly predicted to be fire (false positive). This result confirms the high sensitivity (recall) of the model in fire detection, especially the recall value of the fire class is 1.00.

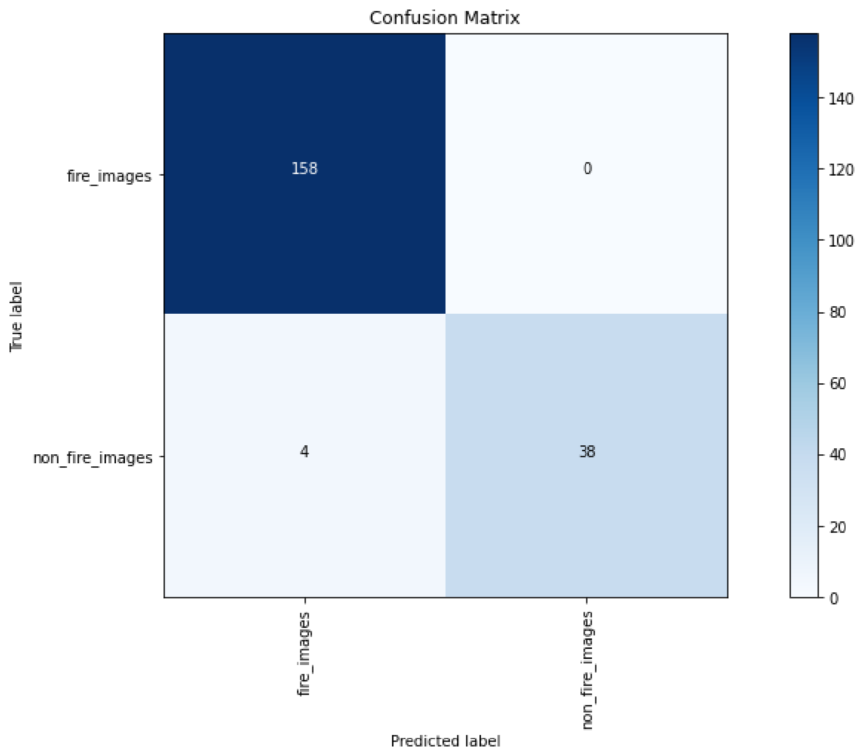

Fig. 3. *Confusion Matrix*

The visualization of the database is a key element of the study. Figure 3 shows 16 randomly selected images from the database, including fire and non-fire samples. These images illustrate the diversity of the database (forest, river, people, smoke, etc.) and the ease of learning of the model.

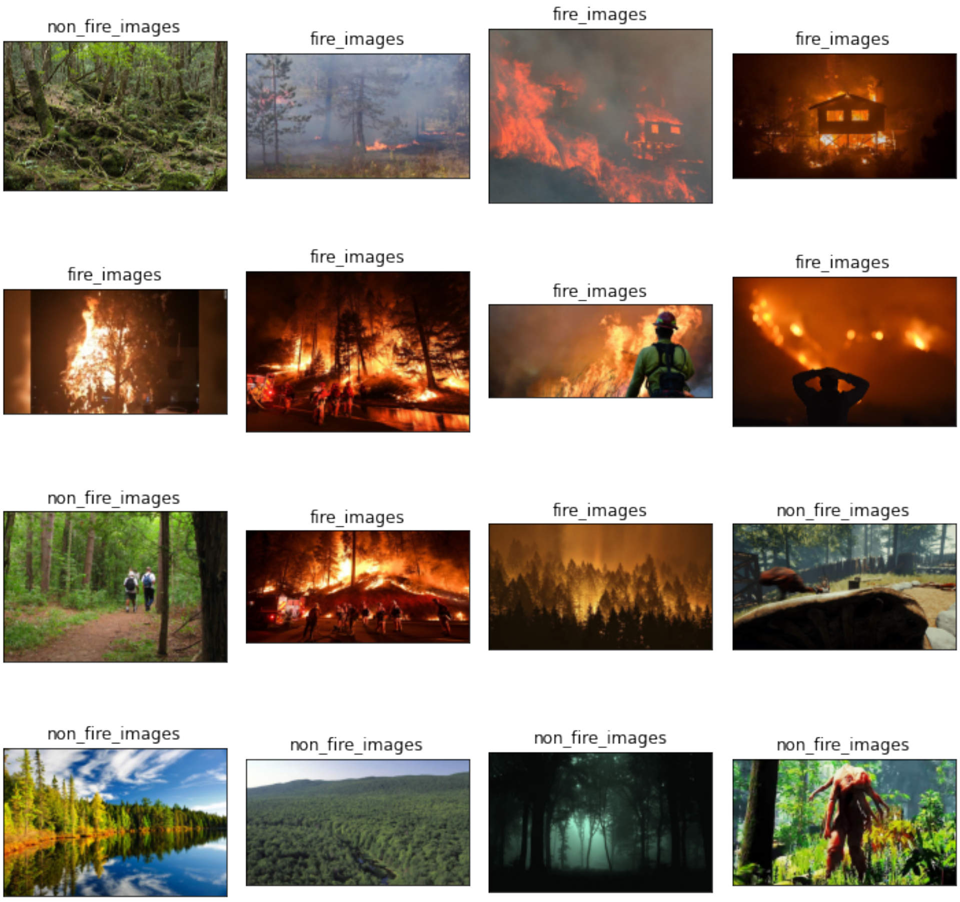

Fig. 4. *Randomly selected image samples from the database*

The predictive ability of the model was tested using 15 random images from the test database (Figure 4). Each image is shown with a true label and a predicted label, with correct predictions marked in green and incorrect ones in red. The results show that most predictions are correct, but there are only a few errors (e.g., smokeless fire images), indicating that the model is sensitive to false positives.

Fig. 5. Predictions on the test database

The results of the classification report are presented in the following table (Table 2). The table includes precision, recall, f1-score and support indicators, which describe the performance of the model for each class. For the fire_images class, precision is 0.98, recall is 1.00 and f1-score is 0.99; for non_fire_images, precision is 1.00, recall is 0.90 and f1-score is 0.95. The average values (macro avg) are high, which confirms the balanced nature of the model, and the weighted avg is calculated taking into account the uneven nature of the database.

Table 2. Classification Report

Class	**Precision**	**Recall**	**F1-Score**	**Support**
fire_images	0.98	1.00	0.99	158
non_fire_images	1.00	0.90	0.95	42
accuracy	-	-	0.98	200
macro avg	0.99	0.95	0.97	200
weighted avg	0.98	0.98	0.98	200

Overall, the results demonstrate the effectiveness of the MobileNetV2 model in fire classification, especially considering its usability on resource-constrained devices. These figures are consistent with similar studies in the literature review (e.g., 82-98% accuracy for YOLOv5-based models), but our approach achieved higher performance with fewer parameters.

CONCLUSION

In this research, a convolutional neural network (CNN) model based on the MobileNetV2 architecture for early fire detection was developed using transfer learning and tested on a database created as part of the NASA Space Apps Challenge 2018 competition. Despite the uneven nature of the database (755 fire images versus 244 non-fire images), the model showed high performance: accuracy reached 98.00% on the test set, recall for the fire class was 1.00, and the overall F1-score was 0.98. Confusion matrix analysis confirmed that the model accurately identified fire images (false negative = 0) and gave only a small number of false positives (false positive = 4) in non-fire images. These results indicate that the model can be reliably used in real-time fire monitoring systems, especially in terms of not missing the first signs of fire.

The MobileNetV2 model was chosen for its lightweight architecture (approximately 3.5 million parameters) and its ability to work efficiently on resource-constrained devices (drones, IoT devices, mobile platforms). Compared to the YOLO series and other heavy models considered in the literature review (e.g., YOLOv5s or Detectron2), our approach achieved similar or higher accuracy with less computational resources. This is an important advantage for deploying fire detection systems in edge computing environments.

The results of the study once again proved the potential of deep learning technologies in the field of early detection and prevention of fire accidents. However, the slightly lower recall value of the model in the no-fire class (0.90) indicates the influence of bias caused by the imbalance of the database. In future studies, it is recommended to use SMOTE, focal loss, or additional databases (e.g., DeepFire or UAV-based datasets) to address class imbalance. Also, the next stages of the work will be to adapt the model to video streams (real-time video surveillance), integrate multimodal data (RGB + IR) and test it in a real environment (forest, indoor). In conclusion, the proposed MobileNetV2-based fire classification model is characterized by high accuracy, low resource consumption and readiness for practical use. This solution can make a real contribution to improving early detection systems for forest fires, indoor accidents and other fire-related hazards, thereby helping to protect human life and property.

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