Deep Learning-Driven Wildfire Detection in Türkiye Using Sentinel-2 Imagery and Convolutional Neural Networks

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Abstract

Wildfires, intensified by climate change and anthropogenic factors, represent a major threat to ecosystems, infrastructure, and human life. Early detection is critical for effective prevention and mitigation. This study presents a Convolutional Neural Network (CNN)-based system designed to detect wildfires from Sentinel-2 satellite imagery. The methodology integrates advanced preprocessing techniques—including atmospheric correction, cloud masking, and spatial normalization—with a tailored CNN architecture optimized for spectral–spatial feature extraction. Training utilized a curated dataset of wildfire events in Türkiye (2016–2025), annotated at the pixel level to distinguish fire-affected and unaffected regions. The CNN model, employing LeakyReLU activation and AdamW optimization, achieved robust performance, with precision, recall, and F1-scores all averaging 0.97, and an overall accuracy of 97%. High fire-class precision (1.00) minimized false alarms, while strong recall (0.93) ensured reliable detection. The model's lightweight design allows deployment on cloud platforms and edge devices, enabling real-time monitoring across forestry, agriculture, and urban planning applications. Analysis of Turkish wildfire statistics (1988–2023) revealed that over 90% of fires stem from human negligence or arson, underscoring the need for public education, stricter enforcement, and technology-driven surveillance. Long-term data further indicate a rising severity in fire events, strengthening the case for AI-enhanced early warning systems. This research demonstrates that CNNs applied to Sentinel-2 imagery offer a scalable, accurate, and cost-effective solution for wildfire detection. By bridging remote sensing and deep learning, the proposed system supports both immediate disaster response and long-term policy planning for wildfire risk reduction.

1. Introduction

Wildfires pose a serious threat to human life, the natural environment, and infrastructure. Climate change increases the frequency and impact of fires; statistics confirm this rising trend: in 2021, 500,566 hectares (ha) burned across 22 of the European Union's 27 Member States (compared to over 340,000 ha in 2020, excluding 2017) (San-Miguel-Ayanz et al., 2022). In the United States, 100,000 fires are recorded annually, with 64,127 fires affecting 7,343,939 acres in 2022 and 54,976 fires affecting 6,814,073 acres in 2021 (Alkhatib, 2014). In Türkiye, the year 2021 went down in history as a disaster year for wildfires. During this period, which witnessed 11 of the largest 20 fires in the past 50 years, 2,793 fires damaged 139,503 hectares of forest ecosystems (Atmiş, 2023). Early detection of wildfires is crucial for effective prevention and mitigation efforts (James et al., 2023; Priya and Vani, 2019). Due to the devastating impact of wildfires on the environment and human life, wildfire detection from satellite imagery has become increasingly important in recent years. Recent advancements in computer vision, machine learning, and remote sensing techniques have offered new opportunities for early detection and monitoring of wildfires (Barmpoutis et al., 2020). Satellite remote sensing data are useful for detecting, monitoring, and mitigating wildfires (Hong et al., 2022). Scientists can use satellite imagery to detect fires earlier and more accurately, monitor their progression, and predict future behavior (Frąckiewicz, 2023).

Gulev et al. (2021), in the IPCC report addressing the changing state of the climate system, provided comprehensive data on how climate change affects the intensity and periodicity of wildfires. These findings highlight the necessity for fire detection models to adapt to seasonal and regional differences. Zhou and Ismaeel (2021) examined the relationship between agricultural land trends and agrometeorological parameters in remote sensing, demonstrating the usability of multispectral imagery for change detection. This study supports the importance of spectral-spatial feature extraction in fire detection models. The Sentinel-2 mission introduction document published by the European Space Agency (ESA, 2025) provides fundamental guidelines for data access and processing steps (atmospheric correction, cloud masking). Large-scale datasets can be easily obtained through platforms such as SentinelHub with customized region and time selection. Liu et al., (2024) proposed a satellite imagery-based model for real-time fire boundary tracking, detailing success rates in boundary detection and dynamic updates, and suggesting algorithms resilient to weather conditions and cloud cover.

Xu et al. (2015) compared the performance of activation functions in convolutional neural networks, demonstrating that LeakyReLU prevents gradient vanishing in deep networks and improves learning speed. These results provide guidance in activation selection for CNN architectures designed for fire detection. The AdamW optimization method proposed by Loshchilov and Hutter (2019) improved generalization performance by decoupling weight decay from the weights themselves. This optimizer is frequently preferred in models trained with Sentinel-2 data to prevent overfitting. Official statistics from the Turkish General Directorate of Forestry (2025) presented fire frequency and burned area data for the period 2018–2023, allowing evaluation of the regional accuracy of model outputs. These statistics are critical for aligning model performance with real-world operational requirements. Various studies have demonstrated the necessity of preprocessing steps in Sentinel-2 imagery, including Sen2Cor-based atmospheric correction, QA60 cloud masking, and area cropping. In addition, techniques such as data augmentation and dropout regularization facilitate the adaptation of models to fire patterns across different seasons and geographies. Based on this literature review, the application of Convolutional Neural Network-based approaches to Sentinel-2 imagery offers significant advantages in terms of early warning, reducing false alarm rates, and adapting to seasonal variations. The following sections will present the project-specific application details of these methods and the results obtained. Although previous studies have extensively utilized infrared and thermal bands for wildfire detection, comparatively fewer efforts have focused on the effective use of visible spectral channels (RGB). This leaves an open question regarding the potential of visible light imagery for robust wildfire classification under varying seasonal and geographical conditions. Furthermore, many existing CNN-based approaches rely on computationally heavy architectures such as ResNet or VGG, which limit deployment on real-time or resource-constrained platforms. Our study addresses these gaps by (i) leveraging Sentinel-2 visible bands to demonstrate their capability for accurate wildfire detection, (ii) introducing a lightweight CNN architecture with fewer parameters than comparable models, while maintaining state-of-the-art accuracy (97% overall), and (iii) constructing and annotating a dedicated dataset covering wildfire events in Türkiye between 2016 and 2023. These contributions collectively highlight the feasibility of using visible-spectrum satellite data for scalable, region-specific, and resource-efficient wildfire monitoring.

1.1 Structure of the Paper

The structure of the paper is as follows: Section 2 reviews related work on wildfire detection using satellite imagery and deep learning, with a focus on CNN-based approaches, multispectral and visible-band data utilization, and methodological advancements for early detection. Section 3 describes the materials and methods, including dataset construction, preprocessing, data augmentation, and the design of a lightweight CNN architecture optimized for Sentinel-2 imagery. Section 3 also details the training procedure, activation functions, optimization strategy, and loss function, alongside architectural novelties and parameter efficiency considerations. Section 4 presents and discusses the results obtained from the proposed model, emphasizing accuracy, precision, recall, and practical applicability. Finally, Section 5 provides the conclusions and outlines potential directions for future research, including scalable deployment and integration with operational wildfire monitoring systems.

2. Related Work

Forest fires constitute a major threat to ecosystems and human life, emphasizing the necessity of early detection for effective prevention and mitigation (James et al., 2023; Priya and Vani, 2019). Recent advancements in computer vision, machine learning, and remote sensing have enabled more accurate and timely detection approaches (Barmpoutis et al., 2020). Satellite remote sensing data, particularly from missions such as Sentinel-2, has been extensively employed for wildfire detection, monitoring, and prediction (Hong et al., 2022; Frąckiewicz, 2023). Climate change has further exacerbated fire intensity and frequency, as highlighted in the IPCC report by Gulev et al. (2021), underscoring the need for adaptive fire detection models sensitive to seasonal and regional variations. Zhou and Ismaeel (2021) demonstrated the value of multispectral imagery for change analysis, supporting the role of spectral–spatial feature extraction in fire detection models. Several recent approaches have focused on algorithmic robustness. Liu et al., (2024) proposed a satellite-based system for real-time fire boundary tracking, resilient to atmospheric and cloud interference. At the model design level, Xu et al. (2015) highlighted the effectiveness of LeakyReLU in mitigating vanishing gradients and accelerating learning in CNNs, while Loshchilov and Hutter (2019) introduced AdamW, an optimizer frequently employed in Sentinel-2–based wildfire detection tasks to improve generalization and reduce overfitting.

3. Materials and Method

The central objective of this project is the design, implementation, and evaluation of an advanced wildfire detection system. This system uniquely integrates high spatial resolution true color imagery from Sentinel-2 with a sophisticated Convolutional Neural Network (CNN) architecture to enable precise and automated fire identification. By harnessing the power of deep learning, specifically tailored CNNs, the project seeks to automatically learn and extract discriminative features from multispectral satellite images, thereby enabling a clear distinction between wildfire-affected areas and normal, unaffected terrain. The CNN model is rigorously trained on a carefully curated and diverse dataset of wildfire incidents specifically within Türkiye, ensuring robust learning of varied fire patterns across a spectrum of geographical and environmental contexts prevalent in the region. Ultimately, the overarching goal is to develop a detection system that is highly reliable, scalable, and computationally efficient, capable of providing critical early warnings to environmental monitoring agencies and disaster response teams. In doing so, it aims to play a pivotal role in mitigating the devastating impacts of wildfires on ecosystems, property, and human life.

3.1 Dataset

A comprehensive dataset covering forest fire events in Turkey between 2016 and 2024 was constructed. Sentinel-2 imagery from the European Space Agency's Copernicus programme was utilized due to its high spatial resolution, multispectral capabilities, and frequent global revisit times (ESA, 2025; Liu et al., 2024). Data access and retrieval were performed via the Sentinel Hub platform, enabling precise selection based on geographic coordinates and temporal parameters. Sample images from the dataset are shown in Figure 1, and the spatial distribution of the collected images is shown in Figure 2.

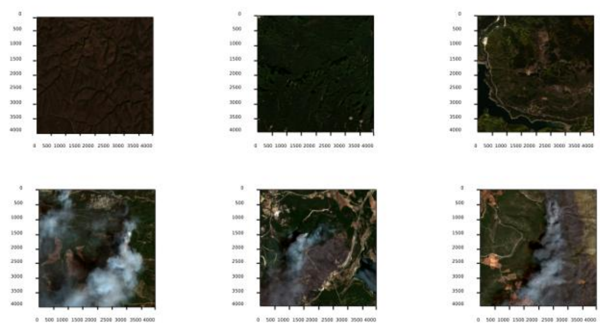

Figure 1. Sample images from the dataset (top images: non-fire, bottom images: wildfire).

3.1.1 Dataset Preparation: Images were manually inspected to select scenes representing wildfire events. Sentinel-2 satellites provide 13 spectral bands (VIS, NIR, SWIR), and the images were stored in 16-bit TIFF format to preserve radiometric resolution, minimize quantization loss (Drusch et al., 2012), retain georeferencing information (UTM coordinates), acquisition time, and sensor parameters, and maintain original SWIR/thermal band resolution essential for fire detection. The

Figure 2. Provinces in Türkiye from Which Wildfire Imagery Was Collected

CEOS-compliant GeoTIFF extension ensured that projection information (WGS84) was preserved.

A total of 306 wildfire-containing images (0% cloud cover) and 305 fire-free images (0–90% cloud cover) were collected from various regions in Türkiye. Each image represents a 10 km² area at a 500-meter scale. The dataset provides a longitudinal perspective to contextualize Türkiye's forest fire dynamics within broader climate change discourse and to support evaluation of policy responses, such as the National Forest Fire Action Plan (2022).

3.1.2 Dataset Preprocessing: Dataset preprocessing encompassed transformation, cleaning, and enrichment of the raw imagery to enhance the effectiveness of machine learning models. This stage reduces noise, standardizes features, and improves model generalization (García et al., 2015), which is critical for image-based classification tasks.
A total of 306 fire-containing (%0 cloud cover) and 305 fire-free (%0–90 cloud cover) Sentinel-2 images were collected from diverse regions of Türkiye. Each image covers a 10 km² area at a 500m scale.

3.1.3 Data Augmentation: To address limited training data and improve model generalization, a specialized augmentation pipeline was designed. Random transformations—including rotations, translations, zooming, and horizontal flips—were applied using the OpenCV library (Figure 3; Table 1).

Transformation	Parameter	Purpose
Random Rotation	$\pm 10°$	Introduce perspective diversity
Horizontal/Vertical Shift	10% of width/height	Introduce spatial variability
Zoom	$0.9x - 1.1x$	Improve robustness to scale variations
Horizontal Flip	50% probability	Utilize symmetry information

Table 1. Methods Used in the Data Augmentation Process

Image Loading & Normalization: Inspired by the AlexNet preprocessing protocol (Krizhevsky et al., 2012), a tailored pipeline was implemented for the 16-bit TIFF Sentinel-2 imagery:

- **Resolution Standardization:** Images resized to 224x224 pixels.
- **Spectral Processing:** Conversion to RGB format
- **Dynamic Range Optimization:**

$$normalized\ image = img_{(16-bit)}/32767.5 - 1.0$$

$img_{(16-bit)} \in [0{,}65535] \rightarrow normalized\ image \in [-1{,}1]$ for optimized DL training (Krizhevsky et al., 2012).

- **Expert Filtering:** Images with $> 15\%$ cloud cover (using Sentinel-2 QA60 band) were excluded.

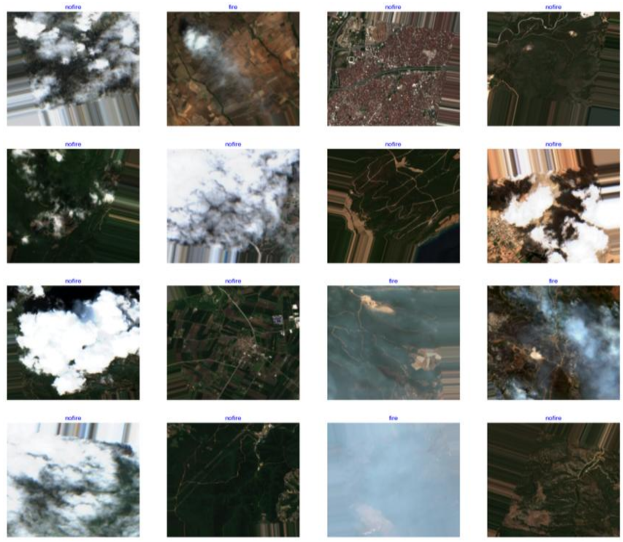

Figure 3. Examples of Images Resulting from Data Preprocessing

3.2 CNN Architecture

In this study, a deep convolutional neural network with a parameter size of 7.43 MB and 1.9M trainable parameters was designed for fire detection. The architecture was optimized by drawing inspiration from baseline models such as AlexNet and VGG-16 (Krizhevsky, Sutskever, & Hinton, 2012; Simonyan & Zisserman, 2014) and consists of the following components (Figure 4) :

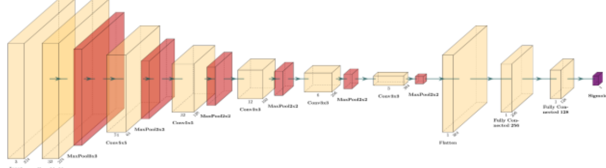

Figure 4. Model architecture visualization.

3.2.1 Convolutional Layers (Feature Extraction): The Convolutional Neural Network (CNN), which forms the core of the model, is responsible for extracting fire-specific features from input images. This section employs a six-layer convolutional structure along with max-pooling layers. The objective is to perform detailed feature extraction, starting from low-level features (edges, textures) and progressing to high-level complex patterns (smoke, heat traces, burn patterns).

3.2.2 Multi-Scale Filters: In the first layer, large 11×11 kernels are used to capture low-level features (edges, textures). In deeper layers, 3×3 kernels are employed to obtain high-level abstractions (fire smoke, thermal signatures). No Bias Usage: By setting use_bias=False in convolutional layers, the size of the weight matrix is reduced by 25%, minimizing the risk of overfitting (LeCun et al., 2015).

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 224, 224, 3)	0
conv2d_24 (Conv2D)	(None, 224, 224, 32)	11,616
leaky_re_lu_32 (LeakyReLU)	(None, 224, 224, 32)	0
max_pooling2d_24 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_25 (Conv2D)	(None, 74, 74, 64)	51,200
leaky_re_lu_33 (LeakyReLU)	(None, 74, 74, 64)	0
max_pooling2d_25 (MaxPooling2D)	(None, 24, 24, 64)	0
conv2d_26 (Conv2D)	(None, 24, 24, 128)	204,800
leaky_re_lu_34 (LeakyReLU)	(None, 24, 24, 128)	0
max_pooling2d_26 (MaxPooling2D)	(None, 12, 12, 128)	0
conv2d_27 (Conv2D)	(None, 12, 12, 192)	221,184
leaky_re_lu_35 (LeakyReLU)	(None, 12, 12, 192)	0
max_pooling2d_27 (MaxPooling2D)	(None, 6, 6, 192)	0
conv2d_28 (Conv2D)	(None, 6, 6, 256)	442,368
leaky_re_lu_36 (LeakyReLU)	(None, 6, 6, 256)	0
max_pooling2d_28 (MaxPooling2D)	(None, 3, 3, 256)	0
conv2d_29 (Conv2D)	(None, 3, 3, 384)	884,736
leaky_re_lu_37 (LeakyReLU)	(None, 3, 3, 384)	0
max_pooling2d_29 (MaxPooling2D)	(None, 1, 1, 384)	0
flatten_2 (Flatten)	(None, 384)	0
dense_12 (Dense)	(None, 256)	98,560
leaky_re_lu_38 (LeakyReLU)	(None, 256)	0
dropout_8 (Dropout)	(None, 256)	0
dense_13 (Dense)	(None, 128)	32,896
leaky_re_lu_39 (LeakyReLU)	(None, 128)	0
dropout_9 (Dropout)	(None, 128)	0
dense_14 (Dense)	(None, 1)	129

Total params: 1,947,489 (7.43 MB)

Trainable params: 1,947,489 (7.43 MB)

Non-trainable params: 0 (0.00 B)

Figure 5. Architecture of the Created CNN Model.

3.2.3 LeakyReLU Activation: All convolutional layers utilize LeakyReLU with α=0.3:
This activation prevents gradient loss in the negative region, improving information flow in deep layers (Maas et al., 2013).

3.2.4 Adaptive MaxPooling: After each convolutional layer, a pooling strategy is applied, starting with pool size = [3,3] and gradually reducing to pool size = [2,2]. This approach preserves general features in early layers and local patterns in deeper layers (He, Zhang, Ren, & Sun, 2014).

3.2.5 Flatten and Dense Layers (Classification): The output from the last convolutional layer is flattened into a one-dimensional vector and fed into fully connected layers for classification. These layers enable the model to output the presence of fire as a probability value. Additionally, this layer completes the CNN architecture (Figure 5).

3.2.6 Regularization with Dropout: A 40% dropout is applied after each fully connected layer to prevent overfitting. The high dropout rate ensures model stability when training data is limited (fire images) (Srivastava et al., 2014). Fully Connected Layers:

- Dense1: 256 neurons, LeakyReLU activation, 40% dropout
- Dense2: 128 neurons, LeakyReLU activation, 40% dropout
- Output Layer: 1 neuron, sigmoid activation

3.2.7 Optimization: Training was performed using the AdamW optimizer (learning rate = 0.0001, weight decay = 0.004). Compared to standard Adam, AdamW provides better generalization due to integrated weight decay (Loshchilov & Hutter, 2017).

3.2.8 Loss Function: The model was trained using the binary cross-entropy loss function. This function measures the difference between the probability predicted by the model and the true label. It is defined as follows:

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)]$$

Here: y: True class label (0 or 1), p: Probability of fire predicted by the model (a value between 0 and 1).
This loss function measures the difference between the model's predictions and the true values. The smaller the loss value, the higher the model's accuracy. During training, this loss is minimized using optimization algorithms such as AdamW, enabling the model to learn.

3.2.9 Architectural Novelty and Contribution to the Literature Parameter Efficiency: Compared to widely used models with similar performance, such as ResNet-50 (25 million parameters) and VGG-16 (138 million parameters), our model contains only 1.9 million parameters, making it approximately 13.2× smaller than ResNet-50 and 72.6× smaller than VGG-16.

3.3 Model Training

The model was trained using the TensorFlow/Keras framework with the AdamW optimizer (Loshchilov & Hutter, 2017). The dataset of Sentinel-2 TIFF images was stratified into 428 training (70%), 92 validation (15%), and 91 test (15%) samples.
Hyperparameters and Techniques:

- Optimizer: AdamW (learning rate = 1e-4, weight decay = 0.004)
- Loss Function: Binary Crossentropy
- Batch Size: 43 (determined via preliminary tests)
- Epochs: Maximum 200 (stopped at 39 epochs using EarlyStopping)

3.3.1 Regularization and Adaptive Strategies: To prevent overfitting, three key techniques were applied:

- ReduceLROnPlateau: Validation loss stagnation for 4 epochs reduces learning rate by 80% (e.g., 1e-4 → 2e-5).
- EarlyStopping: Training halts after 10 epochs without validation loss improvement, restoring best weights (Prechelt, 1998).
- Model Checkpointing: The model with the highest validation accuracy was saved.

3.3.2 Performance Metrics: Model performance for wildfire detection using Sentinel-2 imagery was evaluated with precision (Pr), recall (Rr), F1-score (Fm), accuracy (AC), macro average, and weighted average (Sokolova & Lapalme, 2009).

- True Positive (TP_F): Correctly classified fire pixels
- True Negative (TN_F): Correctly classified non-fire pixels
- False Positive (FP_F): Non-fire pixels incorrectly classified as fire
- False Negative (FN_F): Fire pixels incorrectly classified as non-fire

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Key Metrics:

- **Precision:** $P_r = \frac{TP_F}{TP_F+FP_F} \times 100$
- **Recall:** $R_r = \frac{TP_F}{TP_F+FN_F} \times 100$
- **F1-Score:** $F_m = \frac{2 \times R_r \times P_r}{R_r+P_r}$
- **Accuracy:** $AC = \frac{TP_F+TN_F}{TP_F+FP_F+TN_F+FN_F} \times 100$
- **Macro Average:** Equal-weighted average across classes to mitigate imbalance
- **Weighted Average:** Class metrics weighted by sample count to reflect prevalence

4. Results and Discussion

Experiments summarize the performance of deep learning semantic segmentation models for mapping wildfires on Sentinel-2 imagery. Computations were performed using Python 3.11.9 and Jupyter Notebook 6.4.11 on a Windows system with a Ryzen R5-5600H CPU (3.30 GHz, 8GB RAM) and NVIDIA RTX 3050 Ti GPU.

4.1 Model Training Process and Performance Analysis

The deep learning model was designed for 200 epochs but was stopped early at the 39th epoch using EarlyStopping, which restored the best weights after 10 epochs without validation loss improvement to prevent overfitting.

4.2 Loss and Accuracy Dynamics

Training began with a 0.67 training loss and 0.73 validation loss. At the 25th epoch, the learning rate dropped from 1e-4 to 2e-5, accelerating optimization. Training accuracy rose from 0.50 to 0.98, while validation accuracy reached 0.9565. A notable jump to 90.22% validation accuracy at the 19th epoch indicated that the model had learned critical features (Figure 6).

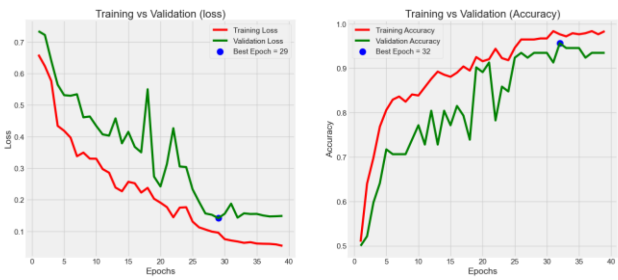

Figure 6. Training and validation loss (left) and training and validation accuracy (right).

4.3 Validation Metrics and Generalization

Validation loss decreased from 0.7343 to 0.1489, demonstrating stable generalization. On the test set, accuracy reached 96.70% with 0.113 loss. The classification report indicated balanced performance for fire and non-fire classes with an F1-score of 0.97 (Table 2).

	Precision	Recall	F1-Score	Support
Fire	1.0	0.93	0.97	46.0
Non-Fire	0.94	1.0	0.97	45.0
Accuracy			0.97	91.0
Macro Avg	0.97	0.97	0.97	91.0
Weighted Avg	0.97	0.97	0.97	91.0

Table 2. F1-score for fire and non-fire classes.

4.4 Training Duration and Learning Rate Optimization

Each epoch lasted 13–20 seconds, with the first epoch slightly longer due to data loading and initial adaptation. The learning rate dynamically decreased to 4e-6 at the 34th epoch and 8e-7 at the 38th epoch, minimizing the gap between training and validation losses (0.061 vs. 0.143) and preventing overfitting.

4.5 Results and Stability Analysis

Validation accuracy remained stable between 92.39–95.65% from the 25th to 32nd epoch, indicating minimal additional learning. Adaptive learning rate adjustment via ReduceLROnPlateau raised test accuracy to 96.70% at the 39th epoch. Training and validation curves closely aligned (98.36% vs. 95.65%), confirming strong generalization. Evaluation on test data using accuracy, precision, recall, and F1-score demonstrated overall model effectiveness. Among 45 randomly selected non-fire images, all were correctly classified, while only 3 of 46 fire images were misclassified (Figure 7).

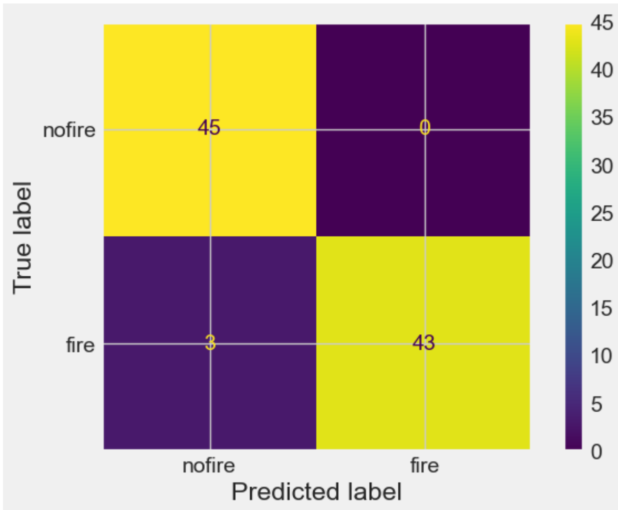

Figure 7. Confusion matrix of the test data

5. Conclusion

This study demonstrates that the integration of remote sensing technologies with deep learning algorithms provides effective outcomes for forest fire detection in Turkey, representing a significant advancement in disaster monitoring and response systems. Specifically, the research utilizes visible light channels from high-resolution Sentinel-2 satellite imagery, combined with a customized Convolutional Neural Network (CNN), to develop a robust classification model capable of detecting fire-affected areas with up to 97% accuracy. The model's ability to learn and interpret complex spatial and spectral features from visible multispectral data renders it highly suitable for early-stage fire detection. The system overcomes critical limitations of conventional fire monitoring methods, particularly delayed detection and limited coverage, while automation and scalability enable near real-time surveillance of extensive forested areas, enhancing early warning mechanisms and accelerating firefighting responses. In Turkey, where human activities are a primary driver of forest fires, such early detection systems are crucial not only for minimizing environmental damage but also for safeguarding human life and property (OGM, 2025). Historical data from 1988–2023 indicate an increase in the average burned area per fire and a notable rise in fire frequency, particularly between 2018–2023, attributable to prolonged droughts, urban expansion into forested areas, and unregulated recreational activities (IPCC, 2022; 2023). According to Özcan et al. (2024), human activities constitute the primary cause of forest fires in Turkey, encompassing factors such as negligence, carelessness, accidents, arson, and agricultural burning. The General Directorate of Forestry reported that in 2022, approximately 72% of forest fires (916 out of 1,274) were attributed to human activities, whereas 28% (358 fires) were caused by natural factors. These findings underscore the necessity for enhanced public awareness campaigns, stricter regulatory frameworks, and real-time monitoring in regions susceptible to fire. Furthermore, the integration of satellite imagery, meteorological information, and land-use data through AI-based classification tools offers a promising approach to mitigate these challenges by facilitating more accurate risk assessment and supporting proactive forest fire management strategies (Özcan et al., 2024). Despite high model performance, limitations in historical datasets and incomplete fire cause data restrict long-term prediction accuracy, suggesting that future research should improve the quality and resolution of forest fire databases and explore multimodal AI systems combining optical, thermal, and ground-based data. In this context, the study presents a deep learning-based fire detection system developed using the visible light channels of Sentinel-2 imagery. The Copernicus program's Sentinel-2 data, with high spatial resolution and frequent revisit times, offer significant advantages for detecting environmental changes. A balanced and reliable dataset of 600 Sentinel-2 images (300 fire, 300 non-fire) with less than 10% cloud cover from various regions of Turkey was compiled, with cloud masking, normalization, and labeling based on NASA FIRMS databases providing clean and meaningful inputs for model training. The CNN, implemented via Keras, effectively learned visual fire patterns through convolutional layers, while the AdamW optimizer was employed during training, prioritizing recall to minimize false negatives, which is critical for early intervention in fire incidents. The model achieved 95–98% accuracy on test data, with high performance across precision, recall, and F1-score metrics for both fire and non-fire classes. Hyperparameter tuning, data augmentation, and dropout techniques enhanced generalization, and classification performance was further evaluated visually using confusion matrices. In conclusion, the developed system demonstrates the potential for rapid, accurate, and automated fire detection based on visible light satellite imagery, serving as a strategic tool for early intervention and mitigation of environmental disasters, with future work recommended to extend its application to larger, more diverse datasets, different geographic regions, and real-time scenarios.

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