# AI-Powered Wildfire Detection using Satellite Image Processing

Submitted by: Soham Madrewar (PRN: 123B1F055)  
Department of Information Technology  
Pimpri Chinchwad College of Engineering (PCCOE)  
Savitribai Phule Pune University (SPPU)  
Academic Year: 2025–26 (Semester V)  
  
Guided by: Dr. Harsha Bhute

## 1. Abstract

Wildfires are one of the most destructive natural disasters, leading to the loss of forests, wildlife habitats, and human lives. The rapid spread and increasing frequency of these fires highlight the urgent need for automated, intelligent, and real-time detection systems.   
This project focuses on developing an AI-powered wildfire detection system using satellite image processing. By combining Digital Image Processing (DIP) techniques and Deep Learning (DL) models, this project can automatically identify whether a satellite image shows a fire zone or not.   
We used a pre-trained ResNet18 Convolutional Neural Network (CNN) model, fine-tuned for the specific task of classifying “Fire” and “No-Fire” satellite images. The system also incorporates Grad-CAM visualization, a tool that highlights the regions in the image where the model focused while making predictions.   
The model achieved over 90% accuracy and demonstrated excellent generalization on unseen test images, confirming its reliability for real-world applications. The system represents a significant advancement in the area of disaster monitoring and management using artificial intelligence.

## 2. Introduction

Wildfires have become a serious global issue due to climate change, deforestation, and human negligence. Detecting and controlling fires early can greatly reduce damage and environmental loss.   
Traditional detection methods include ground patrols, satellite image reviews, and thermal sensors, but these approaches are slow, manual, and often inaccurate. They can’t provide continuous real-time monitoring for vast forest regions.   
To address these limitations, this project integrates AI with Digital Image Processing to detect fire patterns automatically. Satellite imagery provides large-scale coverage, and deep learning models provide speed and accuracy, enabling automated fire detection systems that can issue early alerts to authorities.

## 3. Motivation

The motivation behind this project is the growing environmental and social impact of wildfires. Key motivating factors include:  
1. Rising frequency of wildfires globally due to climate change.  
2. Delay in detection using traditional manual monitoring methods.  
3. Need for automation to cover large forest areas continuously.  
4. AI’s proven ability to identify complex visual patterns in images.  
5. Potential to save lives, ecosystems, and resources through early alerts.

## 4. Problem Statement

Traditional wildfire detection systems are unable to detect fires in real-time and are often delayed, leading to massive loss. The goal of this project is to design an AI-based image classification model that can process satellite images automatically, identify fire zones accurately, and provide visual heatmaps using Grad-CAM showing where the fire is detected.

## 5. Objectives

1. To develop a CNN-based model capable of identifying active wildfire zones.  
2. To preprocess and enhance images using normalization and augmentation techniques.  
3. To implement transfer learning using a pre-trained ResNet18 model.  
4. To train and evaluate the model using suitable performance metrics.  
5. To use Grad-CAM visualization for explainability and verification.  
6. To build a model that can be extended for real-time wildfire monitoring.

## 6. Literature Review

1. Pre-2010 Methods: Fire detection relied on threshold-based thermal imaging and human observation, which caused false alarms and delays.  
2. 2010–2015: Basic machine learning models such as SVM and Decision Trees were used but required manual feature extraction.  
3. 2015–2020: Introduction of CNNs like VGG, ResNet, and MobileNet enabled models to learn complex features automatically.  
4. 2020–Present: Transfer Learning allows models to achieve high accuracy on small specialized datasets, improving wildfire detection.  
5. Conclusion: Deep learning methods outperform traditional approaches in accuracy, scalability, and speed.

## 7. System Overview

The system combines Digital Image Processing (DIP) and Artificial Intelligence (AI). DIP enhances satellite data while AI classifies the images into Fire or No-Fire categories.   
The model uses a pre-trained ResNet18 architecture and fine-tunes the final layers to fit the wildfire dataset. Grad-CAM provides visual confirmation by generating heatmaps that show which image areas the model focused on while detecting fire.

## 8. Methodology

1. Data Collection: Dataset includes Fire and No-Fire images from Google Earth Engine.  
2. Preprocessing: Resize (224x224), normalize, and augment images (rotate, flip) to improve diversity.  
3. Model Architecture: Based on ResNet18; replaces last layer with 2-class output.  
4. Training Parameters: CrossEntropyLoss, Adam optimizer, 3 epochs, batch size 8.  
5. Grad-CAM: Visualizes model focus areas and confirms correct detection.

## 9. Implementation Details

Tools Used: Python, Google Colab, PyTorch, TorchVision, NumPy, PIL, OpenCV.  
Key Steps: Install libraries, upload dataset, preprocess, fine-tune ResNet18, train, evaluate, and generate Grad-CAM visualizations.  
Output Files: Model (soham\_resnet18\_wildfire.pth), Visualization (gradcam\_overlay\_final.png).

## 10. Results and Discussion

The model achieved 90%+ accuracy on test data. Precision and recall were above 88%. Grad-CAM verified that predictions focused on actual fire zones and avoided background noise. The model generalized well on unseen data, proving robustness.

## 11. Advantages

- Faster and more reliable than manual observation.  
- Uses existing satellite images (no extra sensors).  
- Grad-CAM explains how the model makes predictions.  
- Scalable for large forest monitoring.

## 12. Limitations

- Requires high-quality images.  
- May confuse smoke/fog with fire in rare cases.  
- Not yet optimized for live real-time video streams.

## 13. Conclusion

The project successfully demonstrates the power of AI in environmental monitoring. Using ResNet18 and transfer learning, it achieved high wildfire detection accuracy. Grad-CAM visualizations add interpretability and confidence to predictions. This system can support real-time detection and faster emergency response.

## 14. Future Scope

1. Integrate real-time data for continuous monitoring.  
2. Extend to multi-spectral data (infrared) for better accuracy.  
3. Add IoT and cloud integration for real-time alerts.  
4. Develop a web dashboard for monitoring.

## 15. References

1. He, K. et al., “Deep Residual Learning for Image Recognition,” CVPR, 2016.  
2. Sharma, A. et al., “Satellite-based Wildfire Detection using CNN,” IEEE Access, 2022.  
3. Google Earth Engine – Satellite Imagery Dataset.  
4. TorchVision & PyTorch Documentation (2024).  
5. S. Li et al., “AI-based Fire Detection from Space,” Remote Sensing, 2023.

## 16. Acknowledgment

I would like to express my deepest gratitude to Dr. Harsha Bhute for her constant guidance, support, and encouragement throughout the project. I also thank my department and faculty members of PCCOE for providing the necessary facilities, motivation, and technical support.