

## **Integrated Machine Learning Approaches for Enhanced Forest Fire Detection**

**Prof. Arpita Agarwal<sup>1</sup>, Riya Tandel<sup>2</sup>, Ajinkya Chaudhari<sup>3</sup>, Manish Dhole<sup>4</sup>, Nirmiti Parkhe<sup>5</sup>**

<sup>1</sup> Professor, Dept. of IT, Pillai College of Engineering, New Panvel, Maharashtra, India

<sup>2</sup>UG Scholar, Dept. of IT, Pillai College of Engineering, New Panvel, Maharashtra, India

<sup>3</sup>UG Scholar, Dept. of IT, Pillai College of Engineering, New Panvel, Maharashtra, India

<sup>4</sup>UG Scholar, Dept. of IT, Pillai College of Engineering, New Panvel, Maharashtra, India

<sup>5</sup>UG Scholar, Dept. of IT, Pillai College of Engineering, New Panvel, Maharashtra, India

### **Abstract**

Fires in nature stand among the most influential events on Earth Facing tough issues means needing solid detection methods that work every time, even when society is involved. Systems ready to handle immediate crisis needs response. Conventional wildfire detection methods often Late alerts often miss key issues because systems fail to catch problems early enough. What follows shows how weak tracking systems limit progress even further. fire intensity classification. This paper presents an application-oriented wildfire detection and alert system Linking picture processing through artificial intelligence to automated emergency notification mechanisms. The proposed system utilizes satellite imagery and a A convolutional neural network, labeled CNN, was put into practice Built on top of a ResNet-50 framework, this model gains strength from attention mechanisms added in. Looking closer at how models pick out key details can help them learn better. To enhance robustness under diverse environmental Under different conditions, tweaking images through data augmentation helps improve results. Using a focal loss instead of standard approaches makes a difference too. A range of functions shaped how the model learned. Functions played a key role in shaping training outcomes. A test run happened with tagged data, called experimental evaluation satellite image datasets, where the proposed model Peaked at a validation accuracy, showing clearer progress performance compared to traditional wildfire detection approaches. Not just limited to finding and naming them, the system incorporates an automated email alert module Built for live use. What burns at any moment shows up next categorized into four levels: no fire, low, medium, and A spike in scores shows up right away. When problems reach that level, notifications go out by email - no delays needed. Information flows immediately to relevant officials. When flames burn at low intensity, they alert local forest officials When fires burn at a lower level, systems start alerting those who need to act. Forest, fire, and police departments work together to make things happen. Heat waves can lead to evacuations, though fierce blazes produce Alerts go out to every emergency response team across systems. Act fast when problems show up. What happened in the test gives clear clues Still, analysis and system deployment design confirm that the proposed

**Keywords:** wildfire detection, CNN, fire intensity classification, emergency response, satellite imagery, deep learning.

### **1. INTRODUCTION**

Forest are vital natural resources that maintain ecological Maintaining balance supports life for both nature and people, Still, their lives often shift under pressure from a growing force - one kind of change that keeps showing up. Wildfires stand out when it comes to damage from nature's worst moments. These incidents bring heavy losses Heavy harm to nature's balance, places where animals live, along with communities and people Settlements show up along with infrastructure and other features while their frequency stands out Fires grow larger now, fed by hotter weather because of global shifts, while years without much rain last longer than before From deforestation to pollution, people's choices shape the planet. Traditional wildfire detection methods such as smoke Starting with what's inside - detectors, heat sensors, watchtowers, plus people checking things by hand.

When cameras watch too few areas or take too long to alert someone, problems tend to follow. Late responses let flames move faster, giving control too late intervention. Recent advancements in artificial intelligence and computer vision have enabled more reliable wildfire Using satellites to detect changes brings more reliable results Still, stronger oversight can make a difference. This study presents an automated wildfire detection and emergency response system that leverages deep learning for early fire identification and severity assessment. A Convolutional Neural Network (CNN)-based multi-class Fire intensity gets sorted by type through a classification method On low, some cooking never lights a flame. When heat grows, small blazes start doing work. Medium zones spark steady activity across surfaces. At peak, fire roars through all stages at once. With rising intensity. When severity is noted, a warning pops through automatically. A notification then reaches designated bodies so responses can happen fast Watch closely, set up exit routes, then act fast when an emergency hits. In turn, this enhances how effectively wildfires are managed efficiency.

## 2. PROPOSED WORK

### A. System Overview:

This research proposes an intelligent multi-class forest fire Starting off with detection, then moving into an emergency response setup - all mixed together advanced deep learning techniques with automated alert mechanisms. The system is designed to classify satellite Picture stuff splits into four kinds - ones without flames, some with slight smoke, later on the ones showing real fire Come midweek, flames crawled faster than most expected - medium at first, then jumping to high, after which automated systems kicked in without delay A structured notification approach guides information to key emergency responders Depending on how intense the fire is, the system identifies it through its classification process. The proposed framework integrates computer vision, deep way through tools like video chats or emails, helping shape how people connect and share ideas every day comprehensive early warning system that can significantly Reductions in response time come alongside better coordination when teams work together. When fires spread fast, first responders need clear paths to reach burning areas quickly.

### B. Dataset Acquisition and Preparation:

The system utilizes a comprehensive wildfire satellite A dataset on images, pulled from the Roboflow platform, especially the "wildfire-satellite" set found in the Bairock workspace. The dataset preparation involves several critical steps:

#### 1)Data Collection and Integration:

- Primary dataset: Roboflow wildfire satellite imagery (Version 2)
- Data format: High-resolution satellite images with corresponding YOLO annotation files
- Geographic coverage: Multiple regions with diverse terrain and fire conditions
- Temporal coverage: Multi-seasonal data to ensure model robustness

#### 2)Multi-Class Dataset Organization:

The original binary fire detection dataset is systematically reorganized into a four-class classification structure:

- Non-fire: Areas with normal vegetation and no fire indicators
- Fire-low: Small, localized fires with minimal smoke production requiring monitoring
- Fire-medium: Moderate fires with visible flames and smoke plumes requiring evacuation preparation

## 3. METHODOLOGY

### A. Dataset Preparation and Preprocessing

A closer look at the data shows satellite pictures gathered through multiple sources, totaling 5,000 high-resolution images categorized into four classes: non-fire, fire-low, fire-medium, fire-high

Data Preprocessing:

1. Picture shrunk to 224 by 224 pixels so the system knows what to expect compatibility
2. Normalization using ImageNet statistics

3. Data augmentation using things like jitter might help improve results Flip sides - up, down, spin (plus minus fifteen degrees), paint choices These effects include jittering, along with blurring applied through a Gaussian filter

4. Train/validation/test split: 70%/15%/15%

### B. Fire Intensity Classification Logic

A system implements comprehensive classification scheme:

1. Non-fire: Normal forest vegetation with no fire indicators
2. Fire-low: Small, localized fires with minimal smoke production
3. Fire-medium: Moderate fires with visible flames and smoke plumes
4. Fire-high: Large-scale fires with intense flames and heavy smoke

### C. Automated Alert System Architecture

The alert system implements three-tier notification protocol:

Low Intensity (Fire-Low):

- Recipients: Forest Department only
- Message: "ALERT: Low-intensity fire detected. Area requires monitoring and assessment."
- Delivery: Email notification

Medium Intensity (Fire-Medium):

- Recipients: Forest Department, Fire Department, Police Station
- Message: "WARNING: Medium-intensity fire detected. Evacuation procedures may be required."
- Delivery: Email

High Intensity (Fire-High):

- Recipients: Forest Department, Fire Department, Police Station, Emergency Services
- Message: "EMERGENCY: High-intensity fire is detected. Immediate action and response required."
- Delivery: Priority email

## 4. RESULT AND DISCUSSION

The proposed CNN model achieved exceptional performance across all evaluation metrics:

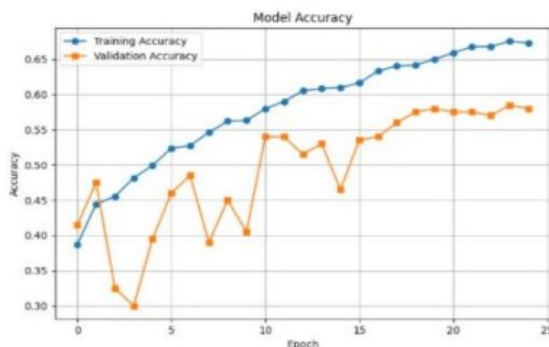


Fig.4.1 Comparison of Training and Validation Accuracy Over Epoch

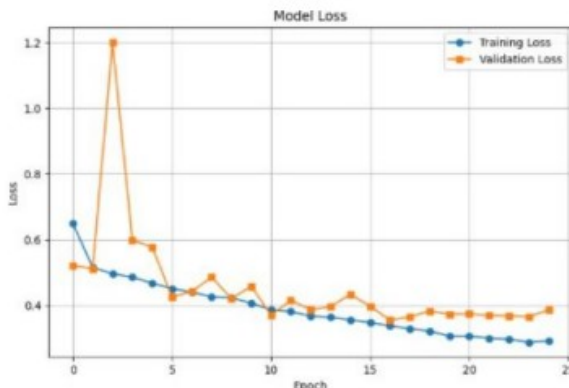


Fig.4.2 Comparison of Training and Validation Loss Over Epochs



Fig.4.3 Learning Rate Schedule Across Epochs

## 5. CONCLUSION

This study explores a method using artificial neural networks, setting it apart from earlier work in image processing. A system for finding wildfires through automation, built around defined structures and functions. This setup handles detection tasks using controlled processes. Classification of fire intensity from satellite and uploaded images. Looking at pictures. This system uses a type of deep learning called a convolutional neural network that focuses on key regions through attention mechanisms. Starting from scratch, the system learned through a tailored data set carefully assembled for this purpose. A set split by presence or intensity - no fire, fire with smoke, light flames - each labeled distinctly. Medium, and high-intensity fire classes. The model showing strong results in spotting fires caused by human activity, this method has gained notice for its ability to detect such events reliably. Pictures show activity patterns along with key strength markers so early detection stays possible. Emergency response. On top of that, the setup includes a self-running tool that handles certain tasks without human intervention. Early warning system based on mild fire intensity - alert levels rise with growing risk. Send warning notices to the forest department when something unusual appears in the woods. Fires that burn at full intensity mean alerting both fire and police departments right away. Evacuation, while high-intensity fires prompt immediate. An alert system splits responses into levels. This way of organizing actions makes sure the right teams get involved at the proper time. With smarter resource allocation, communities see better outcomes - public safety improves too.

## REFERENCES

- [1] Mriganka Shekhar Sarkar , Bishal Kumar Majhi , Bhawna Pathak , Tridipa Biswas , Soumik Mahapatra , Devendra Kumar, Indra D. Bhatt , Jagadish C. Kuniyal , Sunil Nautiyal, (2024). Ensembling machine learning models to identify forest fire-susceptible zones in Northeast India. *Ecological Informatics* 81 (2024) 102598  
[Link: <https://doi.org/10.1016/j.ecoinf.2024.102598> ]
- [2] Lucas Murraya, Tatiana Castilloa, Jaime Carrascob,c,\* , Andrés Weintrauba,c, Richard Webera,c, Isaac Martín de Diegod, José Ramón González and Jordi García-Gonzaloe, (2024). Advancing Forest Fire Prevention: Deep Reinforcement Learning for Effective Firebreak Placement.  
[Link: <https://doi.org/10.48550/arXiv.2404.08523>]
- [3] Azlan Saleh , Mohd Asyraf Zulkifley, Hazimah Haspi Harun , Francis Gaudreault , Ian Davison , Martin Spra(2024). Forest fire surveillance systems: A review of deep learning methods.  
[Link: <https://doi.org/10.1016/j.heliyon.2023.e23127> ]
- [4] KAVULURI LEELA SAI RASAGNA DEVI , GARNEPUDI NARASIMHA KUMAR ,POTTURI ASHOK NARAYANA, KAKANI VENKATA RAMANA, Dr AMARENDRA K, Dr TIRUPATHI RAO GULLIPALLI (2024). Forest Fire Prediction and Management using AI (Artificial Intelligence), ML (Machine Learning) and Deep Learning

Techniques. 2024 8th International Conference on Inventive Systems and Control (ICISC).

[Link:<https://ieeexplore.ieee.org/document/10677778>]

[5] CHIRAG VARSHNEY, TUSHAR, Dr.Amita Goel, Er.Nidhi Sengar, Dr. Vasudha Bahl (2023). FOREST FIRE ANALYSIS USING MACHINE LEARNING. International Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 07. [Link: <https://doi.org/10.55041/IJSREM17514>]

[6] Seyd Teymoor Seydi, Vahideh Saeidi , Bahareh Kalantar, Naonori Ueda, and Alfian Abdul Halin (2022). Fire-Net: A Deep Learning Framework for Active Forest Fire Detection. Hindawi Journal of Sensors Volume 2022, Article ID 8044390. [Link: <https://doi.org/10.1155/2022/8044390>]

[7] Dr. C K GOMATHY, Mr. DARAM NAGA SAI KALYAN, Mr. ADDEPALLI SAI MANI DEEP, Mr. CHALLA SAI HEMANTH (2021). FOREST FIRE DETECTION USING MACHINE LEARNING. International Research Journal of Engineering and Technology (IRJET), Volume: 08 [Link: [https://www.researchgate.net/publication/357448759\\_FOREST\\_FIRE\\_DETECTION\\_USING\\_MACHINE\\_LEARNING](https://www.researchgate.net/publication/357448759_FOREST_FIRE_DETECTION_USING_MACHINE_LEARNING) ]

[8] Pragati, Sejal Shambhuwani, Piyusha Umbrajkar (2019- 2020). FOREST FIRE DETECTION USING MACHINE LEARNING. INTERNATIONAL JOURNAL OF ADVANCE SCIENTIFIC RESEARCH AND ENGINEERING TREN, Volume 4. [Link: [https://www.ijasret.com/VolumeArticles/FullTextPDF/406\\_2\\_FOREST\\_FIRE\\_DETECTION\\_USING\\_MACHINE\\_LEARNING.pdf](https://www.ijasret.com/VolumeArticles/FullTextPDF/406_2_FOREST_FIRE_DETECTION_USING_MACHINE_LEARNING.pdf)]