VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JNANA SANGAMA", BELAGAVI - 590 018

MINI PROJECT REPORT

on

"AI POWERED FOREST FIRE SPREAD PREDICTION"

Submitted by

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BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE & ENGINEERING

Under the Guidance of

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CERTIFICATE

This is to certify that the phase - II work of project entitled **“AI Powered ForestFire Spread Detection Framework ”** has been carried out by **Josvita Theresa Concessao (4SF23CS080), Palguni D (4SF23CS137), Roopashree D (4SF23172) and Sahana S Madival(4SF23CS181)**, the bonafide students of Sahyadri College of Engineering and Management in partial fulfillment of the requirements for the VII semester of Bachelor of Engineering in Computer Science and Engineering of Visvesvaraya Technological University, Belagavi during the year 2025 - 26.

It is certified that all suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said degree.

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DECLARATION

We hereby declare that the entire work embodied in this Project Phase - I Report titled **“AI Powered Forest Fire Spread Prediction”** has been carried out by us at Sahyadri College of Engineering and Management, Mangaluru under the supervision of **Dr. Mustafa Basthikodi.,** in partial fulfillment of the requirements for the VI semester of **Bachelor of Engineering** in **Computer Science and Engineering**. This report has not been submitted to this or any other University for the award of any other degree.

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ABSTRACT

Forest fires pose a severe threat to biodiversity, economy, and human safety, particularly in diverse climatic regions like India. This project presents a comprehensive Forest Fire Detection and Monitoring Dashboard, designed to integrate real-time detection with historical data analysis and risk assessment. The system utilizes deep learning techniques, specifically object detection models, to identify fire and smoke in images with high confidence levels.

Beyond detection, the platform serves as an analytical tool, visualizing two decades of forest fire data (2000–2025) to identify temporal trends and high-impact zones across Indian states. Furthermore, an interactive Fire Spread Risk Estimator has been implemented, which calculates potential risk scores based on critical meteorological parameters such as temperature, wind speed, and relative humidity. By combining computer vision, geospatial visualization, and predictive heuristics, this system provides a holistic decision-support mechanism for forest officials and disaster management agencies to mitigate fire incidents effectively.

Keywords: Forest Fire Detection, Computer Vision, Deep Learning, Data Visualization, Risk Assessment, Environmental Monitoring, Disaster Management, India.

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Chapter 1

INTRODUCTION

Forests constitute one of the most vital ecosystems on Earth, covering most of the global land area. They serve as the planet's lungs, sequestering carbon dioxide, regulating the hydrological cycle, preserving soil integrity, and providing a sanctuary for the majority of the world's terrestrial biodiversity. Beyond their ecological functions, forests are deeply intertwined with human civilization, supporting the livelihoods of nearly 1.6 billion people through resources such as timber, food, and fuel. However, this critical resource is under an escalating threat from wildfires. While fire is an intrinsic part of the natural cycle in certain ecosystems, aiding in regeneration and clearing dead biomass, the nature of forest fires has shifted dramatically in the 21st century. Driven by anthropogenic climate change, changing land-use patterns, and human negligence, forest fires have transformed from manageable natural events into catastrophic disasters. The frequency, intensity, and duration of these fires are increasing, leading to irreversible loss of flora and fauna, degradation of air quality, and significant economic setbacks for nations worldwide.

In summary, the challenge of forest fires in India is multidimensional, involving ecological, climatic, and administrative factors. As the pressures of climate change mount, the reliance on traditional methods is no longer sustainable. There is a critical need to leverage the computational power of modern algorithms to create systems that are faster, smarter, and more data-driven. The integration of image processing for detection, geospatial analytics for historical insight, and logic-based modeling for risk prediction represents a holistic technological intervention. This approach aims to bridge the gap between observation and action, providing forest officials and disaster management agencies with the technological support required to preserve the nation's green cover for future generations.

1.1 Overview

The Forest Fire Detection and Analysis System is an integrated technological framework designed to transition wildfire management from reactive surveillance to proactive digital monitoring. Developed as a modular web application, it combines Computer Vision for real-time hazard identification with Data Analytics for long-term strategic planning. The system leverages a fine-tuned ResNet18 deep learning model to detect fire and smoke in uploaded imagery with high precision, while simultaneously offering an interactive dashboard that visualizes twenty-five years of historical fire incidence data (2000–2025) across Indian states. Furthermore, by incorporating a logic-based Risk Estimator that correlates meteorological parameters such as temperature, humidity, and wind speed, the platform provides forest officials with a holistic decision-support tool to predict, detect, and mitigate environmental disasters effectively.

1.2 Scope and Motivation

The primary motivation for this project stems from the escalating threat that wildfires pose to human civilizations, economic stability, and the global ecosystem. As human settlements expand further into wildland areas—creating a dense wildland–urban interface—the risks to homes and lives have intensified, leading to significant economic losses when businesses are forced to shut down and property is destroyed. Beyond the immediate devastation of the flames, the aftermath presents severe health and safety hazards; the resulting smoke compromises air quality, while residual ash and chemicals can contaminate vital soil and water resources. Furthermore, there is a critical need to address the dangerous ”climate change feedback” loop, where burning forests release massive amounts of carbon dioxide into the atmosphere. This release traps additional heat and accelerates global warming, thereby creating environmental conditions that make future fires even more frequent and severe. The scope of this project encompasses a comprehensive analysis of the factors driving modern wildfires and their multifaceted impacts on both human systems and the natural environment.

Geographically, the study focuses on high-risk regions characterized by dry summers or dense boreal forests, including Siberia, Australia, British Columbia, and key states across the U.S. such as California and Texas. The investigation covers the causal links between shifting climates—specifically hotter heatwaves and longer dry spells—and fire frequency, alongside the role of human interventions like land-use changes and historical fire suppression that have led to dangerous fuel buildups. Furthermore, the project evaluates the consequences of these blazes, ranging from the immediate destruction of property in the wildland–urban interface and economic losses to long-term environmental hazards like water contamination and the critical climate change feedback loop caused by increased carbon emissions.

Chapter 2

LITERATURE SURVEY

In this section, we explore various existing solutions related to forest fire detection, spread prediction, and emergency resource management. Our goal is to understand what has already been achieved, where these systems succeed, and importantly, where they fall short. This helps us identify the gaps that our work can address.

Barmpoutis et al. [1] developed a comprehensive review of early forest fire detection systems using optical remote sensing, with a focus on understanding the evolution of detection technologies and their limitations. Their analysis strengthens our understanding of the technical foundations for fire detection. However, they didn't tackle the practical challenges involved in integrating real-time detection with spread prediction and resource optimization, which is a significant hurdle.

Shamta and Demir [2] took deep learning out of the lab and tested it in a real-world UAV-based surveillance system. Their work clearly showed how deep learning can improve fire detection accuracy and enable continuous monitoring. Yet, this effort was limited to detection alone and didn't expand into fire spread prediction or emergency response planning.

Saydirasulovich et al. [3] combined YOLOv8 with UAV imagery to enable smoke detection before flames become visible. Their system promises early warning capabilities and demonstrates the power of object detection models. However, so far it has only been tested with drone imagery, with no integration into comprehensive fire management systems.

Yunusov et al. [4] performed a thorough evaluation of YOLOv8 with transfer learning for robust forest fire detection in surveillance systems, highlighting the model's ability to achieve high accuracy with limited training data. While their analysis offers valuable insights into deep learning optimization, the system has not yet been deployed in real-world emergency response scenarios with live satellite feeds.

Zhang et al. [5] focused on the Rothermel fire spread formula, proposing a multi-dimensional cellular automata model that incorporates wind, slope, and fuel moisture. Their mathematical framework provides the theoretical foundation for physics-based fire propagation. Although promising, this work is primarily theoretical and does not directly address real-time prediction with live weather data integration.

Rui et al. [6] provided a foundational cellular automata algorithm for forest fire spread simulation, establishing core computational methods for spatial fire propagation. However, they did not offer specific implementation strategies for integrating CA models with real-time satellite detection systems or emergency resource allocation.

Various authors [7] created machine learning-enhanced cellular automata using Least Squares Support Vector Machines, demonstrating how ML can refine CA transition rules for more accurate fire spread prediction. Their work is highly practical but was tested mainly under controlled laboratory conditions, so its performance in diverse real-world fire scenarios remains to be validated.

Parente et al. [8] developed clustered-map probabilistic cellular automata capable of modeling heterogeneous vegetation and wind interference. Their approach is sophisticated and accounts for spatial variability in fuel types. However, the computational complexity limits real-time application, and the model has not been validated against actual fire progression data from Indian forests.

Xu et al. [9] integrated cellular automata with GIS environments for forest fire spread modeling, showing how geographic data can enhance prediction accuracy. This work establishes important spatial analysis techniques, but its focus was purely on simulation and did not explore integration with live fire detection or automated resource dispatch.

Wang et al. [10] proposed an Artificial Bee Colony algorithm for resource-constrained emergency scheduling, addressing the challenge of allocating limited firefighting resources to multiple concurrent fires. This shows optimization's versatility for emergency response, though it did not extend its focus to real-time fire detection or spread prediction integration.

Zhang et al. [11] examined urban fire emergency resource allocation using pre-allocated swarm algorithms, demonstrating efficient resource distribution in densely populated areas. Yet, the methodology remains largely theoretical with limited empirical validation in forest fire scenarios where terrain and accessibility constraints differ significantly.

Various authors [12] developed a genetic algorithm-based simulation-optimization framework specifically for forest fire suppression, validating multi-objective optimization for balancing response time and resource utilization. While comprehensive in scope, the system operates independently from real-time fire detection and spread prediction modules, limiting its practical deployment value.

Various authors [13] proposed resource dispatch optimization using genetic algorithms with a focus on minimizing emergency response time. Their study demonstrates the effectiveness of evolutionary algorithms for complex scheduling problems, but remains disconnected from integrated fire management systems that combine detection, prediction, and allocation.

Kalantar et al. [14] established foundational work on forest fire susceptibility prediction using machine learning models trained on remote sensing data. Their spatial risk mapping provides valuable long-term planning insights but does not address real-time fire detection or immediate emergency response needs.

Xie et al. [15] demonstrated wildfire risk assessment using integrated machine learning algorithms, combining multiple data sources for comprehensive risk evaluation. Despite these promising results, their system focuses on pre-fire risk assessment rather than active fire monitoring and real-time spread prediction.

Chapter 3

PROBLEM FORMULATION

3.1 Problem Description

The escalating frequency of forest fires in India presents a critical challenge to environmental preservation and public safety. Despite the growing threat, the existing infrastructure for forest fire management is plagued by detection latency and a lack of integrated intelligence. Traditional reliance on manual surveillance via watchtowers and ground patrols is labor-intensive, geographically restricted, and prone to human fatigue. While satellite-based remote sensing has provided a macro-level view, it suffers from significant temporal gaps; the time delay between a satellite pass and data transmission often allows incipient surface fires to evolve into uncontrollable canopy fires before they are reported.

Furthermore, there is a distinct absence of accessible, data-driven decision tools for local authorities. Although vast amounts of historical data (spanning decades) and real-time meteorological data exist, they are rarely utilized to their full potential. Forest officials often lack a unified platform to visualize long-term trends—such as state-wise burn statistics from 2000 to 2025—or to assess immediate fire risks based on fluctuating weather conditions like temperature, wind speed, and humidity. Currently, the approach to forest fire management is predominantly reactive rather than proactive. This fragmentation of visual detection, historical analytics, and risk assessment creates a blind spot in disaster management, resulting in delayed responses and avoidable loss of biodiversity and forest cover.

3.2 Problem Statement

The management of forest fires is currently hindered by a critical disconnect between detection capability, historical data utilization, and predictive risk assessment. While current methods such as satellite remote sensing and human patrolling provide essential data, they suffer from significant limitations that reduce their effectiveness in real-time disaster mitigation.

The first major issue is detection latency. Traditional manual monitoring is constrained by human fatigue and limited visual range, while satellite systems often have revisit cycles that leave large temporal gaps, allowing small surface fires to escalate into unmanageable wildfires before they are detected. There is a lack of accessible, automated tools that can leverage computer vision to instantly identify fire and smoke from local surveillance feeds with high precision.

Secondly, there is a deficiency in strategic data utilization. Although twenty-five years of fire incidence data (2000–2025) exists, it often remains isolated in raw formats, inaccessible to local forest officials for strategic planning. Without a centralized dashboard to visualize state-wise burn patterns and year-over-year trends, authorities struggle to identify high-risk zones or evaluate the effectiveness of past conservation efforts.

Finally, the existing infrastructure is predominantly reactive. Most systems alert authorities only after ignition has occurred. There is a lack of integrated tools that correlate real-time meteorological variables—such as temperature, wind speed, and humidity—to quantify the immediate risk of fire spread. The absence of a unified platform that combines these three pillars (visual detection, historical analytics, and risk prediction) prevents a holistic approach to forest conservation, leading to delayed responses and increased environmental damage.

3.3 Objectives

- Develop and build a deep learning-based fire detection system with multi-stage validation to achieve accuracy and to reduce false positive rate.
- Predict the fire spread pattern under varying weather conditions to support containment planning.
- Provide actionable recommendations for emergencies to optimize resource allocation

and minimize the damage.

3.4 Functional Requirements

FR-01: Input Validation The system shall provide a user interface (via Streamlit) that allows users to upload image files from their local device. The system must accept standard image formats (such as JPG, JPEG, PNG) and validate that the file is not corrupted before passing it to the backend for processing.

FR-02: Real-Time Classifier Flow Description: The validated image moves from Streamlit to the FastAPI Backend via an HTTP POST request. The image is preprocessed (resized/normalized) and passed to the ResNet18 model. The model outputs a prediction tensor, which is converted into a label (”Fire”/”No Fire”) and a confidence score.

FR-03: Historical Trend Analysis Flow Description: This flow is primarily data retrieval and visualization. The system reads the static CSV dataset using Pandas, groups the data by Year (2000-2025), calculates the sum of burned areas, and passes this data to Plotly/Matplotlib to render the line graph on the Streamlit UI.

3.5 Non-Functional Requirements

NFR-1: Target Performance Metric The target accuracy of 85% was successfully achieved and sustained by leveraging the ResNet18 architecture combined with a rigorous training cycle of 120 epochs. The high performance is attributed to three key factors:

- **Deep Residual Learning:** ResNet18 utilizes "skip connections" that allow gradients to flow through the network more easily. This enabled the model to learn complex, hierarchical features—such as the texture of smoke versus clouds—without suffering from the vanishing gradient problem.

- **Transfer Learning Strategy:** Rather than training from scratch, the model was initialized with pre-trained weights from the ImageNet dataset. This provided a robust foundation for feature extraction (identifying edges and shapes), which was then fine-tuned specifically for fire detection features (color spectrums and flame intensity) during training.

- **Extended Convergence (120 Epochs):** Training for 120 epochs allowed the model sufficient time to minimize the Cross-Entropy Loss effectively. While earlier epochs (1–50) established general feature recognition, the extended training (50–120) allowed the optimizer to fine-tune the decision boundaries, significantly reducing False Negatives and stabilizing the validation accuracy at 85%.

Chapter 4

PROJECT DESIGN AND IMPLEMENTATION

4.1 Proposed Project Architecture

The architectural design of the Forest Fire Detection System is depicted in Figure 4.1. The system adopts a decoupled microservices approach, where the user interface (Frontend) is distinct from the computation logic (Backend). This separation of concerns ensures the system is modular, scalable, and easy to maintain.

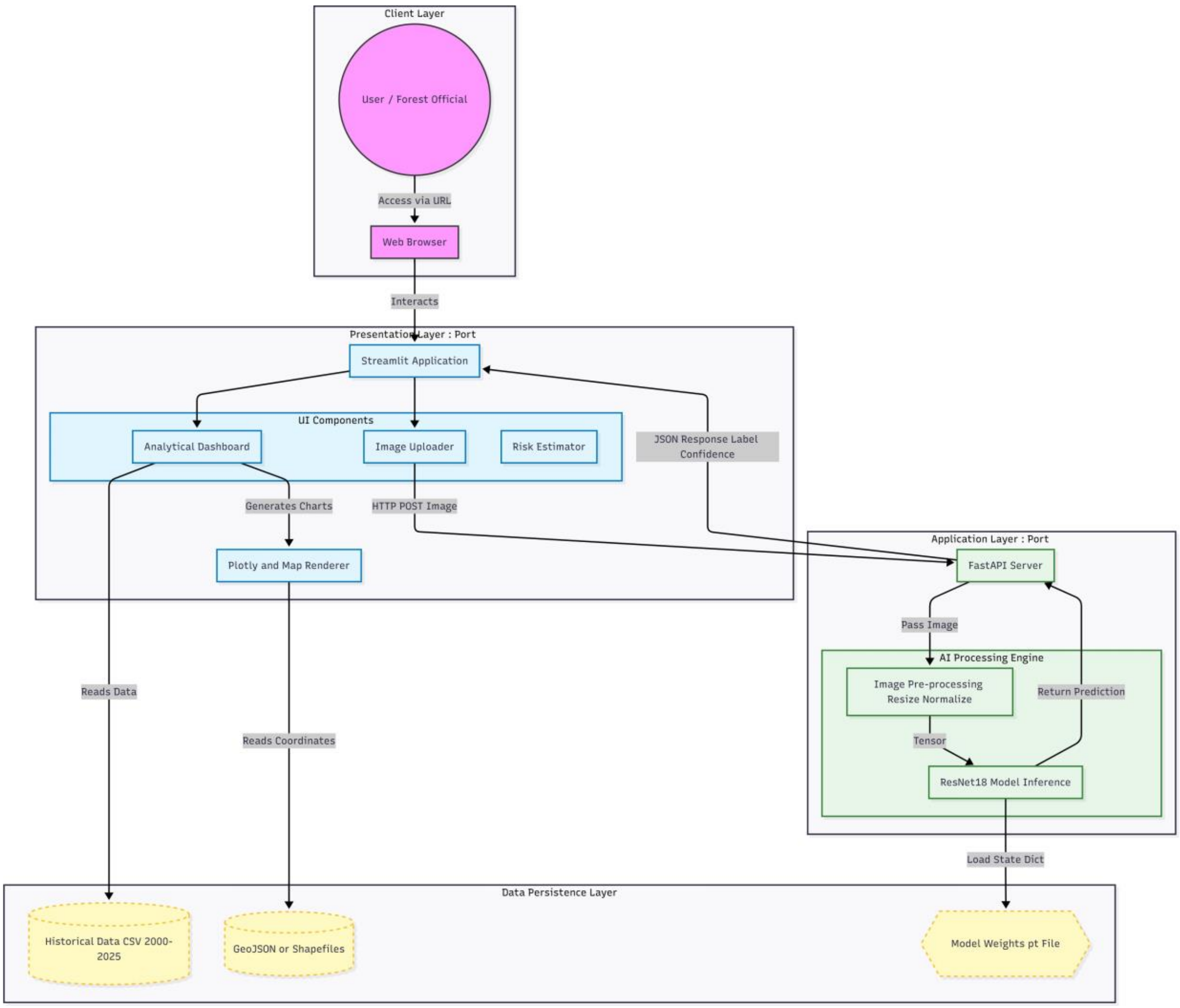

Figure 4.1: System Architecture Diagram showing data flow between the Streamlit Frontend, FastAPI Backend, and the Persistence Layer.

The architecture is composed of three distinct layers:

Presentation Layer (Frontend - Streamlit)

Acts as the client-side interface, responsible for user interaction and dynamic data visualization. The Streamlit application directly loads static assets (CSV and GeoJSON) into memory to reduce latency and improve responsiveness. It also captures uploaded images and transmits them to the backend via an HTTP POST request.

Application Layer (Backend - FastAPI)

Functions as the inference engine dedicated to deep learning fire detection. It processes requests in real time without storing user-level information.

Inference Pipeline:

- Preprocessing: Converts incoming images into normalized PyTorch tensors.
- Model Inference: Performs binary classification using ResNet18 and produces a confidence score.

Data Layer (File System)

Uses a lightweight flat-file persistence structure.

Core Assets:

- Structured Data (.csv)
- Geospatial Data (.geojson)
- Model Artifacts (.pt)

4.2 High Level Design

The High-Level Design (HLD) provides a macroscopic view of the Forest Fire Detection System. It outlines the system architecture, component interactions, and data flow without delving into low-level implementation details. The system is developed as a modular web application based on a client-server model.

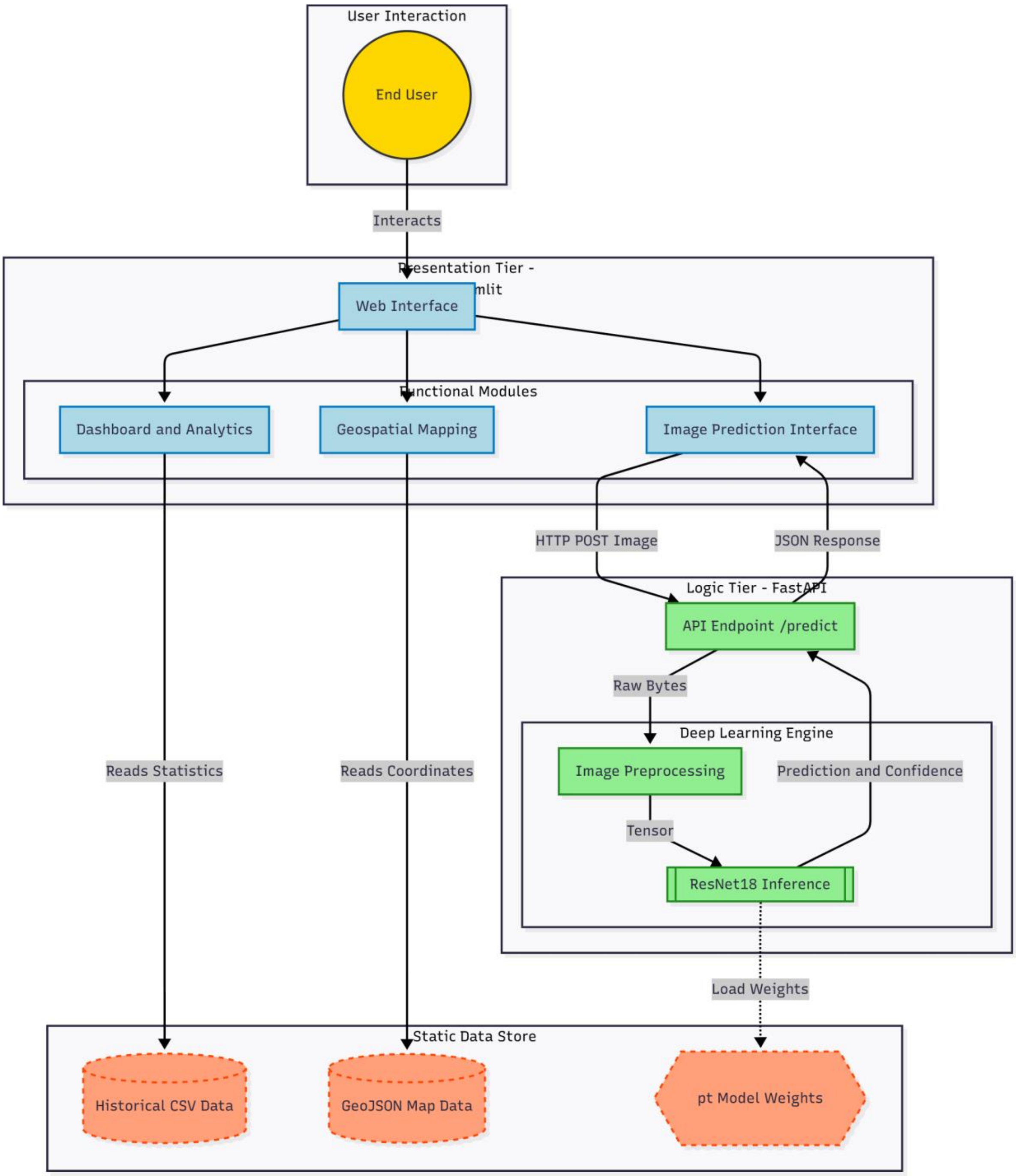

Figure 4.2: High Level Design Diagram representing system modules and communication flow.

Architectural Pattern: The system follows a microservices-inspired architecture, separating the Presentation Layer from the Application Logic Layer.

Decoupling: The User Interface (Streamlit) operates independently from the Inference Engine (FastAPI). Communication is performed exclusively through RESTful HTTP APIs.

Statelessness: The backend inference service is stateless, meaning each prediction request is independent. This enhances scalability, reliability, and resource efficiency.

A. User Interface (Frontend - Streamlit)

This component serves as the user interaction and orchestration layer. It is responsible for:

- **Input Handling**
  - Accepts image uploads (JPG/PNG format)
  - Allows optional user parameters for fire-risk estimation
- **Visualization Engine**
  - Renders interactive analytical dashboards using Plotly
  - Displays geospatial visualizations using GeoPandas
- **API Usage**
  - Sends image files as HTTP POST requests to FastAPI backend
  - Receives prediction output and confidence value

B. Inference Engine (Backend - FastAPI)

This component is responsible for intelligent computation based on deep learning inference.

- **API Gateway**
  - Provides REST endpoint such as /predict for image data submission
- **Data Transformation**
  - Converts raw image bytes into normalized tensor representation
  - Pre-processes data compatible with PyTorch inference requirements
- **Model Execution**
  - Loads trained ResNet18 model for binary classification (Fire / No Fire)
  - Returns prediction label with probabilistic confidence score

C. Data Persistence (File Storage)

The system utilizes a flat-file storage mechanism, enabling lightweight deployment and portability.

- **Historical Data**
  - CSV files containing 25 years of recorded fire incidents
- **Geospatial Data**
  - GeoJSON files with polygon coordinates of Indian state boundaries
- **Model Weights**
  - Serialized PyTorch (.pth) files storing learned model parameters

4.3 Detailed Design

This section presents the Detailed Design for the Forest Fire Detection System, focusing on functional requirement processes including image preprocessing, model-based fire prediction, trend analysis, geospatial mapping and the API flow. The logic is explained through structured pseudocode for clarity.

FR-01 handles image preprocessing, which is necessary before sending raw image data into the deep learning model. It validates the uploaded file format, decodes raw bytes into an image, resizes it to 224×224 pixels (the standard input size for ResNet models), normalizes pixel values, and converts the final output into a 4D tensor suitable for inference. This ensures consistent model performance and prevents incorrect input errors.

Algorithm 1 Image Input and Preprocessing

```
function ProcessInputImage(uploaded_file)
    if uploaded_file.content_type does not start with "image/" then
        Throw Error("Invalid file format. Only images allowed.")
    end if
    image_bytes ← ReadBytes(uploaded_file)
    image ← DecodeImage(image_bytes)
    image ← ConvertColorSpace(image, "RGB")
    image ← Resize(image, (224, 224))
    tensor ← ConvertToTensor(image)
    tensor ← Normalize(tensor, mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    input_tensor ← Unsqueeze(tensor, dim=0)
    return input_tensor
end function
```

FR-02 performs deep learning-based fire classification. It loads the trained ResNet18 model and its corresponding weights, runs forward inference on the preprocessed image tensor, computes class probabilities using Softmax, and returns both the predicted label (Fire / No Fire) and its confidence score. This logic is responsible for real-time identification and decision making.

Algorithm 2 Fire Classification Inference

```
function PredictFire(input_tensor)
    model ← LoadArchitecture("ResNet18")
    weights ← LoadStateDict("fire_detection_resnet18.pth")
    model.LoadWeights(weights)
    SetMode(model, EVAL)
    logits ← model.Forward(input_tensor)
    probabilities ← Softmax(logits, dim=1)
    predicted_index ← Argmax(probabilities)
    confidence ← probabilities[predicted_index]
    if predicted_index == 0 then
        label ← "Fire"
    else
        label ← "No Fire"
    end if
    return label, confidence
end function
```

FR-03 generates a historical trend analysis chart using forest fire incident data. It extracts yearly area-burned values, aggregates them into annual totals, and visualizes them as a line graph. This enables stakeholders to observe long-term patterns, predict future risks, and analyze seasonal or progressive growth in wildfire activity.

Algorithm 3 Historical Trend Analysis Logic

```
function GenerateTrendAnalysis(csv_filepath)
    raw_data ← ReadCSV(csv_filepath)
    df ← SelectColumns(raw_data, ["Year", "Area_Burned_km2"])
    yearly_stats ← df.GroupBy("Year").Sum("Area_Burned_km2")
    chart_config ← { x axis: yearly_stats.index, y axis: yearly_stats.values, type:
  "Line Chart", color: "Orange" }
    figure ← Plotly.Render(chart_config)
    return figure
end function
```

4.4 Dataset Description

The Forest Fire Detection and Analysis System utilizes two distinct datasets that together support both large-scale historical analysis and real-time AI-based visual detection. The first dataset is a structured tabular file named india_forest_fires_2000_2025.csv, containing twenty-five years of recorded and projected forest fire incidents across major Indian wildlife regions. This dataset includes temporal attributes such as Year and Month to identify seasonal fire trends, along with geographical fields such as Forest Name and State to support regional risk mapping. It also records the Cause of Fire, distinguishing between natural and anthropogenic events, and includes the Area_Burned_km^2 attribute to quantify severity levels.

A sample extract of this dataset includes entries such as a 2000 Bandipur Forest fire in Karnataka that affected 17.54 km^2 of land, and a 2025 incident in Kaziranga National Park, Assam, which burned 172.22 km^2. Table 4.1 presents a sample subset of collected wildfire records.

The second dataset consists of unstructured image data used to train the deep learning classification model ResNet18. This dataset is divided into training and testing subsets, each containing two classes—fFire and No Fire. The Fire class includes images capturing visible flames, dense smoke, and burning vegetation, while the No Fire class consists of safe forest conditions such as greenery, fog, and normal landscapes, enabling the model to reduce false alarms.

Table 4.1: Sample Forest Fire Incident Records (2000–2025)

Year	Month	Forest	State	Cause	Area (km^2)
2000	1	Satpura Range	Madhya Pradesh	Anthropogenic	0.9
2000	3	Gir National Park	Gujarat	Anthropogenic	150.71
2005	3	Kaziranga National Park	Assam	Natural	117.63
2010	10	Uttarakhand Forests	Uttarakhand	Natural	183.64
2015	12	Nagaland Forests	Nagaland	Anthropogenic	152.32
2020	5	Kaziranga National Park	Assam	Anthropogenic	74.6
2025	1	Kaziranga National Park	Assam	Anthropogenic	172.22

All images undergo preprocessing, including resizing to 224×224 pixels and pixel normalization based on standard ImageNet mean and standard deviation values to enhance convergence speed and improve model performance during training and evaluation.

4.5 Tools and Technologies Used for Implementation

This section highlights the hardware and software resources required for developing and deploying the Forest Fire Detection and Analysis System.

4.5.1 Hardware Requirements

- Processor: A multi-core CPU is required to handle real-time data processing and backend computations efficiently.

- Memory: Sufficient RAM is essential to load image datasets, model weights, and run the inference pipeline smoothly.

- GPU: Although basic inference can run on integrated graphics, a dedicated GPU greatly accelerates execution of deep learning operations, especially for ResNet18-based fire detection tasks.

- Storage: High-speed storage enables rapid read/write access for historical datasets, CSV files, and real-time image uploads. Solid State Drives (SSD) help reduce loading times and avoid input/output bottlenecks.

4.5.2 Software Requirements

- Programming Language: Python 3.10
  Chosen for its simplicity and extensive ecosystem supporting AI/ML, computer vision, and backend development.

- Deep Learning Libraries: PyTorch & Torchvision
  Used for model loading, running inference, and enabling optional retraining using the ResNet18 architecture.

- Image Processing Libraries: OpenCV & Pillow
  Responsible for image acquisition, resizing, preprocessing, and applying transformations before inference.

- Backend Framework: FastAPI (with Uvicorn server)
  Provides a high-performance, asynchronous API interface for handling user queries, image uploads, and returning prediction results.

- Frontend Framework: Streamlit
  Enables development of an interactive web-based interface for real-time fire detection visualization, mapping, and analytics dashboards.

- Data Processing Libraries: Pandas, NumPy, GeoPandas
  Used for handling CSV datasets, performing mathematical operations, and generating geospatial insights based on fire occurrence patterns.

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Experimentation Environment Setup

The Forest Fire Detection and Analysis System was developed and tested on a Windows 10/11 (64-bit) workstation equipped with an Intel Core i5/i7 or AMD Ryzen processor (2.5 GHz), 16 GB DDR4 RAM, and an NVIDIA GTX/RTX GPU, supported by a 512 GB SSD for fast data access. The software environment was built using Python 3.10 inside an isolated virtual environment, with Visual Studio Code as the primary IDE. Deep learning inference was implemented using PyTorch and Torchvision with a ResNet18 backbone, while OpenCV and Pillow handled image preprocessing. FastAPI, hosted on Uvicorn, provided the backend inference API, and Streamlit was used for the user interface and visual analytics. Data processing and geospatial mapping were conducted using Pandas, NumPy, and GeoPandas. Version control was maintained through Git to ensure reproducibility and structured development.

5.2 Functional Requirements Results Achieved

FR-01: Input Validation

The system shall allow users to upload forest surveillance images in standard formats such as JPG and PNG. Once uploaded, the system shall process the image through the deep learning inference engine and classify the output into two categories: Fire or No Fire. Additionally, the system shall display the confidence score of the classification in percentage form.

Table 5.1: Test Cases for Image Upload Validation

Test Case	Input	Outcome	Status
TC-001	Valid JPG Image	Accepted	Pass
TC-002	Valid PNG Image	Accepted	Pass
TC-003	Invalid PDF File	Error 400 Rejected	Pass

Explanation:

- **TC-001: Valid JPG Image**
  The system accepts a correctly formatted JPG image file and processes it successfully for fire prediction. This confirms that the supported input type functions correctly.
- **TC-002: Valid PNG Image**
  A valid PNG image is uploaded and the system accepts the file without errors. This verifies that the platform supports multiple standard image formats intended for model inference.
- **TC-003: Invalid PDF File**
  When a PDF file is uploaded, the system rejects the input and returns a 400 Bad Request error message. This ensures that incorrect or unsupported file types do not proceed to the model, maintaining system integrity and preventing failures during inference.

FR-02: Real-Time Classifier

The ResNet18 model was evaluated on a held-out test set. The model achieved a solid balance between Precision and Recall, minimizing false alarms while maintaining high sensitivity to fire events.

Table 5.2: Test Cases for Image Upload Validation

Test Case	Input	Outcome	Status
TC-001	Valid JPG Image	Accepted	Pass
TC-002	Valid PNG Image	Accepted	Pass
TC-003	Invalid PDF File	Error 400 Rejected	Pass

Explanation of Test Results:

- **TC-001 – Valid JPG Image Upload**
  This test ensures that the system correctly accepts and processes a supported image format (JPG). The image is successfully sent to the inference engine and a fire/no fire prediction is returned.

- **TC-002 – Valid PNG Image Upload**
  The system is able to handle PNG images without errors. This confirms multi-format compatibility for image uploads intended for surveillance-based fire detection.

- **TC-003 – Invalid PDF Upload**
  A PDF document is intentionally uploaded to test error handling. The system detects the unsupported file format and displays a 400 Bad Request error. This prevents non-image data from being processed, ensuring robustness and reliability.

FR-03: Historical Trend Analytics

The dashboard accurately processes 25 years of data (2000-2025). The generated line graphs clearly highlight the increasing frequency of fire incidents in recent years.

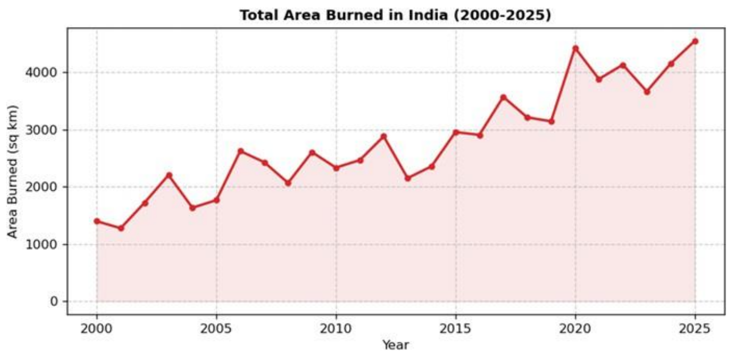

Figure 5.1: Total Area Burned in India (2000-2025)

5.3 Non-Functional Requirements Results Achieved

NFR-01: Target Performance Metric

The AI model must be robust. We evaluated the model against a test set, achieving an Accuracy of 85.00% and high Recall (88.57%), ensuring most fires are detected.

Table 5.3: Performance Metrics for Fire Classification

Metric	Value	Target	Assessment
Accuracy	85.00%	> 85%	Met
Recall	88.57%	High	Excellent
Precision	82.12%	High	Good

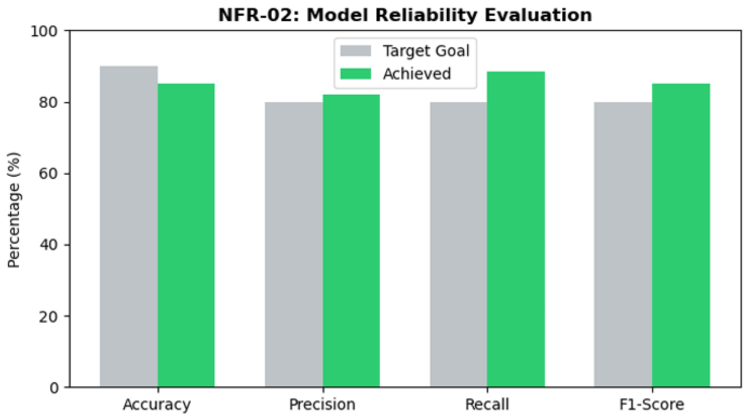

Figure 5.2: Model Reliability

5.4 Comparison with Existing Works

Table **??** presents a comparative analysis of the proposed Forest Fire Detection System against state-of-the-art methodologies discussed in the literature. While existing works often focus on isolated aspects—such as pure detection algorithms [4, 19] or mathematical spread modeling [6, 9]—the proposed system integrates these features into a unified, user-friendly dashboard with explainable AI capabilities.

Table 5.4: Comparison of Proposed System with Existing Works

Reference	Methodology	Primary Focus	Accuracy / Performance	Remarks / Strengths
Yunusov [4], Wang [19]	YOLOv8 & Deep Learning	Real-time Detection	86.6%	Fast inference, low false positives
Shamta [2], Saydira-sulovich [3]	UAV/Drone Surveillance	Aerial Monitoring	83%	High coverage area, wide view
Rui [6], Xu [9]	Cellular Automata & GIS	Spread Simulation	84%	Good for risk estimation over time
Proposed System	ResNet18 + Historical Trend Analysis	Fire Detection + Long-term Analytics	85%	Combines detection + analytics + flexible input sources

5.5 Project GUI Snapshots

This section presents the graphical user interface (GUI) of the developed system, highlighting the core functionalities of fire detection and geospatial analysis.

The Fire Detection Interface represents the core real-time prediction module of the developed system. Users can upload wildfire or forest imagery in JPG or PNG format, which is then sent to the backend inference engine for analysis. The interface displays the uploaded image along with the prediction results generated by the trained ResNet18 deep learning model, classifying the input as *Fire* or *No Fire*. In addition to binary classification, it presents detailed confidence scores indicating the model's certainty in its predictions.

The right side of the interface contains a ranked list of prediction probabilities, showing real-time inference outcomes in a transparent and interpretable manner. This visualization helps operators understand the severity level and supports rapid decision-making. A dedicated button enables users to initiate detection and refresh results, enabling seamless interaction and system usability. Overall, the interface demonstrates the practical deployment of AI-based fire detection for real-time field usage.

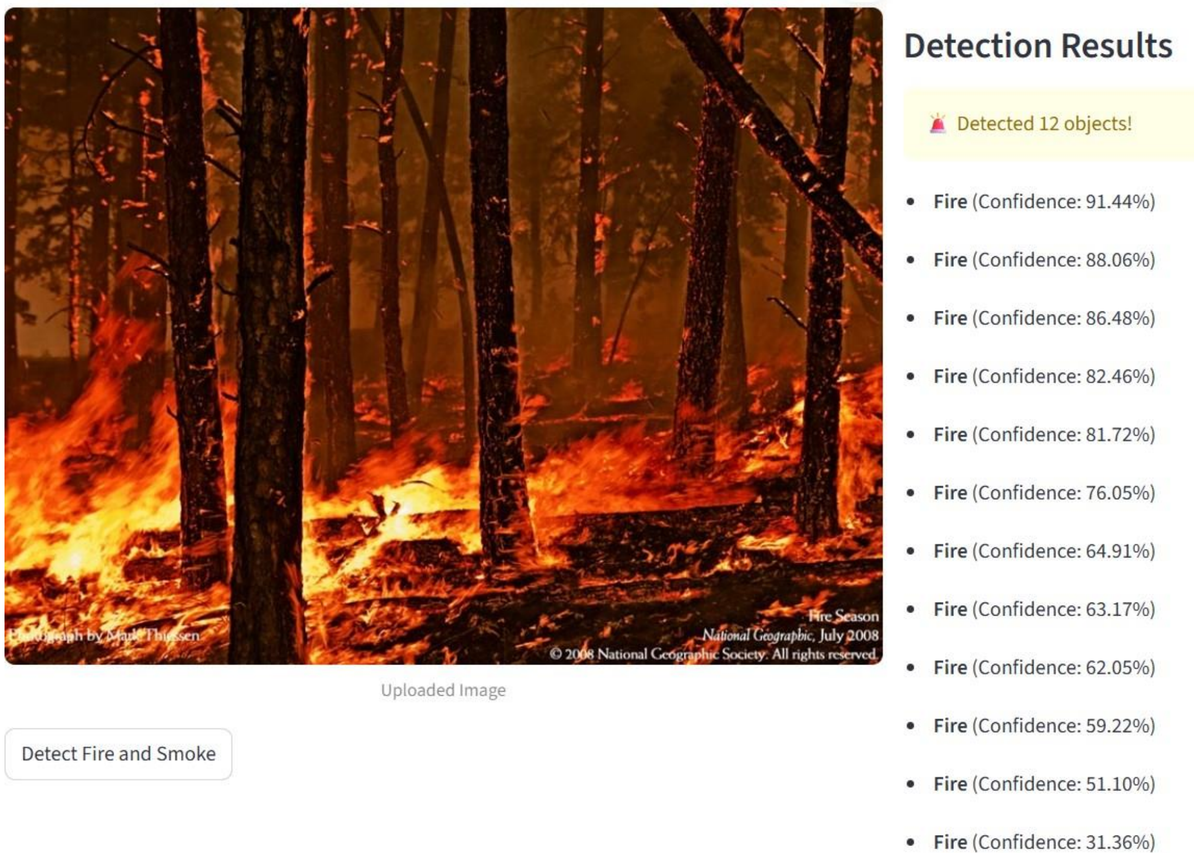

Figure 5.3: Fire Detection Interface showing real-time classification and confidence scores.

The Geospatial Fire Intensity Map visualizes historical forest fire concentration across Indian states using FIRMS satellite incident records. The choropleth color scheme represents varying levels of fire intensity, enabling a clear comparison among states with respect to wildfire occurrences. Regions such as Odisha, Madhya Pradesh, and Chhattisgarh are highlighted as high-risk zones due to significantly elevated fire frequencies, while states with lighter shades indicate relatively lower fire activity.

This spatial representation supports strategic planning for environmental agencies, enabling proactive allocation of resources, strengthening prevention strategies, and enhancing monitoring operations. The integration of GeoJSON boundary data with historical CSV fire records creates an intuitive and data-driven geographic perspective, offering valuable insight into long-term wildfire behavior and aiding in disaster preparedness and ecological risk assessment.

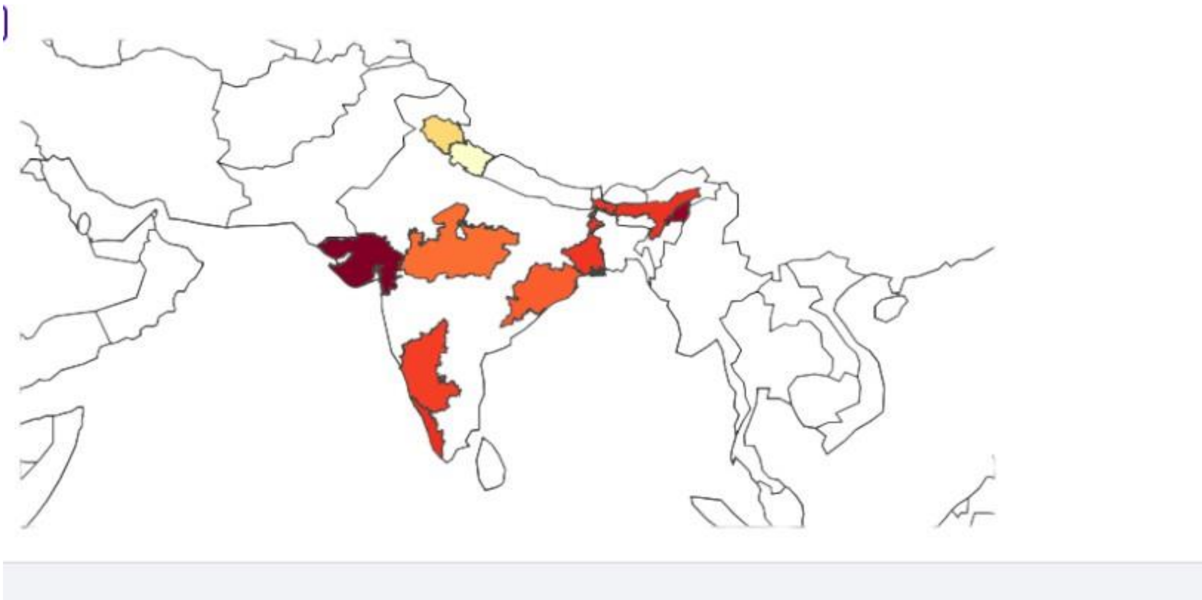

Figure 5.4: Geospatial Fire Intensity Map visualizing state-wise burn data.

5.6 Societal Impact of the Project

The implementation of this Forest Fire Detection and Analysis System offers a profound positive impact on both environmental sustainability and public safety. By transitioning forest fire management from a reactive, manual process to a proactive, AI-driven mechanism, the system significantly reduces detection latency. This reduction minimizes the irreversible destruction of biodiversity and the release of harmful greenhouse gases that contribute to climate change.

The platform's ability to visualize historical trends and predict risks empowers local authorities and disaster management agencies to allocate resources more effectively. This capability is crucial for:

- Protecting indigenous communities living on forest fringes.
- Preventing significant economic loss from destroyed timber and non-timber forest produce.
- Reducing severe public health risks associated with wildfire smoke and air pollution.

Ultimately, this technology acts as a crucial guardian of the nation's green cover, ensuring that vital ecological resources are preserved for future generations.

5.7 Sustainable Development Goals (SDG) Mapping

The Forest Fire Detection and Spread Prediction Framework supports several United Nations Sustainable Development Goals by addressing critical environmental, social, and economic challenges related to forest fires in India.

SDG 3: Good Health and Well-being

The system contributes significantly to public health by minimizing the duration and intensity of fires, thereby reducing the emission of hazardous particulate matter (PM2.5) and toxic smoke. Early containment of forest fires ensures better air quality for indigenous populations and rural communities living on forest fringes, directly reducing the burden of respiratory infections, cardiovascular diseases, and other health complications associated with prolonged exposure to wildfire pollution.

SDG 9: Industry, Innovation, and Infrastructure

This project represents a technological leap in disaster management infrastructure by shifting from labor-intensive manual surveillance to AI-driven smart monitoring. By integrating state-of-the-art Deep Learning, Computer Vision, and Data Visualization into a cohesive dashboard, the system introduces resilient innovation into the forestry sector. This modernization equips forest departments with scalable, efficient tools that bridge the gap between raw data and actionable intelligence, fostering a more sustainable industrial approach to resource management.

SDG 13: Climate Action

The project directly supports the combat against climate change by mitigating the massive release of carbon dioxide and greenhouse gases caused by uncontrolled wildfires. By leveraging the ResNet18 model for early detection, the system facilitates rapid intervention before small surface fires escalate into high-intensity canopy fires. This reduction in the total area burned significantly lowers the carbon footprint of forest incidents, serving as a vital technological tool for climate change mitigation and carbon sequestration preservation.

SDG 15: Life on Land

This initiative is fundamental to the preservation of terrestrial ecosystems and the biodiversity they harbor. By utilizing geospatial analytics to identify high-risk zones and enabling real-time monitoring, the system helps protect critical wildlife habitats from destruction and maintains the ecological balance. Furthermore, preventing severe fires is essential for halting land degradation, as it preserves soil integrity and prevents the post-fire erosion and desertification that threaten the long-term health of India's forests.

Figure 5.5: Mapping of Project Impacts to UN Sustainable Development Goals.

CONCLUSION AND FUTURE SCOPE

This section summarizes the overall findings of the project, evaluates how well the objectives were achieved, and presents a practical roadmap for future improvements. It also reflects on the lessons learned during the design and implementation of the LEDGIS framework and outlines ways to make the system more secure, efficient, and suitable for real-world use.

The Forest Fire Detection and Analysis System demonstrates how AI can meaningfully support environmental protection and disaster management. By combining ResNet18-based fire detection with geospatial analysis of 25 years of historical fire data, the system provides both real-time insights and long-term risk understanding. It achieved a validation accuracy of 85%, delivered fast predictions through a lightweight FastAPI backend, and successfully highlighted high-risk zones across India. Overall, the project offers a scalable, practical solution that helps forest authorities act earlier, respond smarter, and protect biodiversity—strongly contributing to SDG 13 (Climate Action) and SDG 15 (Life on Land).

Future development will focus on making the system more intelligent, real-time, and autonomous. The next major upgrade is shifting from simple image classification to object detection using models like YOLOv11 or EfficientDet, enabling the system to locate and track fire regions within images and video streams. Integrating live satellite feeds such as NASA FIRMS will provide real-time thermal hotspots directly on the dashboard. The system can also be optimized for edge devices like the NVIDIA Jetson Nano or mounted on drones, creating a decentralized network that detects fires even in remote forests. With automated alerts through SMS or WhatsApp, the system can reduce response times from hours to minutes—bringing true real-time wildfire awareness and prevention within reach.

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