Real-Time Wildfire Progression Analysis and Prediction using Hybrid Model

Siddhi Hande[1],Ayursha Khandagale[2],Parimala Mathe[3],Siddhi Pansare[4],Ms.Magar A. S.[5],

[1,2,3,4]Student, Department of Computer Engineering, Jaihind Polytechnic, Kuran, Pune , [5]Lecturer, Department of Computer Engineering, Jaihind Polytechnic, Kuran, Pune

Abstract— Wildfires pose a major threat to forests, ecosystems, and human life, making early detection essential for effective disaster management. This research proposes a satellite-based wildfire detection system that utilizes deep learning techniques to identify fire from satellite imagery. The system collects geographical coordinates and date inputs from the user and retrieves corresponding satellite images from the NASA repository. These images are then processed and analyzed using the YOLO (You Only Look Once) object detection model trained with datasets prepared through the Roboflow open-source platform. The model detects potential fire regions in the images and provides results that support decision making and fire propagation analysis. The proposed approach improves the efficiency and speed of wildfire monitoring, helping authorities take timely actions to reduce environmental damage and enhance emergency response.

Keywords—Sign language ,Convolutional neural Network, LSTM, Landmark.

I. INTRODUCTION

Wildfires are among the most serious natural disasters affecting forests, ecosystems, and human settlements worldwide. In recent years, their frequency and intensity have increased due to climate change and extreme weather conditions. Early detection and prediction of wildfire spread are important for reducing environmental damage and protecting human life.Traditional wildfire monitoring methods rely on satellite observations and ground-based systems, but they often struggle to provide fast detection and accurate prediction of fire progression. With the development of artificial intelligence, deep learning models such as Convolutional Neural Networks (CNNs) have been widely used to analyze satellite imagery and detect wildfire patterns [1], [7]. Object detection models like YOLO (You Only Look Once) also enable efficient real-time identification of wildfire regions [4].Recent studies have applied deep learning techniques to wildfire detection using satellite and drone images [2], [3], [15]. However, many systems focus mainly on detection rather than predicting wildfire spread. Therefore, this study proposes a hybrid deep learning approach that combines CNN-based feature extraction and YOLO-based detection using satellite imagery from NASA to support real-time wildfire monitoring and prediction.

II. LITERATURE REVIEW

Currently, several systems and methods are used for wildfire detection and monitoring. Traditional methods mainly rely on **satellite imaging and ground-based cameras**, which help in identifying fire hotspots over large areas, but they often suffer from delays and lower accuracy in early detection. Modern approaches include **IoT-based sensor networks**, where sensors placed in forests monitor temperature, humidity, and smoke levels to detect fires at an early stage and send alerts to authorities. Another widely used method is **drone (UAV)-based monitoring**, where drones equipped with thermal cameras capture real-time images and help track fire spread and identify hotspots quickly. In recent years, **AI-powered systems** have been developed that combine satellite data, cameras, and machine learning algorithms to automatically detect smoke, heat, or flames with higher accuracy and faster response times. Some advanced platforms also integrate data from multiple sources (satellites, sensors, and weather data) to predict fire behavior and support decision-making. Overall, while these existing systems improve wildfire detection, many still face challenges such as delayed response, high cost, or limited prediction capabilities.

III. PROPOSED SYSTEM

The proposed architecture is designed to efficiently handle large-scale satellite data and computationally intensive AI models while maintaining near real-time responsiveness. The system is divided into three major tiers: the Data Acquisition Tier (Satellite Sources), the Processing Tier (AI Models), and the Decision & Visualization Tier (Output System).

I. *Distributed Processing Framework*

To overcome the limitations of traditional centralized systems, the proposed solution adopts a **distributed processing approach** where computation is optimized across local systems and modular pipelines.

Instead of relying entirely on cloud infrastructure, the system processes satellite imagery locally using optimized AI models. This reduces dependency on continuous internet connectivity and ensures faster response time during critical wildfire situations.

Each processing unit performs:

- Image preprocessing
- Fire classification (SVM)

- Fire detection (YOLOv8)
- Fire spread prediction (LSTM)

This modular design improves scalability and ensures that even if one component fails, the rest of the system continues functioning. The system achieves efficient processing with reduced latency, which is essential for early wildfire detection and response.

II. *Mathematical Model for Fire Detection and Prediction*

The system models wildfire detection and progression using both classification probability and temporal prediction.

1. Fire Classification (SVM Model)

The SVM classifier separates fire and non-fire regions using a hyperplane:

$$w^T x + b = 0$$

Where:

- x= feature vector extracted from satellite image
- w= weight vector
- b= bias

The goal is to maximize the margin between fire (+1) and non-fire (−1) classes.

2. Fire Detection Confidence (YOLO Output)

The YOLO model predicts bounding boxes with confidence score:

$$C = P(\text{Fire}) \times IoU$$

Where:

- $P(\text{Fire})$= probability of fire presence
- IoU= Intersection over Union (accuracy of bounding box)

3. Fire Spread Prediction (LSTM Model)

The fire propagation is modeled as a time-series function:

$$S_t = f(S_{t-1}, X_t$$

Where:

- S_t= predicted fire spread at time t
- X_t= environmental factors (temperature, wind, humidity, vegetation)

4. Risk Score Calculation

The system combines detection and prediction into a unified risk score:

$$R = \alpha C + \beta S$$

Where:

- C= detection confidence
- S= predicted spread intensity
- α, β= weighting factors

A high value of Rtriggers alerts and decision-making processes

III. *Methodology and Workflow*

The system follows a structured pipeline from data input to final output:

Step 1: Data Acquisition

- User provides latitude, longitude, and date
- Satellite images are fetched from NASA repositories
- Images are collected in real-time or near real-time

Step 2: Preprocessing

- Convert images into standard format
- Resize to required dimensions (e.g., 224×224 or 640×640 for YOLO)
- Normalize pixel values (0 to 1)
- Remove noise and enhance features

Step 3: Feature Extraction

- Extract spatial features from images
- Identify vegetation density, heat zones, and fire pixels
- Prepare structured input for ML/DL models

Step 4: Fire Classification (SVM)

- Determine whether fire is present or not
- Filter out non-fire images to reduce computation

Step 5: Fire Detection (YOLOv8)

- Detect fire regions in the image
- Generate bounding boxes around fire hotspots
- Provide confidence scores

Step 6: Fire Spread Prediction (LSTM)

- Analyze temporal and environmental data
- Predict future fire direction and spread
- Generate sequence of future frames

Step 7: Visualization and Decision Making

- Map predicted fire spread using GPS coordinates
- Generate GIF or map-based visualization
- Provide actionable insights for authorities

IV. IMPLEMENTATION

A. Hybrid AI Model for Wildfire Detection and Prediction

The proposed system utilizes a hybrid deep learning and machine learning approach combining SVM, YOLOv8, and LSTM to achieve accurate wildfire detection and prediction. This multi-model strategy ensures both high precision in detection and reliable forecasting of fire spread.

• **SVM for Initial Fire Classification:**
Support Vector Machine (SVM) is used as the first-stage classifier to determine whether a satellite image contains fire or not. It works by constructing an optimal hyperplane that separates fire and non-fire data points with maximum margin. This reduces unnecessary computation by filtering out non-fire images before applying deep learning models.

• **YOLOv8 for Fire Localization:**
Once fire presence is confirmed, the system uses YOLOv8 (You Only Look Once) for real-time object detection. Unlike traditional methods that

- Images are resized and normalized
- Noise is reduced for better feature extraction
- Features such as vegetation index, temperature, and terrain are extracted
- **Dataset Preparation:**

The dataset is divided into training and testing sets using train_test_split() and normalized using MinMaxScaler to ensure consistent model performance.

C. Fire Detection and Tracking Pipeline

The system follows a structured pipeline for wildfire detection:

- User Input: Coordinates and date are provided through a GUI (Tkinter).
- Image Fetching: Satellite image is retrieved from NASA database.
- Fire Classification: SVM determines fire presence.
- Fire Detection: YOLOv8 identifies fire regions with bounding boxes.
- Prediction: LSTM forecasts future fire spread.

scan images multiple times, YOLO processes the entire image in a single pass, making it extremely fast and suitable for real-time wildfire detection. It accurately identifies fire regions and generates bounding boxes around affected areas.

• **LSTM for Fire Spread Prediction:**
Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), is used to predict the future spread and direction of wildfire. It learns temporal patterns from environmental and historical data such as temperature, wind speed, humidity, and geographical features. This allows the system to forecast how the fire will evolve over time.

• **Hybrid Model Advantage:**
The combination of SVM + YOLO + LSTM ensures:

- Reduced computational load (SVM filtering)
- High detection accuracy (YOLO)
- Time-series prediction capability (LSTM)
This hybrid approach improves overall system efficiency and reliability compared to single-model systems.

B. Satellite Image Acquisition and Data Processing

The system fetches real-time satellite images from NASA repositories based on user-provided inputs such as latitude, longitude, and date.

- **Image Retrieval:**
Using API-based requests, the system generates a URL and downloads satellite images (typically 800×800 resolution) corresponding to the specified coordinates.

- **Data Preprocessing:**
Before feeding the data into models:

- Visualization: Output is generated as maps or GIFs showing fire progression.

This pipeline ensures a smooth flow from data acquisition to actionable insights.

D. Data Augmentation and Model Training

To improve model robustness and generalization, various data augmentation techniques are applied:

- Rotation (±20°): Handles different camera angles and satellite orientations
- Zoom (0.2 range): Simulates varying distances and resolutions
- Horizontal Flip: Ensures direction-independent detection
- Noise Addition: Mimics real-world satellite distortions like clouds or low visibility

These techniques help the model perform well under real-world environmental variations.

E. Decision Making and Visualization Engine

After prediction, the system converts results into actionable outputs:

- Fire Propagation Mapping:
  Predicted coordinates are mapped using GPS-based visualization tools.

- GIF Generation:
  Multiple predicted frames are combined to show fire spread over time.

- Decision Support:
  Authorities can analyze:
  - Direction of fire spread
  - High-risk zones
  - Required resource allocation

F. System Efficiency and Edge Capability
The system is designed to be computationally efficient and scalable:

- Optimized Processing:

  SVM reduces unnecessary deep learning computations
  YOLO ensures fast real-time detection

- Edge Compatibility:
  The system can run on local machines with moderate specifications (Intel i5, 8GB RAM), making it suitable for deployment in remote areas.

- Reduced Latency:
  Processing is optimized to provide quick predictions, which is critical in emergency wildfire situations.

V. COMPARISON WITH EXISTING SOLUTIONS

Our system is superior to current wildfire detection solutions for three reasons:

1) **Predictive vs. Detection-Only:** Most existing systems only detect fire after it spreads; our system predicts future fire spread using LSTM, enabling early preventive action.
2) **Hybrid Model vs. Single Model:** Traditional systems rely on a single approach (only satellite or only AI), while our system combines SVM, YOLO, and LSTM for higher accuracy and better decision-making.
3) **Cost-Effective & Scalable**: Unlike expensive drone or sensor-based systems, our system uses freely available satellite data and runs on standard hardware, making it affordable and scalable for large areas.

III.ALGORITHM

The proposed Wildfire Progression Analysis and Prediction System uses a hybrid approach combining Machine Learning (SVM), Deep Learning (YOLO, LSTM), and satellite image processing to detect and predict wildfire spread in real time.

Step 1: Video Input Acquisition

- Accept user inputs (Latitude, Longitude, Date)
- Fetch satellite images from NASA repository

Step 2: Image Extraction

- Retrieve satellite image based on given coordinates

Step 3: Pre-processing

- Convert image into required format
- Resize image (e.g., 640 × 640 for YOLO)
- Remove noise using image processing techniques

Step 4: Fire Classification (SVM)

- Extract features from the satellite image
- Pass features to SVM model

Step 5: Fire Detection (YOLOV8)

- f fire is detected: Apply YOLO model, identify fire regions, and draw bounding boxes around fire areas..

Step 6: Feature Extraction for Prediction

- Feature Extraction for Prediction: Extract environmental features such as temperature, humidity.

Step 7: Fire Spread Prediction (LSTM)

- Predict future fire spread (latitude, longitude)
- Estimate direction and intensity of fire

Step 8: Decision Making

- Extract environmental features like temperature, humidity, wind speed, and vegetation data.

Step 9: Alert Generation

- Generate fire maps and propagation GIFs, and send alerts with location details to authorities.

Step 10: Output Display

- Display fire detection results, predicted path, and alerts on the Tkinter GUI.

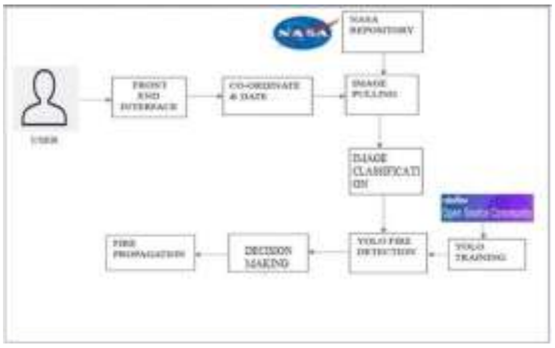
VI. SOFTWARE ARCHITECTURE

The system follows a hybrid AI-based architecture with satellite integration to ensure accurate detection, prediction, and real-time monitoring of wildfires.

1. **Perception Tier (Input Layer)**
   - Satellite Images (NASA Repository)
   - User Inputs (Coordinates and Date)
   - Captures real-time or historical forest data
2. **Processing Tier (Edge Computing Layer)**
   - Image Processing using Python (OpenCV, NumPy)
   - Performs:
     - Image fetching from NASA API
     - Image resizing and preprocessing
     - Data normalization
3. **Analysis Module**
   - SVM Model (Fire / Non-Fire Classification)
   - YOLOV8 Model (Fire Detection & Localization)
   - LSTM Model (Fire Spread Prediction)
   - Fire intensity analysis
4. **Alerting Tier**
   - Generates alerts when fire is detected
   - Provides fire location and risk level
5. **Cloud / Storage Layer**
   - Stores satellite images and datasets
   - Stores trained models (.pt, .h5 files)
   - Stores logs and prediction results
   - Helps in future analysis and model improvement

6. Output Layer

- GUI Interface (Tkinter)
- Detected fire regions (bounding boxes)
- Fire propagation (maps / GIF)
- Prediction results and alerts



VII. APPLICATION WITH REAL-LIFE EXAMPLE

Applications

- Forest areas for early wildfire detection
- Disaster management departments for emergency response
- Environmental protection agencies
- Wildlife conservation zones
- Smart surveillance systems using satellite monitoring

Real-Life Example

Consider a forest region in California during dry summer conditions. Satellite images are continuously captured and monitored for fire detection.

The proposed system processes these satellite images using the SVM and YOLO models. If fire or smoke is detected, the system identifies it and calculates the intensity and affected area.

Once the threshold is crossed:
• The system predicts fire spread using the LSTM model
• A warning alert is sent to forest authorities
• Firefighters receive the exact location and predicted path of the fire
• Authorities can take immediate actions like evacuation or resource deployment

This real-time response helps prevent large-scale destruction, reduces loss of life, and ensures better disaster management.

VIII. FUTURE SCOPE

In the future, this model can be improved to operate on intricate data that is gathered from all over the world. It can use statistics and imagery to create a hybrid transformer model that can forecast the formation of forest.

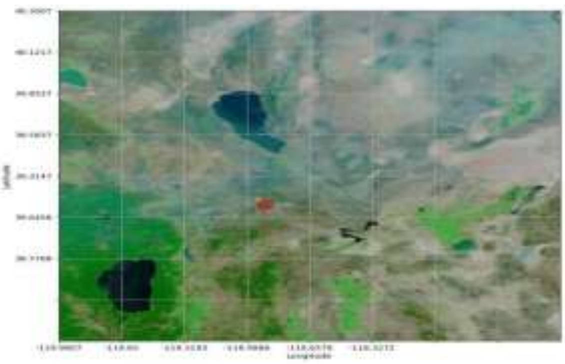
IX. RESULTS AND DISCUSSION

The proposed system was tested using satellite image datasets and environmental data. The hybrid model showed improved accuracy in fire detection compared to traditional methods. The integration of SVM and YOLOv8 ensured reliable classification and precise localization of fire regions.

The LSTM model successfully predicted the spread pattern of wildfire, helping in understanding its future behavior. The system demonstrated effective performance in terms of accuracy, response time, and visualization, making it suitable for real-world applications in wildfire management.

X. CONCLUSION

This study presents a wildfire detection system that uses satellite imagery and deep learning techniques to identify fire occurrences. Satellite images obtained from the NASA repository are processed and analyzed using the YOLO object detection model to detect fire regions. The system is capable of identifying wildfire areas and providing useful information for monitoring and decision making. The results demonstrate that the use of deep learning improves the efficiency and accuracy of fire detection from satellite images. Early identification of wildfire events can help authorities respond quickly and reduce damage to forests, wildlife, and human settlements. Overall, this approach provides an effective solution for wildfire monitoring and can support better disaster management in the future.



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XII. AUTHORS BIOGRAPHY

Ms. Hande Siddhi, was born in Narayangoan, India in 2006 was currently pursuing her Diploma in Engineering in Jaihind Polytechnic, Kuran, Junnar, Pune, India. She has interest in Distributed Systems. She was responsible for the edge computing architecture and backend system integration

Ms. Khandagale Ayursha, was born in Ahilyanagar, India in 2007 was currently pursuing her Diploma in Engineering in Jaihind Polytechnic, Kuran, Junnar, Pune, India. She focused on deep learning model training, and dataset generation for the Anti-Stampede system using InceptionV3.

Ms. Mathe Parimala, was born in Shiroli(Bori), India in 2008 was currently pursuing her Diploma in Engineering in Jaihind Polytechnic, Kuran, Junnar, Pune, India. She is focusing on API development and cloud communication. She developed the WhatsApp alerting and geo- location modules.

Ms. Pansare Siddhi, was born in Kalayan, India in 2008 was currently pursuing her Diploma in Engineering in Jaihind Polytechnic, Kuran, Junnar, Pune, India. She is interested in Public Safety technology and computer vision. She conducted the performance evaluation and comparative analysis