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Wildfire Detection and Tracking System

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Abstract

To create a precise forecast of the wildfire, it is crucial to possess the capability to recognize it and anticipate how it will distribute. The devastation of vegetation, the loss of assets, the rise in greenhouse gases, the extinction of Numerous animal species and even human fatalities can all result from wildfires. To trim back this danger, there must be a mechanism capable of detecting a fire the moment it begins to escalate so that we can extinguish the fires before they escalate into a wildfire. Generally, conventional methods depend on machine learning. models to predict the presence of a fire. We must determine how the fire is spreading if we want to protect. additional lives and inventory, and this isn't proving very useful. Consequently, to achieve this, the proposed model categorizes fires in images sourced from NASA's database utilizing the given latitude and longitude utilizing a Fire pixel. After obtaining the satellite image, the YOLO model is used to detect the flame. Finally, we can provide the wildfire's development path following the implementation of the decision-making model. In addition to detection, the proposed system incorporates a fire spread prediction module that estimates the future progression of wildfire using environmental parameters such as humidity, wind speed. Furthermore, an automated email alert mechanism is generated to notify concerned authorities in real time by sending fire detection results along with image attachments. This combines approach enhances situational awareness and supports faster decision making in emergency scenarios.

Keywords: Fire pixel model, YOLO model, decision making, email alert, wildfire detection

INTRODUCTION

Scientists have studied and developed ways to put out wildfires, and a variety of technologies, approaches, and strategies have been developed to combat them. Furthermore, a great deal of academic research is being done in this area in order to improve existing methods and obtain new insights [1]. While there has Although there has been some progress, the study highlights how serious the wildfire problem is. Therefore, our biggest concern is finding a quick, accurate, and efficient solution to the wildfire issue. When given enough training data, machine learning and artificial intelligence (AI) have significantly improved event detection capabilities [2]. This project's goal is to use hybrid learning to predict how much wildfires will spread in the future and deep learning models to identify fires in a specific area and the system further enhances its functionality by incorporating an automated alert mechanism. Some of the worst wildfires in the country occur in California [3]. According to recent data, California wildfires have burned around 273,000 acres of land, destroyed 2,800 homes, and killed 15 people—three of them firefighters—during the past four years [4]. Our primary objective is to compile, analyze, and develop a database of wildfire data from California in order to detect, manage, and eradicate these fires. We shall then proceed to broaden our scope by reviewing the data on such regions. We will be able to handle the wildfire data from the various regions if we can make sure our model works well and is accurate enough [5,6].

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WORKING PRINCIPLE

The working principle of the wildfire detection and tracking system is based on a combination of deep learning, image processing, and environmental data analysis. The system operates in a sequential pipeline consisting of detection, classification, prediction, and alert generation [7].

Step 1: Data Acquisition

The system begins by collecting input data from multiple sources:

- Satellite images obtained from NASA or similar datasets
- Aerial images captured using drones (if available)

Environmental Data Such As:

- Temperature
- Humidity

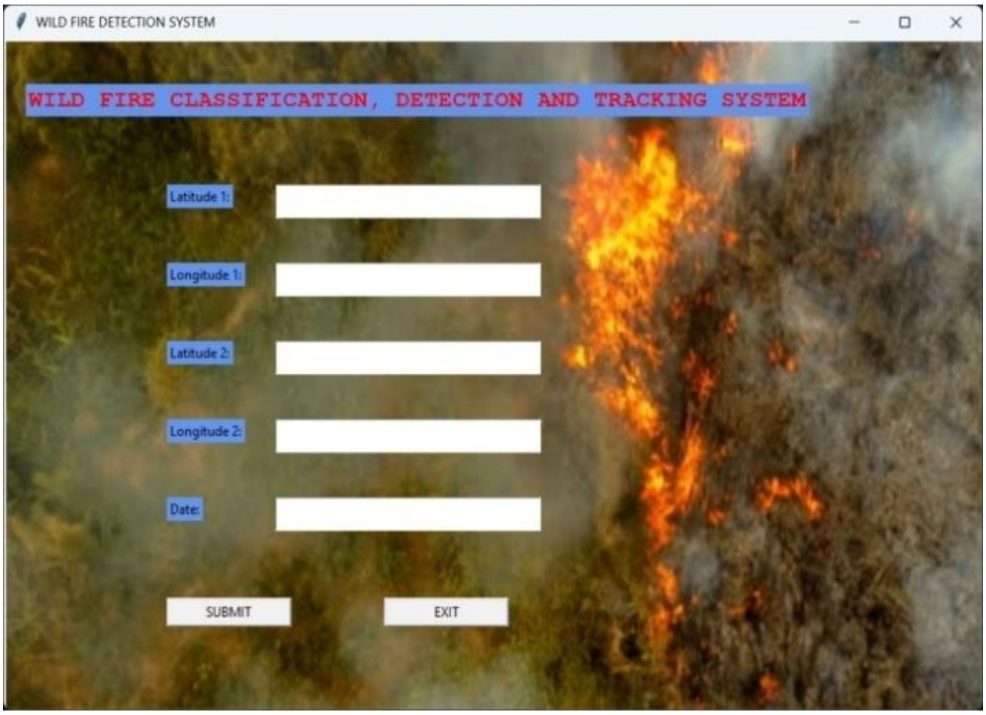

Figure 1. User interface for wildfire detection system.

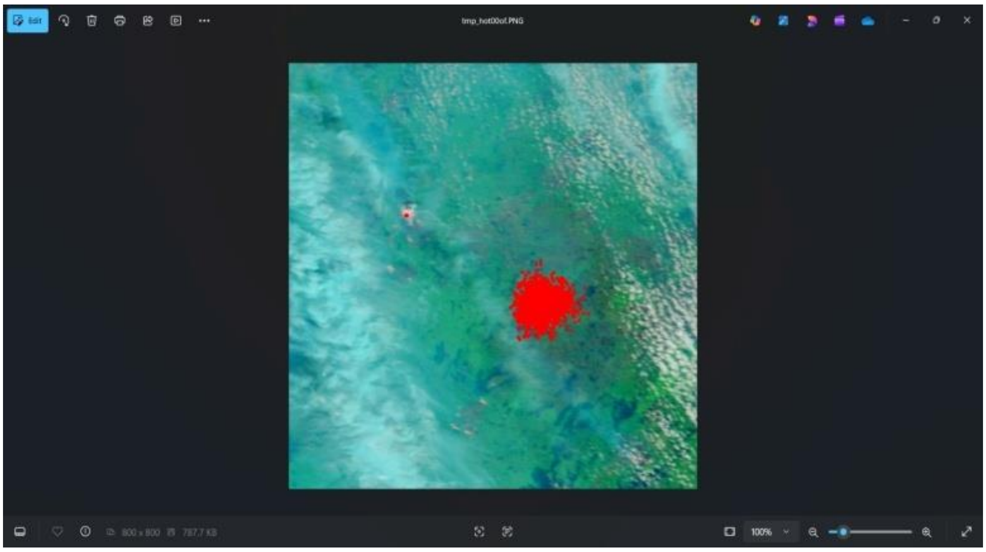

Figure 2. Wildfire detection output using YOLO model.

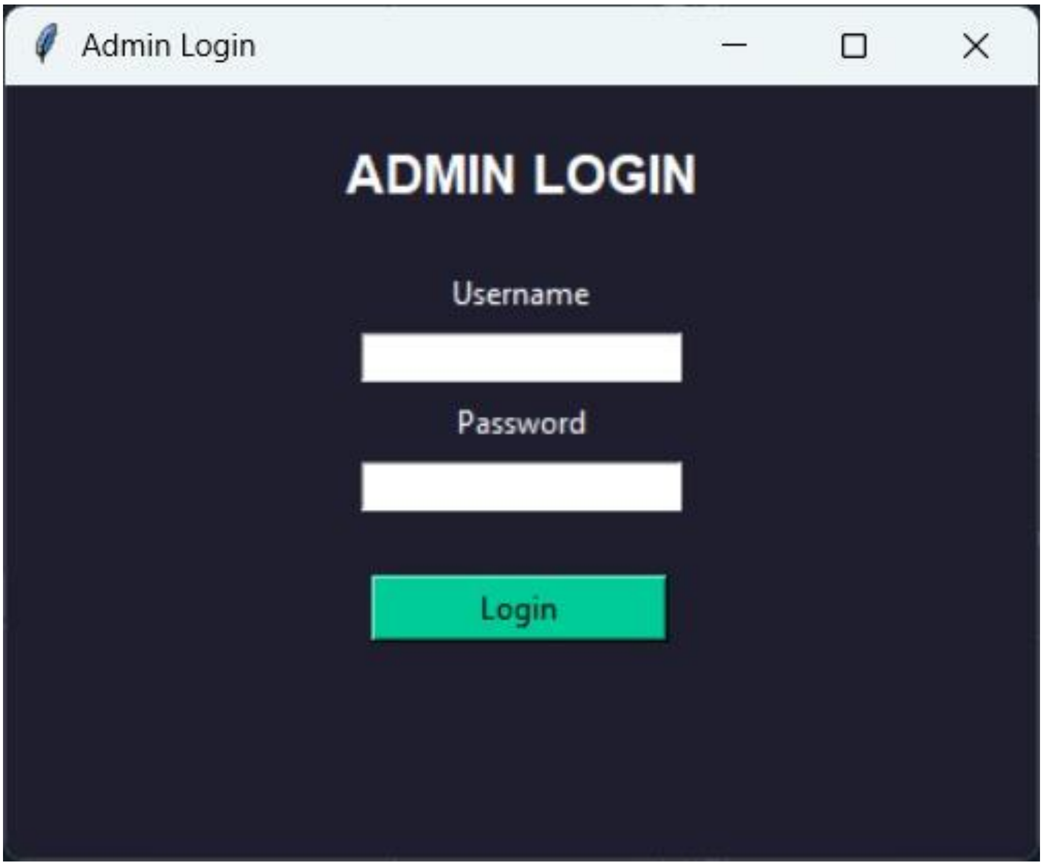

Figure 3. Admin login module.

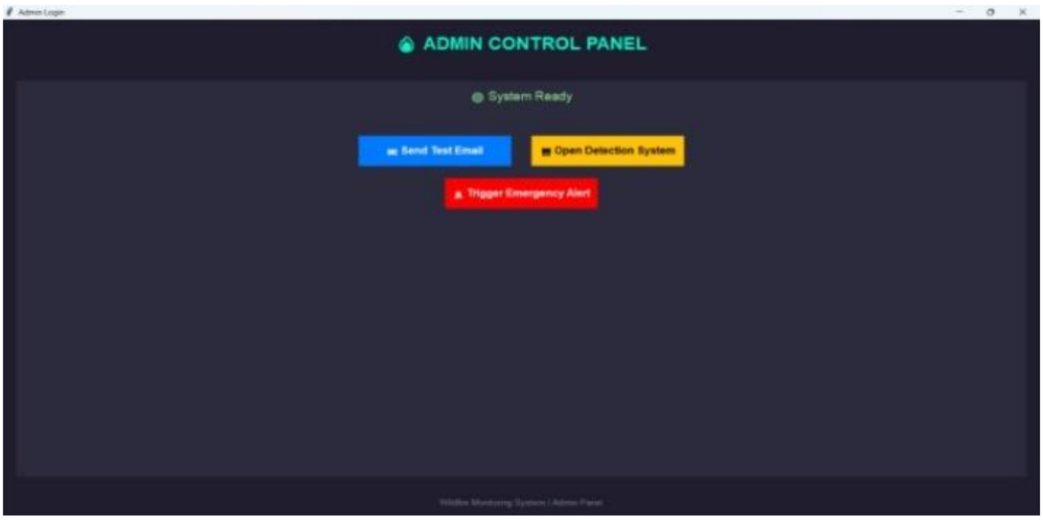

Figure 4. Admin control panel.

The developed system includes a user-friendly interface for entering coordinates, date, and monitoring wildfire detection processes. The login module ensures secure access for administrators, while the control panel allows system operations such as starting detection and triggering alerts. The graphical user interface of the system is shown in Figure 1, Figure 3 and Figure 4.

The output of the wildfire detection model highlights the identified fire regions in the satellite image using bounding markers. The detected fire area is clearly visualized, demonstrating the effectiveness of the YOLO-based detection model, as shown in Figure 2.

Step 2: Fire Classification
The system classifies the image into:
- Wildfire detected
- No fire detected

This classification is performed using trained machine learning or deep learning models. The classifier verifies whether the detected pixels or regions truly represent a wildfire, thereby reducing false alarms [8].

Step 3: Fire Detection using Fire Pixel Model and YOLO
The detection process involves two important techniques:

a. Fire Pixel Model
    - The system analyzes individual pixels in the image

Fire regions are identified based on:
- Brightness
- Color intensity (reddish/orange hues)
- Thermal characteristics
- Pixels that match fire characteristics are marked as fire pixels

This helps in detecting small or early-stage fires with higher precision.

b. YOLO (You Only Look Once) Model
    - The YOLO model processes the entire image in a single forward pass
    - It divides the image into grids and predicts bounding boxes around fire regions

YOLO ensures real-time detection with high speed and accuracy

Step 4: Fire Spread Prediction
Once a fire is detected, the system predicts how it will spread in the future using environmental parameters.

Key factors used:
- Wind speed and direction
- Humidity
- Temperature
- Vegetation density
- Geographic terrain

Using these inputs, the system:
- Estimates fire propagation direction

This step helps in anticipating the future behavior of the wildfire.

Step 5: Decision-Making and Tracking
The decision-making module integrates detection and prediction results to:
- Assess the severity of the wildfire
- Identify high-risk zones
- Track fire movement over time

The tracking system visualizes fire spread on a map, allowing authorities to monitor the fire progression effectively.

Step 6: Alert Generation System

The final step in the working principle is the alert system.

When a wildfire is detected:

- An alert is automatically generated

The system sends notifications via:

- Email

The alert includes:

- Fire location (latitude and longitude)
- Detected images
- Prediction details

This enables quick response and minimizes damage.intends to look at more extreme weather in subsequent research. High-quality flame images are essential for the safe operation of ultra-high voltage converter stations, and experimental findings showed that the flame image dehazing network could accomplish this goal [9]

PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed as an integrated wildfire monitoring framework that combines detection, prediction, and alerting into a single automated pipeline.

The proposed system consists of the following major modules:

Input Module

This module is responsible for collecting and preparing input data.

Inputs include:

- Satellite images
- Environmental parameters (temperature, humidity, wind speed)
- Vegetation data

The input data is preprocessed before being sent to the detection module.

The overall architecture of the proposed wildfire detection and tracking system is divided into multiple layers, including input, processing, and output layers. Each layer performs specific tasks such as data acquisition, fire detection, prediction, and alert generation. The complete architecture is illustrated in Figure 5.

Overview of System Modules

Detection Module (YOLO-Based)

This is the core component of the system.

- Uses YOLOv8 deep learning model
- Performs real-time object detection
- Identifies wildfire regions in images
- Outputs bounding boxes around fire areas

This module ensures:

- Fast processing
- High accuracy
- Real-time detection capability

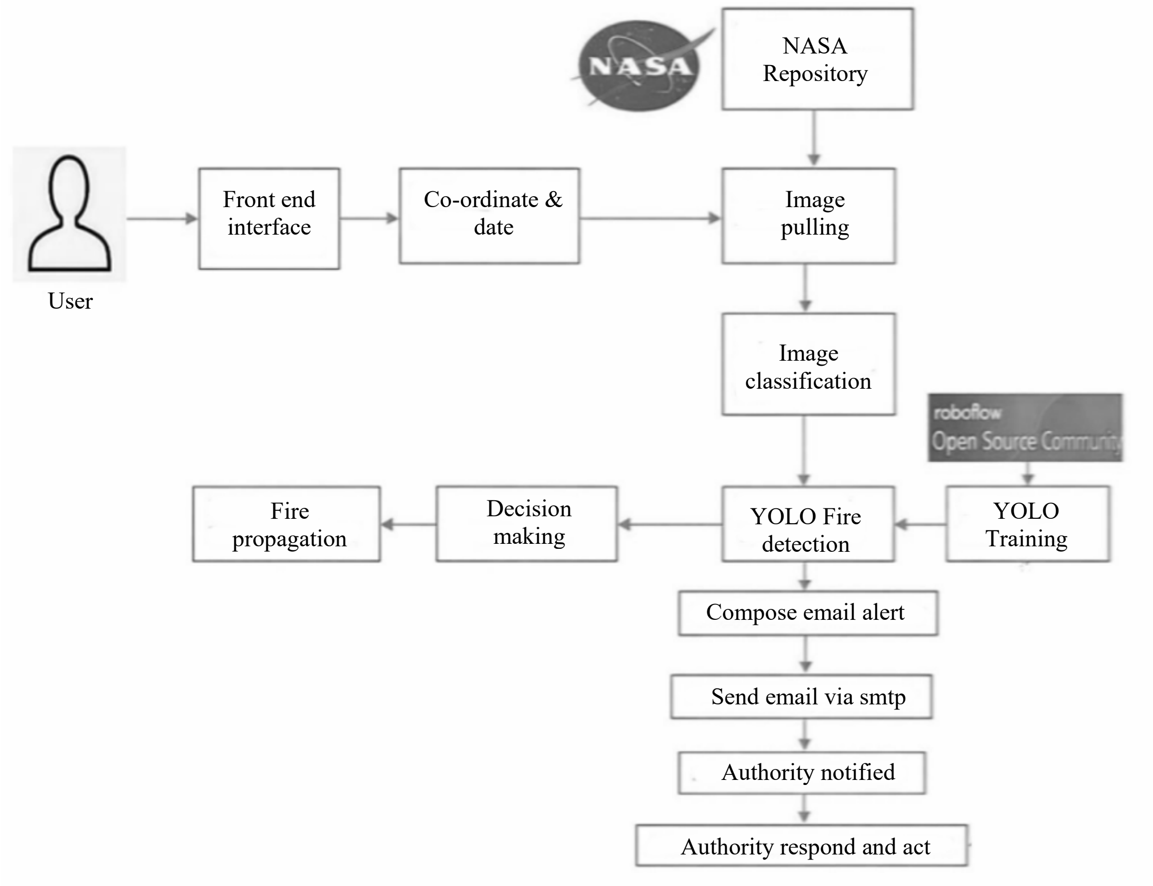

Figure 5. Architecture of wildfire detection and tracking system.

Fire Pixel Enhancement Module

Along with YOLO, the system uses pixel-level analysis to improve detection accuracy.

- Detects fine-grained fire regions
- Enhances small or early-stage fire detection
- Reduces misclassification

Prediction Module

This module predicts future wildfire behavior.

Techniques used:

- Machine learning models
- Statistical analysis
- Environmental parameter analysis

Outputs include:

- Fire spread direction
- Fire intensity prediction
- Affected area estimation

Tracking Module

The tracking module continuously monitors fire movement.

- Tracks fire location over time
- Updates fire spread on maps
- Helps in understanding fire progression

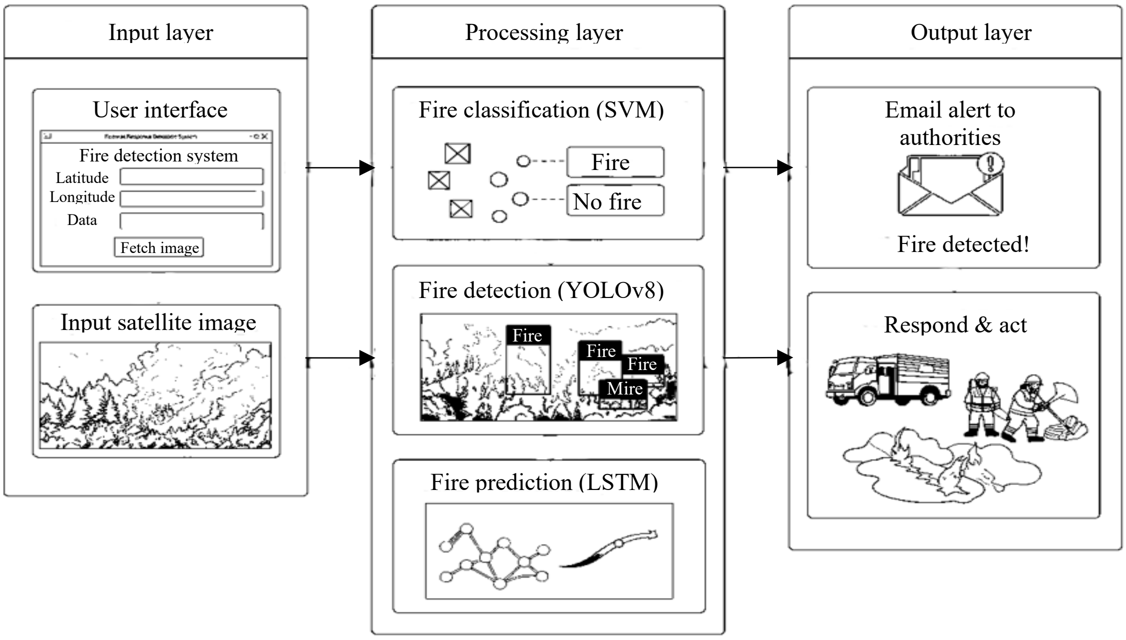

Figure 6. Input–processing–output model of system.

This module is essential for real-time monitoring and decision-making.

Decision-Making Module

This module analyzes outputs from detection and prediction systems.

It:
- Evaluates fire severity
- Determines risk level
- Assists in emergency planning

Alert and Notification Module

This is the final stage of the system.
- Sends automated alerts to authorities
- Includes fire location and visual evidence

Communication methods:
- Email system

Overall Workflow of Proposed System

The system follows a structured pipeline consisting of input, processing, and output stages. The input layer collects satellite and environmental data, the processing layer performs classification, detection, and prediction, and the output layer generates alerts and supports response actions. This workflow is depicted in Figure 6.

The system follows this workflow:
1. Input data is collected from satellites and sensors
2. Data is preprocessed and cleaned
3. YOLO model detects wildfire in images
4. Fire Pixel Model enhances detection accuracy
5. Classification confirms fire presence
6. Prediction model estimates fire spread
7. Tracking module monitors fire movement

8. Decision-making module analyzes risk
9. Alert system sends notifications

CONCLUSION

Based on the comprehensive studies conducted on wildfire detection and the analysis of progression prediction, the proposed model presents a distinctive approach to achieve favorable outcomes in near real-time. This particular challenge has been tackled through the implementation of three distinct steps. The three phases are classification, detection, and prediction. The model gathered all necessary data for detection and classification from the images. Aerial and satellite images of the wildfire, along with the Shasta County Vegetation dataset, were obtained through Roboflow, Google, and the Mendeley databases. Utilizing a pre-trained support vector machine (SVM) model, the model successfully identified the image as depicting a wildfire. To accurately determine the fire's location within the image, the model utilized the YOLOv8 framework.TheYOLOv8 model was trained using 1631 training images and 102 testing images. The dataset underwent training for 50 epochs in a Google Colab environment, with an image size of 640 and a batch size of 32, to yield the most effective trained data encapsulated in the .pt file. The application of the YOLOv8 model resulted in superior outcomes for the test set images. Due to its rapid testing duration, the YOLOv8 model is particularly well-suited for the real-time detection of wildfires. In summary, the YOLOv8 model stands out as an excellent option for detecting fires in aerial images captured by drones or satellites. Over the forthcoming five days, the proposed model may utilize YOLOv8 to forecast potential fire expansion areas. We provided the model with data regarding weather conditions, existing fires, and vegetation. Environmental factors such as temperature, humidity, and vegetation indices (including acres burned, NDVI, NDMI, etc.) significantly affect fire behavior. The acquired datasets are subjected to cleaning and format modification. Various dispersion metrics, including standard deviation, range, and mean, are employed to evaluate the model. In addition to detection, the integration of a fire spread prediction model significantly enhances the capability of the system by providing insights into the possible future behavior of wildfire. The use of environmental parameters enables a realistic estimation of fire propagation patterns, which can assist in identifying high risk zones. The visualization of predicted fire spread further supports decision making processes. Moreover, the implementation of an automated email alert system ensures timely notification to authorities, enabling quicker response and mitigation efforts. This combination of classification, detection, prediction and alerting makes the system more practical and efficient for real-world applications

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