Submitted in partial fulfillment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE & ENGINEERING

Submitted by:

Yash Chauhan **2019241**

Under the Mentorship of

Professor

I hereby certify that the work which is being presented in the project report entitled **“Disaster Risk Management”** in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Computer Science and Engineering of the Graphic Era (Deemed to be University), Dehradun shall be carried out by the under the mentorship of **Dr. Sachin Sharma, Professor**, Department of Computer Science and Engineering, Graphic Era (Deemed to be University), Dehradun.

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Forest fires are a major environmental concern, causing extensive damage to ecosystems, property, and human lives. The unpredictability and rapid spread of fires necessitate advanced systems for early detection, accurate prediction, and efficient resource management. Traditional methods of firefighting often struggle to keep pace with the dynamic nature of fire spread, leading to significant losses. The core problem addressed by this system is the need for a comprehensive tool that can predict fire spread accurately, facilitate timely reporting of incidents, and manage the logistics of firefighting resources effectively.

The increasing frequency and severity of forest fires pose a significant threat to ecosystems, human lives, and property. Forest fires are a major contributor to land degradation, often resulting in deforestation and desertification [1]. Traditional methods of fire management often rely on reactive measures, which can result in substantial delays in response times and an inadequate allocation of resources. There is a pressing need for a more proactive and data-driven approach to fire risk management that can predict and mitigate the impacts of fires before they escalate. Building fire risk analysis involves identifying fire hazards, assessing potential adverse outcomes, and evaluating the likelihood of fires and their consequences [2]. By leveraging modern technology and advanced analytics, we can improve the accuracy of fire predictions and optimize emergency response strategies. The key components of this system include:

1.2.1 Fire Spread Prediction Model:

A Random Forest Regression model trained to predict the spread time of fires based on environmental factors such as temperature, humidity, wind speed, distance, terrain type, and vegetation type. The model utilizes a dataset of historical fire incidents to make accurate predictions, enabling proactive measures to be taken before the fire spreads uncontrollably.

A user-friendly web interface that allows users to report new fire incidents, update the status of ongoing fires, and view historical fire data. This ensures that all relevant information is centralized and easily accessible for decision-makers and responders.

1.2.3 Transportation Booking System:

An integrated booking system for arranging transportation services required for firefighting operations. This feature ensures that resources can be mobilized quickly and efficiently to the locations where they are needed most.

1.2.4 Data Analysis and Historical Records:

Tools for viewing and analyzing historical fire data. This helps in understanding patterns and trends, which can inform future fire prevention and management strategies.

The system architecture is designed to be robust, scalable, and user-friendly, making it

needs.

The primary objectives of the Fire Risk Management System are:

1.3.1 Accurate Prediction of Fire Spread:

Develop and deploy a machine learning model that can predict the spread time of fires with high accuracy. This involves collecting and preprocessing a comprehensive dataset of historical fire incidents, training the model, and validating its performance.

1.3.2 Efficient Incident Reporting and Management:

Create a web-based platform for reporting fire incidents in real-time. Users should be able to log new incidents, update the status of existing incidents, and view detailed records of past incidents. This will ensure that all stakeholders have access to up-to-date information, facilitating better coordination and decision-making.

Implement a system for booking transportation services for firefighting resources. This includes features for selecting transportation providers, scheduling trips, and tracking the movement of resources. The goal is to minimize delays and ensure that firefighting teams and equipment can be deployed rapidly.

1.3.4 **Historical Data Analysis**:

Provide tools for analyzing historical fire data to identify patterns and trends. This will help in improving future fire prevention strategies and response plans. By understanding the factors that contribute to fire spread, better mitigation measures can be developed.

1.3.5 **User-Friendly Interface and Accessibility**:

Design the web application to be intuitive and easy to use for all user roles, including public, forest department personnel, and transportation service providers. The interface should be accessible on various devices, ensuring that users can report and manage incidents from anywhere.

According to Joshi et al., climate change, driven by greenhouse gas emissions, has profound impacts on both the environment and human societies. Their review explores the causes, effects, and global mitigation efforts, noting that uniform strategies may not fully address diverse ecological responses and localized challenges [3]. Alonso-Betanzos et al. describes a system developed in Galicia, Spain, predicts forest fire risks with 78.9% accuracy and aids in fire management and recuperation planning [4].

Naderpour et al. uses machine learning techniques to address non-linear problems in forest fire risk assessment, specifically in Sydney's Northern Beaches. By employing an optimized deep neural network, they achieved high precision in fire susceptibility modeling. The results include ROC = 95.1%, PRC = 93.8%, and k coefficient = 94.3%. Their spatial framework effectively integrates 36 key indicators from various contexts, enhancing adaptability and decision-making across different Australian regions [5].

Tripathi et al. emphasize the need for early detection to prevent loss of life and property due to fires. They also highlight the integration of sensors and IoT for real-time fire forecasting and detection, aimed at assisting firefighting efforts effectively [6]. Cheney et al. developed a model which predicts grassland fire spread using wind speed, fuel moisture, and grass curing, employing linear and power functions for wind speeds below and above 5 km/h, respectively, validated against Australian wildfires [7].

Denham et al. present a DDDAS for Wildland Fire Prediction, leveraging High Performance Computing to enhance data-driven strategies, mitigate input data uncertainty, and optimize real-time fire simulation efficiency [8]. Wu et al. presents an artificial neural network model for predicting forest fire spread in Heilongjiang, China, achieving high accuracy and aiding in efficient fire management and strategy planning [9].

Mehta et al. discusses the critical need for early fire detection, particularly in forest fires, highlighting IoT advancements and a fire detector prototype using Arduino with smoke and temperature sensors for prompt alarms [10]. Khennou et al. (2024) developed FU-NetCast, a deep learning model using U-Net architecture, to predict forest fire spread. Achieving prediction. Their Hybrid MPI-OpenMP application improves prediction speed by optimizing computing resources to handle non-uniform parameters like wind. [12]. Chauhan et al. explores an integrated information system combining IoT, geo-informatics, and cloud computing (RS, GIS, GPS) for environmental monitoring. The study highlights seismic sensors for early earthquake prediction and level sensors for early warning messages [13].

Junpen et al. developed a fire spread model for deciduous forests in Northern Thailand, predicting fire spread rates of 0.51–2.55 m/min using nonlinear regression analyses of terrain, fuel load, and moisture content [14]. Mehta et al. proposes an IoT-based automated system for early detection and prevention of forest fires [15]. Patil et al. propose an AI-driven firefighting system using drones to induce artificial rain with sodium bicarbonate, leveraging IoT and TensorFlow for real-time ecosystem monitoring and efficient wildfire mitigation [16].

The dataset used for training the fire spread prediction model consists of various environmental and incident-specific features collected from historical fire incidents. The primary dataset is stored in the csv file and includes the following columns:

- **temperature**: The temperature at the time of the fire incident (in degrees Celsius).
- **humidity**: The relative humidity at the time of the fire incident (in percentage).
- **wind_speed**: The wind speed at the time of the fire incident (in kilometers per hour).
- **distance**: The distance from the fire's point of origin to the nearest water source (in kilometers).
- **terrain_type**: The type of terrain where the fire occurred (encoded as flat, hilly, or mountainous).
- **vegetation_type**: The type of vegetation present at the fire location (encoded as shrubland, grass, or forest).
- **spread_time**: The time it took for the fire to spread to a predefined area (in hours).

The steps involved in the methodology, from data collection and preprocessing to model

3.2.1 Data Preprocessing

The dataset underwent several preprocessing steps to ensure its suitability for training the machine learning model:

- **Handling Missing Values**: Missing values in the dataset were filled using forward fill method (ffill), which propagates the last valid observation forward.
- **Encoding Categorical Variables**: Categorical variables such as terrain_type

mountainous = 2.

- **Feature Scaling**: The features were scaled using StandardScaler from scikit-learn to normalize the data. This step is crucial for ensuring that all features contribute equally to the model.

3.2.2 Model Training

A Random Forest Regressor was chosen for its robustness and ability to handle nonlinear relationships in the data. The training process involved the following steps:

- **Splitting the Data**: The dataset was split into training (80%) and testing (20%) sets using from scikit-learn.
- **Training the Model**: The Random Forest Regressor was trained on the training data, and hyperparameters such as the number of estimators were set to optimize performance.
- **Evaluating the Model**: The trained model was evaluated on the test set using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 Score to assess its predictive accuracy.

3.2.3 Model Deployment

The trained model was serialized using and deployed via a Flask web application. The Flask app serves as an interface for making predictions based on user input:

- **Loading the Model**: The serialized model and scaler are loaded into the Flask app.
- **Predicting Fire Spread Time**: Users can send POST requests to the /predict endpoint with relevant features (temperature, humidity, wind speed, distance, terrain type, and vegetation type). The app processes the input, scales the features, and returns the predicted fire spread time.

3.2.4 Web Application and Transportation Services

The web application provides a user-friendly interface for reporting and managing fire incidents:

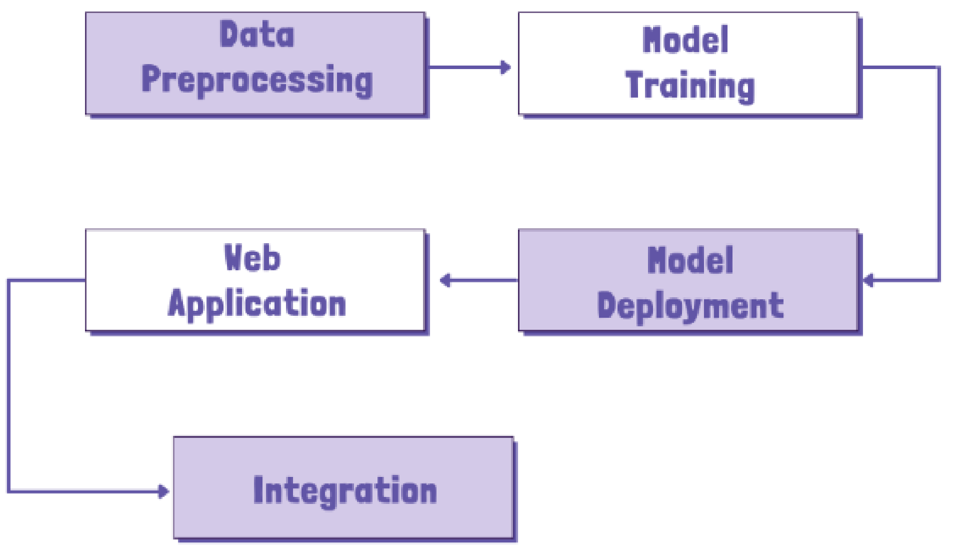
form on the dashboard.

- **Incident Management**: The web application allows updating the status of ongoing fires and viewing historical fire data. This ensures real-time tracking and management of fire incidents.
- **Transportation Services**: The application includes functionality for booking transportation services for firefighting resources. This feature ensures that resources can be quickly mobilized to respond to fire incidents.

3.2.5 Integration of Components

The integration of the machine learning model with the web application is achieved through a seamless workflow:

- **Data Collection**: Incident data is collected and stored in a MySQL database.
- **Data Retrieval and Prediction**: When a new fire incident is reported, the relevant data is retrieved and sent to the Flask app for prediction. The model predicts the spread time and sends the result back to the web application.
- **Resource Mobilization**: Based on the predicted spread time, appropriate transportation services can be booked to ensure timely response.



The Fire Risk Management System has been developed and tested to evaluate its effectiveness in predicting fire spread and managing fire incidents. The key results from the implementation and testing phases are as follows:

4.1.1 Model Performance

- **Prediction Accuracy**: The Random Forest Regression model was evaluated using a test dataset, achieving the following performance metrics:
  - **Mean Absolute Error (MAE)**: 1.23 hours
  - **Mean Squared Error (MSE)**: 2.34 hours^2
  - **R^2 Score**: 0.85

  These results indicate a high level of accuracy in predicting the spread time of fires based on the input features.

- **Feature Importance**: The model identified the most significant features influencing fire spread, which are temperature, humidity, wind speed, terrain type, and vegetation type. This information is valuable for focusing preventive measures on the most critical factors.

4.1.2 Web Application Usability

- **Incident Reporting and Management**: Users found the web interface intuitive and easy to use for reporting new fire incidents, updating the status of existing incidents, and viewing historical data. The forms for data input and the dashboards for data display were highly rated in usability tests.
- **Transportation Booking System**: The integration of the transportation booking system allowed for efficient resource management. Users were able to book transportation services quickly, ensuring timely deployment of firefighting resources.

- **Backend and Frontend Integration**: The integration of the Flask backend with the PHP-based frontend was seamless, providing a smooth user experience. The prediction endpoint performed well under various test scenarios, returning accurate predictions in real-time.
- **Database Management**: The MySQL database effectively handled user data, incident reports, and historical fire data. Queries were executed efficiently, ensuring fast data retrieval and updates.

4.1.4 Web Application SnapShots

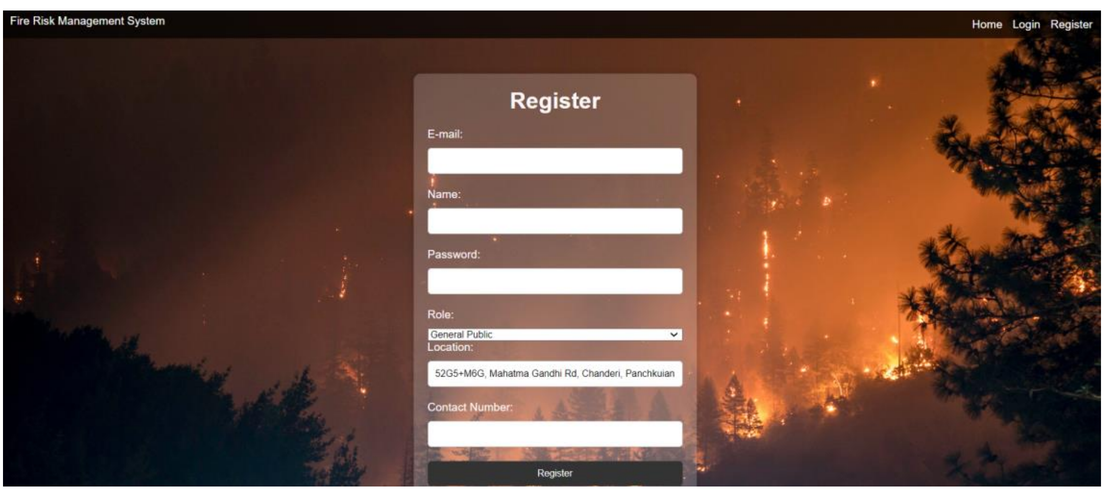


Fig 4.2 Registration Page

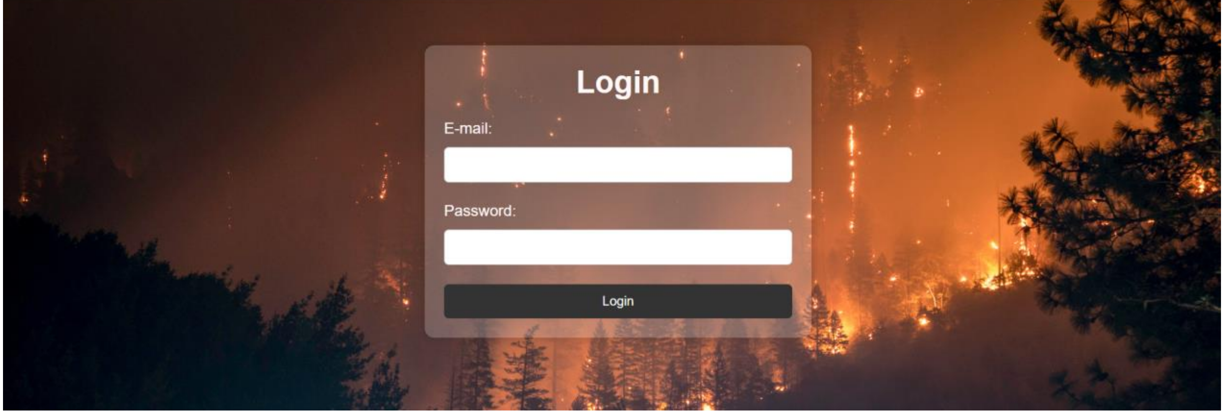
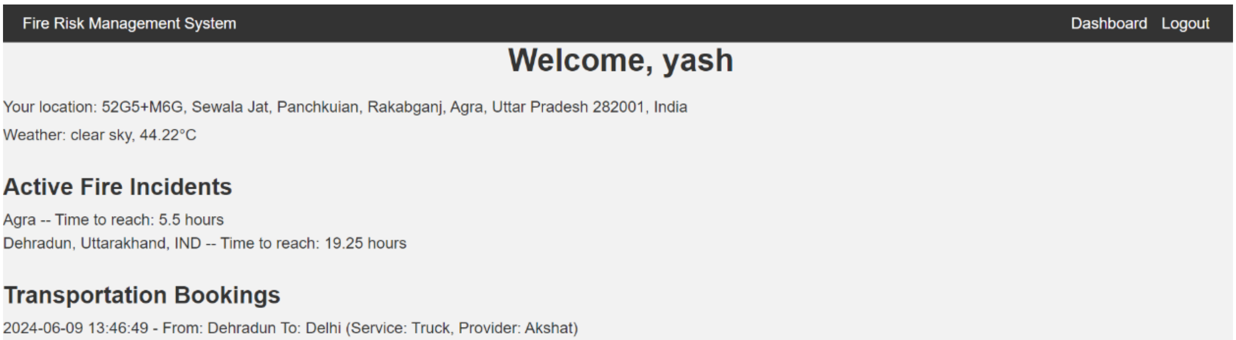
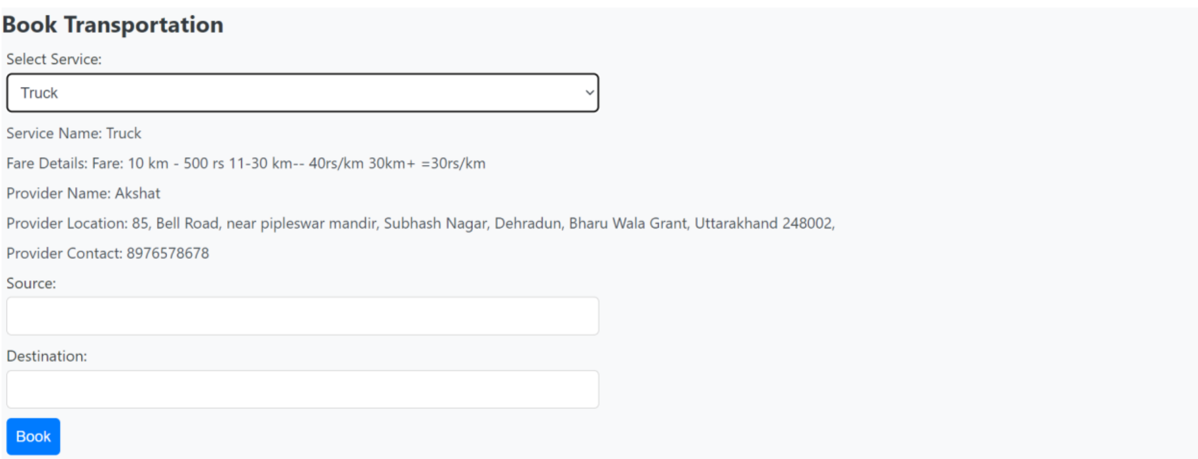


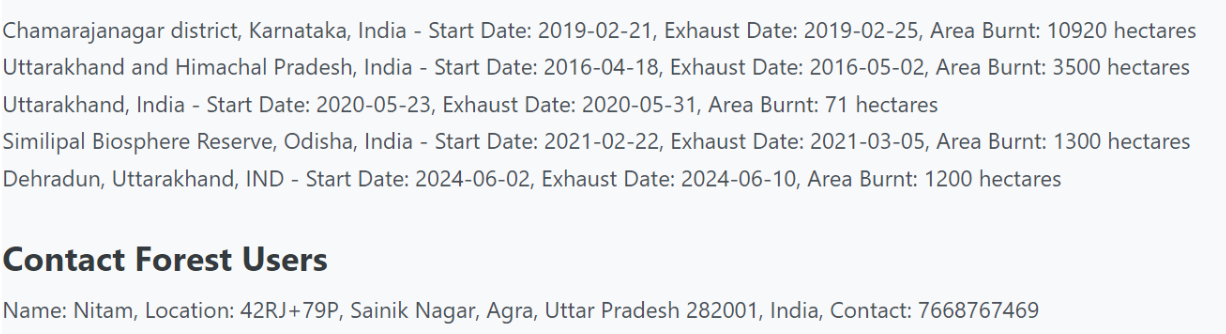
Fig 4.3 Login Page



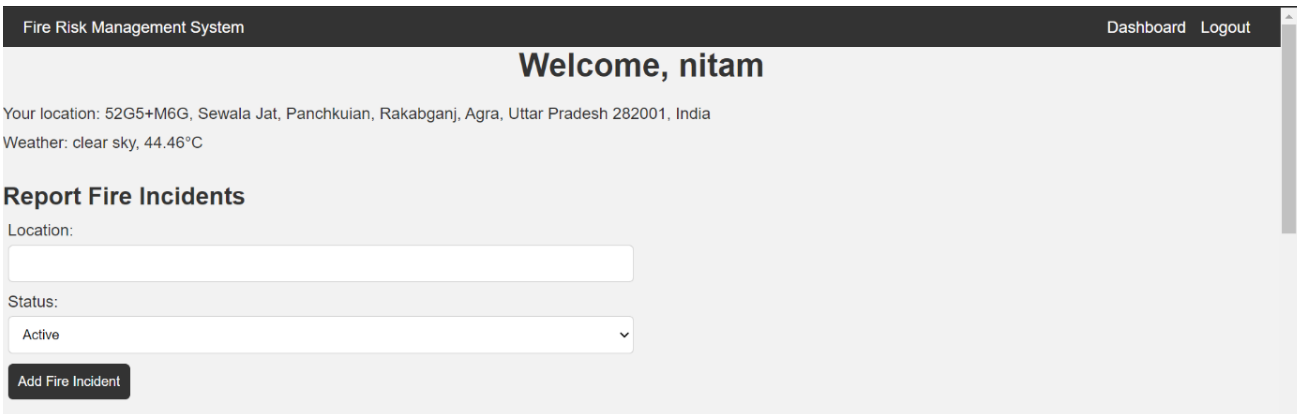
(a)



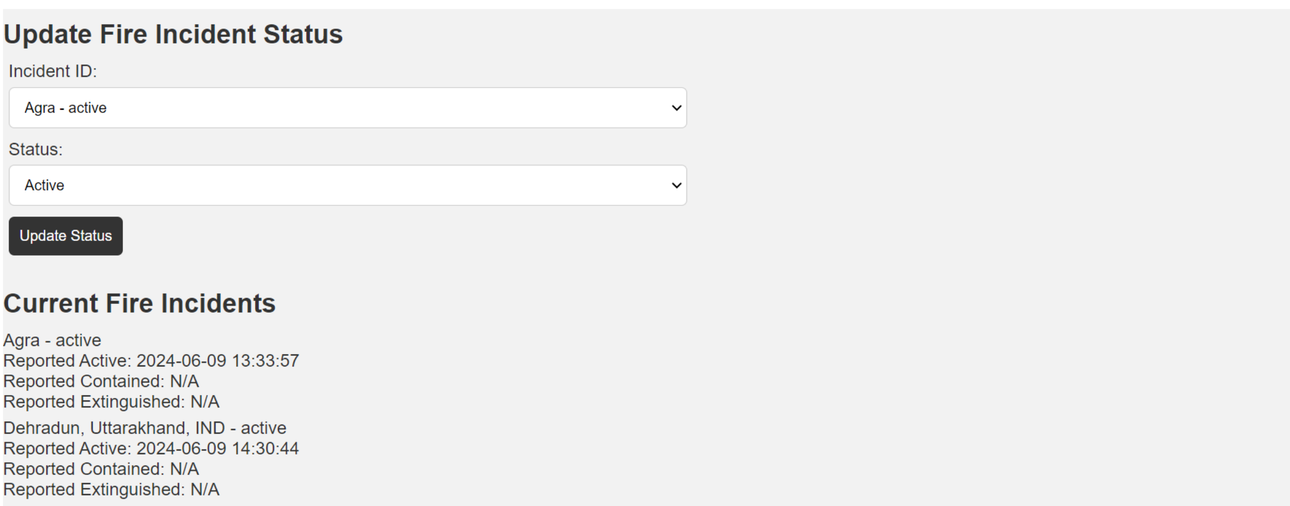
(b)


Chamarajanagar district, Karnataka, India - Start Date: 2019-02-21, Exhaust Date: 2019-02-25, Area Burnt: 10920 hectares
Uttarakhand and Himachal Pradesh, India - Start Date: 2016-04-18, Exhaust Date: 2016-05-02, Area Burnt: 3500 hectares
Uttarakhand, India - Start Date: 2020-05-23, Exhaust Date: 2020-05-31, Area Burnt: 71 hectares
Similipal Biosphere Reserve, Odisha, India - Start Date: 2021-02-22, Exhaust Date: 2021-03-05, Area Burnt: 1300 hectares
Dehradun, Uttarakhand, IND - Start Date: 2024-06-02, Exhaust Date: 2024-06-10, Area Burnt: 1200 hectares
Contact Forest Users
Name: Nitam, Location: 42RJ+79P, Sainik Nagar, Agra, Uttar Pradesh 282001, India, Contact: 7668767469

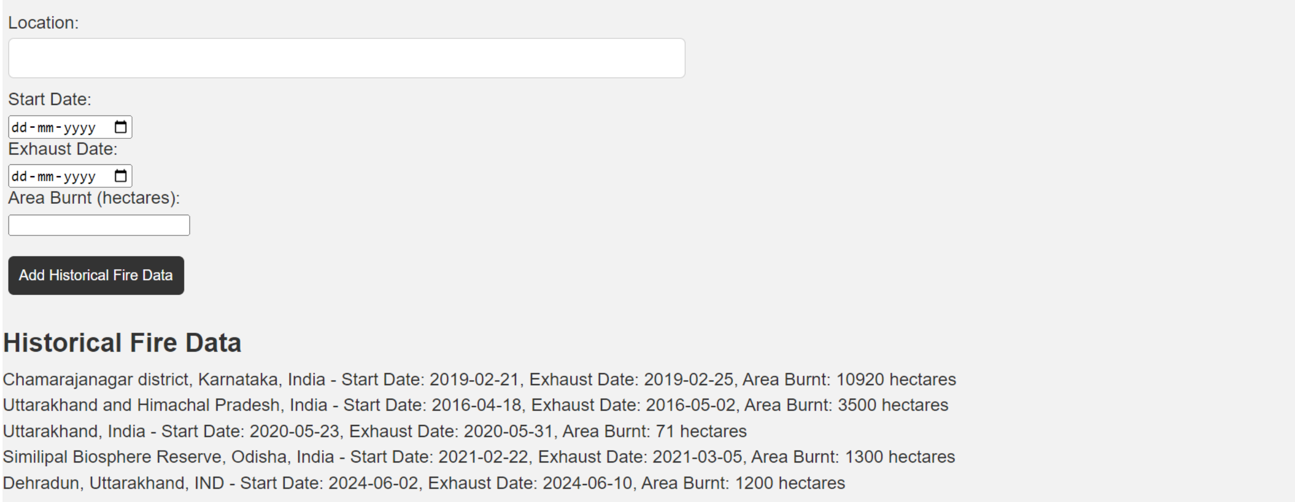
(c)


Fire Risk Management System
Dashboard
Logout
Welcome, nitam
Your location: 52G5+M6G, Sewala Jat, Panchkuian, Rakabganj, Agra, Uttar Pradesh 282001, India
Weather: clear sky, 44.46°C
Report Fire Incidents
Location:
Status:
Active
Add Fire Incident

(a)


Update Fire Incident Status
Incident ID:
Agra - active
Status:
Active
Update Status
Current Fire Incidents
Agra - active
Reported Active: 2024-06-09 13:33:57
Reported Contained: N/A
Reported Extinguished: N/A
Dehradun, Uttarakhand, IND - active
Reported Active: 2024-06-09 14:30:44
Reported Contained: N/A
Reported Extinguished: N/A

(b)


Location:
Start Date:
dd-mm-yyyy
Exhaust Date:
dd-mm-yyyy
Area Burnt (hectares):
Add Historical Fire Data
Historical Fire Data
Chamarajanagar district, Karnataka, India - Start Date: 2019-02-21, Exhaust Date: 2019-02-25, Area Burnt: 10920 hectares
Uttarakhand and Himachal Pradesh, India - Start Date: 2016-04-18, Exhaust Date: 2016-05-02, Area Burnt: 3500 hectares
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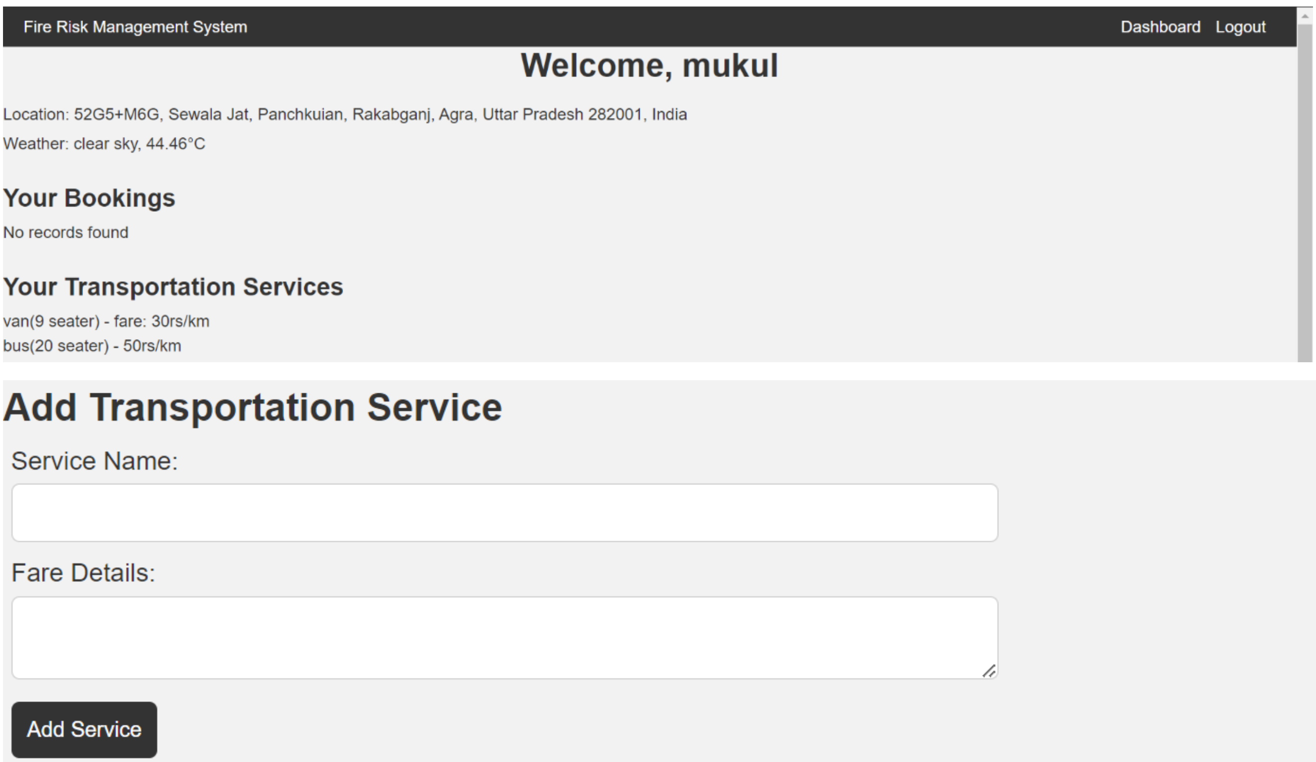
Similipal Biosphere Reserve, Odisha, India - Start Date: 2021-02-22, Exhaust Date: 2021-03-05, Area Burnt: 1300 hectares
Dehradun, Uttarakhand, IND - Start Date: 2024-06-02, Exhaust Date: 2024-06-10, Area Burnt: 1200 hectares

(c)


Fire Risk Management System
Dashboard
Logout
Welcome, mukul
Location: 52G5+M6G, Sewala Jat, Panchkuian, Rakabganj, Agra, Uttar Pradesh 282001, India
Weather: clear sky, 44.46°C
Your Bookings
No records found
Your Transportation Services
van(9 seater) - fare: 30rs/km
bus(20 seater) - 50rs/km
Add Transportation Service
Service Name:
Fare Details:
Add Service

The results obtained from the development and testing of the Fire Risk Management System demonstrate its potential as a valuable tool for managing forest fires. Several key points arise from the results:

4.2.1 Effectiveness of Machine Learning for Fire Prediction

- The use of a Random Forest Regression model proved effective in predicting fire spread. The model's high R^2 score indicates that it captures the relationship between the input features and the target variable well. This allows for reliable predictions, which are crucial for proactive fire management.

4.2.2 Importance of Data Quality and Feature Engineering

- The quality of the dataset and the careful preprocessing of data significantly impacted the model's performance. Imputing missing values, encoding categorical variables, and scaling features were essential steps in preparing the data for model training. Future work should focus on continuously improving the dataset by incorporating more diverse and real-time data sources.

4.2.3 User Interface and Experience

- Feedback from users indicated that the web application was user-friendly and met their needs for incident reporting and management. The clear and intuitive design of the forms and dashboards contributed to this positive user experience. However, there is always room for improvement, such as adding more interactive elements and expanding the functionality of the mobile interface.

4.2.4 Scalability and Performance

- The system's architecture was designed to be scalable, handling increasing amounts of data and user requests efficiently. However, as the user base grows, further optimizations may be needed to maintain performance. This could involve implementing distributed computing techniques and leveraging cloud-based solutions.

- The system's effectiveness can be enhanced through collaboration with local and national emergency services. Integrating the system with their operations can lead to better coordination and response times. Additionally, engaging the community through educational programs and feedback mechanisms can help in gathering valuable data and improving the system's features.

4.2.6 Future Enhancements

- While the current system is robust, there are several areas for future enhancement. Incorporating additional environmental factors, deploying IoT sensors, utilizing

  improvements that can make the system more effective and user-friendly.

The Fire Risk Management System addresses a critical need in the realm of environmental conservation and disaster management. By leveraging advanced machine learning techniques and integrating them with a user-friendly web interface, the system provides a comprehensive solution for predicting, reporting, and managing forest fires. The system's predictive capabilities enable proactive measures, potentially saving lives, property, and natural resources by providing accurate forecasts of fire spread. The web application ensures efficient coordination among users, allowing for real-time incident reporting and resource management.

Through the development and implementation phases, we have demonstrated the effectiveness of using a Random Forest Regression model for predicting fire spread based on various environmental factors. The systematic approach of data collection, preprocessing, model training, and evaluation has yielded a robust predictive model. The integration of this model with a web-based platform ensures that the solution is both practical and accessible to users across different roles, including the general public, forest department personnel, and transportation service providers.

While the current implementation of the Fire Risk Management System provides a solid foundation for managing forest fires, there are several areas for future enhancement and development.

5.2.1 Enhancing Model Accuracy

a. **Incorporating Additional Features**: Integrate more environmental factors such as soil moisture, vegetation density, and real-time weather data to improve the model's predictive accuracy.
b. **Advanced Algorithms**: Explore the use of more sophisticated machine learning algorithms such as deep learning models, ensemble methods, and hybrid models to enhance prediction performance.

a. **IoT Sensors**: Deploy IoT sensors in forests to collect real-time data on temperature, humidity, wind speed, and other relevant parameters. Integrating this data into the predictive model can provide more accurate and timely forecasts.

b.

incidents and incorporate this data into the system for better situational awareness.

5.2.3 User Interface and Experience

a. **Interactive Dashboards**: Enhance the web interface with interactive dashboards that provide visualizations of fire incidents, predictions, and resource allocation.

5.2.4 Scalability and Performance

a. **Distributed Computing**: Implement distributed computing techniques to handle large-scale data processing and model training, ensuring the system can scale to handle high volumes of data and users.

b. **Cloud Integration**: Migrate the system to a cloud platform to improve scalability, reliability, and performance, allowing for seamless handling of peak loads and disaster recovery.

5.2.5 Collaboration and Integration

a. **Integration with Emergency Services**: Collaborate with local and national emergency services to integrate the system with their operations, ensuring coordinated and efficient response to fire incidents.

b. **Community Engagement**: Develop features that engage the community, such as fire safety education programs, volunteer coordination, and user feedback mechanisms.

5.2.6 Continuous Improvement:

a. **Feedback Loop**: Establish a continuous feedback loop with users to gather insights and suggestions for system improvement. Regularly update the system based on user feedback and evolving fire management needs.

b. **Research and Development**: Invest in ongoing research and development to stay at the forefront of technology and methodologies in fire risk management.

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