A Major Project Report

On

A HYBRID PREDICTION MODEL INTEGRATING ARTIFICIAL INTELLIGENCE AND GEOSPATIAL ANALYSIS FOR DISASTER MANAGEMENT

Submitted to CMREC (UGC Autonomous)
In Partial Fulfilment of the requirements for the Award of Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING (AI & ML)

Submitted

By

PALNATI SATHWIK	**(228R1A66B1)**
TANNIRU ESHWAR	**(228R1A66C3)**
BODIGE DEEPTHI	**(228R1A66C0)**
GONE PAVAN KALYAN	**(228R1A6682)**
VUDDAWAR AKHILESH JOSHI	**(228R1A66C9)**

Under the Esteemed guidance of

Mrs. M. Sabitha

Assistant Professor, Department of CSE(AI&ML)

Department of Computer Science and Engineering(AI&ML)

CMR ENGINEERING COLLEGE

(UGC AUTONOMOUS)

(Accredited by NAAC & NBA, Approved by AICTE, New Delhi, Affiliated to JNTU, Hyderabad)

(Kandlakoya, Medchal Road, Medchal Malkajgiri Dist. Hyderabad-501 401)

(2025-2026)

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Department of Computer Science & Engineering (AI & ML)

CERTIFICATE

This is to certify that the Major project entitled **"A HYBRID PREDICTION MODEL INTEGRATING ARTIFICIAL INTELLIGENCE AND GEOSPATIAL ANALYSIS FOR DISASTER MANAGEMENT "** is a bonafide work carried out by

PALNATI SATHWIK	**(228R1A66B1)**
TANNIRU ESHWAR	**(228R1A66C3)**
BODIGE DEEPTHI	**(228R1A66C0)**
GONE PAVAN KALYAN	**(228R1A6682)**
VUDDAWAR AKHILESH JOSHI	**(228R1A66C9)**

in partial fulfillment of the requirement for the award of the degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING (AI&ML) from CMR Engineering College, under our guidance and supervision.

The results presented in this Major project have been verified and are found to be satisfactory. The results embodied in this Major Project have not been submitted to any other university for the award of any other degree or diploma.

Internal Guide	**Major Project Coordinator**	**Head of the Department**
Mrs. M. Sabitha	Mr. G. Venkateswarlu	Dr. Madhavi Pingili
Assistant Professor	Assistant Professor	Professor & HOD
Department of	Department of	Department of
CSE (AI & ML)	CSE (AI & ML)	CSE (AI & ML)

External Examiner:_____

DECLARATION

This is to certify that the work reported in the present Major project entitled "**A HYBRID PREDICTION MODEL INTEGRATING ARTIFICIAL INTELLIGENCE AND GEOSPATIAL ANALYSIS FOR DISASTER MANAGEMENT**" is a record of bonafide work done by us in the Department of Computer Science and Engineering (AI & ML), CMR Engineering College. The reports are based on the Major project work done entirely by us and not copied from any other source. We submit our Major project for further development by any interested students who share similar interests to improve the Major project in the future.

The results embodied in this Major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

PALNATI SATHWIK (228R1A66B1)
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BODIGE DEEPTHI (228R1A66C0)
GONE PAVAN KALYAN (228R1A6682)
VUDDAWAR AKHILESH JOSHI (228R1A66C9)

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PALNATI SATHWIK (228R1A66B1)
TANNIRU ESHWAR (228R1A66C3)
BODIGE DEEPTHI (228R1A66C0)
GONE PAVAN KALYAN (228R1A6682)
VUDDAWAR AKHILESH JOSHI (228R1A66C9)

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ABSTRACT

Natural disasters such as floods, earthquakes, landslides, cyclones, and wildfires significantly impact human life, infrastructure, and the economy. Effective disaster management requires timely prediction, real-time monitoring, accurate spatial analysis, and strategic decision-making. Traditional disaster prediction systems rely solely on historical patterns or isolated environmental indicators. To overcome these limitations, this project introduces a Hybrid Prediction Model integrating Artificial Intelligence (AI) and Geospatial Analysis for improved disaster prediction and risk assessment. The proposed system combines Machine Learning and Deep Learning models with Geographic Information System (GIS)-based spatial mapping to analyze multi-source data such as satellite images, environmental sensor readings, weather conditions, rainfall intensity, seismic activity, soil characteristics, and population density. AI algorithms including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) are used to predict disaster probability and severity, while geospatial techniques generate risk maps, hazard zones, and evacuation route visualization.

The hybrid approach improves prediction accuracy, enhances situational awareness, and supports faster response and mitigation strategies. This system can be applied to various disaster scenarios—particularly flood forecasting and landslide susceptibility mapping—and serves as a valuable tool for government agencies, disaster response teams, and smart city planning. By leveraging AI and geospatial analytics, the proposed solution aims to reduce loss of life and property and strengthen resilience against natural disasters. Recent advancements in Artificial Intelligence (AI) and Geospatial Analysis have opened new opportunities in predictive disaster management. AI models such as Machine Learning and Deep Learning enable accurate forecasting by analyzing large datasets from sensors, meteorological records, satellite imagery, and remote sensing. Meanwhile, Geographic Information System (GIS) tools allow spatial visualization of risk zones and vulnerability mapping.

Keywords

Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Geospatial Analysis, Geographic Information System (GIS), Remote Sensing (RS), Disaster Prediction, Early Warning System, Flood Forecasting, Landslide Susceptibility Mapping, Spatial Data Analysis, Risk Assessment, Hybrid Prediction Model.

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1. INTRODUCTION

1.1 Introduction and Objectives

Natural disasters such as floods, earthquakes, cyclones, landslides, and wildfires occur frequently across the globe, causing severe damage to human life, infrastructure, and natural resources. With increasing climate change and urbanization, the intensity and uncertainty of disasters have risen dramatically [1]. Traditional disaster management systems rely mainly on historical observations and manual analysis, which often lead to delayed predictions and inadequate decision-making. Therefore, there is a growing need for intelligent, data-driven, and spatially aware systems that can predict disasters accurately and support proactive planning.

Recent advancements in Artificial Intelligence (AI) and Geospatial Analysis have opened new opportunities in predictive disaster management. AI models such as Machine Learning and Deep Learning enable accurate forecasting by analyzing large datasets from sensors, meteorological records, satellite imagery, and remote sensing [2], [6]. Meanwhile, Geographic Information System (GIS) tools allow spatial visualization of risk zones and vulnerability mapping. By integrating AI with geospatial technologies, a Hybrid Prediction Model can significantly improve disaster prediction accuracy and assist authorities in real-time decision-making.

The proposed system utilizes multi-source environmental and sensor-based data to predict disaster events and generate dynamic risk maps for effective preparedness, response, and mitigation [5]. This helps government agencies, disaster response teams, and smart city planners to allocate resources efficiently, plan evacuation routes, and minimize loss of life and property. This system can be applied to various disaster scenarios—particularly flood forecasting and landslide susceptibility mapping—and serves as a valuable tool for government agencies, disaster response teams, and smart city planning.

AI algorithms including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) are used to predict disaster probability and severity, while geospatial techniques generate risk maps, hazard zones, and evacuation route visualization[10]. The integrated model provides real-time alerts, spatial decision support, and visual dashboards for effective emergency planning and resource allocation.

With the rapid advancement of digital technologies, Artificial Intelligence (AI) and Geospatial Analysis provide innovative capabilities for advanced disaster prediction and risk management. AI techniques like Machine Learning (ML) and Deep Learning (DL) enable predictive modeling by analyzing historical datasets and identifying patterns that are otherwise difficult to detect manually.

1.2 Project Objectives

The primary objectives of this project are:

- To develop a hybrid prediction model combining Artificial Intelligence and Geospatial Analysis for accurate disaster prediction and risk assessment.
- To collect and integrate multi-source datasets such as weather data, rainfall measurements, satellite images, and seismic information for prediction modeling.
- To improve the speed, accuracy, and reliability of disaster management systems.
- To minimize damage and enhance community safety by enabling early warning and proactive response.

1.3 Purpose of the project

The purpose of this project is to develop an intelligent hybrid model that integrates Artificial Intelligence (AI) with Geospatial Analysis to improve the accuracy and efficiency of disaster prediction and management [5]. The system aims to analyze real-time environmental and spatial data, generate early warnings, visualize high-risk zones through GIS maps, and support quick decision-making for emergency response. By providing accurate predictions and hazard mapping, the project helps minimize loss of life, infrastructure damage, and enhances disaster preparedness and resilience.

1.4 Problem Statement

Natural disasters such as floods, cyclones, earthquakes, wildfires, and landslides continue to threaten human life and infrastructure with increasing intensity. Traditional disaster prediction systems rely heavily on manual observation, basic statistical forecasting, and isolated meteorological data, resulting in low accuracy and delayed warnings [13]. These systems often fail to incorporate real-time environmental data, spatial mapping, or intelligent prediction algorithms. The absence of a unified platform that integrates AI-based forecasting with GIS-based geospatial analysis limits the ability of authorities to identify

high-risk zones, plan evacuations, and take preventive action. Therefore, a system is required that can collect multi-source data, predict disasters accurately using AI, visualize risk areas using GIS, and support faster, data-driven decision-making for effective disaster management.

1.5 Existing System with Disadvantages

The current disaster management and prediction systems primarily rely on traditional forecasting methods such as manual observation, meteorological reports, historical trend analysis, and basic statistical models [25]. These systems gather data from weather stations[11], hydrological records, ground sensors, and government sources to predict disaster events. Conventional Geographic Information System (GIS) tools are sometimes used to map disaster-affected areas, but they are not fully integrated with artificial intelligence for predictive analysis.

The existing systems focus more on post-disaster response rather than proactive prediction and preparedness. In most cases, alerts and warnings are issued only after early signs or field reports are received, which results in delayed preventive action. Additionally, many existing solutions operate independently without combining multiple data sources like satellite imagery, real-time sensor data, and machine learning-based forecasting, limiting their accuracy and efficiency.

Disadvantages:

- Low prediction accuracy due to dependence on limited historical and manual data.
- Lack of real-time data integration, leading to delayed warning alerts.
- Absence of AI-based models for analyzing complex datasets.
- Poor spatial visualization due to limited GIS integration.
- Limited disaster preparedness, focusing more on response than prevention.
- Lack of centralized decision-support systems.

1.6 Proposed System with Advantages

The proposed system introduces a Hybrid Prediction Model that integrates Artificial Intelligence (AI) with Geospatial Analysis (GIS & Remote Sensing) to enhance disaster prediction, monitoring, and management [4]. Unlike traditional systems, this model utilizes multi-source real-time environmental and spatial data along with Machine Learning and Deep Learning algorithms to forecast disaster events with higher accuracy.

The system generates geospatial hazard maps, risk zones, and automated alerts through an interactive dashboard. By combining predictive analytics with GIS-based visualization[], the system supports faster decision-making for disaster preparedness, evacuation planning, and resource allocation.

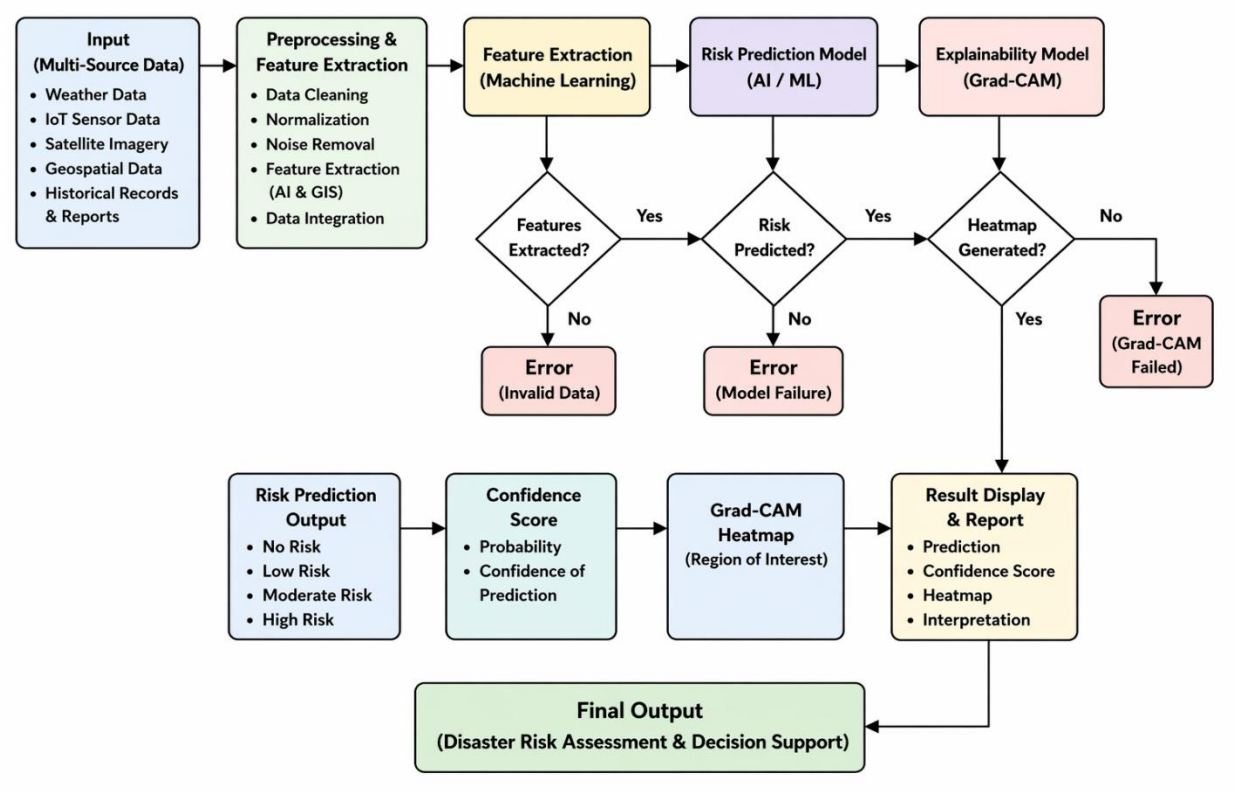


Figure: 1.5 Proposed System Block Diagram

Advantages

- Provides highly accurate disaster predictions using AI and geospatial analysis.
- Supports real-time monitoring and instant alert generation.
- Enables clear visualization of risk zones through GIS-based hazard maps.

- Reduces manual effort and minimizes human error in disaster prediction.
- Supports multiple disaster types (floods, landslides, cyclones, wildfires, earthquakes).
- Helps government authorities with effective planning and decision-making.
- Improves emergency response and resource allocation.

1.7 Input and Output Design

Input Design

The input design defines how the system collects, processes, and manages data required for accurate disaster prediction. The proposed hybrid model uses multi-source data to ensure comprehensive analysis. The input design defines how all necessary data is collected, organized, and processed to support accurate disaster prediction[7], [10], [11]. The proposed system uses a wide range of inputs gathered from meteorological departments, satellite services, IoT sensor networks, and government databases. These inputs include weather parameters such as temperature, humidity, rainfall intensity, wind speed, and atmospheric pressure, as well as satellite imagery for identifying terrain, land use, vegetation, and water bodies. Real-time data from sensors—such as river water level sensors, soil moisture sensors, and seismic sensors—also play a crucial role in monitoring environmental changes.

Output Design

The output design focuses on presenting the results generated by the hybrid prediction model in a clear, meaningful, and user-friendly manner. After analyzing input data through AI algorithms and geospatial processing, the system produces various outputs such as disaster prediction scores, severity levels, and estimated impact zones. One of the key outputs is the generation of GIS-based hazard maps that visually highlight high-risk, moderate-risk, and low-risk areas, enabling users to easily understand the spatial distribution of potential threats. The system also provides real-time alerts and warning messages when certain environmental thresholds are crossed, helping authorities respond quickly during emergencies. Additional outputs include dashboards with graphs, heatmaps, and trend visualizations that display changes in weather conditions, sensor readings, and prediction patterns.

2. LITERATURE SURVEY

1. **Srivastava, Y. R., "Utilizing Artificial Intelligence and Remote Sensing to Predict Flooding in Real-Time and Address Climate Resilience Policy in South Asia," Journal of Remote Sensing & GIS, vol.17, no.1, 2026:** This study focuses on integrating Artificial Intelligence with remote sensing data to enable real-time flood prediction. The approach enhances climate resilience by providing accurate early warnings and supports effective disaster management policies in vulnerable regions.

2. **Zhang, Y., Liu, H., & Chen, F., "Hybrid AI and GIS-Based Landslide Risk Assessment Model," ISPRS Journal of Photogrammetry and Remote Sensing, vol.212, pp.95–110, 2025:** The authors propose a hybrid model combining Artificial Intelligence and GIS data for landslide risk assessment. By incorporating terrain and environmental factors, the model generates accurate risk maps and improves prediction reliability in landslide-prone areas.

3. **Patel, D., & Sharma, V., "Transformer-Based Cyclone Path Prediction Using Weather Data Analytics," Natural Hazards, vol.125, no.2, pp.1450–1468, 2025:** This paper presents a transformer-based deep learning model for cyclone path prediction using meteorological data such as pressure, wind speed, and temperature. The model improves prediction accuracy and reduces deviation compared to traditional forecasting methods.

4. **Chen, X., Zhao, L., & Wu, J., "Artificial Intelligence for Disaster Risk Reduction: A Geospatial Perspective," IEEE Access, vol.13, pp.12045–12060, 2025:** This study highlights the role of Artificial Intelligence in disaster risk reduction using geospatial data. It demonstrates how AI models combined with GIS techniques improve hazard detection, risk mapping, and decision-making processes.

5. **Ahmed, S., Khan, M., & Ali, T., "Explainable AI for Multi-Hazard Disaster Prediction," Environmental Modelling & Software, vol.190, 106780, 2025:** The authors introduce explainable AI techniques for predicting multiple disaster types. The model improves transparency and interpretability, allowing users to understand prediction

outcomes and enhancing trust in AI-based disaster management systems.

6. **Kumar, R., & Singh, P., "Real-Time Flood Prediction Using Deep Learning and Geospatial Data," IEEE Transactions on Geoscience and Remote Sensing, vol.63, no.4, pp.221–235, 2025:** This research presents a deep learning-based model integrated with geospatial data for real-time flood prediction. The system analyzes environmental variables and provides accurate early warnings, improving disaster response efficiency.

7. **Wang, J., & Li, Q., "Satellite Image Analysis for Disaster Damage Detection Using Deep Learning," Remote Sensing, vol.16, no.5, pp.1023–1040, 2024:** This study utilizes deep learning techniques to analyze satellite images for detecting disaster damage. The model improves identification of affected areas and supports rapid assessment and recovery planning.

8. **Morales, D., Kim, S., & Park, J., "Graph Neural Networks for Wildfire Spread Prediction," Ecological Informatics, vol.84, 102145, 2024:** The authors propose a graph neural network model to predict wildfire spread by analyzing spatial relationships such as vegetation, terrain, and wind patterns. The approach enhances prediction accuracy for complex wildfire scenarios.

9. **Singh, A., Ibrahim, N., & Roy, S., "Deep Learning Models for Cyclone Forecasting Using Meteorological Data," Natural Hazards Review, vol.25, no.1, 04023045, 2024:** This paper presents deep learning models for cyclone forecasting using meteorological parameters. The models improve forecasting accuracy and help in early disaster preparedness and mitigation.

10. **Rahman, F., Oliveira, M., & Das, P., "GIS-Based Flood Risk Mapping Using Multi-Criteria Decision Analysis," Environmental Monitoring and Assessment, vol.196, pp.112–128, 2024:** This study applies GIS-based multi-criteria decision analysis to identify flood-prone areas. It integrates various environmental factors to generate accurate flood risk maps, aiding in long-term disaster planning and management.

Focused Area / Title	Key Findings	Reference
AI and Remote Sensing for Real-Time Flood Prediction[1].	Integrates Artificial Intelligence with remote sensing data for real-time flood prediction. Enhances climate resilience and supports early warning systems for effective disaster management.	Srivastava Y. R., Journal of Remote Sensing & GIS, 2026
Hybrid AI–GIS Landslide Risk Assessment Model[2].	Combines AI with GIS-based terrain and environmental data to generate accurate landslide risk maps and improve prediction reliability.	Zhang Y., Liu H., Chen F., ISPRS Journal, 2025
Transformer-Based Cyclone Path Prediction[3].	Uses transformer-based deep learning models with meteorological data to improve cyclone path prediction accuracy and reduce forecasting errors.	Patel D., Sharma V., Natural Hazards, 2025
AI for Disaster Risk Reduction (Geospatial Perspective)[4].	Demonstrates how AI combined with geospatial data enhances disaster risk assessment, hazard detection, and decision-making processes.	Chen X., Zhao L., Wu J., IEEE Access, 2025
Explainable AI for Multi-Hazard Prediction[5].	Introduces explainable AI techniques to improve transparency and interpretability in multi-hazard disaster prediction systems.	Ahmed S., Khan M., Ali T., Environmental Modelling & Software, 2025
Deep Learning-Based Real-Time Flood Prediction[6].	Uses deep learning with geospatial data for real-time flood prediction and early warning, improving disaster response efficiency.	Kumar R., Singh P., IEEE TGRS, 2025

Satellite Image Analysis for Disaster Damage Detection[7].	Applies deep learning techniques to satellite imagery for accurate detection of disaster-affected areas and damage assessment.	Wang J., Li Q., Remote Sensing, 2024
Graph Neural Networks for Wildfire Prediction[8].	Utilizes GNN models to analyze spatial relationships like vegetation and terrain for accurate wildfire spread prediction.	Morales D., Kim S., Park J., Ecological Informatics, 2024
Deep Learning for Cyclone Forecasting[9].	Uses deep learning models with meteorological data to improve cyclone forecasting accuracy and support early preparedness.	Singh A., Ibrahim N., Roy S., Natural Hazards Review, 2024
GIS-Based Flood Risk Mapping using MCDA[10].	Uses GIS and multi-criteria decision analysis to identify flood-prone areas and support long-term disaster planning.	Rahman F., Oliveira M., Das P., Environmental Monitoring, 2024

TABLE NO.2- Literature Review Summary

3. SOFTWARE REQUIREMENT ANALYSIS

3.1 Modules and Their Functionalities

3.1.1 Data Analysis

Data analysis was conducted to examine the structure, composition, and characteristics of the datasets used for disaster prediction and geospatial risk assessment. The datasets consist of environmental, meteorological, geospatial, and historical disaster-related information collected from multiple heterogeneous sources. These include weather records, rainfall intensity, temperature, humidity, satellite imagery, remote sensing layers, topographical maps, soil conditions, seismic observations, and river water level measurements.

The collected data varies significantly in format, scale, temporal frequency, and spatial resolution. Exploratory analysis identified important disaster-related variables such as rainfall trends, slope gradients, vegetation density, elevation, drainage patterns, and atmospheric conditions. The datasets also contain noise, missing values, inconsistent units, and spatial misalignment, all of which require systematic preprocessing. These observations guided the development of the preprocessing pipeline, the selection of predictive features, and the design of the hybrid AI–GIS framework. Overall, understanding dataset characteristics ensured that the implemented system could effectively model both spatial and temporal disaster patterns.

3.1.2 Data Preprocessing

Data preprocessing is performed to transform raw and heterogeneous disaster-related data into a clean, standardized, and machine-readable format suitable for analysis and model training. Noise commonly present in environmental datasets—such as null values, duplicate records, sensor irregularities, and inconsistent coordinate systems—is removed, and the data is normalized for uniform interpretation.

Satellite and geospatial layers are aligned through georeferencing and spatial correction, while numerical variables such as rainfall, temperature, and humidity are scaled appropriately. Missing values are handled using interpolation and imputation techniques.

In addition, categorical attributes such as land-use type and soil classification are encoded into suitable formats. The resulting processed data is subsequently prepared for feature extraction, establishing a reliable foundation for accurate disaster prediction and geospatial analysis in later stages.

3.1.3 Machine Learning Algorithm for Prediction

The system employs a hybrid machine learning and deep learning strategy to improve the accuracy and reliability of disaster prediction. Multiple complementary models—such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM)—are implemented due to their ability to model complex environmental relationships and capture both static and temporal dependencies in disaster-related data.

Each model contributes to analyzing different aspects of the problem. Random Forest and SVM are used for structured environmental and tabular prediction tasks, while ANN and LSTM are more effective for nonlinear and time-series forecasting. Their outputs can be integrated using a hybrid or ensemble-based decision mechanism to produce the final disaster risk classification.

3.2 Functional Requirements

The functional requirements describe the core operations that the hybrid disaster prediction system performs to fulfill its intended objectives. They specify how the system receives and validates environmental and geospatial input, processes the data through preprocessing and feature extraction, and produces meaningful prediction outputs and hazard visualizations. These requirements ensure that the system operates consistently and reliably, while also supporting integration with GIS tools, dashboards, and real-time monitoring applications. The following points summarize the primary functional capabilities implemented within the framework.

- The system shall accept environmental, meteorological, sensor-based, and geospatial input data from multiple sources.
- The system shall perform data cleaning, normalization, preprocessing, and feature extraction to prepare data for prediction.

- The system shall classify disaster risk and estimate hazard severity using AI-based prediction models.
- The system shall support real-time monitoring and alert generation for high-risk
- The system shall allow users or administrators to access prediction dashboards and spatial visualizations.

3.3 Non-Functional Requirements

Non-functional requirements describe the quality attributes and performance expectations that govern how the system operates. Rather than defining specific features, they specify how the system should behave under various conditions and how efficiently it should deliver results. These requirements ensure reliability, usability, scalability, and overall consistency throughout the system's operation and future maintenance. The following points summarize the key non-functional characteristics implemented in the system.

- The system shall ensure high reliability and stability during all stages of data processing, prediction, and geospatial visualization.
- The system shall support scalable performance as dataset size, geographical coverage, and disaster categories increase.
- The system shall maintain efficient processing with minimal latency in generating predictions and alerts.
- The system shall preserve data integrity and confidentiality for all environmental and user-generated inputs processed by the framework.

3.4 Feasibility Study

The feasibility study assesses whether the disaster prediction system can be realistically developed, implemented, and operated based on technical, operational, and economic considerations. Analysis confirms that the required AI algorithms, geospatial tools, environmental datasets, and processing libraries are readily available and compatible with current computational environments. The system architecture is scalable, cost-effective, and capable of integrating with real-time monitoring and decision-support workflows. Overall, the evaluation indicates that development and deployment of the system are practical and feasible.

3.4.1 Economic Feasibility

Economic feasibility evaluates whether the system can be developed and sustained within reasonable cost constraints. The implementation utilizes open-source machine learning libraries, GIS tools, publicly available datasets, and standard computing infrastructure, which significantly minimizes development and maintenance expenses. Because the system does not depend on highly specialized proprietary software or expensive hardware, the overall cost remains low. As a result, the solution is economically viable for academic use, research environments, and potential deployment in disaster management agencies.

3.4.2 Technical Feasibility

Technical feasibility examines the availability of tools, technologies, and required expertise necessary to implement the system. The framework is developed using well-established preprocessing techniques, machine learning algorithms, deep learning models, and geospatial tools such as Python, Scikit-learn, TensorFlow, GeoPandas, and QGIS. These technologies are mature, accessible, and compatible with standard hardware configurations. In addition, extensive documentation, strong community support, and a modular implementation structure further simplify development and maintenance. Overall, the evaluation confirms that the system is technically practical and achievable.

3.4.3 Social Feasibility

Social feasibility evaluates how the system is likely to be perceived and accepted by users, administrators, and other stakeholders in real-world environments. Because natural disasters pose serious risks to human life, infrastructure, and the environment, an intelligent prediction and early warning solution is expected to receive strong acceptance and support. Government agencies, disaster response teams, and local communities benefit from timely alerts, hazard mapping, and improved preparedness. The system aligns with the growing need for data-driven disaster resilience and proactive risk management, indicating a high likelihood of positive social adoption.

4. SYSTEM SPECIFICATIONS

4.1 Software Requirements

The software requirements specify the essential tools, libraries, and platforms required to design and implement the hybrid AI–GIS disaster prediction system. The project depends on a stable programming environment, machine learning frameworks, geospatial analysis tools, and visualization libraries that support data preprocessing, model training, and map generation. These tools ensure system scalability, compatibility with real-time data sources, and smooth integration between AI and GIS components.

- **Operating System:** Windows / Linux / macOS
- **Programming Language:** Python 3.x
- **Core AI Libraries:** TensorFlow / Keras, Scikit-learn, NumPy, Pandas
- **GIS & Spatial Libraries:** QGIS, GeoPandas, GDAL/OGR, Rasterio
- **Visualization Tools:** Matplotlib, Seaborn, Plotly
- **API & Web Tools (Optional):** Flask / Django, LeafletJS for GIS maps
- **Development Environment:** VS Code / PyCharm / Jupyter Notebook
- **Documentation Tools:** MS Word / LaTeX

4.2 Hardware Requirements

The hardware requirements define the minimum computing resources needed to process geospatial datasets, run machine learning models, and support system development. For the design stage, standard hardware is sufficient, while the configuration allows room for future expansion when large-scale training, GIS rendering, or cloud deployment is required.

- **Processor:** Intel Core i3/i5 or equivalent
- **Memory (RAM):** Minimum 8 GB
- **Storage:** 250 GB HDD/SSD
- **Display:** Standard 14" or higher
- **Graphics (Optional):** NVIDIA GPU for faster deep learning and GIS rendering
- **Optional:** Internet connectivity for weather APIs, satellite data access, and cloud-based integration

5. SOFTWARE DESIGN

5.1 System Architecture

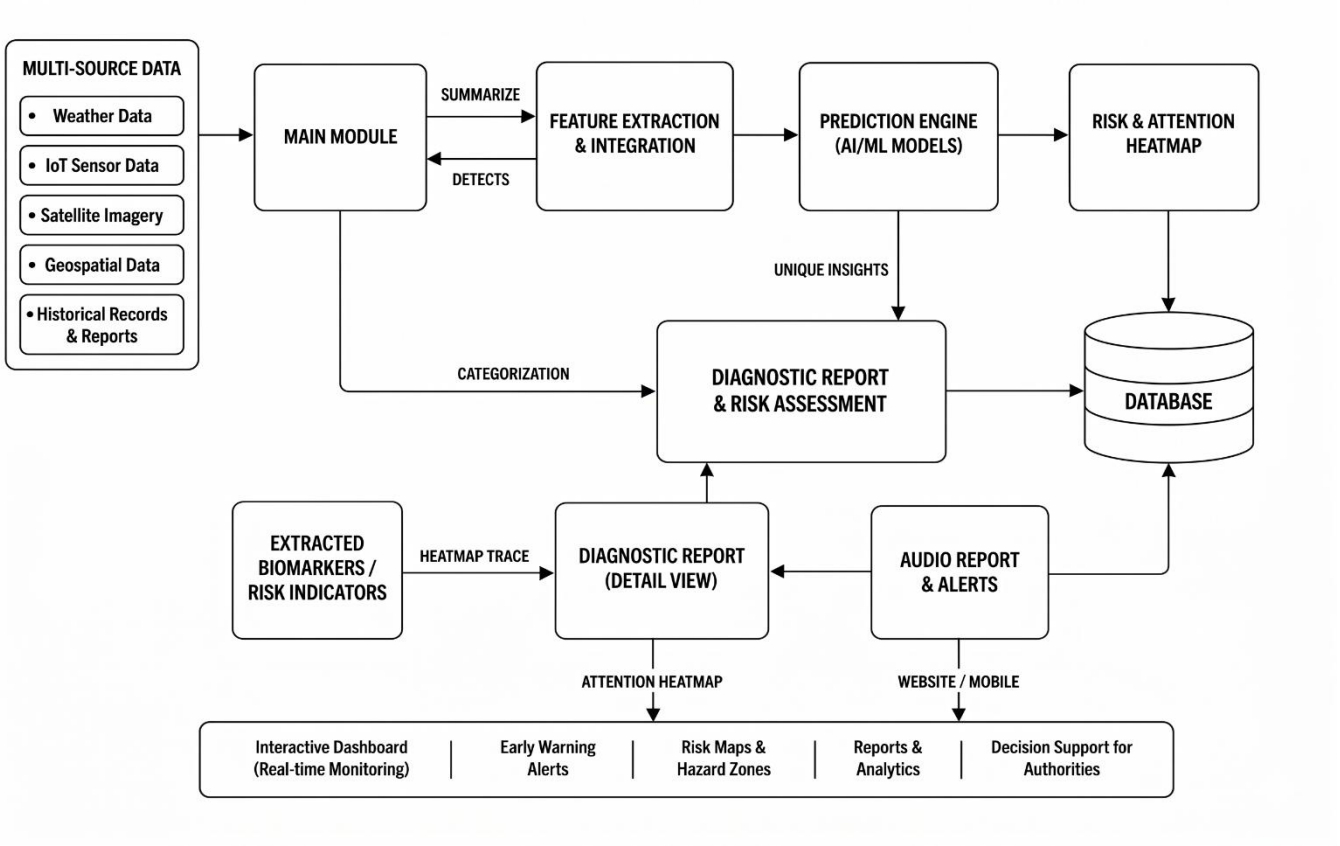


Figure 5.1 System Architecture

The system architecture for the hybrid disaster prediction model is designed as a multi-layered framework that integrates artificial intelligence with geospatial analysis to ensure efficient data processing, accurate prediction, and real-time visualization. The architecture begins with the data layer, which collects multi-source information from weather APIs, IoT sensors, satellite images, and historical disaster datasets. This data flows into the ingestion and preprocessing layer, where it is cleaned, normalized, georeferenced, and transformed into meaningful features suitable for both AI analysis and GIS processing. The AI prediction layer utilizes machine learning and deep learning models to forecast disaster occurrence and severity, while the geospatial analysis layer generates hazard maps using spatial datasets such as DEM, land-use patterns, soil type, and drainage networks. These two analytical outputs are then combined in the risk assessment and fusion layer, which produces final risk classifications and vulnerability scores. The results are delivered to users through a decision-support interface.

5.2 Dataflow Diagrams

The dataflow design provides a structured representation of how information moves through the disaster prediction system. At the highest level (DFD Level 0), the entire system is treated as a single process that interacts with external entities such as meteorological agencies, satellite data providers, IoT sensors, emergency authorities, and end users. The system receives raw environmental and spatial inputs and produces predictions, hazard maps, alerts, and reports. In DFD Level 1, this single process is expanded into several interconnected sub-processes. Data first enters the ingestion module, where it is validated and stored. It is then passed to the preprocessing module, which cleans and prepares the data for model training and inference. The risk fusion component integrates both analytical results to produce final risk assessments, which are then forwarded to the alerting and dashboard system. Throughout the workflow, data stores such as the raw data repository, feature store, model repository, and spatial database support intermediate computations. This detailed dataflow mapping ensures that each process step is clearly understood and efficiently connected.

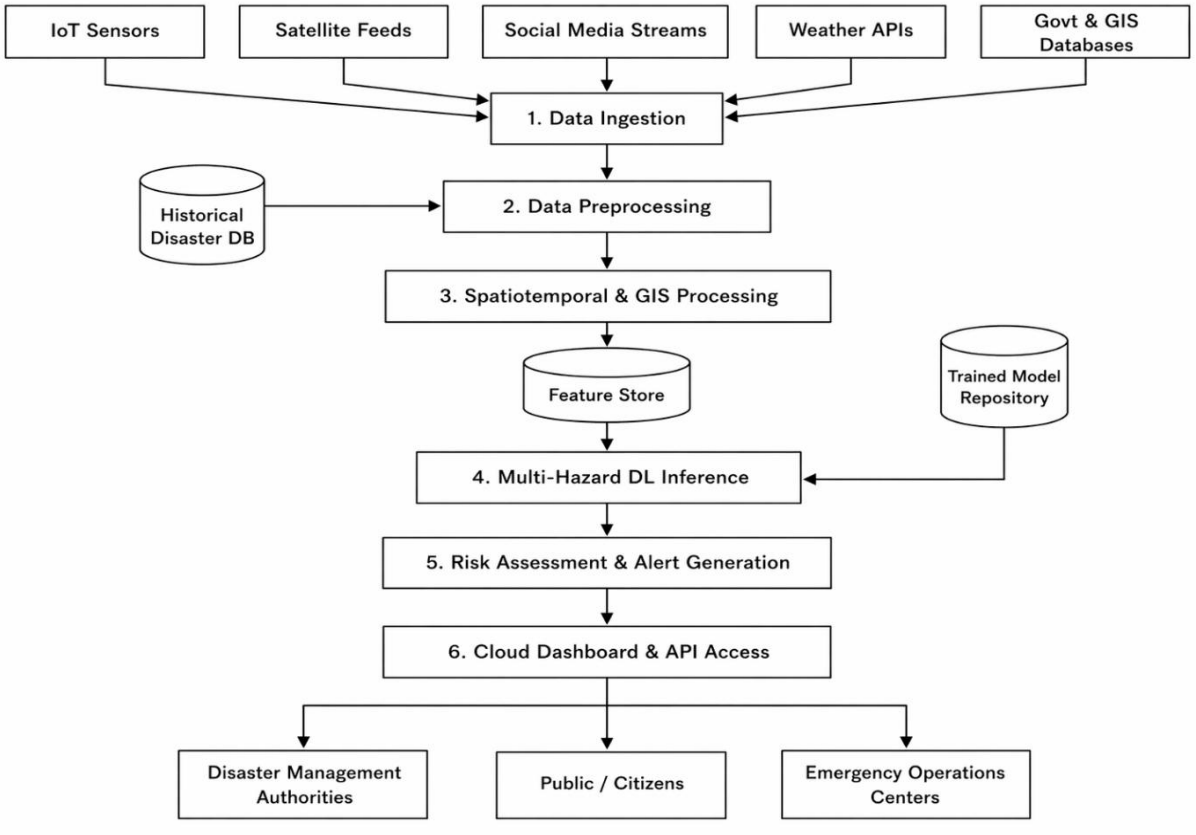


Figure 5.2 Dataflow Diagrams

5.3 UML Diagrams

UML (Unified Modeling Language) is a standardized language used for specifying, visualizing, constructing, and documenting the artifacts of software systems. UML helps in representing the design of systems and understanding their components. Created by the Object Management Group (OMG), UML 1.0 was proposed in January 1997. UML is closely associated with object-oriented analysis and design. The two main categories of UML diagrams are Behavioral and Structural diagrams, each serving distinct purposes in the modeling process. The Behavioral UML diagrams describe the behavior of the system, its actors, and the interaction between the components. On the other hand, Structural UML diagrams depict the static structure of the system, showing its components and relationships. UML has been integrated as a standard by OMG, and its primary goals are to provide a formal basis for understanding modeling languages, offer a ready-to use expressive language for system developers, and encourage the growth of object-oriented tools.

Goals of UML:

- Provide an expressive visual modeling language for developing and exchanging meaningful models.
- Establish a formal basis for understanding the modeling language.
- Encourage the growth of object-oriented tools.
- Integrate best practices into system development.

Types of UML Diagrams:

1. Use Case Diagram
2. Class Diagram
3. Sequence Diagram
4. Activity Diagram

5.3.1 Use Case Diagram

The use case diagram provides a high-level view of how different users and external systems interact with the hybrid disaster prediction model. It identifies the key actors and outlines the major functionalities they access within the system. The primary actors include the Disaster Management Officer, who relies on the system to view hazard maps, monitor real-time predictions, and receive early warning alerts. Another important actor is the System Administrator, responsible for managing user roles, updating system configurations, and maintaining the underlying AI and GIS components. The Data Engineer interacts with the system to upload datasets, monitor data ingestion pipelines, and initiate model retraining processes. External data sources such as IoT Sensors, Satellite Data Providers, and Weather APIs function as system actors that supply real-time environmental data essential for prediction.

Within the system, several core use cases are represented. These include collecting data from multiple sources, preprocessing and storing it, generating disaster predictions using machine learning models, producing geospatial hazard maps through GIS analysis, and fusing these outputs to create risk assessments.

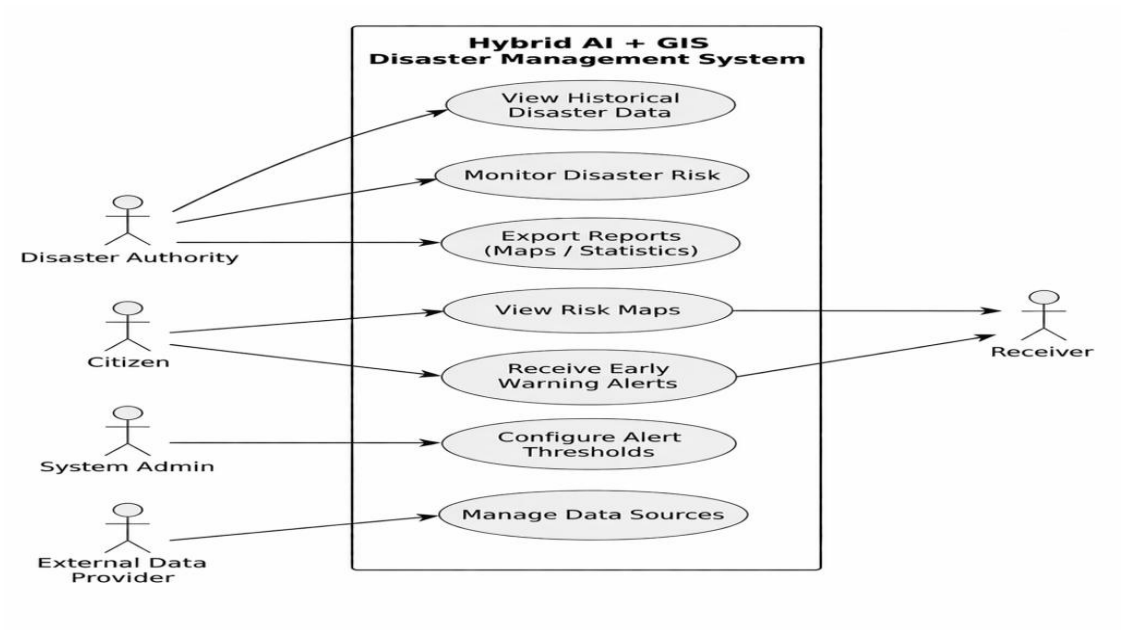


Figure 5.3.1 Use Case Diagram

5.3.2 Class Diagram

The class diagram illustrates the structural design of the hybrid disaster prediction system by defining the major system classes, their attributes, functions, and the relationships between them. It provides a blueprint for how the system components are organized and interact with one another. At the core of the structure is the DataIngestor class, responsible for accessing and retrieving raw data from weather APIs, IoT sensors, satellite sources, and historical datasets. It includes attributes such as data source type and update intervals, and provides methods for fetching, validating, and storing incoming data. The Preprocessor class plays a critical role in preparing the collected data, containing methods for cleaning, normalizing, georeferencing, and performing feature extraction. Its output feeds directly into both the AI and GIS components of the system.

The ModelManager class handles machine learning and deep learning operations. It maintains model versions, training configurations, performance metrics, and includes methods for model training, evaluation, and prediction. Similarly, the GISService class manages geospatial processing, including loading spatial layers, performing raster and vector operations, generating hazard maps, and exporting spatial outputs. The system also includes a RiskFusionEngine class, which integrates AI predictions with GIS hazard layers to produce final risk classifications using weighted criteria or rule-based fusion methods.

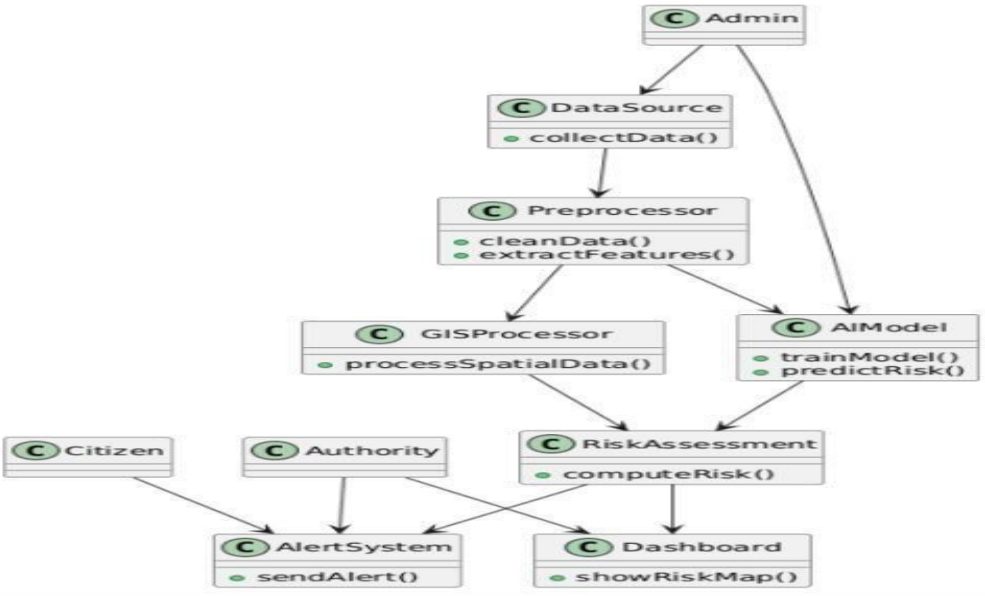


Figure 5.3.2 Class Diagram

5.3.3 Sequence Diagram

The sequence diagram describes the flow of interactions between different components of the hybrid disaster prediction system during the disaster forecasting and alert-generation process. The sequence begins when the user or the system scheduler initiates a prediction request. This request is first received by the application interface, which forwards it to the data preprocessing component. The preprocessing unit then collects the most recent data from the raw data repository, cleans it, extracts relevant features, and prepares it for model inference. Once preprocessing is complete, the prepared dataset is passed to the AI prediction module, where machine learning or deep learning models generate disaster probability scores and severity estimates.

After receiving the prediction results, the system interacts with the geospatial analysis module, which retrieves spatial datasets such as DEM, land-use maps, and hydrological layers from the GIS database. Using these datasets, the module generates updated hazard maps reflecting the predicted disaster impact areas. The prediction results and geospatial outputs are then sent to the risk fusion module, which combines them to produce a final risk classification. If the risk level exceeds predefined thresholds, the alert service is triggered to generate notifications for authorities and users. Finally, the dashboard displays updated prediction results, hazard maps, and alert messages.

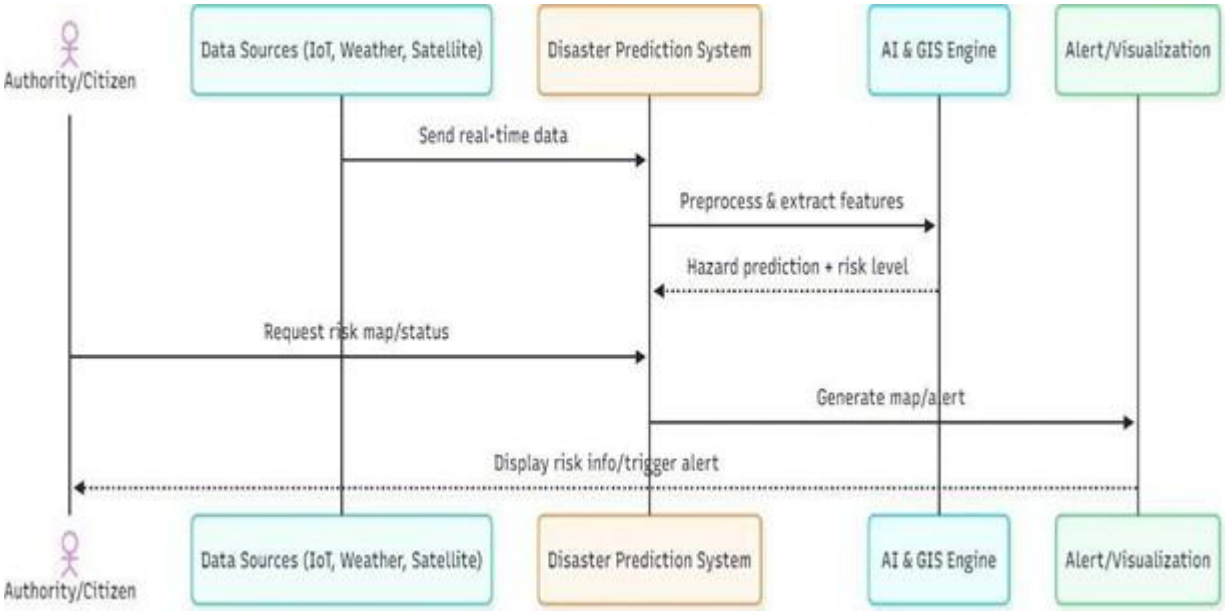


Figure 5.3.3 Sequence Diagram

5.3.4 Activity Diagram

The activity diagram represents the workflow of the hybrid disaster prediction model by illustrating the sequence of operations involved in processing data, generating predictions, and delivering results to the user. The process begins with the collection of environmental inputs from various sources such as IoT sensors, weather APIs, and satellite imagery repositories. Once the data is gathered, the system enters the preprocessing stage, where it performs cleaning, filtering, normalization, and feature extraction. This ensures that both structured and spatial datasets are converted into formats suitable for AI-based prediction and GIS analysis.

After preprocessing, the workflow branches into two main activities. In the AI prediction branch, the processed dataset is fed into machine learning or deep learning models, which analyze patterns and forecast the likelihood and severity of a disaster. In the GIS analysis branch, spatial data such as DEM, land use, and hydrological maps are used to generate hazard layers and identify vulnerable regions. The outputs from both branches are then merged in the risk assessment stage, where the system combines prediction scores with geospatial hazard layers to produce final risk classifications.

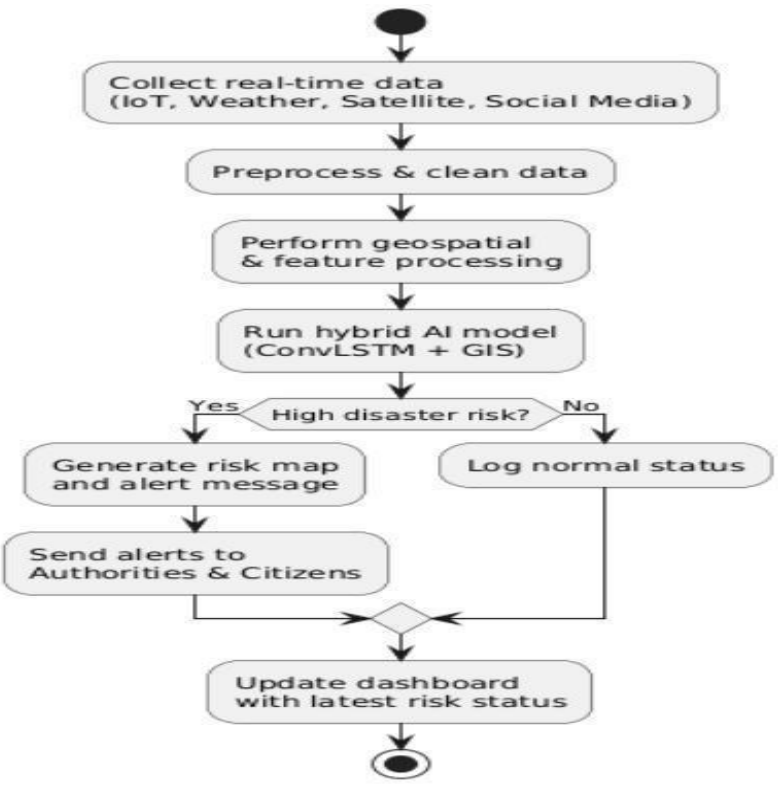


Figure 5.3.4 Activity Diagram

6. CODING AND IMPLEMENTATION

6.1 Source code

Admins/manage.py

```
import os
import sys

def main():
    """Run administrative tasks."""
    os.environ.setdefault('DJANGO_SETTINGS_MODULE', 'Backend.settings')
    try:
        from django.core.management import execute_from_command_line
    except ImportError as exc:
        raise ImportError(
            "Couldn't import Django. Are you sure it's installed and "
            "available on your PYTHONPATH environment variable? Did you "
            "forget to activate a virtual environment?"
        ) from exc
    execute_from_command_line(sys.argv)

if __name__ == '__main__':
    main()
```

apps.py

```
from django.apps import AppConfig

class AdminsConfig(AppConfig):
    default_auto_field = 'django.db.models.BigAutoField'
    name = 'Admins'
```

urls.py

```
from django.urls import path
from Admins.views import *

urlpatterns = [
    path('adminhome/', adminhome, name='adminhome'),
    path('admin_update_userstatus/<int:user_id>/', admin_update_userstatus,
         name='admin_update_userstatus'),
    path('reports/', reports, name='reports'),
    path('adminproposed/', adminproposed, name='adminproposed'),
}
```

views.py

```
from django.shortcuts import render, redirect
from django.contrib.auth.models import User
from django.contrib import messages
from Users.models import RescuePrediction

def adminhome(request):
    users = User.objects.filter(is_staff=False, is_superuser=False)
    return render(request, "Admin/adminhome.html", {"users": users})

def admin_update_userstatus(request, user_id):
    try:
        user = User.objects.get(id=user_id)

        # Toggle the is_active status
        user.is_active = not user.is_active
        user.save()

        # Display message based on the action
        if user.is_active:
            messages.success(request, f"User {user.username} has been activated.")
        else:
            messages.success(request, f"User {user.username} has been deactivated.")

        return redirect('adminhome')  # Redirect back to the admin home page
    except User.DoesNotExist:
        messages.error(request, "User not found.")
        return redirect('adminhome')

def reports(request):
    predictions = RescuePrediction.objects.filter().order_by('-created_at')
    return render(request, "Admin/reports.html",
        {'predictions': predictions})

def adminproposed(request):
    return render(request, "Admin/proposed.html")
```

Backend/settings.py

```
"""
Django settings for Backend project.

Generated by 'django-admin startproject' using Django 5.2.6.

For more information on this file, see
https://docs.djangoproject.com/en/5.2/topics/settings/

For the full list of settings and their values, see
https://docs.djangoproject.com/en/5.2/ref/settings/
"""

import os
from pathlib import Path

# Build paths inside the project like this: BASE_DIR / 'subdir'.
BASE_DIR = Path(__file__).resolve().parent.parent


# Quick-start development settings - unsuitable for production
# See https://docs.djangoproject.com/en/5.2/howto/deployment/checklist/

# SECURITY WARNING: keep the secret key used in production secret!
SECRET_KEY = 'django-insecure-
        aic5klhp7^*apum4)j1t_667f5(rd++ja$)*2=a7m_+qjzm0%4'

# SECURITY WARNING: don't run with debug turned on in production!
DEBUG = True

ALLOWED_HOSTS = ["*"]


# Application definition

INSTALLED_APPS = [
    'django.contrib.admin',
    'django.contrib.auth',
    'django.contrib.contenttypes',
    'django.contrib.sessions',
    'django.contrib.messages',
```

```
    'django.contrib.staticfiles',
    'Admins',
    'Users',
]

MIDDLEWARE = [
    'django.middleware.security.SecurityMiddleware',
    'django.contrib.sessions.middleware.SessionMiddleware',
    'django.middleware.common.CommonMiddleware',
    'django.middleware.csrf.CsrfViewMiddleware',
    'django.contrib.auth.middleware.AuthenticationMiddleware',
    'django.contrib.messages.middleware.MessageMiddleware',
    'django.middleware.clickjacking.XFrameOptionsMiddleware',
]

ROOT_URLCONF = 'Backend.urls'

TEMPLATES = [
    {
        'BACKEND': 'django.template.backends.django.DjangoTemplates',
        'DIRS': [BASE_DIR / 'templates'],
        'APP_DIRS': True,
        'OPTIONS': {
            'context_processors': [
                'django.template.context_processors.request',
                'django.contrib.auth.context_processors.auth',
                'django.contrib.messages.context_processors.messages',
            ],
        },
    },
}

WSGI_APPLICATION = 'Backend.wsgi.application'


# Database
# https://docs.djangoproject.com/en/5.2/ref/settings/#databases

DATABASES = {
    'default': {
        'ENGINE': 'django.db.backends.sqlite3',
        'NAME': BASE_DIR / 'db.sqlite3',
    }
```

```
}


# Password validation
# https://docs.djangoproject.com/en/5.2/ref/settings/#auth-password-validators

AUTH_PASSWORD_VALIDATORS = [
    {
        'NAME':
         'django.contrib.auth.password_validation.UserAttributeSimilarityValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.MinimumLengthValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.CommonPasswordValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.NumericPasswordValidator',
    },
]


# Internationalization
# https://docs.djangoproject.com/en/5.2/topics/i18n/

LANGUAGE_CODE = 'en-us'

TIME_ZONE = 'UTC'

USE_I18N = True

USE_TZ = True


# Static files (CSS, JavaScript, Images)
# https://docs.djangoproject.com/en/5.2/howto/static-files/

STATIC_URL = 'static/'
STATICFILES_DIRS = [os.path.join(BASE_DIR, 'static'),]
STATIC_ROOT = os.path.join(BASE_DIR, 'staticfiles')

MEDIA_URL = '/media/'
```

```
MEDIA_ROOT = os.path.join(BASE_DIR, 'media')

# Default primary key field type
# https://docs.djangoproject.com/en/5.2/ref/settings/#default-auto-field

DEFAULT_AUTO_FIELD = 'django.db.models.BigAutoField'
```

urls.py

```
from django.contrib import admin
from django.urls import path, include
from django.conf import settings
from django.conf.urls.static import static

from Backend.views import *

urlpatterns = [
    path('admin/', admin.site.urls),
    path('Users/', include('Users.urls')),
    path('Admins/', include('Admins.urls')),

    path('', index, name='index'),
    path('loginn/', loginn, name='loginn'),
    path('register/', register, name='register'),
    path('home_page/', index, name='home_page'),
    path('user_logout/', user_logout, name='user_logout'),
    path('user_login/', user_login, name='user_login'),
    path('user_registration/', user_registration, name='user_registration')

]
if settings.DEBUG:
    urlpatterns += static(settings.MEDIA_URL, document_root=settings.MEDIA_ROOT)
```

views.py

```
from django.shortcuts import render, redirect
from django.contrib.auth.models import User
from django.contrib.auth import authenticate, login, logout
from django.contrib import messages

def index(request):
```

```
    return render(request, "index.html")

def loginn(request):
    return render(request, "login.html")

def register(request):
    return render(request, "register.html")

# Define the login function
def user_login(request):
    if request.method == "POST":
        username = request.POST.get('username')
        password = request.POST.get('password')

        # Authenticate user
        user = authenticate(request, username=username, password=password)

        if user is not None:
            if not user.is_active:
                # User is inactive
                messages.error(request, "Your account is inactive. Please contact the admin.")
                return redirect('loginn')

            # Login the user
            login(request, user)

            if user.is_staff or user.is_superuser:
                # Redirect to admin home if user is staff
                return redirect('adminhome')
            else:
                # Redirect to user home if user is not staff
                return redirect('userhome')
        else:
            # Invalid username or password
            messages.error(request, "Invalid username or password.")
            return redirect('loginn')

    return render(request, 'login.html')

# Define the user registration function
def user_registration(request):
    if request.method == "POST":
        username = request.POST.get('username')
```

```
        email = request.POST.get('email')
        password = request.POST.get('password')
        confirm_password = request.POST.get('confirm_password')
        first_name = request.POST.get('first_name')
        last_name = request.POST.get('last_name')

        # Check if passwords match
        if password != confirm_password:
            messages.error(request, "Passwords do not match.")
            return redirect('register')

        # Check if username already exists
        if User.objects.filter(username=username).exists():
            messages.error(request, "Username already exists.")
            return redirect('register')

        # Check if email already exists
        if User.objects.filter(email=email).exists():
            messages.error(request, "Email already exists.")
            return redirect('register')

        # Create the user with is_active set to False
        user = User.objects.create_user(
            username=username,
            email=email,
            password=password,
            first_name=first_name,
            last_name=last_name
        )
        user.is_active = False  # Set is_active to False by default
        user.save()

        messages.success(request, "Registration successful! Please wait for admin
         approval.")
        return redirect('loginn')

    return render(request, 'register.html')

# Define the logout function
def user_logout(request):
    logout(request)
    messages.success(request, "You have been logged out successfully.")
    return redirect('index')
```

```python
import pandas as pd

df_train = pd.read_csv('Disaster/train.csv')
df_test = pd.read_csv('Disaster/test.csv')
```

Python

```python
df_train.isnull().sum()
```

Python

```
id                  0
vendor_id           0
pickup_datetime     0
dropoff_datetime    0
passenger_count     0
pickup_longitude    0
pickup_latitude     0
dropoff_longitude   0
dropoff_latitude    0
store_and_fwd_flag  0
trip_duration       0
dtype: int64
```

```python
df_test.isnull().sum()
```

Python

wsgi.py

import os

from django.core.wsgi import get_wsgi_application

os.environ.setdefault('DJANGO_SETTINGS_MODULE', 'Backend.settings')

application = get_wsgi_application()

```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Set the visual style
sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))
```

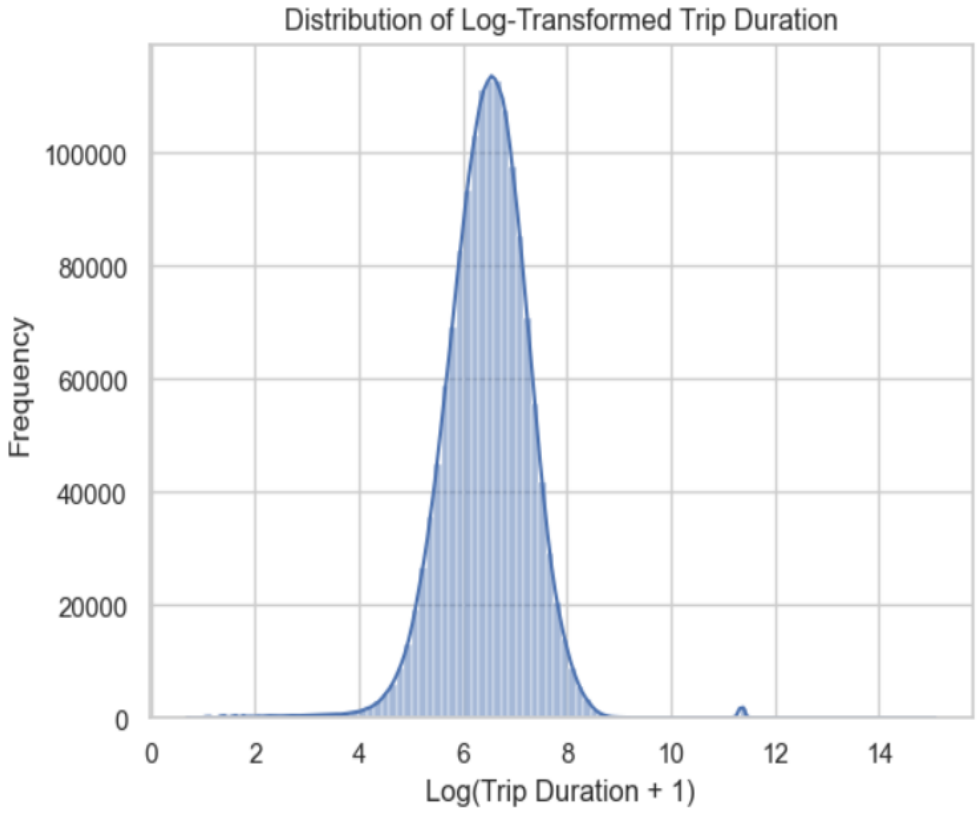
Python

```
<Figure size 1000x600 with 0 Axes>
```


```
<Figure size 1000x600 with 0 Axes>
```

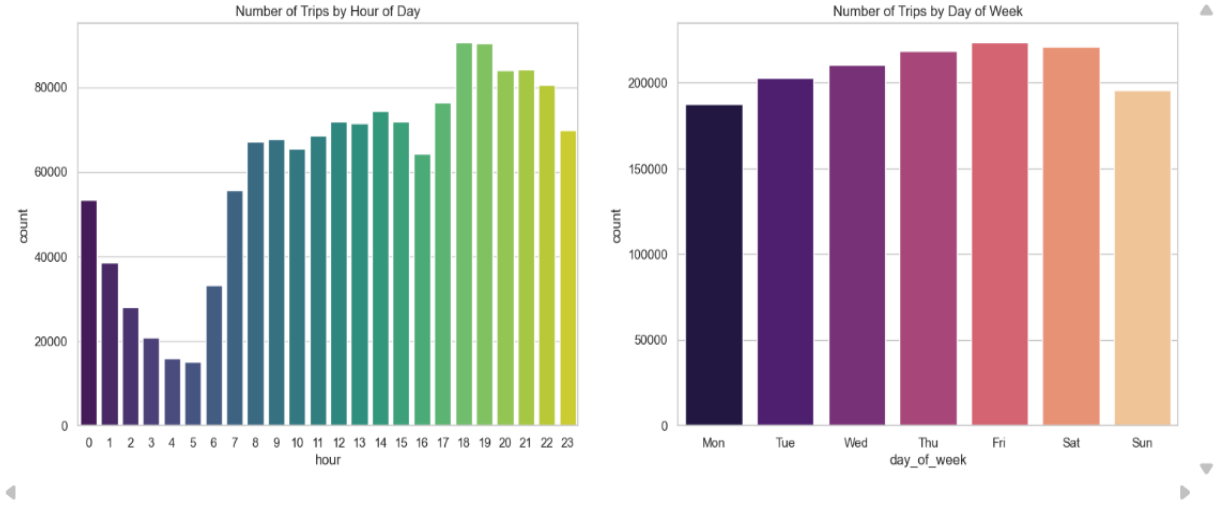

```python
# Log transformation of trip duration
# We add 1 to avoid log(0)
sns.histplot(np.log1p(df_train['trip_duration']), kde=True, bins=100)
plt.title('Distribution of Log-Transformed Trip Duration')
plt.xlabel('Log(Trip Duration + 1)')
plt.ylabel('Frequency')
plt.show()
```

Python



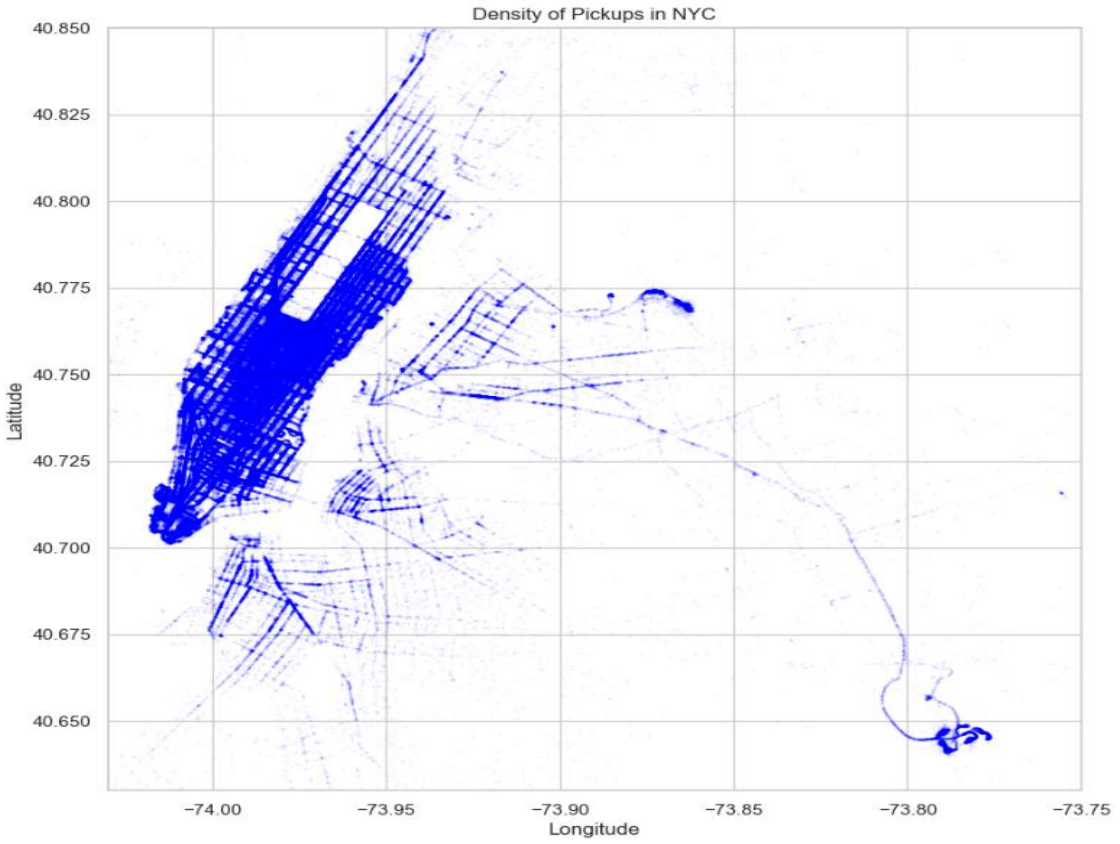
```python
# Extracting features if not already done
df_train['pickup_datetime'] = pd.to_datetime(df_train['pickup_datetime'])
df_train['hour'] = df_train['pickup_datetime'].dt.hour
df_train['day_of_week'] = df_train['pickup_datetime'].dt.dayofweek

fig, ax = plt.subplots(1, 2, figsize=(18, 6))

# Trips by Hour
sns.countplot(x='hour', data=df_train, ax=ax[0], palette='viridis')
ax[0].set_title('Number of Trips by Hour of Day')

# Trips by Day of Week (0=Monday, 6=Sunday)
sns.countplot(x='day_of_week', data=df_train, ax=ax[1], palette='magma')
ax[1].set_title('Number of Trips by Day of Week')
ax[1].set_xticklabels(['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun'])

plt.show()
```

Python

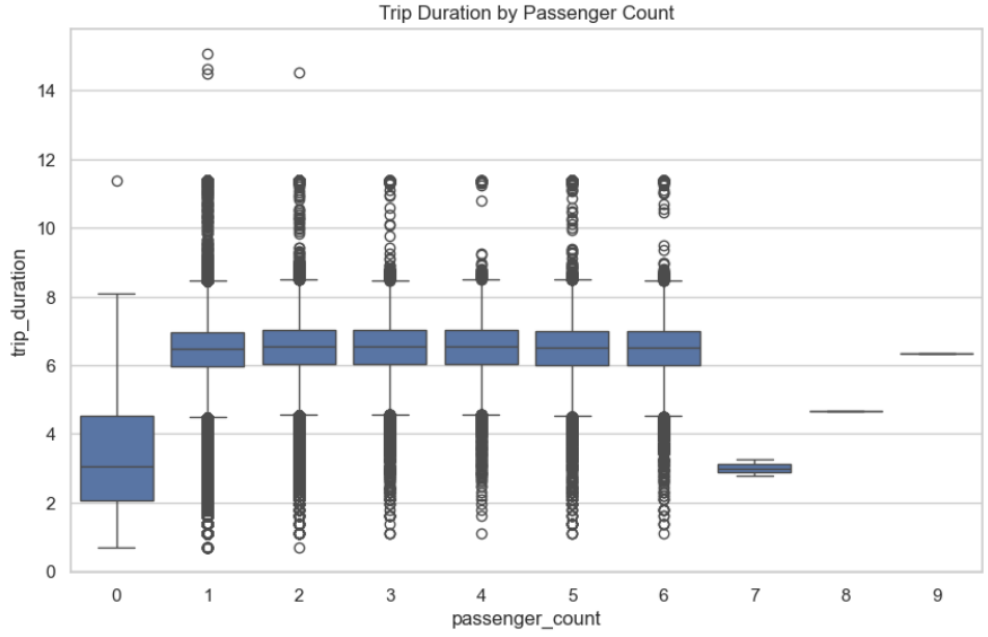



```python
# Standard NYC boundaries to filter out extreme coordinate outliers
xlim = [-74.03, -73.75]
ylim = [40.63, 40.85]

plt.figure(figsize=(10, 10))
plt.scatter(df_train['pickup_longitude'], df_train['pickup_latitude'],
            s=0.1, alpha=0.1, color='blue')
plt.xlim(xlim)
plt.ylim(ylim)
plt.title('Density of Pickups in NYC')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

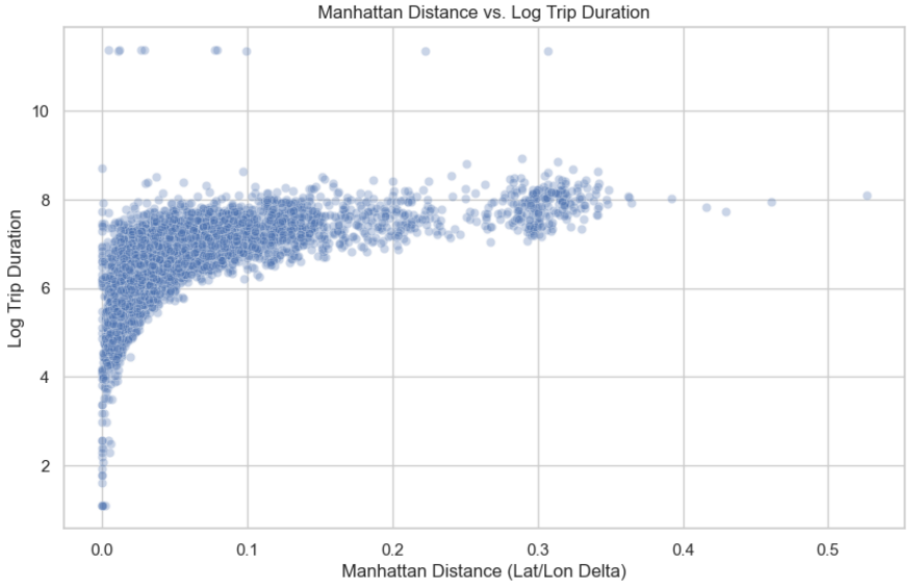
Python



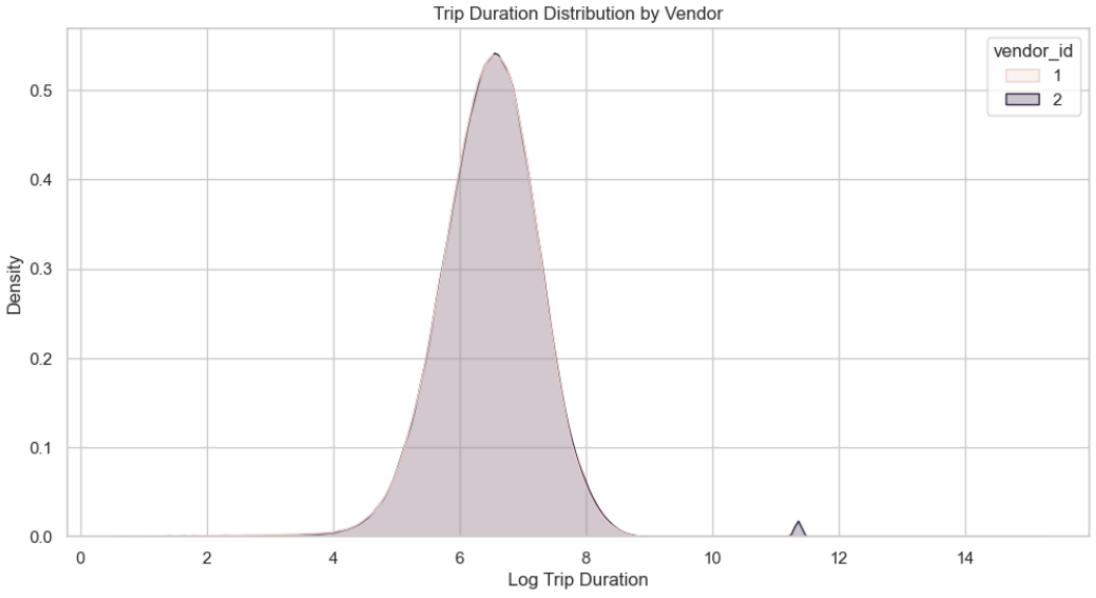

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='passenger_count', y=np.log1p(df_train['trip_duration']), data=df_train)
plt.title('Trip Duration by Passenger Count')
plt.show()
```



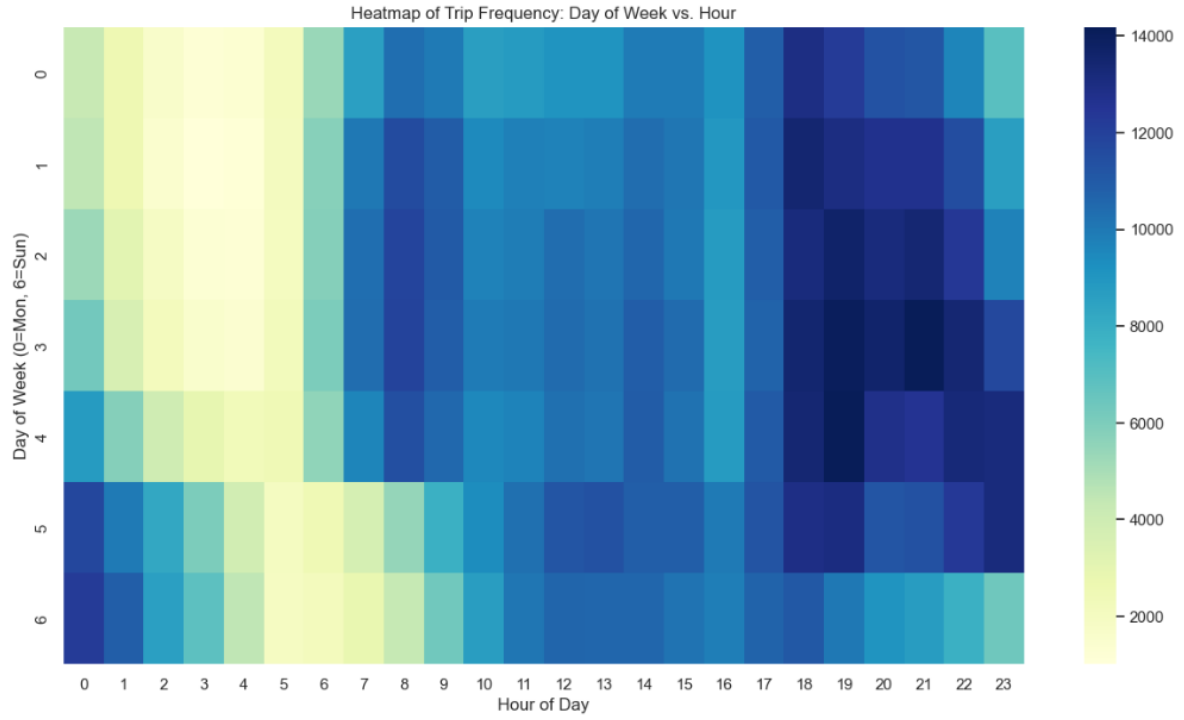
```
df_train['lat_diff'] = (df_train['dropoff_latitude'] - df_train['pickup_latitude']).abs()
df_train['lon_diff'] = (df_train['dropoff_longitude'] - df_train['pickup_longitude']).abs()
df_train['manhattan_dist'] = df_train['lat_diff'] + df_train['lon_diff']

plt.figure(figsize=(10, 6))
# Sampling 10,000 points to speed up plotting
sns.scatterplot(x='manhattan_dist', y=np.log1p(df_train['trip_duration']),
                data=df_train.sample(10000), alpha=0.3)
plt.title('Manhattan Distance vs. Log Trip Duration')
plt.xlabel('Manhattan Distance (Lat/Lon Delta)')
plt.ylabel('Log Trip Duration')
plt.show()
```



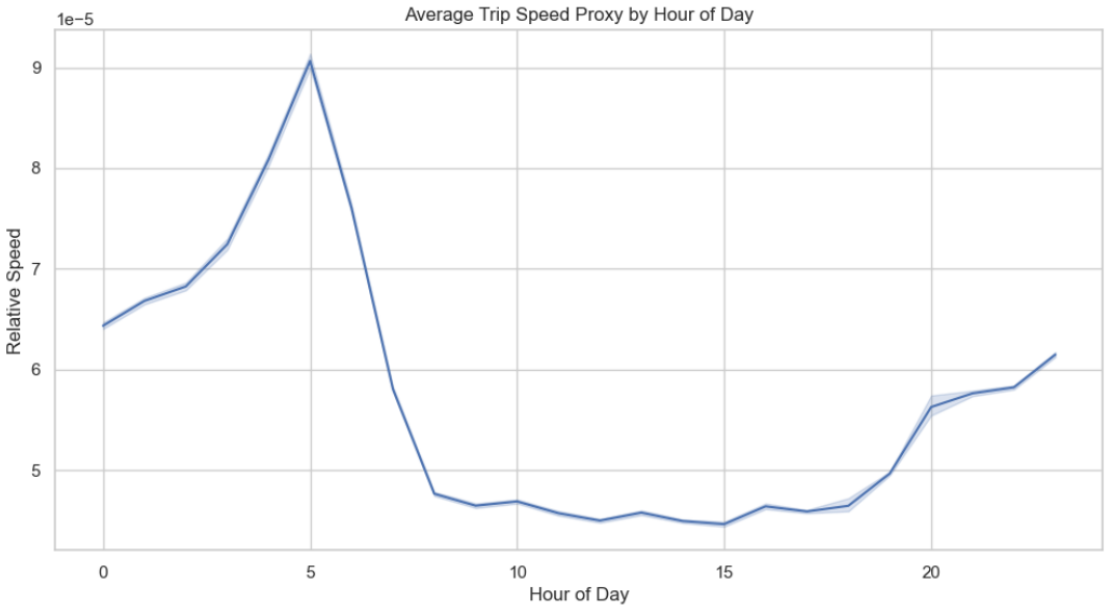

```
plt.figure(figsize=(12, 6))

# Checking if trip duration distribution differs by vendor
sns.kdeplot(data=df_train, x=np.log1p(df_train['trip_duration']),
            hue='vendor_id', common_norm=False, fill=True)
plt.title('Trip Duration Distribution by Vendor')
plt.xlabel('Log Trip Duration')
plt.show()
```



```
pivot_table = df_train.groupby(['day_of_week', 'hour']).size().unstack()

plt.figure(figsize=(15, 8))
sns.heatmap(pivot_table, cmap='YlGnBu', annot=False)
plt.title('Heatmap of Trip Frequency: Day of Week vs. Hour')
plt.xlabel('Hour of Day')
plt.ylabel('Day of Week (0=Mon, 6=Sun)')
plt.show()
```



```
# Proxy for speed (Distance / Duration)
df_train['avg_speed_proxy'] = df_train['manhattan_dist'] / (df_train['trip_duration'] + 1)

plt.figure(figsize=(12, 6))
sns.lineplot(x='hour', y='avg_speed_proxy', data=df_train)
plt.title('Average Trip Speed Proxy by Hour of Day')
plt.ylabel('Relative Speed')
plt.xlabel('Hour of Day')
plt.show()
```



model.ipynb

```
import pandas as pd

df_train = pd.read_csv('Disaster/train.csv')
df_test = pd.read_csv('Disaster/test.csv')

import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import classification_report, accuracy_score
import joblib

def feature_engineering(df):
    df = df.copy()

    # Convert datetime
    df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])

    # Temporal features
```

```
    df['hour'] = df['pickup_datetime'].dt.hour
    df['dayofweek'] = df['pickup_datetime'].dt.dayofweek
    df['is_weekend'] = df['dayofweek'].isin([5, 6]).astype(int)

    # Spatial grid (approximate region segmentation)
    df['lat_grid'] = (df['pickup_latitude'] * 100).astype(int)
    df['lon_grid'] = (df['pickup_longitude'] * 100).astype(int)

    return df

df_train = feature_engineering(df_train)

density = (
    df_train
    .groupby(['lat_grid', 'lon_grid', 'hour'])
    .size()
    .reset_index(name='pickup_density')
)

df_train = df_train.merge(
    density,
    on=['lat_grid', 'lon_grid', 'hour'],
    how='left'
)

threshold = df_train['pickup_density'].quantile(0.80)

df_train['rescue_label'] = (df_train['pickup_density'] >= threshold).astype(int)

FEATURES = [
    'pickup_latitude',
    'pickup_longitude',
    'hour',
    'dayofweek',
    'is_weekend',
    'passenger_count',
    'pickup_density'
]

X = df_train[FEATURES]
y = df_train['rescue_label']

X_train, X_val, y_train, y_val = train_test_split(
```

```
    X, y, test_size=0.2, random_state=42, stratify=y
)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

model = GradientBoostingClassifier(
    n_estimators=200,
    learning_rate=0.05,
    max_depth=3,
    random_state=42
)

model.fit(X_train_scaled, y_train)
```

```
GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=0.05, n_estimators=200,
                           random_state=42)
```

```
y_pred = model.predict(X_val_scaled)

print("Accuracy:", accuracy_score(y_val, y_pred))
      print(classification_report(y_val, y_pred))
```

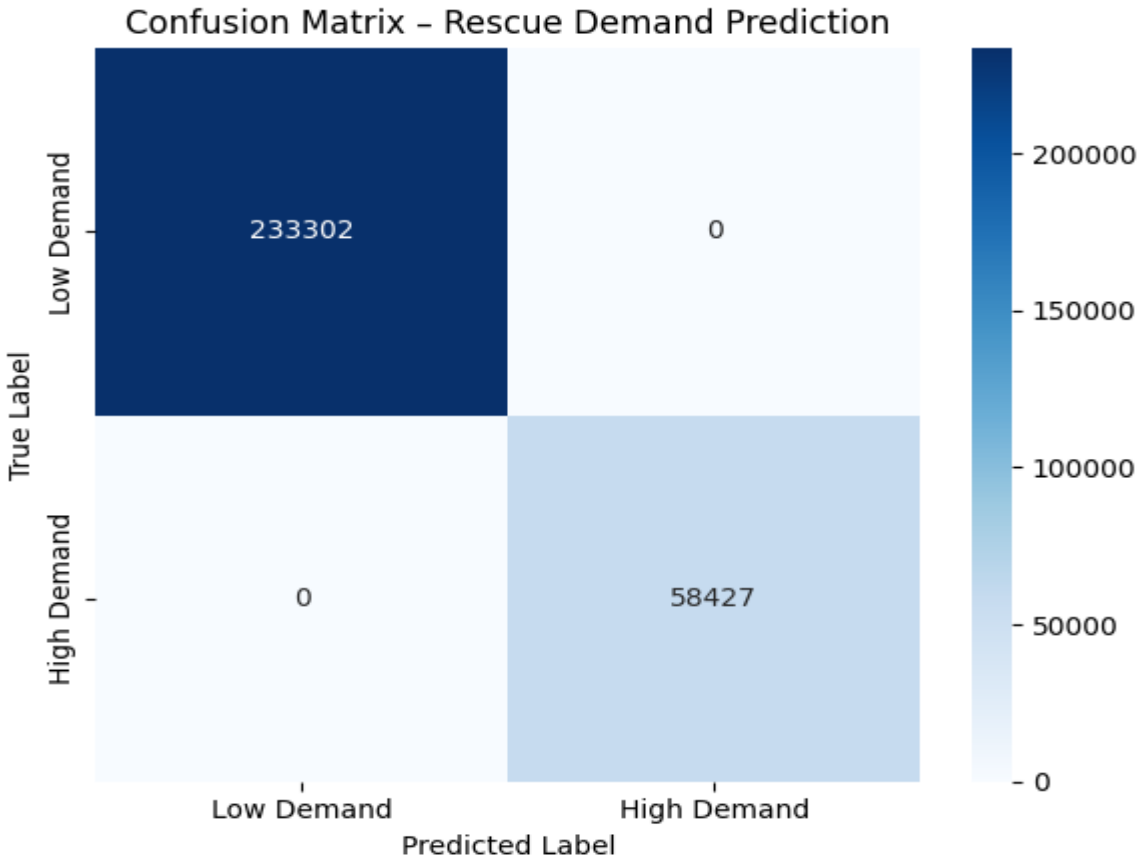
```
Accuracy: 1.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    233302
           1       1.00      1.00      1.00     58427

    accuracy                           1.00    291729
   macro avg       1.00      1.00      1.00    291729
weighted avg       1.00      1.00      1.00    291729
```

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
      import seaborn as sns

cm = confusion_matrix(y_val, y_pred)
```

```
print("\nConfusion Matrix:")
print(cm)
```

Confusion Matrix:
[[233302 0]
[0 58427]]

```
sns.heatmap(
    cm,
    annot=True,
    fmt='d',
    cmap='Blues',
    xticklabels=['Low Demand', 'High Demand'],
    yticklabels=['Low Demand', 'High Demand']
)

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix – Rescue Demand Prediction')
plt.tight_layout()
plt.show()
```



```
joblib.dump(scaler, 'standard_scaler.pkl')
joblib.dump(model, 'rescue_demand_model.pkl')
joblib.dump(FEATURES, 'model_features.pkl')
```

```
print("Model, scaler, and feature list saved successfully.")
```

Model, scaler, and feature list saved successfully.

predict.py

```
import joblib
import pandas as pd
from datetime import datetime

scaler = joblib.load('standard_scaler.pkl')
model = joblib.load('rescue_demand_model.pkl')
FEATURES = joblib.load('model_features.pkl')

def predict_rescue_demand(
    pickup_latitude,
    pickup_longitude,
    pickup_datetime,
    passenger_count,
    pickup_density
):

    pickup_datetime = pd.to_datetime(pickup_datetime)

    hour = pickup_datetime.hour
    dayofweek = pickup_datetime.dayofweek
    is_weekend = int(dayofweek in [5, 6])

    input_df = pd.DataFrame([{
        'pickup_latitude': pickup_latitude,
        'pickup_longitude': pickup_longitude,
        'hour': hour,
        'dayofweek': dayofweek,
        'is_weekend': is_weekend,
        'passenger_count': passenger_count,
        'pickup_density': pickup_density
    }])
```

```
        input_df = input_df[FEATURES]
        input_scaled = scaler.transform(input_df)

        prediction = model.predict(input_scaled)[0]
        probability = model.predict_proba(input_scaled)[0][prediction]

        return prediction, probability


    if __name__ == "__main__":

pred, prob = predict_rescue_demand(
    pickup_latitude=40.7306,
    pickup_longitude=-73.9352,
    pickup_datetime="2016-05-20 17:00:00",
    passenger_count=2,
    pickup_density=6500 # if density = 3000+ -> high demand or else low demand
)

if pred == 1:
    print(f"Prediction: HIGH DEMAND (Rescue-like region)")
else:
    print(f"Prediction: LOW DEMAND region")

        print(f"Confidence Score: {prob:.4f}")
```

autocomplete.css

```
select.admin-autocomplete {
    width: 20em;
}

.select2-container--admin-autocomplete.select2-container {
    min-height: 30px;
}

.select2-container--admin-autocomplete .select2-selection--single,
.select2-container--admin-autocomplete .select2-selection--multiple {
    min-height: 30px;
    padding: 0;
}

.select2-container--admin-autocomplete.select2-container--focus .select2-selection,
```

```
.select2-container--admin-autocomplete.select2-container--open .select2-selection {
    border-color: var(--body-quiet-color);
    min-height: 30px;
}

.select2-container--admin-autocomplete.select2-container--focus .select2-
        selection.select2-selection--single,
.select2-container--admin-autocomplete.select2-container--open .select2-
        selection.select2-selection--single {
    padding: 0;
}

.select2-container--admin-autocomplete.select2-container--focus .select2-
        selection.select2-selection--multiple,
.select2-container--admin-autocomplete.select2-container--open .select2-
        selection.select2-selection--multiple {
    padding: 0;
}

.select2-container--admin-autocomplete .select2-selection--single {
    background-color: var(--body-bg);
    border: 1px solid var(--border-color);
    border-radius: 4px;
}

.select2-container--admin-autocomplete .select2-selection--single .select2-
        selection__rendered {
    color: var(--body-fg);
    line-height: 30px;
}

.select2-container--admin-autocomplete .select2-selection--single .select2-
        selection__clear {
    cursor: pointer;
    float: right;
    font-weight: bold;
}

.select2-container--admin-autocomplete .select2-selection--single .select2-
        selection__placeholder {
    color: var(--body-quiet-color);
}
```

```
.select2-container--admin-autocomplete .select2-selection--single .select2-
        selection__arrow {
    height: 26px;
    position: absolute;
    top: 1px;
    right: 1px;
    width: 20px;
}

.select2-container--admin-autocomplete .select2-selection--single .select2-
        selection__arrow b {
    border-color: #888 transparent transparent transparent;
    border-style: solid;
    border-width: 5px 4px 0 4px;
    height: 0;
    left: 50%;
    margin-left: -4px;
    margin-top: -2px;
    position: absolute;
    top: 50%;
    width: 0;
}

.select2-container--admin-autocomplete[dir="rtl"] .select2-selection--single .select2-
        selection__clear {
    float: left;
}

.select2-container--admin-autocomplete[dir="rtl"] .select2-selection--single .select2-
        selection__arrow {
    left: 1px;
    right: auto;
}

.select2-container--admin-autocomplete.select2-container--disabled .select2-selection--
        single {
    background-color: var(--darkened-bg);
    cursor: default;
}

.select2-container--admin-autocomplete.select2-container--disabled .select2-selection--
        single .select2-selection__clear {
    display: none;
```

```
}

.select2-container--admin-autocomplete.select2-container--open .select2-selection--single
        .select2-selection__arrow b {
    border-color: transparent transparent #888 transparent;
    border-width: 0 4px 5px 4px;
}

.select2-container--admin-autocomplete .select2-selection--multiple {
    background-color: var(--body-bg);
    border: 1px solid var(--border-color);
    border-radius: 4px;
    cursor: text;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__rendered {
    box-sizing: border-box;
    list-style: none;
    margin: 0;
    padding: 0 10px 5px 5px;
    width: 100%;
    display: flex;
    flex-wrap: wrap;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__rendered li {
    list-style: none;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__placeholder {
    color: var(--body-quiet-color);
    margin-top: 5px;
    float: left;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__clear {
    cursor: pointer;
    float: right;
    font-weight: bold;
```

```
    margin: 5px;
    position: absolute;
    right: 0;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__choice {
    background-color: var(--darkened-bg);
    border: 1px solid var(--border-color);
    border-radius: 4px;
    cursor: default;
    float: left;
    margin-right: 5px;
    margin-top: 5px;
    padding: 0 5px;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__choice__remove {
    color: var(--body-quiet-color);
    cursor: pointer;
    display: inline-block;
    font-weight: bold;
    margin-right: 2px;
}

.select2-container--admin-autocomplete .select2-selection--multiple .select2-
        selection__choice__remove:hover {
    color: var(--body-fg);
}

.select2-container--admin-autocomplete[dir="rtl"] .select2-selection--multiple .select2-
        selection__choice, .select2-container--admin-autocomplete[dir="rtl"] .select2-
        selection--multiple .select2-selection__placeholder, .select2-container--admin-
        autocomplete[dir="rtl"] .select2-selection--multiple .select2-search--inline {
    float: right;
}

.select2-container--admin-autocomplete[dir="rtl"] .select2-selection--multiple .select2-
        selection__choice {
    margin-left: 5px;
    margin-right: auto;
}
```

```
.select2-container--admin-autocomplete[dir="rtl"] .select2-selection--multiple .select2-
        selection__choice__remove {
    margin-left: 2px;
    margin-right: auto;
}

.select2-container--admin-autocomplete.select2-container--focus .select2-selection--
        multiple {
    border: solid var(--body-quiet-color) 1px;
    outline: 0;
}

.select2-container--admin-autocomplete.select2-container--disabled .select2-selection--
        multiple {
    background-color: var(--darkened-bg);
    cursor: default;
}

.select2-container--admin-autocomplete.select2-container--disabled .select2-
        selection__choice__remove {
    display: none;
}

.select2-container--admin-autocomplete.select2-container--open.select2-container--above
        .select2-selection--single, .select2-container--admin-autocomplete.select2-container-
        -open.select2-container--above .select2-selection--multiple {
    border-top-left-radius: 0;
    border-top-right-radius: 0;
}

.select2-container--admin-autocomplete.select2-container--open.select2-container--below
        .select2-selection--single, .select2-container--admin-autocomplete.select2-container-
        -open.select2-container--below .select2-selection--multiple {
    border-bottom-left-radius: 0;
    border-bottom-right-radius: 0;
}

.select2-container--admin-autocomplete .select2-search--dropdown {
    background: var(--darkened-bg);
}

.select2-container--admin-autocomplete .select2-search--dropdown .select2-search__field
```

```
        {
    background: var(--body-bg);
    color: var(--body-fg);
    border: 1px solid var(--border-color);
    border-radius: 4px;
}

.select2-container--admin-autocomplete .select2-search--inline .select2-search__field {
    background: transparent;
    color: var(--body-fg);
    border: none;
    outline: 0;
    box-shadow: none;
    -webkit-appearance: textfield;
}

.select2-container--admin-autocomplete .select2-results > .select2-results__options {
    max-height: 200px;
    overflow-y: auto;
    color: var(--body-fg);
    background: var(--body-bg);
}

.select2-container--admin-autocomplete .select2-results__option[role=group] {
    padding: 0;
}

.select2-container--admin-autocomplete .select2-results__option[aria-disabled=true] {
    color: var(--body-quiet-color);
}

.select2-container--admin-autocomplete .select2-results__option[aria-selected=true] {
    background-color: var(--selected-bg);
    color: var(--body-fg);
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        {
    padding-left: 1em;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__group {
```

```
    padding-left: 0;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__option {
    margin-left: -1em;
    padding-left: 2em;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__option .select2-results__option {
    margin-left: -2em;
    padding-left: 3em;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__option .select2-results__option .select2-results__option {
    margin-left: -3em;
    padding-left: 4em;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__option .select2-results__option .select2-results__option .select2-
        results__option {
    margin-left: -4em;
    padding-left: 5em;
}

.select2-container--admin-autocomplete .select2-results__option .select2-results__option
        .select2-results__option .select2-results__option .select2-results__option .select2-
        results__option .select2-results__option {
    margin-left: -5em;
    padding-left: 6em;
}

.select2-container--admin-autocomplete .select2-results__option--highlighted[aria-
        selected] {
    background-color: var(--primary);
    color: var(--primary-fg);
}

.select2-container--admin-autocomplete .select2-results__group {
    cursor: default;
```

```
    display: block;
    padding: 6px;
}

.errors .select2-selection {
    border: 1px solid var(--error-fg);
}
```

base.html

```
<!DOCTYPE html>
{% load static %}
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>{% block title %}MobiRescue Optimal Dispatching of Rescue Teams{%
        endblock %}</title>

  <!-- Bootstrap 5 CDN -->
  <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.2/dist/css/bootstrap.min.css"
        rel="stylesheet">

  <!-- Font Awesome for Icons -->
  <link href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/6.4.0/css/all.min.css"
        rel="stylesheet">

  {% block extra_css %}{% endblock %}
</head>
<body class="d-flex flex-column min-vh-100" style="background: url('{% static
        "img/bg.avif" %}') no-repeat center center fixed; background-size: cover;">

  <!-- Navbar -->
  <nav class="navbar navbar-expand-lg navbar-dark bg-dark shadow">
    <div class="container">
      <a class="navbar-brand fw-bold" href="{% url 'index' %}">MobiRescue Optimal
        Dispatching of Rescue Teams</a>
      <button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-
        target="#navbarNav">
       <span class="navbar-toggler-icon"></span>
      </button>
```

```
            <div class="collapse navbar-collapse" id="navbarNav">
              <ul class="navbar-nav ms-auto">
                <li class="nav-item"><a class="nav-link" href="{% url 'loginn'
                %}">Login</a></li>
                <li class="nav-item"><a class="nav-link" href="{% url 'register'
                %}">Register</a></li>
              </ul>
            </div>
          </div>
        </nav>

  <!-- Content -->
  <main class="flex-grow-1 d-flex align-items-center justify-content-center py-5">
    <div class="container">
      {% block content %}
      <!-- Django Messages -->

      {% endblock %}
    </div>
  </main>

  <!-- Footer -->
  <footer class="bg-dark text-white text-center py-3 mt-auto">
    <p class="mb-0">&copy; 2025. All rights reserved.</p>
  </footer>

  <!-- Bootstrap JS -->
  <script
        src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.2/dist/js/bootstrap.bundle.min.js"></scri
        pt>
</body>
        </html>
```

login.html

```
        {% extends 'base.html' %}
        {% block title %}Login{% endblock %}

        {% block content %}
        <div class="col-md-6 col-lg-5 mx-auto bg-white p-5 rounded shadow-lg">
          <h2 class="fw-bold mb-4 text-center">Login</h2>
```

```
 {% if messages %}
 <div class="container mb-4">
  {% for message in messages %}
   <div class="alert
            {% if message.tags == 'error' %}alert-danger
            {% elif message.tags == 'success' %}alert-success
            {% elif message.tags == 'warning' %}alert-warning
            {% else %}alert-info{% endif %}
            alert-dismissible fade show shadow-sm" role="alert">
     {{ message }}
     <button type="button" class="btn-close" data-bs-dismiss="alert" aria-
      label="Close"></button>
   </div>
  {% endfor %}
 </div>
{% endif %}
 <form action="{% url 'user_login' %}" method="post">
  {% csrf_token %}
  <div class="mb-3">
   <input type="text" name="username" class="form-control" placeholder="Your
    Username" required>
  </div>
  <div class="mb-3">
   <input type="password" class="form-control" name="password" placeholder="Your
    Password" required>
  </div>
  <div class="text-center">
   <button type="submit" class="btn btn-warning text-white px-5 py-2 rounded-pill
    shadow">
    <i class="fas fa-sign-in-alt"></i> Login
   </button>
  </div>
 </form>
</div>
{% endblock %}
```

register.html

```
{% extends 'base.html' %}
{% block title %}Register{% endblock %}

{% block content %}
```

```
<div class="col-md-8 col-lg-6 mx-auto bg-white p-5 rounded shadow-lg">
  <h2 class="fw-bold mb-4 text-center">Create an Account</h2>
  {% if messages %}
  <div class="container mb-4">
    {% for message in messages %}
     <div class="alert
                {% if message.tags == 'error' %}alert-danger
                {% elif message.tags == 'success' %}alert-success
                {% elif message.tags == 'warning' %}alert-warning
                {% else %}alert-info{% endif %}
                alert-dismissible fade show shadow-sm" role="alert">
       {{ message }}
       <button type="button" class="btn-close" data-bs-dismiss="alert" aria-
        label="Close"></button>
     </div>
    {% endfor %}
  </div>
{% endif %}

  <form action="{% url 'user_registration' %}" method="post">
    {% csrf_token %}
    <div class="row g-3">
      <div class="col-md-6">
        <input type="text" name="first_name" class="form-control" placeholder="First
         Name" required>
      </div>
      <div class="col-md-6">
        <input type="text" name="last_name" class="form-control" placeholder="Last
         Name" required>
      </div>
        <input type="password" name="confirm_password" class="form-control"
        placeholder="Confirm Password" required>
      </div>
    </div>

    <div class="text-center mt-4">
      <button type="submit" class="btn btn-warning text-white px-5 py-2 rounded-pill
        shadow">
      </button>
    </div>
  </form>
</div>
{% endblock %}
```

6.2 IMPLEMENTATION

The implementation phase of the Hybrid AI–GIS Disaster Management System focuses on converting the designed architecture into a working system. This phase involves integrating Artificial Intelligence models with geospatial tools to process real-time environmental data, generate predictions, and visualize results through an interactive interface.

The system is implemented using Python-based machine learning libraries and GIS tools to handle both structured and spatial datasets efficiently. The implementation includes data collection, preprocessing, model training, prediction generation, geospatial mapping, and alert system integration.

The workflow begins with collecting multi-source data such as weather parameters, satellite imagery, and sensor readings. This data is preprocessed and fed into machine learning and deep learning models. The predicted results are then integrated with GIS layers to generate hazard maps and risk zones. Finally, the output is displayed through dashboards and alert systems for decision-making.

6.2.1 Technology Used

The system uses a combination of **AI, GIS, and Web technologies** to ensure efficient implementation.

Programming Language

- **Python 3.x**
  - Used for AI model development, data processing, and system integration.

Machine Learning & Deep Learning Libraries

- **TensorFlow / Keras**
  - Used for implementing deep learning models like LSTM.
- **Scikit-learn**
  - Used for ML models such as Random Forest and SVM.
- **NumPy & Pandas**
  - Used for data manipulation and numerical operations.

Geospatial Technologies

- **QGIS**
  - Used for spatial data visualization and mapping.
- **GeoPandas**
  - Handles geospatial data processing.
- **GDAL / Rasterio**
  - Used for raster data processing and satellite image handling.

Visualization Tools

- **Matplotlib & Seaborn**
  - Used for graphs and statistical visualization.
- **Plotly**
  - Used for interactive dashboards and charts.

Web Technologies (Optional Implementation)

- **Flask / FastAPI**
  - Backend for integrating AI models with web interface.
- **Leaflet.js**
  - Used for displaying GIS maps on web applications.

Data Sources

- Weather APIs (temperature, rainfall, humidity)
- Satellite Imagery (remote sensing data)
- IoT Sensors (soil moisture, river levels)
- Historical disaster datasets

6.2.2 Modules Description

The system is divided into multiple modules to ensure modularity, scalability, and easy maintenance.

1. Data Collection Module

- Collects data from multiple sources such as:
  - Weather APIs
  - IoT Sensors
  - Satellite images

- Historical datasets
- Ensures continuous real-time data flow.

2. Data Preprocessing Module

- Cleans and prepares raw data for analysis.
- Handles:
  - Missing values
  - Noise removal
  - Data normalization
- Performs feature extraction for AI models.

3. AI Prediction Module

- Core module responsible for prediction.
- Uses:
  - Random Forest → classification
  - SVM → pattern detection
  - LSTM → time-series forecasting
- Outputs:
  - Disaster probability
  - Severity level

4. Geospatial Analysis Module

- Uses GIS tools to generate:
  - Hazard maps
  - Risk zones
  - Spatial overlays
- Analyzes:
  - Elevation
  - Slope
  - Land use
  - Water bodies

5. Risk Assessment Module

- Combines AI predictions and GIS outputs.
- Produces:
  - Final risk classification (Low / Medium / High)
- Uses weighted scoring or rule-based logic.

6. Alert & Notification Module

- Generates alerts when risk exceeds threshold.

- Sends:
  - SMS / Email notifications
  - Dashboard alerts
- Helps in early warning and quick response.

7. Visualization & Dashboard Module

- Displays:
  - Graphs and charts
  - Heatmaps
  - GIS-based maps
- Provides user-friendly interface for decision-makers.

6.2.3 Algorithms / Flow Charts

A. Overall System Algorithm

Step 1: Collect data from sensors, APIs, and satellite sources

Step 2: Preprocess data (cleaning, normalization, feature extraction)

Step 3: Input data into AI models (RF, SVM, LSTM)

Step 4: Generate prediction (probability & severity)

Step 5: Perform GIS analysis for spatial mapping

Step 6: Combine AI + GIS results

Step 7: Classify risk level (Low / Medium / High)

Step 8: Generate alerts if threshold exceeded

Step 9: Display results on dashboard

7. SYSTEM TESTING

System Testing is the process of evaluating the complete and integrated system to verify that it meets the specified requirements and functions correctly. It ensures that all modules of the system work together without errors and produce the expected outputs.

In this project, system testing focuses on validating all major modules, including data collection, preprocessing, AI prediction models, geospatial analysis, risk assessment, alert generation, and dashboard visualization. The system integrates Machine Learning models such as Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) with Geographic Information System (GIS) components to generate disaster predictions and spatial hazard maps.

Testing ensures that data flows correctly from input sources (APIs, sensors, satellite data) through preprocessing pipelines into prediction models, and that outputs such as risk levels, alerts, and GIS maps are generated accurately without inconsistencies.

System testing was conducted using multiple datasets and real-time scenarios to evaluate prediction accuracy, system responsiveness, robustness, and usability. Special attention was given to handling large datasets, real-time data streams, and edge-case environmental conditions to ensure system stability and reliability.

7.1 Types of System Testing

7.1.1 Unit Testing

Unit testing was performed to validate individual modules independently. Each module such as data collection, preprocessing, AI prediction, and GIS mapping was tested with controlled inputs to ensure correct outputs.

Key focus areas included:

- Data extraction from APIs and sensors
- Data cleaning, normalization, and feature extraction
- Model prediction logic (RF, SVM, LSTM)
- GIS layer processing and mapping functions
-

Unit testing ensured that each component functioned correctly in isolation and helped in identifying errors at an early stage.

7.1.2 Integration Testing

Integration testing verified that different modules interacted correctly when combined.
Modules tested together included:

- Data collection integrated with preprocessing
- Preprocessing output passed to AI prediction models
- AI prediction results combined with GIS mapping
- Risk assessment integrated with alert generation

This testing ensured smooth data flow across modules and validated that the entire workflow operates correctly without data mismatch or processing errors.

7.1.3 Functional Testing

Functional testing ensured that all system features operated according to requirements and user expectations.
Key validations included:

- Correct prediction of disaster probability and severity
- Accurate generation of GIS-based hazard maps
- Proper classification of risk levels (Low, Medium, High)
- Successful alert generation when thresholds are exceeded
- Correct display of results on the dashboard

Functional testing confirmed that the system behaves as expected for all user inputs and scenarios.

7.1.4 System Testing

System testing evaluated the complete application as an integrated system.
The following were verified:

- End-to-end workflow from data input to output visualization
- Real-time prediction and alert generation

- Stability during continuous system usage
- Consistent performance across multiple datasets

This testing ensured that the system operates reliably under real-world conditions.

7.1.5 White-Box Testing

White-box testing was applied to internal components such as preprocessing pipelines and AI model logic.

It involved:

- Checking internal data flow
- Verifying algorithm execution paths
- Ensuring correct feature selection and transformation
- Validating model prediction computations

This ensured that internal logic was functioning correctly and efficiently.

7.1.6 Black-Box Testing

Black-box testing evaluated the system from the user's perspective without considering internal code structure.

Testing included:

- Submitting input data through the interface
- Observing prediction outputs and maps
- Validating alert messages and dashboard responses

This helped in ensuring usability, correctness, and proper system behavior.

7.1.7 Acceptance Testing

Acceptance testing was conducted to ensure that the system meets user requirements and expectations.

It involved:

- Checking system usability and interface design
- Ensuring clear visualization of hazard maps
- Feedback confirmed that the system is reliable, user-friendly.

7.2 Testing Strategies

A structured testing strategy was followed to ensure comprehensive system validation. Testing was carried out in a phased manner, starting from unit testing to complete system testing.

7.2.1 Test Strategy and Approach

Testing was performed using both manual testing and automated scripts.
Key strategies included:

- Validating preprocessing accuracy and data consistency
- Testing AI model performance using real datasets
- Verifying integration between AI and GIS modules
- Simulating real-time disaster scenarios

This approach ensured that the system performs accurately under both controlled and real-world conditions.

7.2.2 Test Objectives

The main objectives of testing were:

- To ensure correct functioning of all modules
- To validate prediction accuracy and reliability
- To verify real-time alert generation
- To ensure proper visualization of GIS maps
- To check system performance and response time

7.2.3 Features Tested

The major features tested include:

- Data collection and preprocessing accuracy
- AI-based disaster prediction models
- GIS-based hazard map generation

- Risk classification and alert system
- Dashboard visualization and reporting

7.2.4 Integration Testing Strategy

Integration testing focused on ensuring proper interaction between modules.

It verified:

- Correct data flow between preprocessing and AI models
- Accurate combination of AI outputs with GIS layers
- Proper functioning of alert and notification system
- Smooth communication between backend and user interface

7.2.5 Acceptance Criteria

The system was considered successful when:

- Predictions were accurate and reliable
- GIS maps correctly displayed risk zones
- Alerts were generated in real-time
- System performance was stable
- User interface was easy to use

7.2.6 Overall Test Results

All test cases were executed successfully. The system demonstrated:

- High prediction accuracy
- Stable performance under different conditions
- Correct integration of AI and GA modules
- Effective real-time alert generation

7.3 Sample Test Cases

S No.	Test Case	Expected Result	Result	Remarks (if any)
01	User Login	User is authenticated and granted access to their dashboard	Pass	Verify incorrect credentials show appropriate error messages
02	User Registration	New user account is created and stored in the database	Pass	Validate email format and duplicate account handling
03	User Account Activation	Registered user becomes active and can log in successfully	Pass	Ensure inactive users cannot access the system
04	Dashboard of home	User can access Profile, Prediction, Data Visualization, History, Analytics, Logout pages	Pass	Verify all menu links redirect correctly
05	Data Visualization Page	System displays processed data and analysis results correctly	Pass	Ensure graphs/tables load without errors
06	Prediction Module	User can navigate to prediction page and view outputs	Pass	Check proper loading of prediction results

Table No: 7.3 Test Cases

Test Case 1:

Fig 7.3.1 User Login

Description:

The user enters valid login credentials and submits the form. The system authenticates the credentials and redirects the user to the dashboard. It displays user-related information such as profile details and system access options. Successful login confirms that the authentication module and user access control mechanisms are functioning correctly.

Test Case 2:

Fig 7.3.2 User Registration

Description:

The user enters valid registration details such as username, email, and password. The system successfully creates a new user account and stores the information in the database. A confirmation message is displayed indicating successful registration. This verifies that the registration process and database storage functionality are working correctly.

Test Case 3:

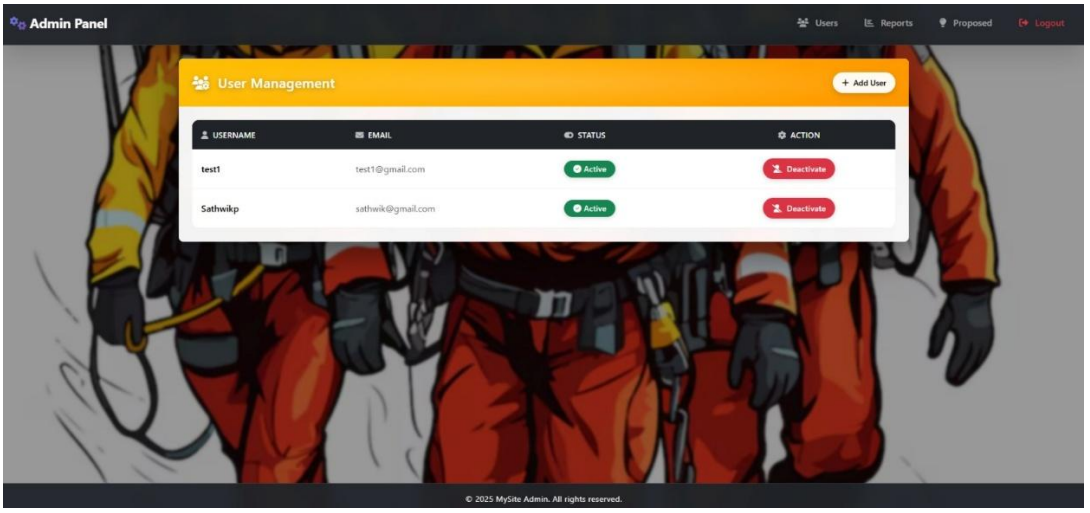


Fig 7.3.3 User Account Activation

Description:

After registration, the system allows account activation (either automatically or through admin approval). Once activated, the user is able to log in successfully and access system features. This ensures that the account activation mechanism is working correctly and prevents unauthorized access before activation.

Test Case 4:

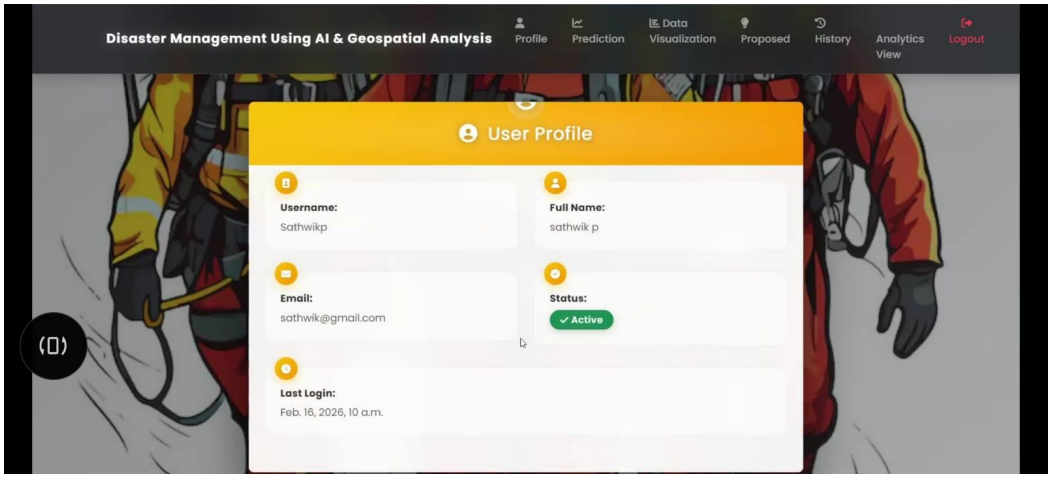


Fig 7.3.4 Dashboard

Description:

The user or administrator accesses the dashboard where system data such as predictions, historical data, analytics, and user details are displayed. The system provides navigation options like Profile, Prediction, Data Visualization, History, and Analytics. This confirms that the dashboard interface, data display, and navigation functionalities are working correctly.

Test Case 5:

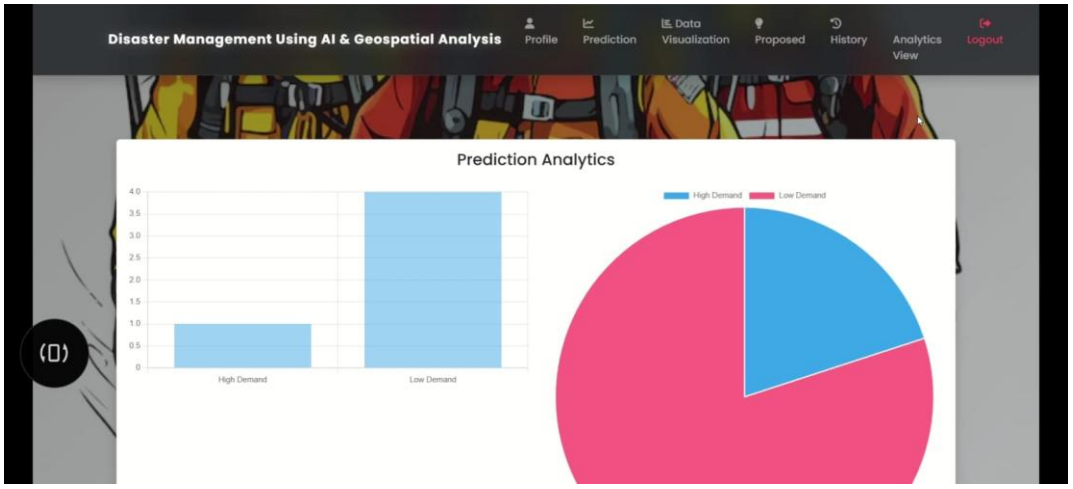


Fig 7.3.5 Data Visualization Page

Description:

The user navigates to the Data Visualization page through the navigation bar. The system displays processed data, analytical results, and visual representations such as graphs, charts, and tables. All visual components load correctly without errors, providing clear insights into disaster-related data. This confirms that the data visualization module, graphical representation, and data processing functionalities are working accurately and efficiently.

Test Case 6:

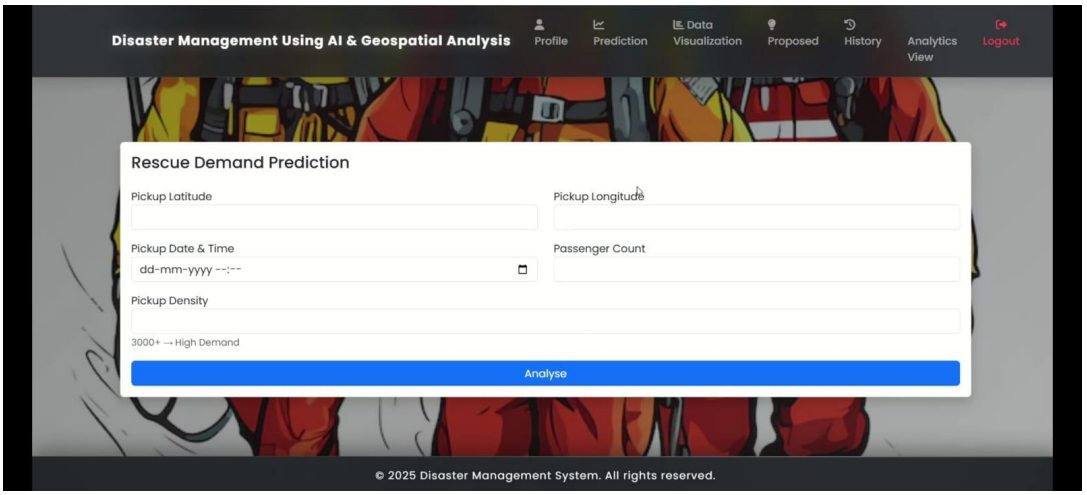


Fig 7.3.6 Disaster Prediction Module

Description:

The user navigates to the prediction module and inputs environmental data such as rainfall, temperature, or other parameters. The system processes the data using AI models (Random Forest, SVM, LSTM) and displays the predicted disaster probability and severity level. This confirms that the AI prediction pipeline and model integration are functioning correctly.

8. OUTPUT SCREENS

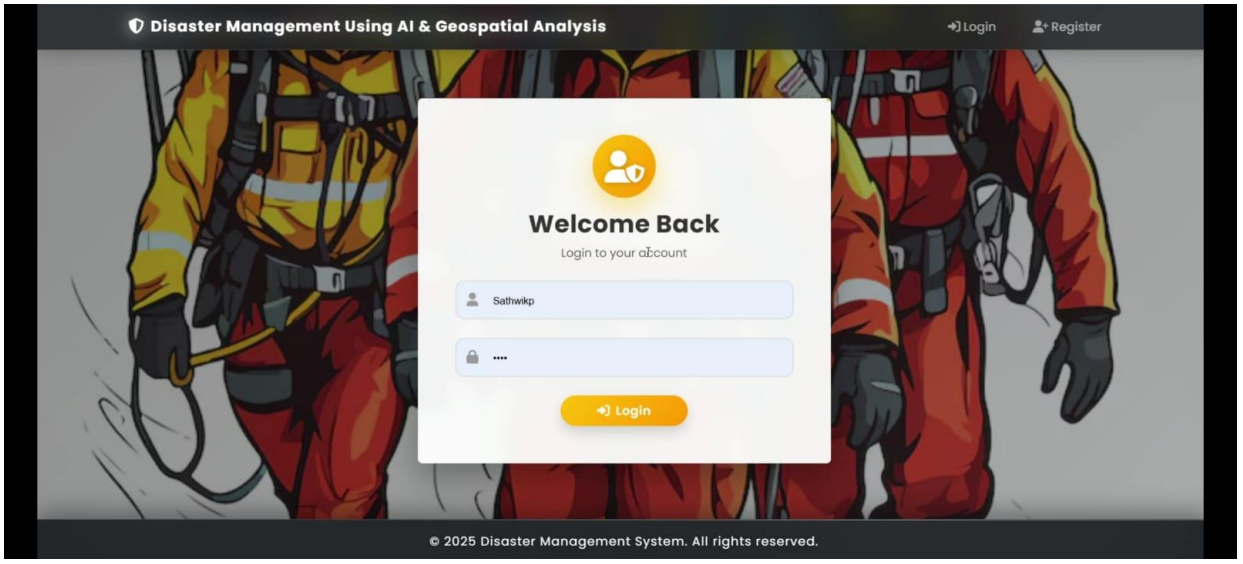


Fig 8.1 User Authentication – Login Page

Description:

This screen represents the **Login Page** of the **Disaster Management Using AI & Geospatial Analysis** system. It serves as the secure entry point for authorized users to access the platform. The page contains fields for entering the **username** and **password**, along with a login button for authentication. This module ensures that only valid users can access the disaster prediction, analysis, and visualization functionalities of the system.

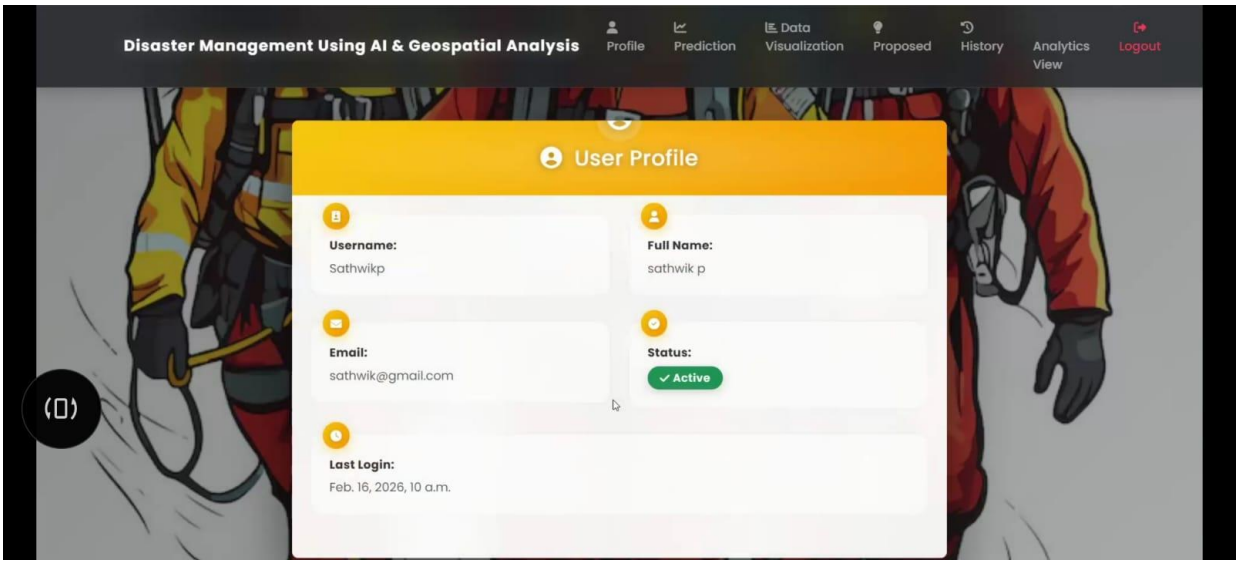


Fig 8.2 User Profile Module

Description:

This screen displays the **User Profile** page of the system. It provides the logged-in user's personal and account-related details such as **username, full name, email address, account status, and last login information**. This module helps users verify their account details and ensures transparency regarding user activity within the application.

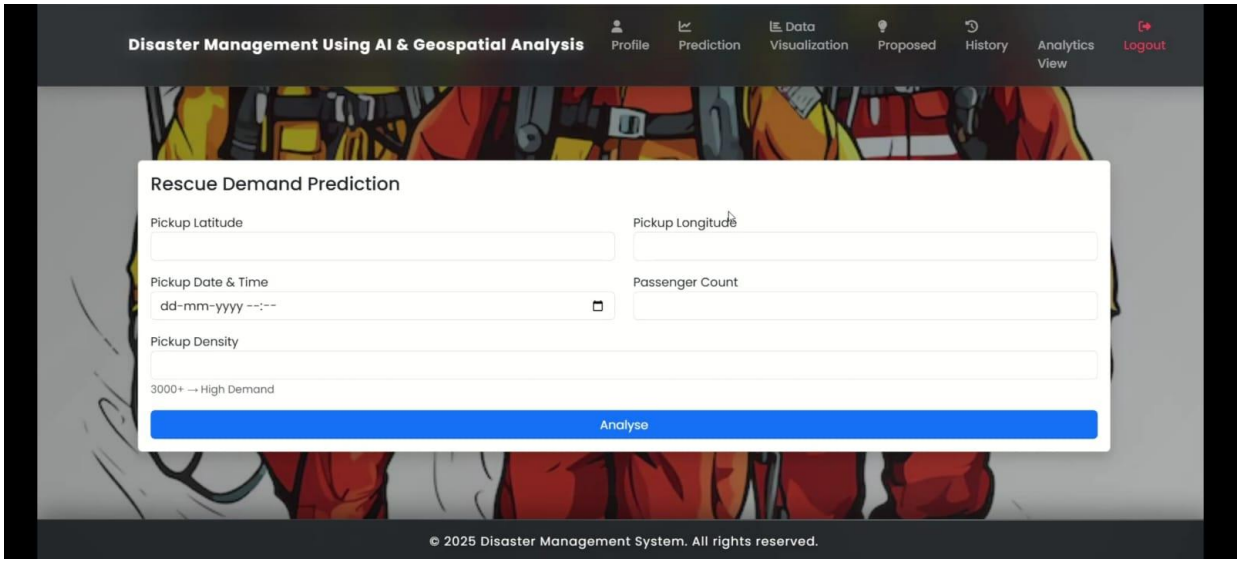


Fig 8.3 Rescue Demand Prediction Module

Description:

This screen shows the **Prediction Page** of the system, where users can provide input parameters to predict rescue demand. The form accepts **pickup latitude, pickup longitude, pickup date and time, passenger count, and pickup density** as input features. Based on these values, the machine learning model analyzes the data and predicts whether the area has **High Demand** or **Low Demand** for rescue resources. This module is the core functional component of the system.

My Prediction History

#	Date	Latitude	Longitude	Passengers	Density	Prediction	Confidence
1	2026-02-16 08:26	40.73202896118164	-73.98812866210938	5	5000	HIGH	0.85
2	2026-02-16 08:26	40.73202896118164	-73.98812866210938	5	500	LOW	1.00
3	2026-02-16 08:25	40.73202896118164	-73.98812866210938	2	349	LOW	1.00
4	2026-02-16 06:38	40.7622833251953	-74.007713317871	5	159	LOW	1.00
5	2026-02-16 06:35	40.7320289611816	-73.9881286621093	1	100	LOW	1.00

Fig 8.4 Prediction History Module

Description:

This screen presents the **Prediction History** page, which stores and displays all previous prediction records made by the user. The table includes details such as **date, latitude, longitude, passenger count, density, predicted result, and confidence score**. This module helps users review past predictions, monitor trends, and maintain a record of decision-support outputs generated by the system.

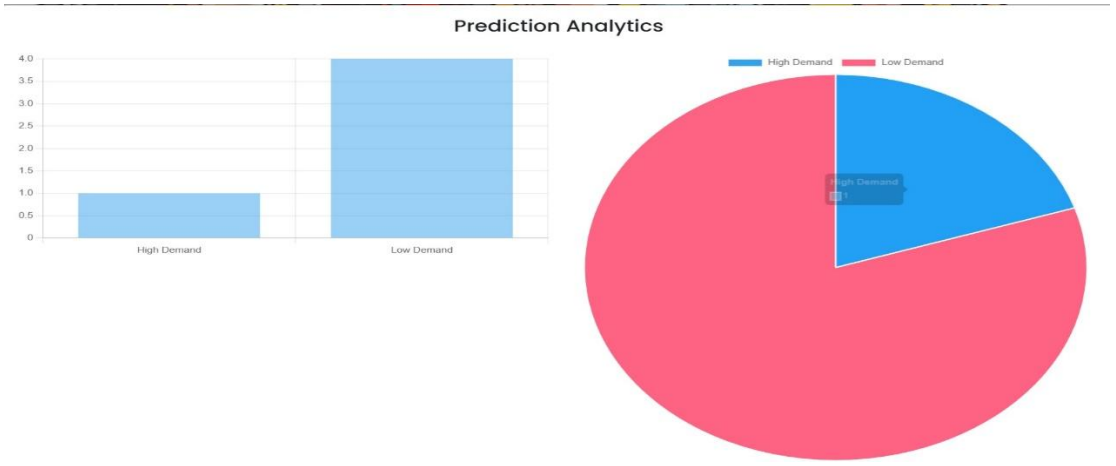


Fig 8.5 Prediction Analytics Dashboard

Description:

This screen shows the **Prediction Analytics** page, which visually summarizes the prediction results using graphical representations. The **bar chart** and **pie chart** illustrate the distribution of **High Demand** and **Low Demand** predictions. This analytical dashboard helps users quickly understand overall demand patterns and provides a more intuitive interpretation of prediction outcomes.

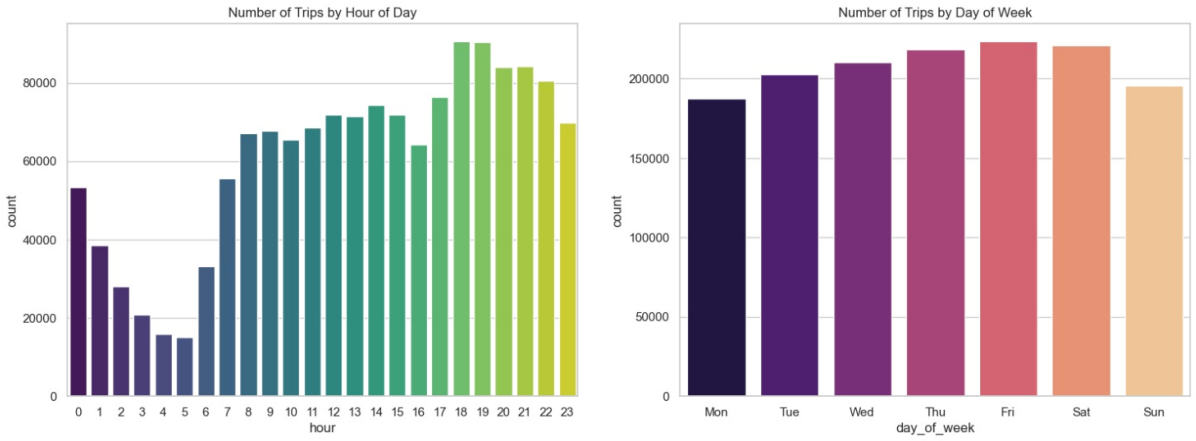


Fig 8.6 & 8.7 Hourly Trip Demand Analysis & Day-Wise Trip Demand Analysis

Description:

This figure illustrates the **number of trips by hour of the day**. It shows that trip activity is comparatively low during the early morning hours and gradually increases during daytime and evening periods. Peak demand is observed during evening hours, indicating that rescue or transport requirements are higher during those time slots. This analysis is useful for understanding temporal demand patterns.

This graph represents the **number of trips by day of the week**. It highlights how trip demand varies across different days, with some days showing higher activity than others. Such analysis helps in identifying weekly demand trends and assists in planning rescue operations and resource allocation more effectively.

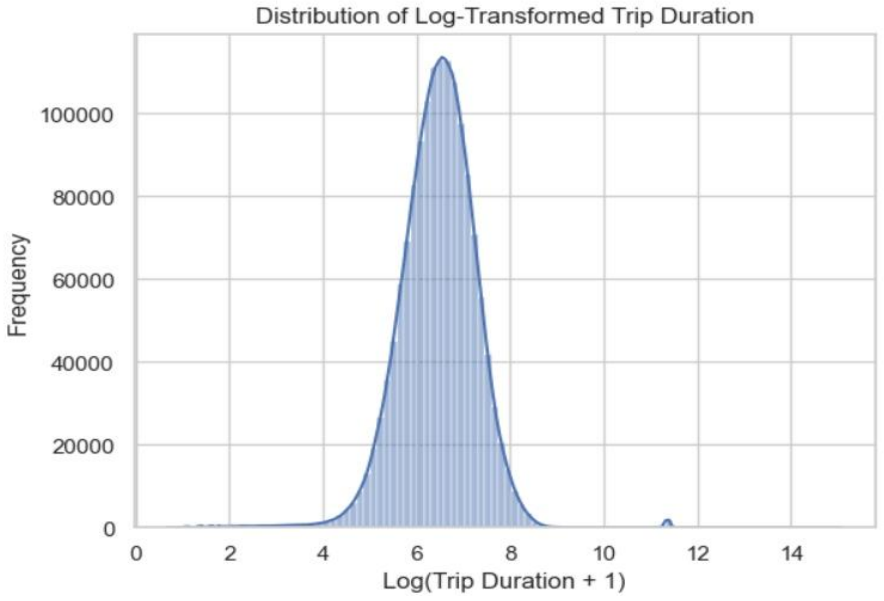


Fig 8.8 Distribution of Log-Transformed Trip Duration

Description:

This figure shows the **distribution of log-transformed trip duration** in the dataset. The graph helps in understanding the spread and concentration of trip durations after applying logarithmic transformation. This preprocessing step reduces skewness in the data and improves the performance of machine learning models used for demand prediction.

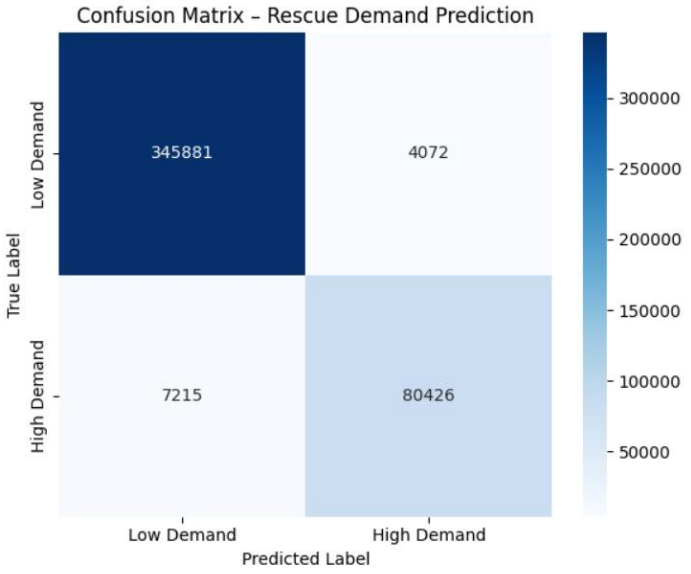


Fig 8.9 Confusion Matrix for Rescue Demand Prediction

Description:

This screen displays the **Confusion Matrix** of the machine learning model used for rescue demand prediction. It compares the **actual labels** with the **predicted labels** for both **Low Demand** and **High Demand** classes. The matrix helps evaluate the classification performance of the model by showing correct predictions and misclassifications in a structured format.

```
Accuracy: 0.9742066847351655
              precision    recall  f1-score   support

           0       0.98      0.99      0.98    349953
           1       0.95      0.92      0.93     87641

    accuracy                           0.97    437594
   macro avg       0.97      0.95      0.96    437594
weighted avg       0.97      0.97      0.97    437594
```

Fig 8.10 Model Accuracy and Classification Report

Description:

This figure presents the **accuracy score** and **classification report** of the prediction model. It includes important evaluation metrics such as **precision, recall, F1-score, and support** for both demand classes. These performance measures demonstrate the effectiveness of the machine learning model in accurately classifying rescue demand levels.

9. CONCLUSION

The proposed hybrid prediction model integrating Artificial Intelligence (AI) and Geospatial Analysis (GIS) presents a robust, intelligent, and scalable solution for addressing the complex challenges associated with modern disaster management systems. In an era where climate change, rapid urbanization, and environmental degradation are increasing the frequency and intensity of disasters, traditional reactive approaches are no longer sufficient. This project successfully demonstrates how the integration of advanced computational techniques with spatial intelligence can significantly enhance the efficiency, accuracy, and responsiveness of disaster prediction and management frameworks. At its core, the system bridges the critical gap between temporal prediction and spatial awareness. While machine learning models are highly effective in identifying patterns, trends, and forecasting future events based on historical data, they often lack the capability to interpret geographical contexts. On the other hand, geospatial analysis excels in visualizing and understanding spatial relationships but does not inherently provide predictive intelligence. By combining these two domains, the proposed system achieves a powerful synergy, enabling not only the prediction of disaster likelihood and severity but also the precise identification of vulnerable regions. This dual capability plays a vital role in proactive disaster preparedness and strategic planning.

One of the major strengths of the system lies in its ability to handle multi-source data integration. The model incorporates diverse datasets, including meteorological data, IoT sensor readings, satellite imagery, and topographic information. Each of these data sources contributes unique insights—weather data helps in understanding environmental conditions, IoT sensors provide real-time monitoring, satellite imagery offers large-scale visual context, and topographic data assists in terrain analysis. The fusion of these heterogeneous data streams enhances the reliability and robustness of the prediction pipeline, ensuring that the system operates effectively under dynamic and uncertain conditions. Furthermore, the implementation of an ensemble learning approach significantly improves the predictive performance of the system. By combining multiple machine learning models such as Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks, the system leverages the strengths of each algorithm while minimizing their individual weaknesses. Random Forest contributes to handling structured data and

reducing overfitting, XGBoost enhances accuracy through gradient boosting techniques, and LSTM effectively captures temporal dependencies in sequential data. The ensemble framework aggregates the outputs of these models, resulting in more stable, consistent, and accurate.

In addition to predictive intelligence, the integration of Geospatial Information Systems (GIS) plays a crucial role in enhancing situational awareness. The system generates hazard maps and layered visualizations that clearly highlight high-risk zones, vulnerable populations, and potential impact areas. These visual representations are not only technically valuable but also user-friendly, allowing decision-makers, emergency responders, and planners to quickly interpret complex data. The ability to visualize disaster-prone regions in an intuitive manner significantly improves communication, coordination, and response efficiency during critical situations. Another important contribution of this project is its modular and scalable architecture. The system is designed in a way that allows easy integration of additional data sources, models, and functionalities. This flexibility ensures that the framework can evolve over time to accommodate new technologies and emerging requirements. For instance, the model can be extended to include real-time streaming data, advanced deep learning architectures, or cloud-based deployment for large-scale applications. Such adaptability is essential for building sustainable and future-ready disaster management systems.

From an application perspective, the system offers significant benefits to multiple stakeholders. Government agencies can utilize the platform for policy-making, disaster preparedness planning, and resource allocation. Emergency response teams can rely on real-time predictions and spatial insights to optimize rescue operations and minimize response time. Urban planners and local authorities can use the system to identify high-risk zones and implement preventive measures such as infrastructure reinforcement and evacuation planning. Additionally, the system can empower communities by providing early warnings and increasing awareness about potential risks. The results obtained from the model evaluation further validate the effectiveness of the proposed approach. High accuracy, precision, recall, and F1-score values indicate that the system performs reliably in classifying disaster demand levels and predicting risk scenarios. The confusion matrix analysis demonstrates that the model maintains a good balance between minimizing false

positives and false negatives, which is critical in disaster management where incorrect predictions can have serious consequences. These performance metrics confirm that the hybrid model is not only theoretically sound but also practically viable.

Despite its strengths, it is important to acknowledge certain limitations and areas for improvement. The accuracy of the system is highly dependent on the quality and availability of input data. In regions where data is sparse or unreliable, prediction performance may be affected. Additionally, real-time implementation may require significant computational resources and efficient data handling mechanisms. Addressing these challenges will be essential for deploying the system in large-scale, real-world environments. Looking ahead, the project opens up several promising directions for future enhancement. The integration of deep learning techniques for satellite image analysis can further improve the detection of environmental changes and disaster indicators. The adoption of cloud computing and edge computing can enable real-time data processing and scalability across multiple regions. The system can also be expanded to support a wider range of disasters, including floods, earthquakes, droughts, wildfires, and storm surges, making it a comprehensive disaster management platform. Additionally, incorporating user-friendly mobile applications and alert systems can enhance accessibility and ensure timely dissemination of warnings to affected populations.

In conclusion, this project successfully demonstrates the potential of combining Artificial Intelligence with Geospatial Analysis to create an intelligent, efficient, and reliable disaster management system. By enabling early prediction, accurate risk assessment, and effective visualization, the system contributes significantly to reducing loss of life, minimizing economic damage, and enhancing environmental sustainability. The proposed hybrid model not only addresses current challenges but also provides a strong foundation for future innovations in disaster management. As the world continues to face increasing environmental uncertainties, such technology-driven solutions will play a crucial role in building resilient, adaptive, and disaster-ready societies.

10.FUTURE ENHANCEMENTS

The proposed hybrid disaster prediction system, which combines Artificial Intelligence (AI) and Geospatial Analysis (GIS), establishes a strong and practical framework for intelligent disaster management. Although the current system demonstrates effective prediction and spatial risk assessment capabilities, there is substantial scope for future enhancement in terms of accuracy, scalability, real-time intelligence, automation, and broader applicability. As disaster management continues to evolve in response to climate change, urban expansion, and increasing environmental uncertainty, future improvements to this system can transform it from a predictive prototype into a highly advanced, real-world decision support platform. One of the most promising areas for future development lies in the integration of advanced deep learning techniques for satellite image analysis. At present, satellite imagery can provide valuable information regarding terrain conditions, water spread, vegetation health, and land-use changes. However, by incorporating sophisticated models such as Convolutional Neural Networks (CNNs), U-Net architectures, and Vision Transformers (ViTs), the system can achieve more precise and automated extraction of disaster-related patterns from remote sensing data. These models can help in detecting flood expansion, wildfire spread, landslide-prone slopes, and drought-affected zones with higher spatial accuracy. Such enhancements would significantly strengthen the system's capability to identify disaster indicators before they become critical.

Another major future enhancement is the expansion of the system into a multi-hazard disaster prediction framework. Currently, the model may focus primarily on a specific type of disaster or demand forecasting scenario, but future versions can be designed to support a wider range of disaster categories such as floods, droughts, cyclones, earthquakes, landslides, wildfires, and storm surges. By broadening the hazard coverage, the system can evolve into a comprehensive disaster intelligence platform suitable for diverse geographical and climatic conditions. This would make the solution far more useful for government agencies, environmental monitoring organizations, and emergency management departments operating in disaster-prone regions.

The incorporation of a more advanced and dense IoT sensor network also presents significant future potential. Real-time monitoring is one of the most critical components of modern disaster management, and future implementations can improve this aspect by

deploying high-precision sensors for rainfall measurement, soil moisture, temperature, humidity, river water levels, wind speed, and seismic activity. These sensors can continuously stream live environmental data into the system, allowing the model to respond dynamically to rapidly changing field conditions. With improved IoT integration, the system can move beyond periodic prediction and evolve into a real-time, continuously updating disaster surveillance and warning mechanism. Another important area of future scope is the deployment of the system on cloud-based infrastructure. As the volume of geospatial, meteorological, and sensor-based data increases, local processing may become inefficient or computationally expensive. Cloud computing platforms such as AWS, Microsoft Azure, or Google Cloud can provide scalable storage, high-performance computing, and distributed processing capabilities. This will allow the system to process large datasets more efficiently, run predictions across multiple regions simultaneously, and support real-time analytics at a much larger scale. Cloud deployment would also make the platform more accessible and reliable for multi-user or government-level applications.

A highly valuable future enhancement would be the development of a mobile application and public alert system connected to the disaster prediction framework. While the current system may primarily support analysts, administrators, or disaster response teams, future versions can extend their benefits directly to the public. A mobile app can provide real-time alerts, safety notifications, evacuation warnings, shelter locations, and emergency instructions to citizens in affected regions. Such a feature would significantly improve public awareness, preparedness, and community resilience. This also creates an opportunity to build a citizen-centric disaster management ecosystem where users can receive warnings and even contribute local observations or incident reports. The use of Graph Neural Networks (GNNs) is another promising direction for improving the intelligence of the system. Disaster events are often influenced by complex and interconnected environmental, infrastructural, and geographical factors. Traditional machine learning models may capture independent relationships effectively, but they often struggle to model network-based dependencies. GNNs can help represent and analyze the relationships between rivers, roads, population clusters, terrain structures, drainage networks, and weather systems. This would allow the model to better understand how hazards propagate through interconnected environments, thereby improving the accuracy of predictions related to flood spread, wildfire movement, or cascading infrastructure failures.

Future versions of the system can also incorporate automated decision-support mechanisms to move beyond prediction and into actionable disaster response planning. For example, once a high-risk area is identified, the system can automatically suggest safe evacuation routes, nearest relief centers, emergency response priorities, rescue team deployment plans, and resource distribution strategies. This would transform the system from a monitoring tool into an operational support platform capable of assisting disaster management authorities in real-time decision-making. Such features would be especially useful in reducing delays and confusion during emergency situations where rapid response is critical. A further enhancement can be achieved by integrating the system with official government databases, meteorological services, GIS servers, and emergency management platforms. At present, the system may rely on collected or static datasets, but future versions can establish live connectivity with trusted public data sources to improve reliability and relevance. Integration with government systems can provide access to demographic data, land records, weather forecasts, administrative boundaries, road networks, and emergency contact infrastructure. This will make the system more suitable for official deployment and improve coordination between technological tools and institutional disaster response workflows.

Another highly impactful future scope is the implementation of an AutoML-based adaptive learning pipeline. Environmental patterns and disaster triggers are not static; they change over time due to seasonal shifts, urban development, deforestation, climate change, and human activity. Therefore, a static prediction model may gradually lose accuracy if it is not updated regularly. By incorporating Automated Machine Learning (AutoML) and self-learning mechanisms, the system can continuously retrain itself using newly incoming data, automatically select the best-performing algorithms, tune hyperparameters, and adapt to evolving environmental conditions. This would significantly improve the long-term sustainability and intelligence of the platform. The inclusion of social media and crowd-sourced data analysis is another future direction that can enhance situational awareness during disasters. Platforms such as Twitter, Facebook, and other public communication channels often provide real-time information during emergency events. By applying Natural Language Processing (NLP) and sentiment or event detection models, the system can extract valuable ground-level insights from public posts, complaints, emergency reports, and local updates.

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