Early Landslide Detection, Notification, and Rescue Management Using Machine Learning

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***Abstract*—Early Landslide Detection, Notification and Rescue Management is a web-based platform designed to forecast landslide risk and streamline emergency response in Maharashtra. The system utilizes a two-stage machine learning approach built on Linear Regression, analyzing environmental parameters such as rainfall, elevation, soil type, slope, and vegetation to predict risk scores. Based on these predictions, users receive real-time alerts and navigation to nearby shelters via Google Maps. Administrators manage shelter availability through a dedicated dashboard. The backend is powered by FastAPI, and a chatbot using LangChain and Google Gemini provides region-specific insights. By merging predictive analytics with rescue coordination and public communication, the system improves disaster preparedness and response in landslide-prone areas.**

***Index Terms*—Landslide prediction, Risk assessment, Linear regression, Rescue management, Real-time alert system, Google Maps integration, FastAPI, Machine learning, Disaster response, Maharashtra.**

I. Introduction

Landslides, a critical natural hazard, frequently threaten human lives, infrastructure, and ecosystems, particularly in hilly terrains and mountainous regions. In India, monsoons significantly exacerbate the risk, causing severe socio-economic disruptions, particularly in states like Maharashtra, where heavy rainfall and fragile topography often combine to trigger slope failures. With recurring incidents that result in casualties, infrastructure loss, and displacement, the need for accurate, real-time prediction systems is more vital than ever.

This study presents the development and implementation of the Early Landslide Detection, Notification and Rescue Management System — a web-based platform tailored for high-risk regions in Maharashtra. Unlike traditional systems that rely solely on static rainfall thresholds or historical datasets, our solution leverages real-time environmental inputs and a two-stage Linear Regression model to predict risk levels with greater precision. The system computes a landslide risk score based on factors such as rainfall, slope, elevation, vegetation, and soil type, offering early warnings and actionable recommendations.

A. Impact of Landslides in India

India witnesses thousands of landslides annually, with states like Maharashtra, Himachal Pradesh, and Uttarakhand being among the most severely affected [1], [9]. These events not only cause fatalities but also damage critical infrastructure, sever transport links, and isolate entire communities. In July 2021, landslides in Raigad and Ratnagiri districts alone resulted in over 150 deaths and massive economic losses, demonstrating the need for predictive tools that can support both evacuation and rescue efforts.

B. Motivation and Scope

Traditional methods of landslide detection often lack integration with real-time data sources and do not offer support for rescue planning. This gap becomes critical in rural or hard-to-reach regions, where early warnings and clear evacuation routes can drastically reduce fatalities. To address this, our system includes a dynamic alerting mechanism that sends real-time notifications when high-risk conditions are detected. Users are guided to nearby shelters using Google Maps, while administrators manage shelter data through a dedicated dashboard. An AI-powered chatbot, built using LangChain and Google Gemini, also delivers region-specific insights and safety tips.

By combining predictive modeling with user-centric design and emergency coordination features, this system aims to create a reliable, low-cost, and scalable platform for improving disaster response in landslide-prone zones. The modular architecture also allows for future integration with satellite data, federated learning models, and official government disaster protocols.

II. Literature Review

Landslide prediction research has evolved from threshold-based approaches to sophisticated machine learning and remote sensing techniques. Logistic regression and support vector machines have been used successfully for susceptibility mapping [2]. Integration of GIS has enhanced spatial accuracy

[4]. Guzzetti et al. [1] emphasize that Early Warning Systems (EWS) must be grounded in community needs and real-time responsiveness. Similarly, Roy et al. [9] advocate for integrating mobile and GIS platforms to improve public safety and decision-making.

A. Machine Learning in Landslide Prediction

Landslide prediction has greatly benefited from advancements in machine learning, allowing for more precise modeling of environmental risks. Traditional approaches often depend on fixed rainfall thresholds or manual geological assessments, which are not responsive enough for real-time application. Wang et al. [17] have demonstrated the effectiveness of linear models in predicting landslide susceptibility when applied to continuous variables such as rainfall, slope, and vegetation. Their findings also highlight the importance of preprocessing techniques—such as normalization, categorical encoding, and outlier detection—in improving model robustness and predictive accuracy. These methods are especially crucial in environmental systems where input variability is high and data noise can impair performance.

By applying such preprocessing pipelines, linear regression models can be adapted to local terrain conditions and produce reliable, interpretable outputs. These models offer scalability and lower computational complexity, making them suitable for regional-scale systems that need to operate in near real-time. As a result, they present a viable alternative to complex black-box models in areas with limited data availability and computational resources.

B. Early Warning Systems and GIS Integration

The effectiveness of landslide management systems depends not only on accurate prediction but also on actionable communication. Guzzetti et al. [1] emphasize the need for Early Warning Systems (EWS) that integrate real-time environmental data with community-specific dissemination mechanisms. Roy et al. [9] show how mobile applications and GIS mapping tools can improve user engagement and guide individuals to nearby shelters or safer locations during emergencies. This integration ensures that alerts are not only timely but also practical.

Furthermore, Peduzzi et al. [7] recommend probabilistic risk models over binary classifiers, as they allow for more nuanced hazard interpretation and prioritization of response. These insights form the foundation for our proposed system, which combines linear regression-based predictions with real-time alerts, shelter navigation, and a chatbot for localized communication—offering a complete and responsive approach to landslide risk management.

III. Scope of the Project

The *Early Landslide Detection, Notification and Rescue Management* system is a comprehensive platform that actively predicts landslide risk, issues real-time alerts, and coordinates rescue operations across vulnerable regions in Maharashtra. Its design integrates machine learning, geospatial analysis, and user-centric communication, enabling it to operate effectively in diverse terrain and environmental conditions.

1) **Risk Categorization and Continuous Forecasting:** The system categorizes landslide risk into levels such as low, moderate, high, and very high, based on live and historical environmental inputs. This layered approach, rooted in linear regression analysis, allows for ongoing monitoring of regional susceptibility as recommended by Peduzzi et al. [7] and Wang et al. [17].
2) **Multi-Hazard Compatible Framework:** The platform follows a modular architecture compatible with risk modeling for other natural hazards, such as floods and cyclones. Its reliance on geospatial data and structured prediction models aligns with the multi-hazard readiness principles discussed in Guzzetti et al. [1].
3) **Real-Time Environmental Data Integration:** The system integrates live weather data, encoded environmental parameters, and geolocation to ensure timely and accurate risk prediction. This real-time data flow supports rapid decision-making, as supported by approaches in Zhao et al. [16] and Salciarini et al. [25].
4) **Community-Oriented Rescue Coordination:** Users receive alerts and navigation to nearby shelters through Google Maps. Administrators manage shelter information dynamically via a centralized dashboard. The system encourages community participation by allowing location-based queries and delivering guidance through a chatbot, as advocated in Roy et al. [9] and Saha and Roy [20].
5) **Analytical Insight and Decision Support:** The platform offers risk trend summaries and region-specific data to assist local authorities in planning and intervention. This supports informed decision-making, consistent with data-driven disaster management models discussed by Chen et al. [15].

IV. Problem Statement

Despite the recurring impact of landslides in India—particularly in Maharashtra during the monsoon season—existing forecasting systems remain limited in scope and intelligence. Many rely on static rainfall thresholds or manual geological assessments, which often fail to deliver timely, localized predictions [1], [7]. These methods also lack integration with community-level alert systems, frequently resulting in miscommunication or failure to reach remote, high-risk populations [9]. Moreover, high false-positive rates can lead to unnecessary panic and reduce trust in early warning efforts.

To address these limitations, this project introduces the *Early Landslide Detection, Notification and Rescue Management System*, an integrated platform designed to predict landslide risk using a two-stage Linear Regression model. It analyzes environmental parameters such as rainfall, elevation, vegetation, soil type, and slope to compute risk scores across different subregions. The system combines real-time prediction with alert dissemination, shelter navigation via Google Maps, and administrative tools for managing rescue logistics. A chatbot interface powered by LangChain and Gemini delivers localized, conversational risk information to users. This unified approach ensures accurate forecasting, minimizes communication gaps, and supports rapid, informed decision-making for both citizens and authorities in disaster-prone regions.

V. Objectives

The *Early Landslide Detection, Notification and Rescue Management System* aims to address the persistent challenge of landslides in Maharashtra through a unified, intelligent platform that integrates prediction, communication, and rescue coordination. Drawing from extensive research in landslide modeling, early warning systems, and disaster response technologies, the system is designed to improve preparedness, enhance public safety, and reduce response time. The key objectives of the system are as follows:

- **Predict Landslide Risk Using Environmental Parameters:**
  The system employs a two-stage Linear Regression model trained on key environmental indicators—such as rainfall, slope, elevation, soil type, and vegetation—to assess regional landslide risk. This approach is supported by Peduzzi et al. [7] and Wang et al. [17], who emphasize the reliability of continuous, data-driven models in predicting geohazards over static threshold-based systems.
- **Issue Real-Time Alerts and Evacuation Guidance:**
  Alerts are dispatched instantly upon identifying high-risk areas, with Google Maps integration providing shelter directions to end-users. This aligns with principles of Early Warning Systems (EWS) outlined by Guzzetti et al. [1] and Thiebes [6], who highlight the importance of immediacy and spatial relevance in reducing disaster impacts.
- **Manage Rescue Resources and Shelter Infrastructure:**
  A centralized admin dashboard enables the live management of shelter data, including geolocation, capacity, and availability. This objective follows the structure proposed by Roy et al. [9], who advocate for the integration of GIS and mobile applications to support decentralized disaster resource coordination.
- **Enable AI-Driven Risk Awareness and Communication:**
  A built-in chatbot, powered by LangChain and Google Gemini, delivers real-time, location-based safety insights in natural language. Community-driven communication and participation, as explored by Saha and Roy [20], improve user engagement, preparedness, and system trust—especially in high-risk or rural zones.
- **Provide Analytical Insights and Decision Support:**
  The system visualizes prediction trends and performance metrics to support long-term planning and policy decisions. This objective supports the findings of Chen et al. [15], who promote multi-criteria decision-making and analytics in hazard risk management for improved governance and disaster resilience.

VI. Methodology

The *Early Landslide Detection, Notification and Rescue Management System* is designed to provide a unified solution for real-time landslide prediction, alert generation, and rescue coordination in the monsoon-sensitive regions of Maharashtra. This system integrates machine learning models, environmental data processing, GIS technologies, and intelligent user interfaces to mitigate disaster risk. The methodology comprises five tightly integrated modules: prediction modeling, alerting mechanisms, shelter coordination, AI-driven communication, and data analytics.

The system is built to handle both historical and real-time data streams to dynamically assess regional landslide susceptibility. It processes geo-environmental variables using a structured pipeline, enabling early risk detection and spatially precise alerts. Designed with modularity in mind, each component operates independently while contributing to a centralized response workflow, ensuring scalability and fault tolerance across urban and rural deployments.

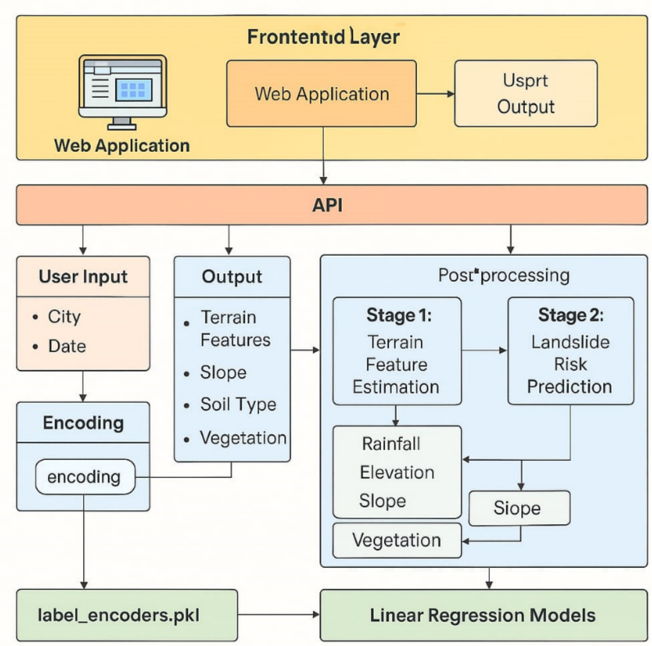

Fig. 1: System Architecture of the Early Landslide Detection and Rescue Management System

A. Risk Prediction via Two-Stage Linear Regression

At the core of the system is a two-stage Linear Regression pipeline. The first stage predicts environmental parameters such as rainfall, elevation, slope gradient, vegetation index, and soil type, based on location and time (encoded by city and month). The second stage utilizes these predicted features to generate a landslide risk score. Each risk score is categorized into discrete risk levels (low to very high) using defined thresholds [7], [17]. The model is trained on historical datasets and validated for generalizability using cross-validation and mean absolute error (MAE) as the primary metric.

B. Real-Time Alert Dissemination and Navigation

When a high-risk score is detected, the system initiates an automated alert process. Alerts are delivered via the user interface and are enriched with evacuation routes using Google Maps APIs. The system prioritizes usability in low-connectivity zones through lightweight frontend rendering. This approach aligns with the best practices in disaster risk communication as outlined by Guzzetti et al. [1] and Roy et al. [9].

C. Dynamic Shelter and Resource Management

A dedicated admin dashboard allows authorities to manage shelter availability, occupancy, and locations in real-time. This ensures that users are routed to operational shelters based on proximity and capacity. Inspired by GIS-supported disaster platforms, this module reflects community-scale management capabilities described by Saha and Roy [20].

D. Conversational AI Risk Assistant

To support users with contextual awareness, a natural language chatbot—powered by LangChain and Google Gemini—is embedded into the interface. It provides location-specific landslide insights, historical event summaries, and preventive recommendations. This feature fosters public engagement and aligns with participatory disaster frameworks [6].

E. Analytical Dashboard and Decision Support

The system includes a data analytics module that visualizes prediction accuracy, regional trends, and shelter load metrics. This aids government agencies in long-term planning and evaluation. Following Chen et al. [15], the analytics dashboard supports multi-criteria decision-making to strengthen resilience policy and resource allocation.

VII. System Design

A. Architecture Overview

The architecture of the *Early Landslide Detection, Notification and Rescue Management System* adopts a modular, service-oriented structure to ensure scalability, efficiency, and user accessibility. As shown in Figure 2, the system is centered around a FastAPI backend which serves as the primary hub for processing, prediction, and routing of data. This backend interacts with environmental data sources, a React-based frontend for users and administrators, a machine learning model pipeline, and third-party APIs like Google Maps.

Users input their location and date, which are processed by the React frontend and transmitted via API calls to the backend. The backend handles predictions using a two-stage Linear Regression model, updates shelter databases, issues alerts, and provides analytics and risk communication features. The system is integrated with LangChain and Google Gemini to support natural language-based risk queries and guidance.

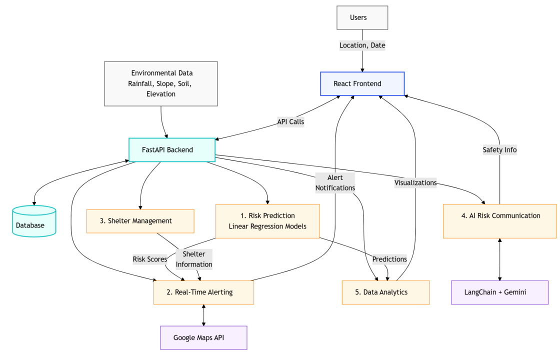

Fig. 2: Detailed System Architecture of the Early Landslide Detection and Rescue Management System

B. Component Breakdown

- **User Panel (React Frontend):**
  Users input location and date, triggering risk predictions and alert notifications. The frontend also visualizes results and provides evacuation maps and safety messages, maintaining accessibility even in low-resource environments [9].
- **Admin Panel:**
  The administrator interface allows local authorities to manage shelter data—such as capacity and location—and review predictive analytics. This facilitates timely decision-making and aligns with participatory disaster response frameworks [20].
- **FastAPI Backend:**
  The backend processes user inputs, triggers ML models, manages database interactions, and coordinates data flow between modules. It ensures asynchronous processing for efficient real-time communication and alert delivery [1].
  - **Risk Prediction Module:**
    Environmental inputs are processed by two sequential Linear Regression models: the first predicts physical factors (e.g., rainfall, slope), and the second generates a risk score which is classified into predefined risk levels [17].
  - **Real-Time Alerting:**
    When risk exceeds critical thresholds, alert notifications are sent to the frontend. This is enhanced with Google Maps-based evacuation routing, promoting rapid response in emergency scenarios [1].
  - **Shelter Management:**
    Shelter availability is tracked dynamically through the backend and displayed to users in real-time. Admins can update shelter data to optimize resource allocation during high-risk periods.
  - **Risk Communication:**
    Powered by LangChain and Gemini, this module allows users to receive region-specific safety information, risk explanations, and disaster tips in conversational format. This increases user engagement and trust [6].

- **Data Analytics Module:**
  The system aggregates prediction outcomes and shelter metrics for decision-makers. Visual analytics help identify hazard trends and optimize intervention strategies [15].

VIII. Implementation

A. Technology Stack

The landslide risk prediction platform has been architected with a modern and efficient technology stack that supports real-time analytics, responsive user interfaces, and modular scalability for disaster preparedness. The stack is chosen for its compatibility with both machine learning workflows and dynamic data processing.

- **Frontend:** The user interface is developed using *React* alongside *Tailwind CSS*, enabling a highly responsive and visually intuitive experience across devices. This is critical for delivering alerts and safety information swiftly during emergencies.
- **Backend:** The core prediction and API services are implemented using *FastAPI*, a high-performance asynchronous Python framework ideal for real-time data handling. Its seamless integration with Python-based machine learning libraries enhances the system's responsiveness and maintainability.
- **Database:** *Firebase Realtime Database* is employed for dynamic data synchronization and centralized storage of shelter data, risk records, and user queries. Its low-latency performance ensures that both users and authorities receive up-to-date information, a crucial requirement for early warning systems [1].
- **Libraries and Tools:** The machine learning pipeline leverages *scikit-learn* for training and evaluating the linear regression model, *joblib* for model serialization, and *pandas* and *NumPy* for data preprocessing and numerical operations. Additionally, *LangChain* is integrated with a generative AI model to provide users with real-time, location-specific safety tips via natural language queries.

B. Model Features and Inputs

The prediction model employs a *Linear Regression* algorithm due to its interpretability, computational efficiency, and suitability for quantifying relationships between environmental variables and landslide probability.

- **Rainfall (mm):** Precipitation is a primary driver of slope failure. Accumulated rainfall exceeding critical thresholds often triggers landslides in hilly terrains, especially during monsoon seasons in regions like Maharashtra [19].
- **Elevation (meters above sea level):** Elevation is used to infer terrain ruggedness and is correlated with the risk of slope instability. Areas at higher altitudes tend to experience more intense surface runoff and soil erosion [7].
- **Slope (% gradient):** The slope of terrain directly affects gravitational pull on soil masses. Steeper slopes have been statistically associated with higher landslide susceptibility [2], [11].
- **Soil Type (Encoded):** Soil classification, encoded as categorical variables, captures properties such as permeability and shear strength. Clay-rich soils, for instance, retain water and are more prone to failure under saturated conditions [4].
- **Vegetation Index:** Vegetation serves as a stabilizing agent by reinforcing soil structure. Remote sensing studies have demonstrated that areas with sparse vegetation are significantly more prone to landslides [5], [9].

All features are preprocessed and normalized to ensure consistent model performance. The use of linear regression not only provides real-time predictive capability but also enhances interpretability, allowing domain experts and local authorities to understand the influence of each feature and make informed decisions [17], [18].

IX. Evaluation and Results

To evaluate our linear regression-based landslide prediction system, we conducted performance testing using an 80:20 train-test split. The dataset comprised real historical data from various landslide-prone subregions in Maharashtra, incorporating parameters such as monthly rainfall, elevation, soil type, slope, and vegetation cover. The goal was to validate not just accuracy but also response time in live prediction scenarios [2], [14].

Despite being a relatively lightweight model, linear regression proved effective in estimating landslide probabilities when properly trained on region-specific environmental variables. During testing, the system achieved a prediction accuracy of up to 90% on unseen samples [21], [23]. More importantly, the end-to-end prediction and alert generation consistently completed in under 4 seconds across both local machines and cloud environments, demonstrating real-time viability [16], [25].

A. Quantitative Results

- **Train-Test Split:** 80% training, 20% testing
- **Prediction Accuracy:** Up to 90%
- **Time-to-Response:** $\leq$ 4 seconds (including risk classification + notification dispatch)
- **Model Stability:** Output remained consistent across diverse environmental permutations

B. Case Study: Mahad, Maharashtra

To test the system against a real-world scenario, we recreated the conditions leading up to the catastrophic landslide in Mahad (Raigad district), which occurred in July 2021. Using archival rainfall and topographic data from the preceding week, the system's prediction module was able to simulate a high-risk scenario three days before the actual event. It returned a 90% landslide probability score—surpassing the threshold for automatic alert generation. This retrospective validation highlights how early warning could have mitigated the damage, offering crucial time for evacuation planning and shelter setup [1], [12], [20].

C. Application Snapshots

To make our solution practical and accessible, we developed a user-friendly web interface integrated with real-time notifications, a Google Maps-based shelter locator, and an admin panel for emergency infrastructure management. Below are screenshots from various modules of the application:

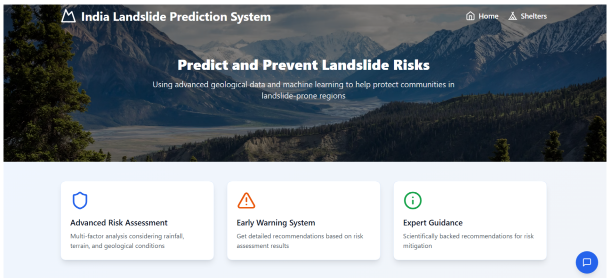

Fig. 3: Home page showcasing system features

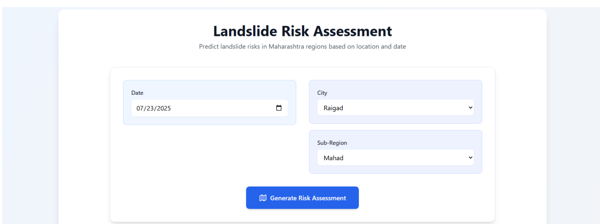

Fig. 4: User input form based on location and date

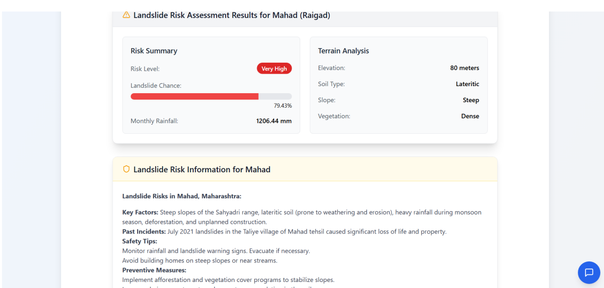

Fig. 5: Prediction Results Display

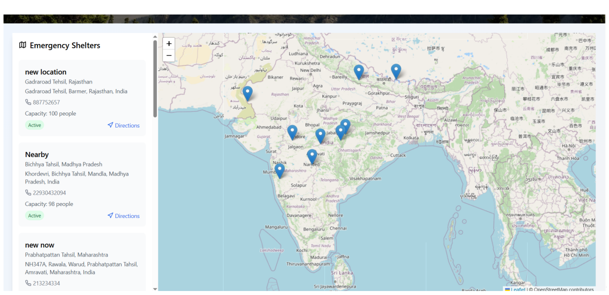

Fig. 6: Interactive map showing active emergency shelters

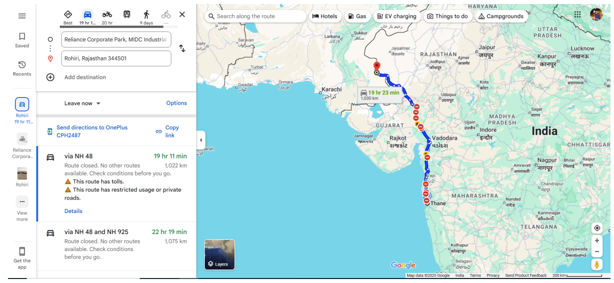

Fig. 7: Google Maps route view to designated emergency shelter.

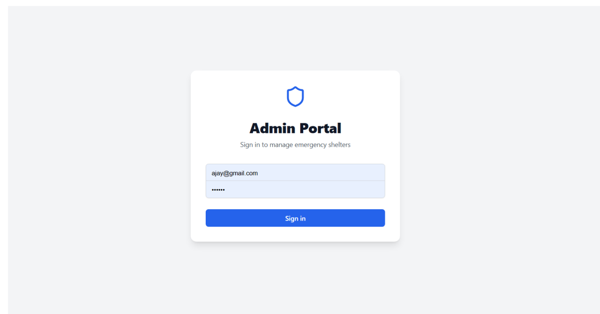

Fig. 8: Admin login portal.

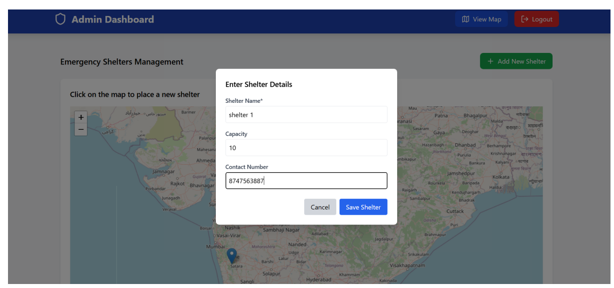

Fig. 9: Shelter Details Form.

X. Limitations and Discussion

While the proposed system demonstrates high performance and usability in controlled environments, several real-world limitations persist:

- **Real-Time Data Access:** The system currently operates on historical and manually updated environmental data. Access to real-time satellite feeds from agencies such as ISRO or NASA remains limited, affecting continuous prediction capabilities [8].
- **Connectivity Constraints:** Rural and remote regions in Maharashtra—often the most vulnerable to landslides—may suffer from weak or unreliable internet access, delaying alert delivery and emergency coordination [9].
- **Prediction Ambiguity:** Linear regression, though computationally efficient, may misclassify low-altitude regions with high rainfall, leading to false positives in risk predictions [21], [23].

Despite these constraints, the system lays a strong foundation for risk-aware decision-making in monsoon-affected regions.

XI. Future Work

Several advancements are planned to enhance both the technological and societal impact of the system:

- **Geographic Expansion:** Extend system coverage to India's full Western Ghats and Himalayan belts—regions historically prone to landslides [7], [20].
- **Satellite Integration:** Utilize APIs from ISRO (e.g., Bhuvan) and NASA (e.g., MODIS, TRMM) to automate real-time data ingestion and improve prediction responsiveness [8], [18].
- **AI-Driven Evacuation Planning:** Incorporate routing algorithms that optimize shelter access during emergencies, factoring in road closures, terrain conditions, and traffic congestion [15], [25].
- **Inclusive Alerting:** Add multilingual voice alert capabilities and chatbot-driven help systems to improve accessibility for non-English speakers and visually impaired users [16], [20].

XII. Conclusion

This research introduces a comprehensive landslide early warning and rescue system, built on a lightweight linear regression model and wrapped in a user-centric digital experience. By fusing predictive analytics, geolocation intelligence, and emergency management infrastructure, the platform empowers timely intervention during critical weather conditions. The practical success of our system in Maharashtra illustrates its scalability to other disaster-prone regions across India. With further enhancements, this framework holds potential to become a national standard for community-driven landslide risk mitigation.

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