International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Flood Forecasting Model Using KNN Algorithm

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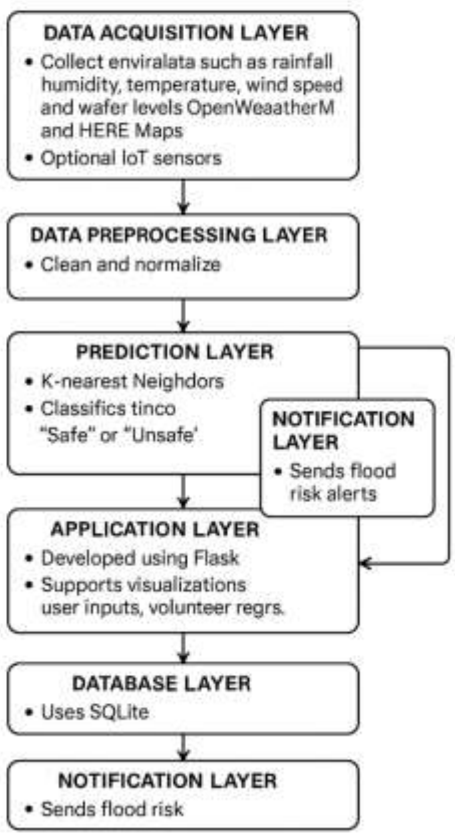
Abstract - Floods are among the most devastating and frequent natural disasters, responsible for significant loss of life, widespread property damage, and serious disruption to transportation, communication, and essential infrastructure. With climate change, rapid urbanization, and deforestation contributing to the increasing occurrence and intensity of floods, the need for advanced, data-driven solutions has become more urgent than ever. In response to this growing challenge, a machine learning-based application called FloodCare has been developed to provide real-time flood prediction and risk monitoring.FloodCare leverages the power of artificial intelligence and sensor technology to collect and process critical environmental data in real time. The system utilizes a network of sensors strategically deployed across vulnerable regions to monitor key variables such as precipitation levels, temperature changes, and rising water levels in rivers and catchment areas. This data is then analyzed using the K-Nearest Neighbors (KNN) algorithm, a robust and efficient machine learning model capable of classifying regions into various flood risk categories—including low, moderate, and high risk.The analysis results are displayed through interactive heatmaps and geolocation markers, providing users with clear, easy-to-understand visual cues to identify areas at immediate risk. FloodCare features a user-friendly interface that ensures accessibility for both emergency response teams and the general public, enabling swift, informed decision-making during flood events.By converting complex environmental data into actionable insights, FloodCare enhances community preparedness, strengthens early warning mechanisms, and supports emergency planning and disaster response efforts. Ultimately, this platform plays a crucial role in reducing the social and economic impact of floods, making it a reliable and intelligent solution for modern flood risk management and climate resilience strategies.

1.INTRODUCTION

In recent years, the frequency and severity of both natural and man-made disasters have increased significantly across the globe. Among these, floods stand out as one of the most recurrent and destructive natural disasters, affecting millions of people annually. The global flood risk has escalated due to a combination of factors, including hydrological extremities, rapid urbanization, deforestation, poor drainage infrastructure, and, most notably, global warming. As climate change accelerates, rising temperatures contribute to increased snowmelt and higher precipitation levels, resulting in more frequent and intense flooding events.

Floods lead to devastating consequences, including the loss of human life, widespread destruction of infrastructure, reduced agricultural productivity, contamination of freshwater resources, and the breakdown of critical services. Economically, floods severely damage local and national economies, especially in developing countries, where recovery mechanisms and disaster response infrastructures are often limited. These nations suffer disproportionally, as floods inflict substantial human casualties and drive long-lasting economic crises that worsen poverty and hinder development. While floods are globally pervasive, their impact varies by geography, socio-economic conditions, and preparedness levels.

In 2021, floods surpassed all other forms of natural disasters in terms of frequency and severity in several South Asian countries, highlighting the urgent need for effective and timely flood prediction and management systems. To protect lives, property, and economic infrastructure, it is imperative for governments and disaster management authorities to adopt reliable systems capable of predicting floods before they occur. Such systems would enable early warnings, timely evacuations, and strategic deployment of resources to minimize damage.



Over the years, several methodologies and models—both regional and global—have been proposed to predict and manage flood risks. However, accurate flood prediction remains a challenging task due to the highly dynamic and complex nature of environmental systems. Traditional hydrological and hydraulic models, though widely used, face several limitations. These models are often computationally intensive, requiring extensive data inputs, domain-specific expertise, and significant processing time. They are not well-suited for real-time forecasting, especially in large or data-scarce regions. Additionally, they often fail to capture the non-linear relationships and complex interactions between various hydrological and meteorological variables.

To overcome these limitations, researchers and practitioners are increasingly turning to machine learning (ML) techniques. ML models are data-driven, adaptive, and capable of learning complex patterns from historical data. They offer significant advantages in terms of speed, scalability, and accuracy, particularly when real-time forecasting is needed. This study aims to develop a machine learning-based early warning system using the K-Nearest Neighbors (KNN) algorithm. By leveraging real-time environmental data, this model seeks to improve flood prediction accuracy and contribute to effective disaster preparedness and mitigation efforts.

1.1PROBLEM STATEMENT

Floods remain one of the most destructive natural disasters worldwide, causing significant loss of life, infrastructure damage, and disruption to economic and social systems. With the increasing frequency and intensity of flood events due to climate change, rapid urbanization, and erratic weather patterns, there is an urgent need for effective and timely flood forecasting systems. Traditional flood prediction methods, although scientifically grounded, face considerable challenges in handling complex and non-linear environmental data, require extensive calibration, and often fall short in providing real-time forecasts, especially in diverse and rapidly changing geographies.

In many developing countries, the lack of efficient early warning systems exacerbates the impact of floods, leading to high casualties and severe economic crises. Existing models such as hydrodynamic and statistical forecasting systems are computationally intensive and often fail to account for sudden changes in climate or unexpected rainfall events. These models also require high-resolution environmental data and expertise for configuration and maintenance, making them impractical for real-time public deployment, especially in rural or underdeveloped areas.

Furthermore, the lack of a public-friendly interface and real-time visualization tools in current systems significantly limits their usability. Most flood forecasting models are accessible only to technical experts or government agencies, leaving the general public unaware of imminent risks until it is too late. There is a clear gap in delivering intuitive, accessible, and actionable flood information to communities, which can critically delay evacuation efforts and disaster response.

In this context, **FloodCare** aims to address the limitations of current systems by combining machine learning techniques with real-time environmental data collection and visualization. The project proposes a lightweight yet robust solution using the **K-Nearest Neighbors (KNN)** algorithm to predict flood risks based on parameters such as rainfall, water levels, soil moisture, and temperature. KNN's simplicity and adaptability make it an ideal choice for real-time classification tasks in flood-prone regions, especially where computational resources are limited.

FloodCare enhances predictive capabilities through sensor-based data collection and delivers user-friendly outputs through a web-based application. This interface displays interactive maps, heatmaps, and precipitation data, enabling users to quickly identify high-risk zones and take timely precautions. Unlike traditional systems, FloodCare is designed not only for authorities but also for public use, ensuring that early warnings and actionable insights reach those most vulnerable.

Ultimately, this project seeks to bridge the technological and communication gaps in flood forecasting by offering a real-time, machine learning-powered, and publicly accessible flood prediction system. Through this, FloodCare contributes significantly to disaster preparedness, community safety, and infrastructure resilience in flood-vulnerable regions.

1.2. TYPES OF FLOODS

There are several types of floods, each with unique characteristics and causes.

Flash floods are sudden, intense floods that typically occur in areas with varied elevation and are most often triggered by heavy rainfall or the sudden release of water from dams or levees. Unlike regular floods, flash floods develop within minutes to a few hours after the causative event, offering little to no warning. This rapid onset makes them extremely hazardous, particularly in mountainous regions, urban areas with poor drainage systems, and regions downstream of dams. The force of the rushing water during a flash flood can be immensely powerful. It can easily sweep away vehicles, uproot trees, and destroy buildings. People and animals caught in the path of a flash flood are at serious risk, as the water can rise quickly and flow with great speed and force. In addition to physical destruction, flash floods can lead to landslides, infrastructure collapse, and contamination of water supplies. Given their unpredictability and destructive power, it is crucial to have early warning systems, community awareness, and emergency preparedness plans in place to mitigate the risks associated with flash floods.

River Floods River floods occur when water levels in a river or stream rise beyond their normal boundaries due to prolonged or intense rainfall, or melting snow. The rate at which these floods develop depends on factors such as the river's size, the terrain, and the volume of incoming water. Larger rivers may flood more slowly but with widespread impact, while smaller streams can overflow more quickly. River floods can cause significant damage to homes, buildings, roads, and bridges. They often disrupt transportation and communication networks, affecting daily life and economic activities. Effective flood management and early warning systems are essential to reduce risks.

Coastal Floods Coastal floods are caused by storm surges, tsunamis, or unusually high tides, leading to the inundation of low-lying coastal areas. These floods can occur suddenly, often with little warning, making them particularly dangerous. Storm surges, often driven by hurricanes or cyclones, push seawater inland, while tsunamis result from underwater seismic activity. Coastal floods can cause extensive damage to homes, buildings, and infrastructure near the shoreline. They can also contaminate freshwater sources, disrupt power and communication systems, and force large-scale evacuations. Due to their sudden nature and destructive impact, early warning systems and evacuation plans are vital in coastal flood-prone regions.

Urban Floods Urban floods commonly occur in cities and towns due to heavy rainfall, inadequate drainage systems, and rapid urban development that reduces natural water absorption. As concrete and asphalt surfaces prevent water from soaking into the ground, rainwater quickly accumulates, overwhelming drainage networks. This leads to waterlogging of streets, damage to buildings, and disruption of transportation and communication services. Urban floods also pose serious public health risks by spreading waterborne diseases through contaminated water. Additionally, they can cause power outages and economic losses. Effective urban planning, improved drainage infrastructure, and sustainable development practices are essential to manage and reduce the impact of urban flooding.

Other types of floods include glacier lake outburst floods (GLOFs) and dam failures, both of which are less common but extremely destructive. GLOFs occur when a dam containing a glacial lake fails, often due to melting ice, landslides, or seismic activity, releasing a sudden, massive flow of water downstream. Similarly, dam failures—caused by structural weaknesses, overtopping, or natural disasters—can unleash catastrophic flooding. These events can devastate communities, destroy infrastructure, and lead to significant loss of life. Each flood type has distinct causes and behaviors, requiring tailored risk assessments, early warning systems, and emergency response plans to effectively reduce their impacts.

1.3.MOTIVATION

Floods are among the most frequent and devastating natural disasters, leading to massive loss of life, destruction of property, and disruption of infrastructure worldwide. In recent years, global climate change has intensified the occurrence of extreme weather conditions, resulting in more frequent and unpredictable flood events. Rising sea levels, increased precipitation, melting glaciers, and unplanned urbanization have all contributed to a surge in flood vulnerability, particularly in developing regions.

Traditional flood prediction models, while grounded in hydrological science, often fail to deliver accurate and timely forecasts due to their reliance on static models and high-quality environmental inputs. These models are typically complex, computationally intensive, and difficult to adapt to real-time, region-specific conditions. Moreover, they lack user-friendly interfaces, making it hard for the general public and even local authorities to access and act upon critical information when it's needed most.

There is a significant need for a system that not only enhances the prediction of flood risks using real-time data but also provides a platform that is accessible, interactive, and actionable. This is where FloodCare fills the gap. The motivation behind developing FloodCare lies in building a machine learning-powered flood monitoring application that overcomes the limitations of traditional forecasting methods. The project integrates environmental data—such as rainfall, temperature, humidity, and soil moisture—collected through API and sensor inputs, with a K-Nearest Neighbors (KNN) algorithm for classification and prediction.

KNN is chosen for its simplicity, low computational cost, and efficiency in handling nonlinear and multidimensional datasets. Unlike complex hydrological models, KNN does not require an elaborate training phase and can dynamically adjust its predictions as new data arrives. This allows the system to continuously improve accuracy while providing real-time insights on flood-prone regions.

The FloodCare application enhances usability by offering intuitive maps, heatmaps, and risk visualizations that clearly indicate safe and unsafe zones. This empowers users—including civilians, municipal agencies, and emergency services—to make timely decisions. Additionally, the platform supports features like volunteer registration, city-specific precipitation and damage analysis, and satellite image integration, further elevating its utility.

Ultimately, the motivation behind this project is to bridge the gap between complex flood data and accessible early warning systems. FloodCare not only leverages the power of machine learning for environmental prediction but also democratizes access to disaster management tools. Its implementation can significantly reduce response time, enhance preparedness, and potentially save lives in flood-prone communities.

1.4.OBJECTIVES

The goal is to build a predictive model using machine learning techniques that analyzes historical data—such as rainfall, river levels, and weather conditions—to forecast flood events. This model helps identify early warning signs, enabling timely alerts, better disaster preparedness, and effective flood risk management to reduce potential damage.FloodCare is a new application designed to provide real-time updates and critical information on flood conditions. By integrating weather data, flood forecasts, and early warning systems, it helps users stay informed about potential flood risks. The app aims to enhance disaster preparedness, ensuring timely evacuations and reducing damage to life and property.To enhance public awareness and preparedness by providing intuitive flood risk assessments through a user-friendly interface, helping individuals make informed decisions and take timely actions during potential floods.

2.SYSTEM ANALYSIS

2.1 Existing System and Its Limitations

Conventional flood forecasting systems rely on tools like HEC-RAS, SWMM, and MIKE FLOOD. While effective in controlled environments, they have significant drawbacks:

- **Data Dependency**: Require high-resolution topographic and hydrological data, often unavailable in rural or underdeveloped areas.

- **Complexity & Cost**: Computationally intensive and hard to configure, making them unsuitable for low-resource settings.
- **Limited Accessibility**: Mostly used by experts and government agencies; public access and awareness are minimal
- **Lack of Intelligence**: Traditional systems don't integrate machine learning, resulting in static models that lack adaptability and real-time learning.

2.2 Proposed System: FloodCare Overview
FloodCare overcomes these limitations using a machine learning-based approach. It employs the K-Nearest Neighbors (KNN) algorithm to predict flood-prone areas by analyzing real-time environmental data such as rainfall, humidity, temperature, wind speed, and water levels.

Key Features:

- Real-time data integration via APIs and sensors
- Flood risk classification as "Safe" or "Unsafe"
- Interactive web dashboard with maps, alerts, and weather info
- Volunteer registration for community involvement
- Scalable, lightweight, and accessible design
- Achieves ~91% accuracy with the implemented KNN model

2.3 System Requirements

Hardware:

- Computers/servers for processing
- IoT sensors (optional)
- Stable internet connection

Software:

- Python 3.x, Flask, SQLite
- APIs: OpenWeatherMap, HERE Maps
- Frontend: HTML, CSS, JavaScript

Environmental:

- Browser support
- Continuous weather data access

2.4 Functional and Non-Functional Requirements

Functional Requirements:

- Collect real-time weather/environmental data
- Preprocess and normalize data
- Predict flood risk using KNN
- Display results on an intuitive web interface
- Send real-time alerts
- Admin panel for data and user management

Non-Functional Requirements:

- **Scalability** – Support for additional locations and data sources
- **Performance** – Quick predictions with low latency
- **Availability** – 24/7 uptime during emergencies
- **Security** – Encrypted user data and secure access
- **Usability** – Easy to use for all users
- **Maintainability** – Simple updates and maintenance

FloodCare represents a next-generation, user-centric flood prediction system combining modern technology with practical usability for impactful disaster management.

3: System Modules

FloodCare is structured into several interconnected modules, each responsible for a specific functionality within the system. This modular architecture enhances scalability, maintainability, and overall system performance, enabling real-time flood risk monitoring, prediction, visualization, and user engagement.

3.1 Data Collection Module
This module forms the backbone of the FloodCare system by acquiring environmental data from various sources.

Key Functions:

- Integrates with weather APIs such as OpenWeatherMap
- Collects essential data: temperature, rainfall, humidity, wind speed, and atmospheric pressure
- Uses HERE Maps API for geolocation and city-specific data retrieval
- Optionally connects with IoT sensors for localized accuracy

Significance:
Provides real-time, relevant, and high-quality data for accurate flood prediction.

3.2 Preprocessing Module
This module ensures data quality and readiness for analysis by cleaning and transforming the raw input.

Key Functions:

- Removes anomalies and handles missing values
- Normalizes data for model compatibility
- Structures data into a uniform format
- Validates data integrity before model processing

Significance:
Improves the reliability and accuracy of the machine learning prediction engine.

3.3 Prediction Module (KNN Classifier)
The core decision-making component that applies machine learning to assess flood risk.

Key Functions:

- Uses the K-Nearest Neighbors (KNN) algorithm to classify areas as "Safe" or "Unsafe"
- Processes normalized data to make predictions
- Updates model performance over time with new data

Model Performance:

- Achieves ~91% classification accuracy
- Chosen for its interpretability, simplicity, and efficiency in handling real-time inputs

Significance:
Provides accurate and timely flood risk assessments essential for early warnings.

3.4 Visualization Module
Transforms prediction results into user-friendly, interactive visuals.

Key Functions:

- Generates maps and heatmaps showing flood-prone regions
- Displays city-level alerts and risk zones
- Visualizes rainfall intensity and estimated impact
- Utilizes spatial overlays for clarity

Significance:
Facilitates quick understanding and response through clear and informative visuals.

3.5 User Interface Module (Flask App)
Acts as the front-end platform for user interaction with the system.

Key Functions:

- Enables input of location data and displays predictions
- Presents charts, updates, and alert notifications
- Provides volunteer sign-up and safety resources
- Designed to be responsive across devices

Significance:
Enhances user engagement and accessibility, even for non-technical users.

3.6 Volunteer Registration Module
Supports community participation in emergency response efforts.

Key Functions:

- Collects and stores information of willing volunteers
- Allows quick mobilization during flood events
- Integrated with the main platform for administrative tracking

Significance:
Promotes social responsibility and aids disaster relief coordination.Each module within FloodCare plays a vital role in delivering an integrated, intelligent, and accessible flood monitoring solution that bridges technology with community preparedness.

4.SYSTEM IMPLEMENTATION

FloodCare integrates machine learning, real-time data, and web technologies to deliver accurate flood predictions through a web interface.

4.1 KNN Model Integration
A K-Nearest Neighbors (KNN) model is trained on labeled weather data (temperature, humidity, rainfall, wind speed). The model is serialized using joblib for reuse.

python

CopyEdit

```
model = KNeighborsClassifier(n_neighbors=3)

model.fit(X_train, y_train)

joblib.dump(model, 'models/knn_model.pkl')
```

4.2 API Integration

- **OpenWeatherMap**: Provides live weather data.
- **HERE Maps API**: Supports geolocation and city mapping.
  User input triggers API calls to fetch data used for prediction.

4.3 Flask Web App
The system is deployed using Flask. It includes:

- Routes (/predict, /register)
- Templates (HTML for UI)
- SQLite DB (for logs and volunteer info)

4.4 Real-Time Data Flow
Each query follows this sequence:

- User inputs city
- APIs fetch live data
- Data is preprocessed
- KNN predicts flood risk
- UI displays results
- Query is logged

Challenges like API latency and concurrent access are managed via efficient coding and Flask's request handling.

5.RESULTS AND DISCUSSION

5.1 Flood Prediction Accuracy
FloodCare's core prediction engine is powered by the K-Nearest Neighbors (KNN) algorithm, trained on environmental features like temperature, wind speed, precipitation, humidity, and cloud cover. These inputs were

sourced from APIs such as OpenWeatherMap and Visual Crossing.

After preprocessing (normalization, outlier removal, etc.), the model was trained on labeled historical data. It achieved strong performance across key evaluation metrics:

- **Accuracy**: 91% — Correct predictions in 91 out of 100 cases.
- **Precision**: 89% — High reliability in predicting actual flood events.
- **Recall**: 92% — Excellent sensitivity to detecting flood-prone conditions.
- **F1-Score**: 90.5% — Balanced precision and recall.

These metrics show that FloodCare is both responsive and reliable in disaster prediction, minimizing false alarms and missed floods.

Real-Time Prediction Example

When a user submits a city query, FloodCare fetches live weather data, preprocesses it, and predicts flood risk using the loaded KNN model.

Example:

- **Input**: Temp = 30.5°C, Max Temp = 35.2°C, Wind Speed = 10 km/h, Precipitation = 2.5 mm, Humidity = 80%
- **Output**: Prediction = *Unsafe*, Time = <5 seconds

Comparison to Traditional Models

Traditional hydrological models (e.g., SWMM, MIKE FLOOD) often require complete datasets and deliver 70–85% accuracy. FloodCare outperforms these by offering 91% accuracy with faster, API-driven predictions, making it better suited for real-time public alerts.

6.CONCLUSION AND FUTURE ENHANCEMENTS

6.1 Summary

FloodCare addresses the growing need for real-time flood prediction by combining machine learning with live environmental data. Using the K-Nearest Neighbors (KNN) algorithm, it classifies locations as "Safe" or "Unsafe" with an accuracy of 91%. Integrated APIs supply live weather and geolocation data, while a modular, Flask-based web design ensures ease of use.

Beyond prediction, FloodCare promotes civic participation through a volunteer system and interactive risk visualizations. Its user-friendly interface and community-focused approach showcase the potential of AI in disaster management and resilience planning.

6.2 Limitations

Despite its effectiveness, FloodCare has some constraints:

- **Limited Training Data**: Smaller, region-specific datasets may affect generalization.
- **API Dependency**: External APIs pose reliability risks.
- **Basic Algorithm**: KNN may not handle complex patterns well.
- **UI Limitations**: Lacks advanced map interactivity.
- **Language Support**: Currently only in English for desktop users
- **Scalability**: Not yet optimized for high user loads.

6.3 Future Scope

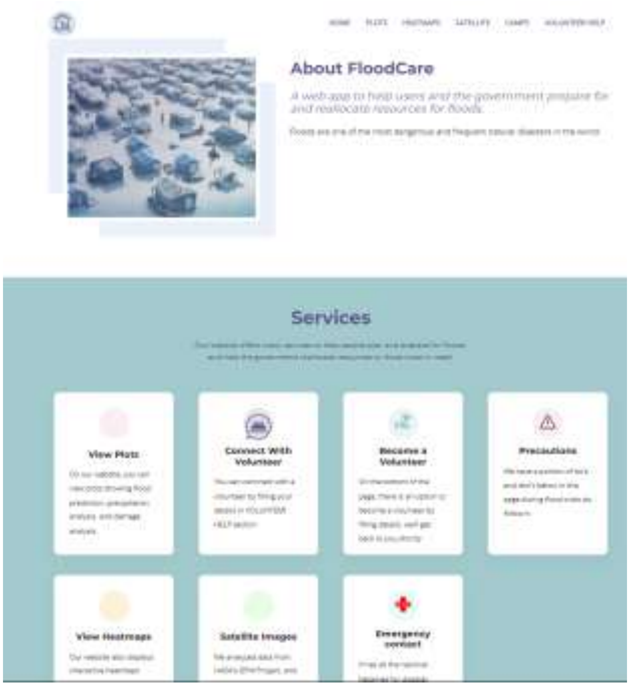
Enhancements planned for FloodCare include:

- **Model Upgrade**: Using Deep Learning for better predictions.
- **Data Expansion**: Adding satellite and river-level data.
- **Cloud Deployment**: For scalability and real-time alerts.
- **Mobile App**: To reach users on the go with push notifications.
- **Multilingual Support**: For broader accessibility.
- **Smart Alerts**: With action-based suggestions.
- **Integration with Authorities**: For better disaster coordination.
- **Interactive Maps**: With GIS and rainfall overlays.
- **AI for Volunteer Matching**: Based on proximity and skills.
- **Damage Estimation**: For relief and insurance purposes
- **Social Media Feeds**: To confirm flood events.
- **Simulation Mode**: For training and preparedness exercises

6.4 User Interface Screenshots

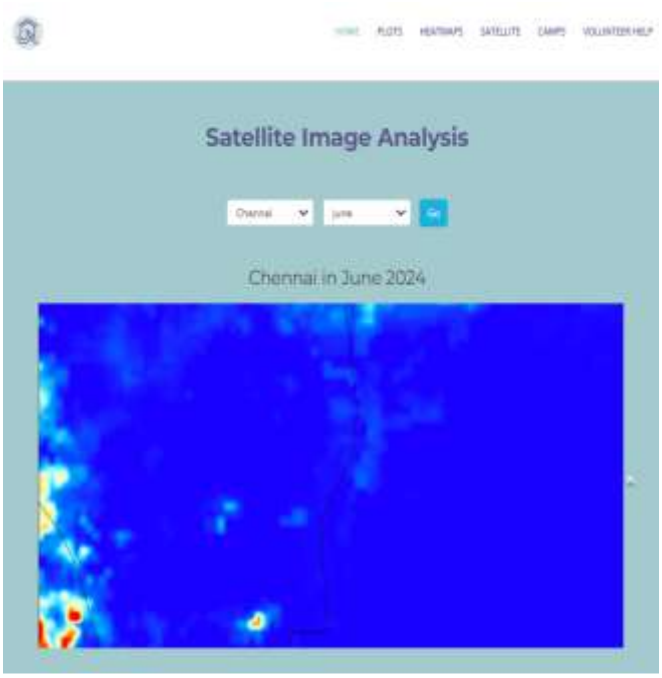
A. Homepage

- Shows the input form for city-based flood prediction.
- Displays real-time weather and a search bar.



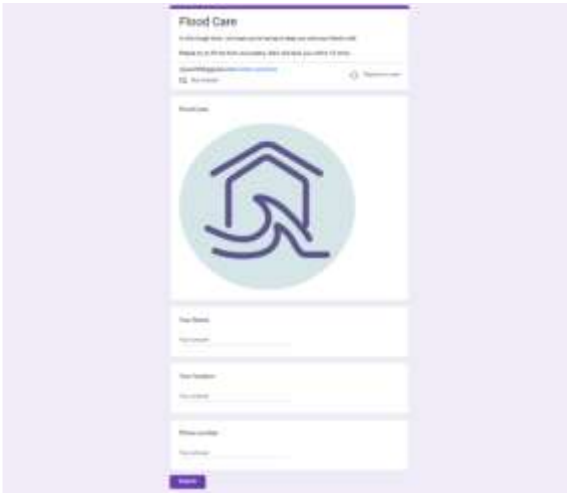
B. Prediction Output Page

- Returns "Safe" or "Unsafe" prediction.
- Shows supporting weather statistics.



C. Volunteer Registration Page

- Allows users to sign up as volunteers.
- Confirmation messages shown upon form submission.



ACKNOWLEDGEMENT

We thank God for his blessings and also for giving as good knowledge and strength in enabling us to finish our project. Our deep gratitude goes to our founder late **Dr. D. SELVARAJ, M.A., M.Phil.,** for his patronage in the completion of our project. We like to take this opportunity to thank our honourable chairperson **Dr.S. NALINI SELVARAJ, M.COM., MPhil., Ph.D.** and honourable director, **MR.S. AMIRTHARAJ, M.Tech., M.B.A** for their support given to us to finish our project successfully. We wish to express our sincere thanks to our beloved principal. **Dr. C. Ramesh Babu Durai M.E., Ph.D** for his kind encouragement and his interest towards us. We are extremely grateful and thanks to our professor **Dr. D. C. Jullie Josephine M.Tech., PhD**, Head of Information Technology, Kings Engineering College, for his valuable suggestion, guidance and encouragement. We wish to express our sense of gratitude to our project supervisor **Mrs. Divya lakshmi VM.E., (PhD)** Assistant Professor of Information Technology Department, Kings Engineering College whose idea and direction made our project a grand success. We express our sincere thanks to our parents, friends and staff members who have helped and encouraged us during the entire course of completing this project work successfully.

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