FLOOD INUNDATION PROBABILITY MAPPING

SUBMITTED IN PARTIAL FULFILLMENT FOR THE REQUIREMENT OF THE AWARD OF DEGREE OF

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE

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May 2025

DECLARATION

I/We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that Project Report entitled "Flood Inundation Probability Mapping" which is submitted by Anubhav Kumar, Ritik Shama, Prajjwal Dwivedi, Adarsh Chaudhary in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

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ABSTRACT

Floods are among the most significant natural hazards globally, causing thousands of deaths and severe disruptions to economies and communities each year. Their increasing frequency is linked to factors like climate change, rapid urban development, and deforestation. Traditional prediction models often fall short due to their inability to adapt to evolving environmental patterns, leading to the rising adoption of machine learning (ML) techniques for more accurate forecasting. This project combines geospatial data science, ML, and web development to provide a real- time flood forecasting system. Utilizing datasets ranging from monsoon intensity, drainage quality, urbanization, and topography, ML algorithms such as logistic regression, XGBoost, and neural networks are trained to evaluate flood susceptibility. The system is focused on interpretability and scalability, with a comparison of model performance to determine best methods for varying datasets.

An easy-to-use web application allows non-technical stakeholders (e.g., policymakers, residents) to engage with the ML model, choosing locations through an interactive map to obtain flood probability scores. Geospatial APIs retrieve real-time meteorological data, and the backend hosts models through cloud-based APIs for low-latency predictions.

Through the integration of actionable analytics and easy-to-understand visualization, this project increases disaster preparedness and community resilience. It fills the gap between data science and disaster management by providing a scalable solution to minimize flood-related vulnerabilities and enable proactive decision-making.

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LIST OF ABBREVIATIONS

ML	Machine Learning
DFD	Daata flow diagram
ROI	Return on investment
CAGR	Compound Annual Growth Rate
API	Application Programming interface
AUC-ROC	Area under the receiver operating characteristic curve
MAE	Mean Absolute Error
Xgboost	Extreme Gradient Boosting

SDG MAPPING WITH JUSTIFICATION

SDG 1: No Poverty: Floods disproportionately affect low-income communities, exacerbating poverty through displacement, loss of livelihoods, and economic disruption. By enabling early flood prediction, the project helps vulnerable populations prepare for disasters, reducing financial losses and preventing poverty escalation. Target 1.5 explicitly mentions building resilience to climate-related disasters .

SDG 2: Zero Hunger: Floods destroy crops, disrupt food supply chains, and undermine food security. Predictive analytics allow farmers to avoid flood impacts on agriculture, in accordance with Target 2.4 (sustainable food production systems resilient to extreme weather).

SDG 3: Good Health and Well-Being: Floods cause injuries, waterborne diseases, and mental illness. Early warnings enable health systems to prepare for heightened demand and protect vulnerable populations, supporting Target 3.d (health system resilience).

SDG 6: Clean Water and Sanitation: Floods contaminate water sources and damage sanitation infrastructure. The project aids in safeguarding water infrastructure, ensuring access to clean water (Target 6.1) and preventing sanitation disruptions .

SDG 9: Industry, Innovation, and Infrastructure: The project leverages ML, geospatial data, and web development to create a novel flood prediction tool. It advances innovation Target 9.5 and builds resilient infrastructure Target 9.1 by providing actionable insights for disaster-proof planning .

SDG 11: Sustainable Cities and Communities: Floods threaten urban safety and sustainability. The web application supports Target 11.5 (reduce disaster-related deaths) and Target 11.b (integrated disaster risk policies), helping cities become inclusive and resilient .

SDG 13: Climate Action Floods are climate change-induced disasters. The project strengthens resilience to climate hazards (Target 13.1), aligning with global efforts to mitigate climate impacts .

SDG 15: Life on Land: Floods degrade terrestrial ecosystems and biodiversity. Predictions help protect ecosystems (Target 15.1) by enabling conservation efforts in flood-prone areas .

SDG 17: Partnerships for the Goals: The project requires collaboration between governments, NGOs, and tech sectors. Partnerships (Target 17.17) are critical for deploying the system and sharing data, ensuring inclusive disaster management .


1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
6 CLEAN WATER AND SANITATION
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
11 SUSTAINABLE CITIES AND COMMUNITIES
THE GLOBAL GOALS
For Sustainable Development
13 CLIMATE ACTION
15 LIFE ON LAND
17 PARTNERSHIPS FOR THE GOALS

SDG MAPPING

CHAPTER 1

INTRODUCTION

1.1 Introduction

Flooding is the foremost visit and obliterating normal catastrophe around the world, influencing millions of lives and causing gigantic financial misfortunes each year. Between 6,000 and 20,000 fatalities are detailed yearly due to floods, whereas incalculable others confront relocation, framework harm, and disturbances to jobs. The expanding recurrence and seriousness of surges are closely connected to climate alter, urbanization, and deforestation, which worsen helplessness in both urban and country zones. As a result, anticipating and mitigating the affect of floods has gotten to be a basic need for governments, communities, and catastrophe administration agencies. Traditional flood expectation strategies depend on hydrological and meteorological information, but they regularly drop short due to the dynamic nature of flooding and the expanding complexity of natural variables. Machine learning (ML), with its capacity to analyze tremendous datasets and reveal hidden patterns, offers a transformative approach to flood forecast. ML models can integrate different inputs, including precipitation, topography, land utilize, and infrastructure conditions, to produce precise and timely predictions. This project centers on leveraging machine learning models like logistic regression, gradient boosting. Utilizing two datasets, this model incorporates different features such as monsoon intensity, drainage quality, urbanization levels, and more , to evaluate flood probabilities successfully. Furthermore, a user-friendly web application is proposed to empower real-time flood chance evaluation based on geological information fetched from APIs. By giving noteworthy bits of knowledge, this work points to back disaster readiness, minimize misfortunes and improve community versatility to flood dangers. Overall, this project presents a novel approach to predict flood occurrence with utilizing web applications that can significantly improve the efficiency and accuracy of the disaster management.

1.2 Project Category

This project falls under the intersection of geospatial data science, web application development, and machine learning deployment. Key categories include:
Geospatial Analysis: Processing and interpreting spatial datasets (e.g., elevation, rainfall, soil type) to model flood susceptibility.

Machine Learning: Training different types of models and understanding their performance, modes which were used for this project are logistic regression, XGBoost, and even neural networks were used to model complex datasets.

Web Development: Building a user-friendly interface for real-time interaction with ML models.

Disaster Risk Reduction: Providing actionable insights to mitigate flood impacts through predictive analytics.

1.3 Objectives

The primary objectives of this project are:

Model Development: Train models like logistic regression, XGBoost , neural networks to predict flood inundation probabilities and then Compare model performance to identify optimal approaches for different datasets.

Model Deployment: The trained machine learning model is then deployed for seamless real-time predictions.

Web Application Deployment: Develop a good website for users to interact with the machine learning model, user can chose a location on map and get prediction for flood depending upon the location and features.

User Accessibility: Ensure non-technical users (e.g., policymakers, residents) can easily interpret flood risk results through visual maps and probability scores.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Review

Recent advancements in machine learning (ML) have revolutionized flood prediction

1- Machine Learning for Flood Prediction

Mosavi et al. (2018) [1] conducted a detailed review exploring the role of machine learning in flood forecasting across various temporal scales. Their work emphasized that ML techniques outperform conventional hydrological models in terms of adaptability, accuracy, and ease of scaling to diverse geographic contexts. Lawal et al. (2021) [2] applied ML models to over 30 years of rainfall data to predict flood risks in Kebbi State, Nigeria. Their findings showed that machine learning could effectively learn from historical meteorological patterns, enabling accurate region-specific flood forecasts. Rajab et al. (2023) [6] developed a deep learning-based flood prediction model using historical climatic data from Bangladesh. Their work highlighted the ability of neural networks to understand intricate environmental trends, especially in handling sequential rainfall data.

2- Algorithmic Innovations in Susceptibility Mapping

Nguyen et al. (2023) [3] compared the performance of K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) for flood susceptibility mapping in Vietnam. ANN emerged as the most reliable due to its capacity to model non-linear relationships among input features. Khalid & Khan (2024) [7] reinforced ANN's effectiveness by conducting rigorous hyperparameter tuning to improve model generalization and accuracy across varying flood-prone terrains in Ontario, Canada. Ahmadlou et al. (2024) [8] proposed a hybrid deep learning model combining a multilayer perceptron (MLP) with autoencoder networks. Their framework improved flood risk map accuracy by extracting both spatial and temporal characteristics from the data.

3- Data Integration and Open-Source Solutions

Hitouri et al. (2024) [4] integrated Synthetic Aperture Radar (SAR) imagery with ML algorithms to monitor flood inundation in areas with limited on-the-ground data. This fusion allowed for real-time flood detection in smaller watersheds, enhancing accuracy in resource-constrained environments. Bhattarai et al. (2024) [5] leveraged freely available geospatial data—such as satellite imagery and elevation models—combined with ANN, SVM, and LSTM models to assess flood risk in Laos. Their study highlighted the potential of open-source resources for cost-effective flood mapping in developing regions.

4- Performance Validation and Gaps

Hasanuzzaman et al. (2022) [9] benchmarked multiple models, including logistic regression, random forests, and ANN, to assess their effectiveness in flood susceptibility analysis. Their study showed that while logistic regression offered better interpretability, ANN achieved higher overall predictive accuracy. Despite the growing adoption of ML in flood prediction, most research remains limited to academic settings without real-world implementation. Few studies emphasize user-facing deployment or integration with live meteorological APIs. This project addresses such limitations by deploying interpretable models like logistic regression and ANN within an interactive web application, enabling real-time flood prediction and public accessibility.

2.2 Research Gaps

(i) Real-Time Accessibility:

Most ML-based flood prediction systems are designed as proof – of - concept models and lack mechanisms for real-time interaction, limiting their usefulness in emergency scenarios.

(ii) Cross-Disciplinary Integration:

Flood prediction typically requires combining geospatial analysis, meteorological data, and machine learning. However, current approaches often treat these components separately. Systems that fuse these elements into a single, cohesive framework remain underdeveloped.

(iii) Scalability and Open Access:

Many models are resource-intensive and rely on proprietary software or high-performance computing setups, which are not feasible in all regions.There is a clear need for systems built on open-source tools that can run efficiently even in low-resource environments

2.3 Problem Formulation

To address these gaps, this project proposes the development of a unified, end-to-end flood prediction system that integrates geospatial analysis, machine learning, and web development. The system is designed to operate in real time, offering predictions through a web-based interface that retrieves live weather and environmental data. ML models such as logistic regression, XGBoost, and neural networks are used to generate flood risk scores based on parameters like rainfall intensity, temperature, elevation, and urban development. By presenting these results through an interactive map, the system enables users—including policymakers and local communities—to assess flood risk and take preventive measures in advance.

CHAPTER 3
PROPOSED SYSTEM

3.1 Proposed System

The proposed system is an end-to-end flood inundation probability mapping platform that integrates geospatial data analytics, machine learning (ML), and web- based visualization to deliver real-time flood risk assessments. The system architecture comprises four core modules:

Data Ingestion & Preprocessing:
Datasets was chosen from multiple authenticated resources such as Kaggle, github repositories. In this module data collection and finding what features are important and what are not was focused.

Machine Learning Engine:
In this module, the aim was to create multiple models on collected datasets, different models were created to analyze the performance of the model. Models were created using libraries such as Scikit-Learn and TensorFlow for neural networks. These libraries provide better efficiency.

Machine Learning Model Deployment:
The trained machine learning model is deployed to huggingface spaces using gradio so that easy and efficient inference server is established between website and the machine learning model.

Web Interface & Deployment:
A React.js frontend allows users to select locations via interactive maps or coordinates. A Flask backend processes requests, invokes ML

models, and returns predictions as probability percentages, good visualisation of features which are being sent to the ML model.

3.2 Unique features of the system

Scalable Open-Source Framework: Built on open-source tools (Python, React.js, Scikit-Learn, TensorFlow, HugginFace) to ensure cost-effective adoption in resource- constrained regions.

Secure: Only authentic users can predict the flood , that makes the system secure from unwanted problems that may arise.
Interoperability: Supports integration with APIs which help todo prediction for live data.

Model accessibility: The machine learning models are deployed on huggingface so anyone can use our work and make it more efficient.

CHAPTER 4
REQUIREMENT ANALYSIS
AND
SYSTEM SPECIFICATION

4.1 Feasibility Study

- Technical Feasibility:

-Tools & Framework: The system leverages proven open-source technologies like python, flask, sickie-learn, tensorflow, mongodb, huggingface and many more which have a robust community support.
-ML Integeration: Existing libraries like scikit-learn, pytorch simplify model training and deployment.

- Economic Feasibility:

-Low-cost-infrastructure: Open-source tools eliminate licensing fees which makes it a very low cost and also due to advance open-source tools like scikit-learn, numpy, python, pytorch, it has become a lot more cost effective.
-ROI: Proactive flood predictions reduce disaster recovery costs for governments and communities.

- Operational Feasibility:

-User Training: Intuitive web interface requires minimal technical expertise.
-Disaster Response: Aligns with UN SDG 11 (Sustainable Cities) by enabling data-driven risk mitigation.

- Market Feasibility:

-Demand: Rising flood frequency due to climate change drives demand for predictive tools.

-Target Audience: Government agencies , private firms dealing in property dealing, travels, NGOs for disaster preparedness, Insurance firms for risk assessment and many more.

-Competitive Edge: Real-time predictions vs. static reports from traditional hydrological models. Cost-effective compared to proprietary solutions e.g., Delft-FEWS.

Market Trends: Global flood analytics market projected to grow at 8.5% CAGR (2023–2030).

4.2 Software Requirement Specification:

4.2.1 Data Requirements:

- Model training: The data is required for the model training, the needs to have features like rainfall, max_temperature, min_temperature, lattitue, longitudes, wind speed etc.
- User Input: When user selects the location we need to get data for that coordinates , the data corresponds to the features of our deployed machine learning model.
- User information: User needs to provide information for authorization on the web application

4.2.2 Functional Requirements:

- User Interface(Frontend): Login or create the new account, select the location on map and then chose the dates ‘from’ and ‘to’, along with what type of model they want to use. The result and feaures data along with good visualisation of data is shown at user side .
- Backend Processing: The backend will process the inputs

from frontend, it could be either to do user authorization or to get predictions, it returns predictions in json format.

- Machine learning Inference server: This helps in communicating with the web application and send the predictions to the frontend through backend.

4.2.3 Performance Requirement:

- Speed: Flood prediction results generated within 5 seconds of user input. Map rendering (heatmaps) loads in <3 seconds on a standard internet connection.
- Resource Usage: Works on machines with 4GB RAM and dual-core processors (no GPU required). ML models optimized for low memory usage (<500MB per inference).
- Concurrency: should Supports 5–10 simultaneous users during testing.

4.2.4 Maintainability Requirement:

- Code Quality: Modular Python/JavaScript code with comments for key functions. Git version control for tracking changes.
- Updates: Easy model retraining via Jupyter Notebook scripts.Dependency management with requirements.txt(py), json .
- Troubleshooting: Basic error logs to troubeshoot.
- Documentation: A simple README file with setup instructions and screenshots.

4.2.5 Security Requirements:

- No Personal Data: The system does NOT collect or store user names, emails, or locations. Users stay anonymous.

- Basic Input Checks: Ensure users can't break the system by typing weird symbols (e.g., !@#) in search boxes. Example: Only allow numbers and commas for coordinates like 12.34, 56.78.
- Safe Libraries: Use well-known Python/JS libraries (e.g., TensorFlow, React.js) and avoid outdated/unofficial tools.Local Testing = Safe Testing: If the app runs only on your computer (localhost), security is already okay. No need for HTTPS. Backup Your Work: Save copies of your code and datasets on Google Drive or a USB (in case your laptop crashes). Or use github.

4.3 SDLC Model Used

This model used Agile methodology, our project involves iterative and incremental nature that's why Agile software development life cycle is best fit. Here's a breakdown of why the agile is good fit for the project:

-Incremental Development: The project is likely to be built with evolving features such as user authentication, prediction page, weather data integration and flood predictions, the agile model allows for releasing small, working modules incrementally, which we can refine as we go.

-Flexibility: Since this project involves various eternal API's like openmeteo for weather data and huggingface gradio applications for prediction, requirements may change as these services evolve. Agile's adaptability is perfect for handling changes in external systems.

-Continuous feedback: We can continuously improve the system from the feedbacks.

-Collaboration: Agile promotes collaboration among all team members, ensuring that everyone stays aligned on objectives

Fig: 4.3(a) – Agile SDLC

4.4 System Design

The system design of the project is simple , it involves four main functions which are defines below, also its been define in fig-4.4(a):

- User Interaction: The user logs in or signs up via the frontend (React). Upon successful login, they navigate to the Prediction Page.

-Weather Data Fetching: The user selects a location and date range on the frontend. The frontend sends these details to the backend (Express). The backend calls the OpenMeteo API to fetch the weather data and then sends this data to the Flask API for flood prediction.

-Prediction: The Flask API processes the weather data and sends it to the Hugging Face model. The Hugging Face model returns the flood prediction to the Flask API, which then sends it back to the backend. The backend sends the prediction result to the frontend to be displayed.

- User Management: The backend handles sign-up, login, and stores user credentials in MongoDB.

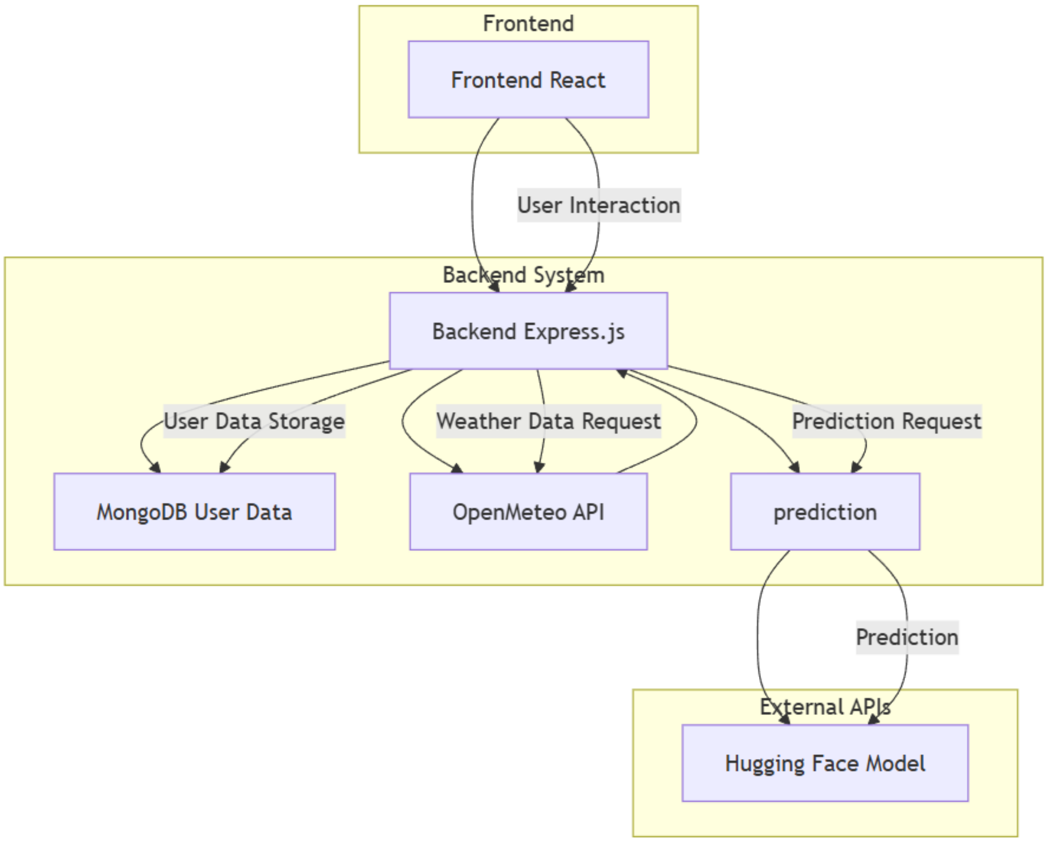


Fig: 4.4(a)- System Design

4.4.1 Data Flow Diagram

The data flow diagram of the project are divided into levels, level-0, level-1 and level-2. The diagrams are given in figures fig-4.4.1(a), fig-4.4.1(b),fig- 4.4.1(c) respectively.

LEVEL-0

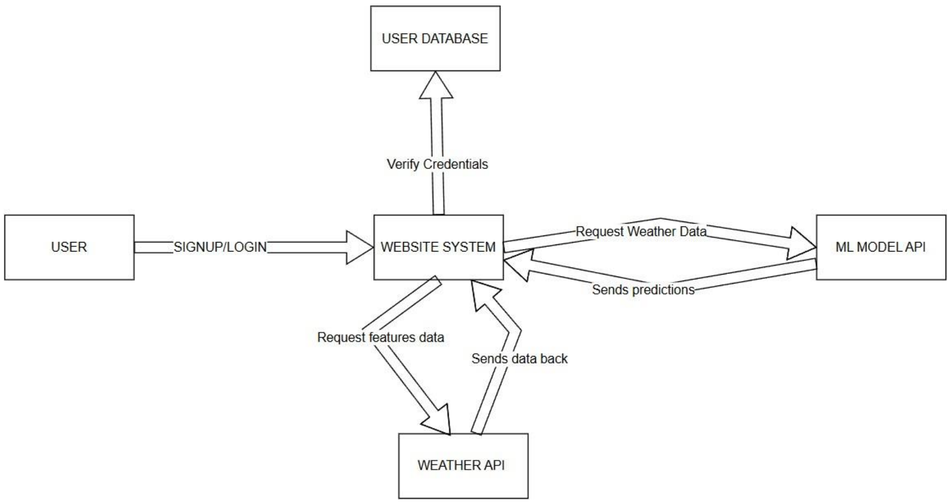


Fig-4.4.1(a) Level-0 DFD

LEVEL-1

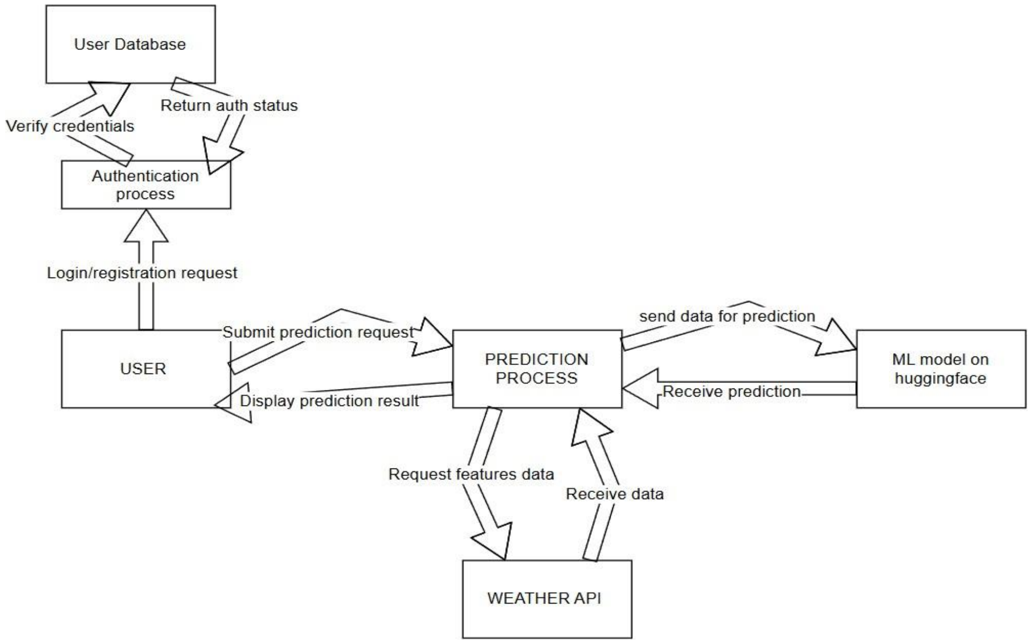


Fig-4.4.1(b) Level-1 DFD

LEVEL-2

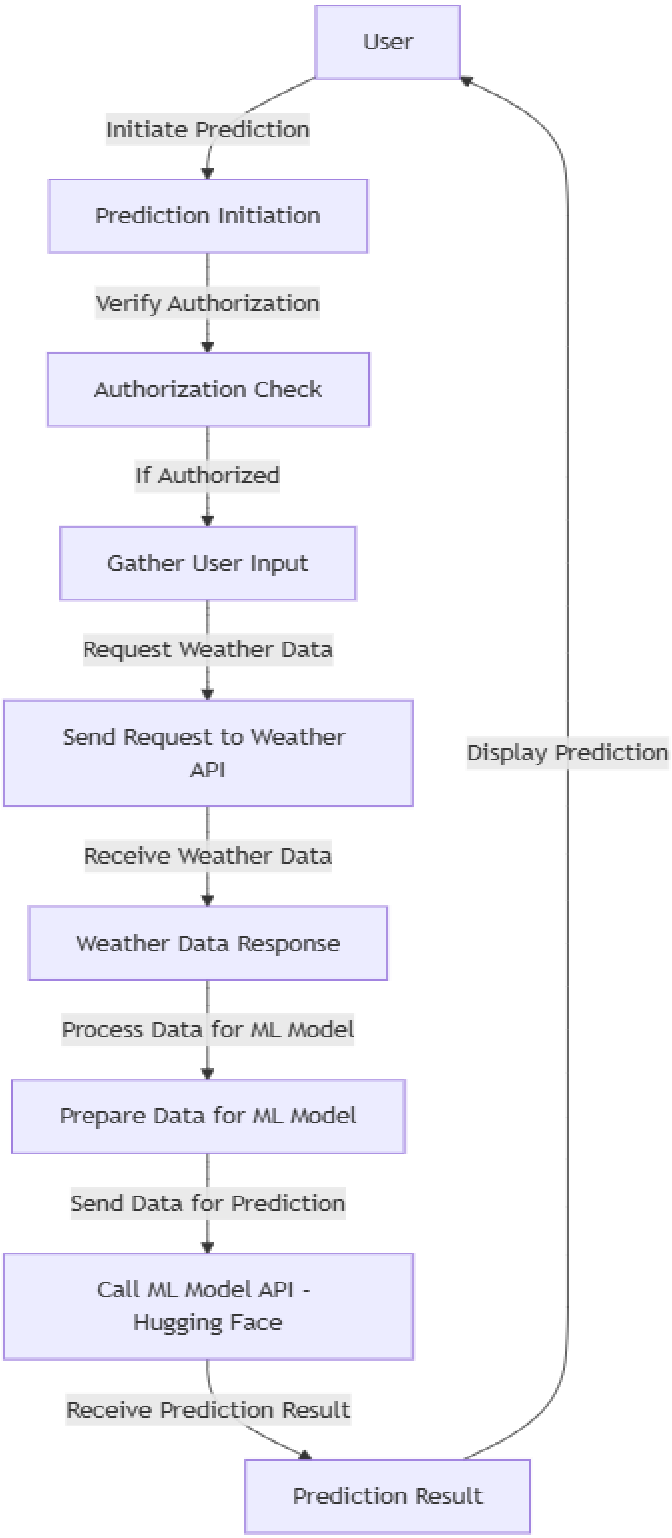


Fig-4.4.1(c)- Level-2 DFD

4.4.2 Use Case Diagram

The use case diagram of the project is given below:

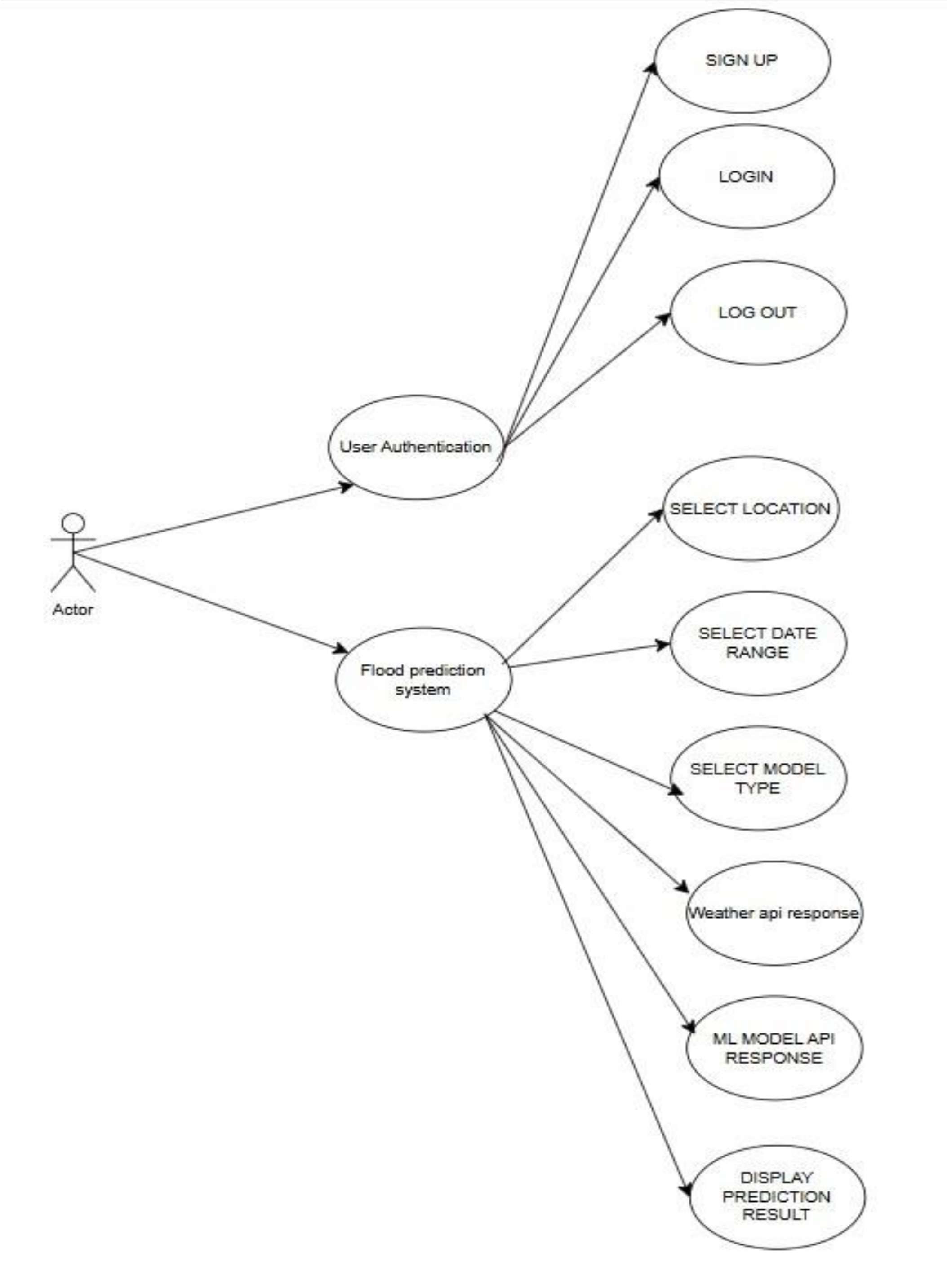


Fig: 4.4.2(a)- use case diagram

4.5 Database Design

At this point, that is currently the project utilises only one database to maintain the user authentication. That is there is single database name “user database”, which have user information i.e Email and password for registered users.

FIELD	DATA TYPE	DISCRIPTION
ID	Integer	Primary key, unique identifier for each user.
Email	Varchar (255)	The user’s email address (must be unique)
Password	Varchar (255)	The user’s hashed password.

Table- 4.5(a) – database design – (user database)

CHAPTER 5
IMPLEMENTATION

5.1 INTRODUCTION & TECHNOLOGIES USED

In this chapter, we discuss the tools and technologies utilized in the development and implementation of the flood prediction model. The implementation process involves data preprocessing, feature engineering, model training, and evaluation. Various software tools, programming languages, and libraries were used to ensure the efficiency and accuracy of the model.

Programming languages: The project uses two core programming languages which are python and java script. Python is used for machine learning model development and javascript is used for developing web applications.

Development Tools: There were various development tools which were used for developing this project, the tools which were used are Google collab, Jupyter Notebook, Vs code, Kaggle.

Libraries and frameworks: This project utilises many libraries and frameworks to make the software more efficient. The main libraries and frameworks which were used for developing this project are : Pandas, NumPy, Matplotlib & seaborn, scikit-learn, XGBoost, React, TensorFlow, tailwindcss, bootstrap, Gradio.

Deployment Platforms: This project utilises deployment platform lie huggingface where the machine learning model is deployed at, it helps in providing better computation and efficiency for flood predictions.

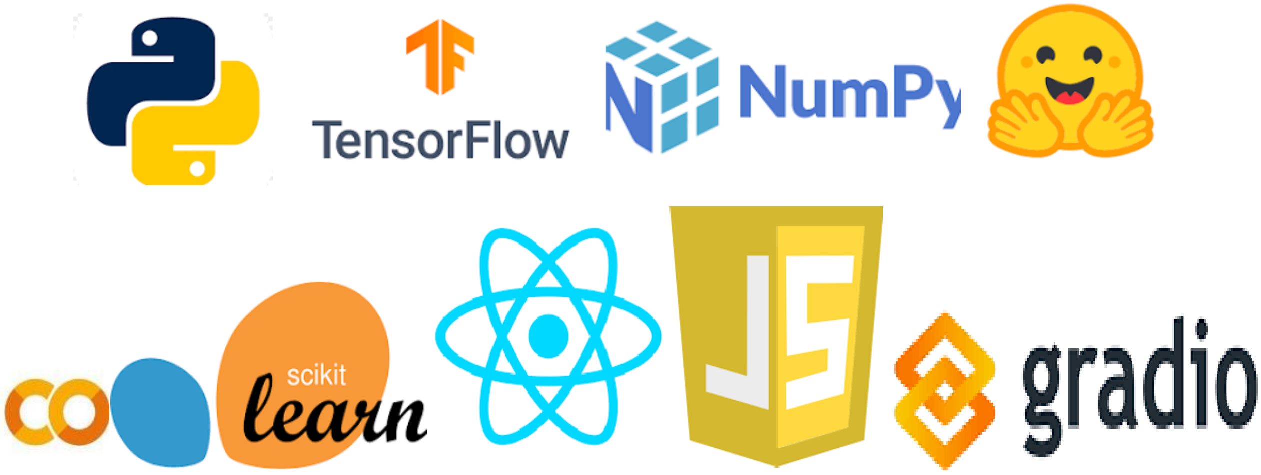


Fig: 5.1(a) overview of tech used

5.2 Dataset Description

The dataset used in this project consists of meteorological and geographical features collected from multiple weather stations. It contains 20,544 records with 19 features. The target variable is Flood?, which indicates whether a flood event occurred, this dataset location is based on Bangladesh, there is one more dataset which focuses on focuses on risk factors like MonsoonIntensity, Deforestation, Urbanization, ClimateChange, DrainageSystems, etc. It has around 50,000 rows and 21 columns with target variable FloodProbability (continuous value between 0 and 1). The one which we are going to use is the one which contains 20,544 records with 19 features.

Some of the parameters which can be use to understand the datasets are given below:

	Unique Values	Mean	Standard Deviation	Min
Sl	20544	10271.50	5930.69	0.00
Year	66	1985.33	17.61	1948.00
Month	12	6.50	3.45	1.00
Max_Temp	247	33.45	2.96	21.60
Min_Temp	265	21.17	4.95	6.20
Rainfall	1241	198.78	240.69	0.00
Relative_Humidity	217	79.50	7.67	34.00
Wind_Speed	284	1.42	1.04	0.00
Cloud_Coverage	115	3.49	2.08	0.00
Bright_Sunshine	429	6.42	1.75	0.00
Station_Number	33	41935.10	36.52	41859.00
X_COR	33	549703.19	116032.08	0.00
Y_COR	33	579280.96	130616.05	0.00
LATITUDE	30	23.33	1.16	20.87
LONGITUDE	33	90.49	1.11	88.56
ALT	17	13.36	13.53	0.00
Period	792	1985.40	17.61	1948.01
Flood?	2	0.92	0.27	0.00

Fig: 5.2(a)- Dataset Description

	25%	50% (Median)	75%	Max
Sl	5135.75	10271.50	15407.25	20543.00
Year	1972.00	1987.00	2000.00	2013.00
Month	3.75	6.50	9.25	12.00
Max_Temp	31.70	33.90	35.40	44.00
Min_Temp	16.90	23.40	25.40	28.10
Rainfall	8.00	111.00	312.00	2072.00
Relative_Humidity	75.00	81.00	85.00	97.00
Wind_Speed	0.70	1.20	1.90	11.20
Cloud_Coverage	1.60	3.30	5.50	7.90
Bright_Sunshine	4.97	6.80	7.80	11.00
Station_Number	41909.00	41941.00	41963.00	41998.00
X_COR	435303.70	540098.60	650012.10	734765.40
Y_COR	504500.30	561770.30	687095.90	844822.30
LATITUDE	22.64	23.17	24.29	25.72
LONGITUDE	89.55	90.41	91.46	92.26
ALT	4.00	7.00	19.00	63.00
Period	1972.05	1987.04	2000.09	2013.12
Flood?	1.00	1.00	1.00	1.00

Feature	Data Type	Non-Null Count	Null Count
Sl	int64	20544	0
Year	int64	20544	0
Month	int64	20544	0
Max_Temp	float64	20544	0
Min_Temp	float64	20544	0
Rainfall	float64	20544	0
Relative_Humidity	float64	20544	0
Wind_Speed	float64	20544	0
Cloud_Coverage	float64	20544	0
Bright_Sunshine	float64	20544	0
Station_Number	int64	20544	0
X_COR	float64	20544	0
Y_COR	float64	20544	0
LATITUDE	float64	20544	0
LONGITUDE	float64	20544	0
ALT	int64	20544	0
Period	float64	20544	0
Flood?	float64	4493	16051

Fig- 5.2(b)- Dataset Description

CHAPTER 6
TESTING & MAINTENANCE

6.1 Testing Techniques and Test Cases Used

Data Validation Testing : Ensured data integrity by checking for missing values, inconsistencies, and outliers. Used statistical methods and visualization techniques to detect anomalies in the dataset.

Model Performance Testing: Evaluated the performance of the machine learning model using:

-Accuracy: Measures correct predictions vs. total predictions.

-Precision, Recall, and F1-Score: Evaluated the model's effectiveness in predicting floods.

-ROC-AUC Score: Assessed the model's ability to distinguish between flood and non-flood instances.

-Confusion Matrix: Analyzed the number of true positives, false positives, true negatives, and false negatives.

Unit Testing: Conducted unit tests on individual functions used for data preprocessing, feature engineering, and model training.Verified that transformations such as normalization and encoding were correctly applied.

Integration Testing: Ensured seamless integration of the trained model with the backend API and frontend application. Checked API request/response handling and model inference correctness.

Deployment and Performance Testing: Tested API deployment on Hugging Face for response time and scalability.

user acceptance testing: We also performed the user acceptance testing. security testing: To test if the database is secured and data fetch and transfer are doing securely.

Test Case ID	Test Scenario	Expected Output	Actual Output	Status
TC-001	Check for missing and invalid values in the dataset	Dataset should not contain null values or incorrect entries	Missing values handled, outliers removed	Passed
TC-002	Doing user registration	Successfully registered	Registered successfully	passed
TC-003	Loggin in	Successfully login	Logged in	passed
TC-004	Evaluate model accuracy using test data	Model accuracy should be above 80%	Accuracy achieved: 95%+	passed
TC-005	Select location on map	Location get selected as long. And lat.	Location gets selected	Passed
TC-006	Select date range , model type and fetch features data from weather API	Features values get as response from the api	Features values did get as a response from api	passed
TC-007	Deployed model on huggingface should work	Shows predictions via a json format response	Shows prediction as json response	passed

TC-008	Send sample data to API and check response	API should return a valid flood probability prediction	API returned predictions within expected range	passed
TC-009	Ensure frontend fetches correct predictions from API	The prediction should be displayed correctly on the user interface	Predictions successfully displayed on UI	Passed
TC-010	Maps getting rendered	Maps is being shown on frontend	Map is visible	passed
TC-011	React components at frontend are getting rendered properly	Components are rendered	It is rendered	passed

Table-6.1(a): Test cases performed

CHAPTER 7
RESULT AND DISCUSSION

7.1 Description of Modules with Snapshots

The flood prediction system consists of multiple modules working together for efficient data processing, model predictions, and user authentication. Below is a description of each module with relevant snapshots:

- Data Preprocessing Module: Loads raw dataset, handles missing values, encodes categorical data, and normalizes numerical features. Ensures data is in the correct format for model training.

```
# Load the dataset
df = pd.read_csv('/kaggle/input/dataset1/FloodPrediction.csv')

# Drop rows with missing values
df = df.dropna()

# Encode categorical variables
le = LabelEncoder()
df['Station_Names'] = le.fit_transform(df['Station_Names'])

# Select features and target variable
X = df.drop(columns=['Flood?'])  # Features
y = df['Flood?']  # Target variable

# Feature Scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

Fig – 7.1(a): snapshot for data preprocessing module

- Machine Learning Model: Trained using the XGBoost algorithm, Logistic reression, neural networks and then identify and analyse which among them works better to predict flood probability. Evaluated using accuracy, precision, recall, and AUC-ROC metrics.

```
# Create a Logistic Regression model
model = LogisticRegression(random_state=42)

# Train the model
model.fit(X_train, y_train)
```

Fig- 7.1(b): model training using logistic regression

```
2. Define the Neural Network Model using TensorFlow Keras
We are using one hidden layer with 16 neurons and ReLU activation.
del = tf.keras.Sequential([
  tf.keras.layers.Dense(16, activation='relu', input_shape=(X_train.shape[1],)),
  tf.keras.layers.Dense(1)  # output layer with 1 neuron for binary classification


Compile the model
Using BinaryCrossentropy with from_logits=True since the final layer does not include a sigmoid activation.
del.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
            loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
            metrics=[tf.keras.metrics.BinaryAccuracy()])

3. Train the Model
Training for 100 epochs with a batch size of 32 and using 10% of training data for validation.
story = model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.1, verbose=2)
```

Fig- 7.1(c): Model training using Neural Networks

```
# Train the XGBoost model
model = xgb.XGBClassifier(objective='binary:logistic',
                          n_estimators=100,
                          learning_rate=0.1,
                          max_depth=6,
                          min_child_weight=1,
                          subsample=0.8,
                          colsample_bytree=0.8)

# Fit the model
model.fit(X_train, y_train)
```

Fig:- 7.1(d): Model training using XGBoost

- <u>API Deployment Module:</u> Model deployed using gradio on huggingface spaces and then Integrated with the frontend for real-time predictions using flask.

```python
# Define Gradio interface components
interface = gr.Interface(
    fn=predict_flood,  # The prediction function
    inputs=[
        gr.Slider(1, 12, 1, label="Month"),
        gr.Number(label="Max Temperature (°C)"),
        gr.Number(label="Min Temperature (°C)"),
        gr.Number(label="Rainfall (mm)"),
        gr.Number(label="Relative Humidity (%)"),
        gr.Number(label="Wind Speed (m/s)"),
        gr.Number(label="Cloud Coverage (%)"),
        gr.Number(label="Latitude"),
        gr.Number(label="Longitude")
    ],
    outputs="text",
    title="💧 Flood Prediction Model",
    description="Predict potential floods using meteorological and geospatial data. The model also provides the probability of a flood."
)

# Launch the Gradio web service
if __name__ == "__main__":
    interface.launch()
```

```python
def predict_flood(month, max_temp, min_temp, rainfall, relative_humidity,
                  wind_speed, cloud_coverage, latitude, longitude):
# def predict_flood(month, max_temp, min_temp, rainfall, relative_humidity,
#                   wind_speed, cloud_coverage,):
    """
    Predicts flood likelihood based on input values and returns the probability.
    """
    # Create a numpy array with the input values in the correct order
    input_data = np.array([[month, max_temp, min_temp, rainfall * 10,
                            relative_humidity, wind_speed, cloud_coverage,latitude, longitude]])

    # Scale the input data
    scaled_data = scaler.transform(input_data)

    # Get prediction (0: No Flood, 1: Flood)
    prediction = model.predict(scaled_data)[0]

    # Get prediction probability for the positive class (flood)
    probability = model.predict_proba(scaled_data)[0][1]

    # Return human-friendly result with probability
    if prediction:
        return f"Flood Alert! Probability: {probability:.2%}"
    else:
        return f"No Flood Detected. Probability: {probability:.2%}"
```

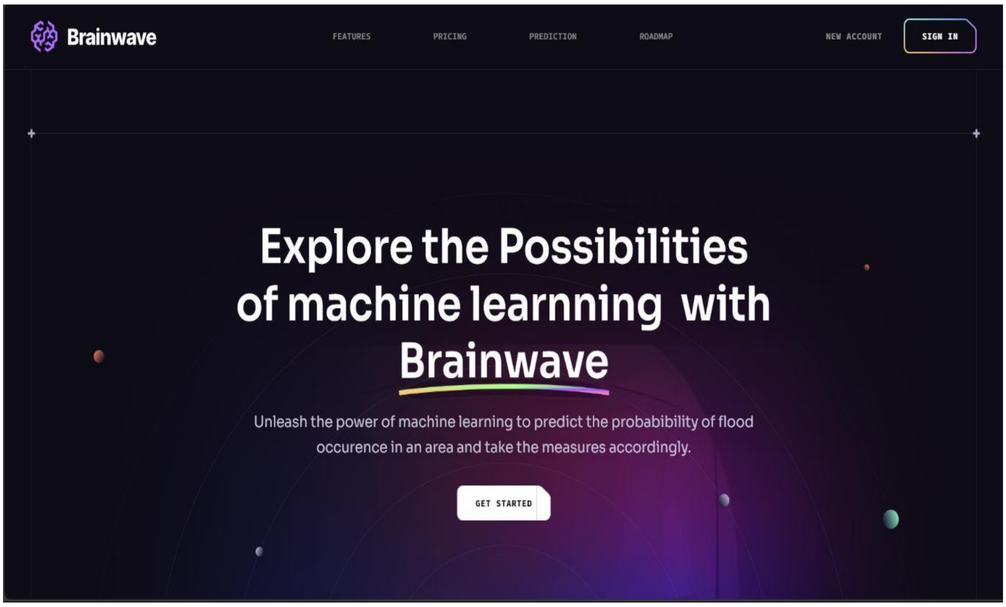
```python
@app.route('/predict', methods=['POST'])
def predict():
    data = request.json
    print("Received payload:", data)  # Debug log
    # Extract data from the request payload
    model_choice = data.get('model', '1')
    month = data.get('month')
    max_temp = data.get('max_temp')
    min_temp = data.get('min_temp')
    rainfall = data.get('rainfall')
    relative_humidity = data.get('relative_humidity')
    wind_speed = data.get('wind_speed')
    cloud_coverage = data.get('cloud_coverage')
    latitude = data.get('latitude')
    longitude = data.get('longitude')

    # Choose the correct client based on model selection
    client = MODEL2_CLIENT if model_choice == "2" else MODEL1_CLIENT

    try:
        result = client.predict(
            month=month,
            max_temp=max_temp,
            min_temp=min_temp,
            rainfall=rainfall,
            relative_humidity=relative_humidity,
            wind_speed=wind_speed,
            cloud_coverage=cloud_coverage,
            latitude=latitude,
            longitude=longitude,
            api_name="/predict"
        )
        return jsonify({"prediction": result})
    except Exception as e:
        # Print the error to the console for debugging
        print("Error in /predict:", e)
        return jsonify({"error": str(e)}), 500
```

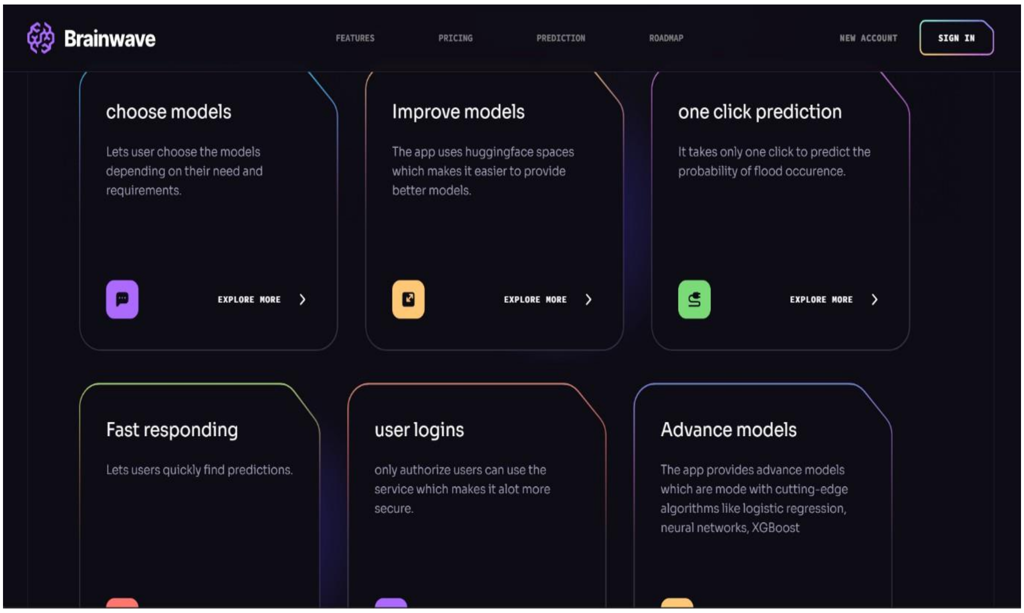
Fig: 7.1(e)- deployment of machine learning model on huggingface using gradio

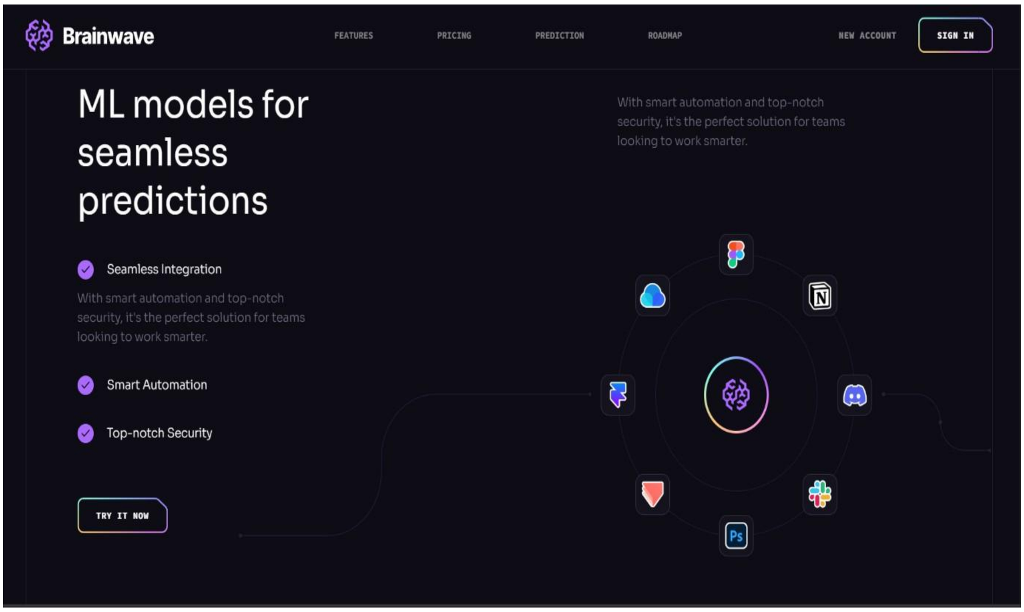
- User Authentication Module (MongoDB): Users can sign up and log in using email and password. Authentication is handled via Express backend with MongoDB as local storage for development and mongo atlas for production.

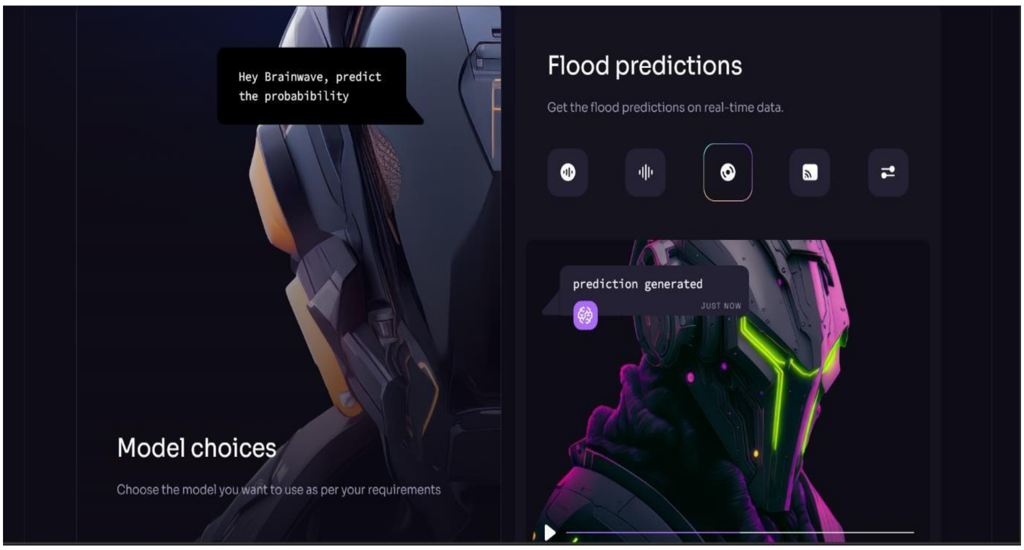
```
mydatabase> db.users.find()
[
  {
    _id: ObjectId('67ab4c81f56141350a3b0499'),
    name: 'Test User',
    email: 'test@example.com',
    password: '123456'
  },
  {
    _id: ObjectId('67ab5143eeb242329a8703e9'),
    name: 'John Doe',
    email: 'johndoe@example.com',
    password: '$2a$10$mjoBAT6PtxJRE0WPeOgN3.nDyMeZv/m5IVBciQpHsOrKb2SI8UJCm',
    __v: 0
  },
  {
    _id: ObjectId('67ab51adeeb242329a8703ec'),
    name: 'cat',
    email: 'cat@cat.com',
    password: '$2a$10$KjjDKGUkOJwVO/ySaa2VTeujQr8yMUxdjNXS1SkB64sVvN8ffocfi',
    __v: 0
  },
  {
    _id: ObjectId('67ab86a54af281bed8bf0b0f'),
    name: 'dog',
    email: 'dog@dog.com',
    password: '$2a$10$fTvDIv7/woHswMC9i145m.RJsbIcetNIux5olvKPERw6wA84UfUye',
    __v: 0
  },
```

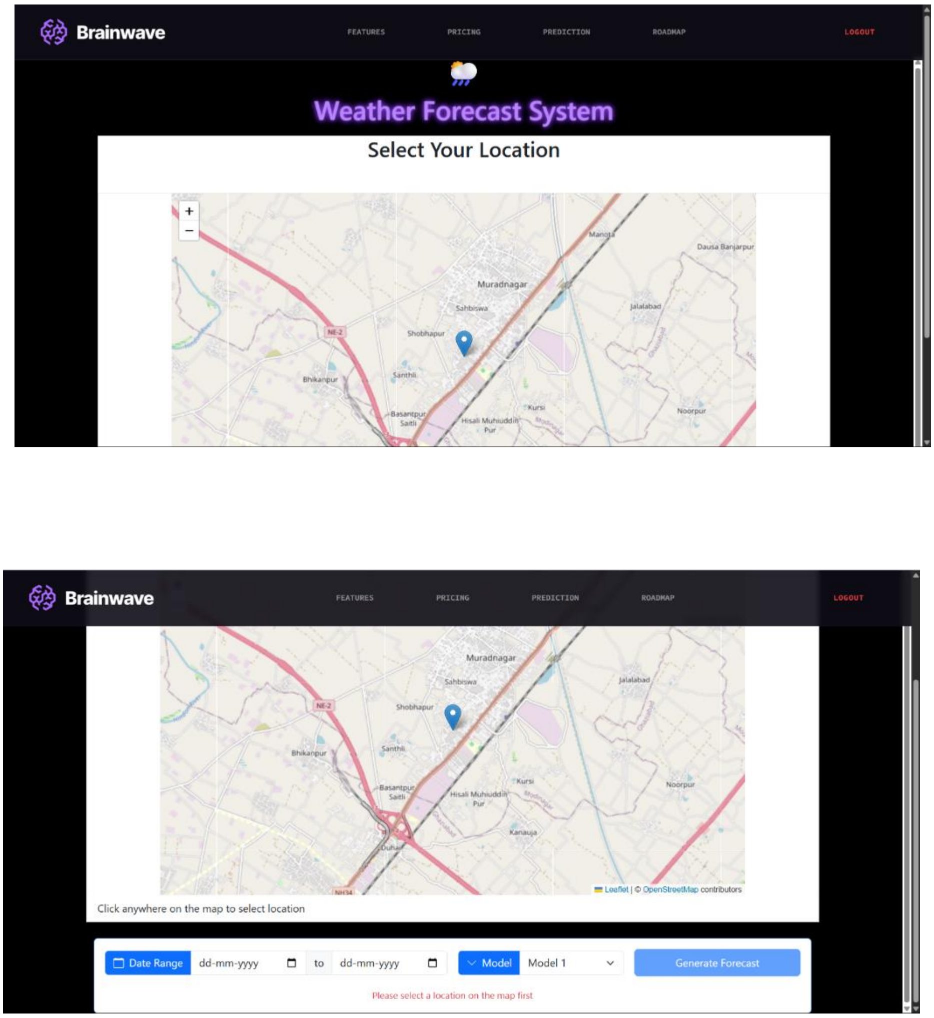
- Frontend: This module deals with designing and making a good frontend that follows good user experience and user interface norms.




Brainwave
FEATURES
PRICING
PREDICTION
ROADMAP
NEW ACCOUNT
SIGN IN
choose models
Lets user choose the models depending on their need and requirements.
EXPLORE MORE
Improve models
The app uses huggingface spaces which makes it easier to provide better models.
EXPLORE MORE
one click prediction
It takes only one click to predict the probability of flood occurence.
EXPLORE MORE
Fast responding
Lets users quickly find predictions.
user logins
only authorize users can use the service which makes it alot more secure.
Advance models
The app provides advance models which are mode with cutting-edge algorithms like logistic regression, neural networks, XGBoost


Brainwave
FEATURES
PRICING
PREDICTION
ROADMAP
NEW ACCOUNT
SIGN IN
ML models for seamless predictions
With smart automation and top-notch security, it's the perfect solution for teams looking to work smarter.
Seamless Integration
With smart automation and top-notch security, it's the perfect solution for teams looking to work smarter.
Smart Automation
Top-notch Security
TRY IT NOW


Hey Brainwave, predict the probabibility
Model choices
Choose the model you want to use as per your requirements
Flood predictions
Get the flood predictions on real-time data.
prediction generated
JUST NOW



<u>Fig-7.1(f)- frontend of website</u>

7.2 Presentation of Results

The system's performance was assessed using various evaluation metrics. The metrices that were used to evaluate the performance of model are Accuracy, Precision, Recall, F1 Score, AUC – ROC for logistic regression and neural networks, apart from these we also used MAE, R-squared score for XGBoost.

I - Evaluation matrices for different models:

Evaluation Metrics on Test Set:

	Metric	Score
0	Accuracy	0.9911
1	Precision	0.9915
2	Recall	0.9988
3	F1 Score	0.9951
4	AUC-ROC	0.9928

Table: 7.2(a)-Logistic regression

Evaluation Metrics on Test Set:

	Metric	Score
0	Accuracy	0.9944
1	Precision	0.9963
2	Recall	0.9976
3	F1 Score	0.9969
4	AUC-ROC	0.993

Table: 7.2(b)- Neural networks

ii – Confusion matrices:

Confusion Matrix:

Actual	Predicted No Flood	Predicted Flood
Actual No Flood	73	7
Actual Flood	1	818

Table: 7.2(c)- Logistic Regression

Confusion Matrix:

	Predicted No Flood	Predicted Flood
Actual No Flood	70	5
Actual Flood	0	4034

Table: 7.2(d)- Neural Network

iii – Feature Importance

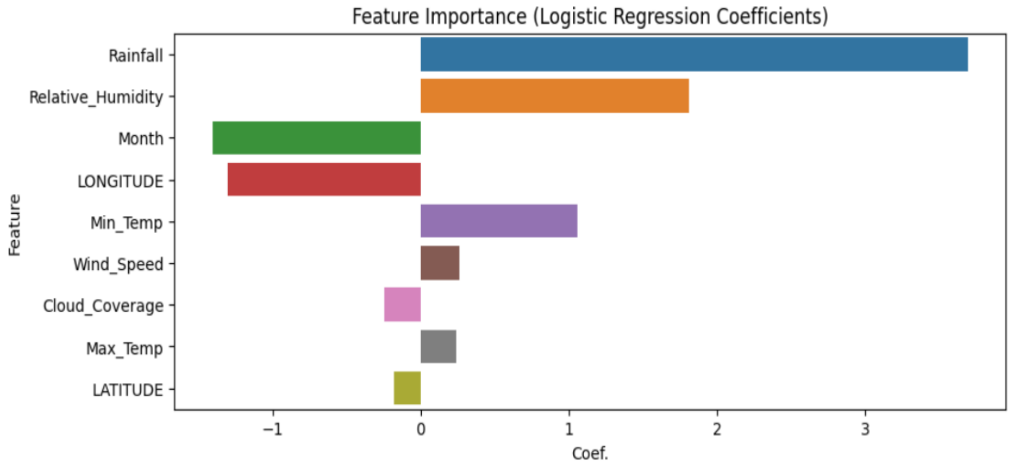


Fig: 7.2(a)- Feature importance (logistic regression)

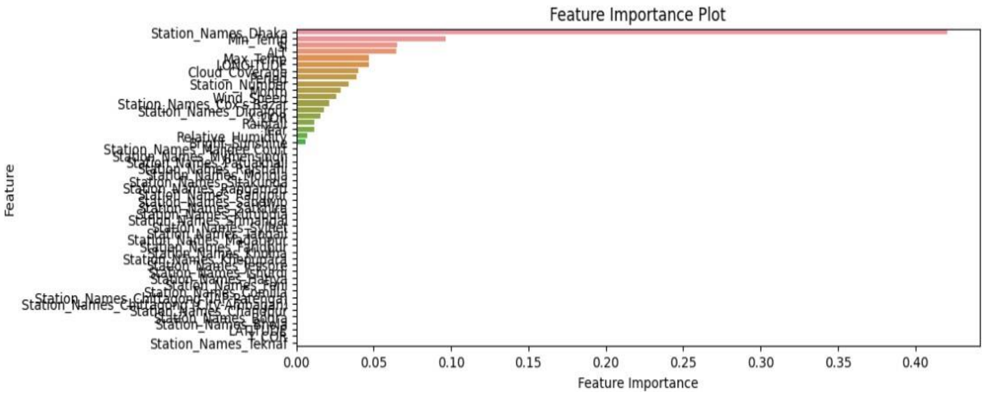


Fig: 7.2(b)- Feature importance (Neural Network)

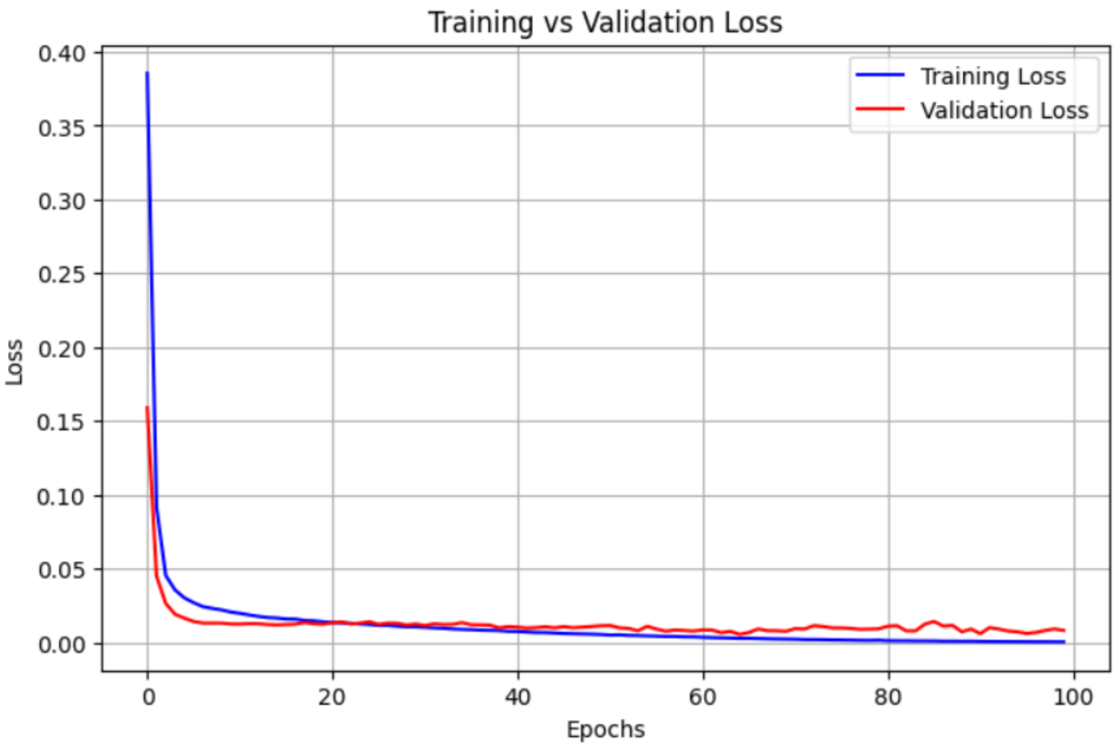


Fig: 7.2(c)- Training vs validation(test) Loss for neural networks

Iv – Results on user end:

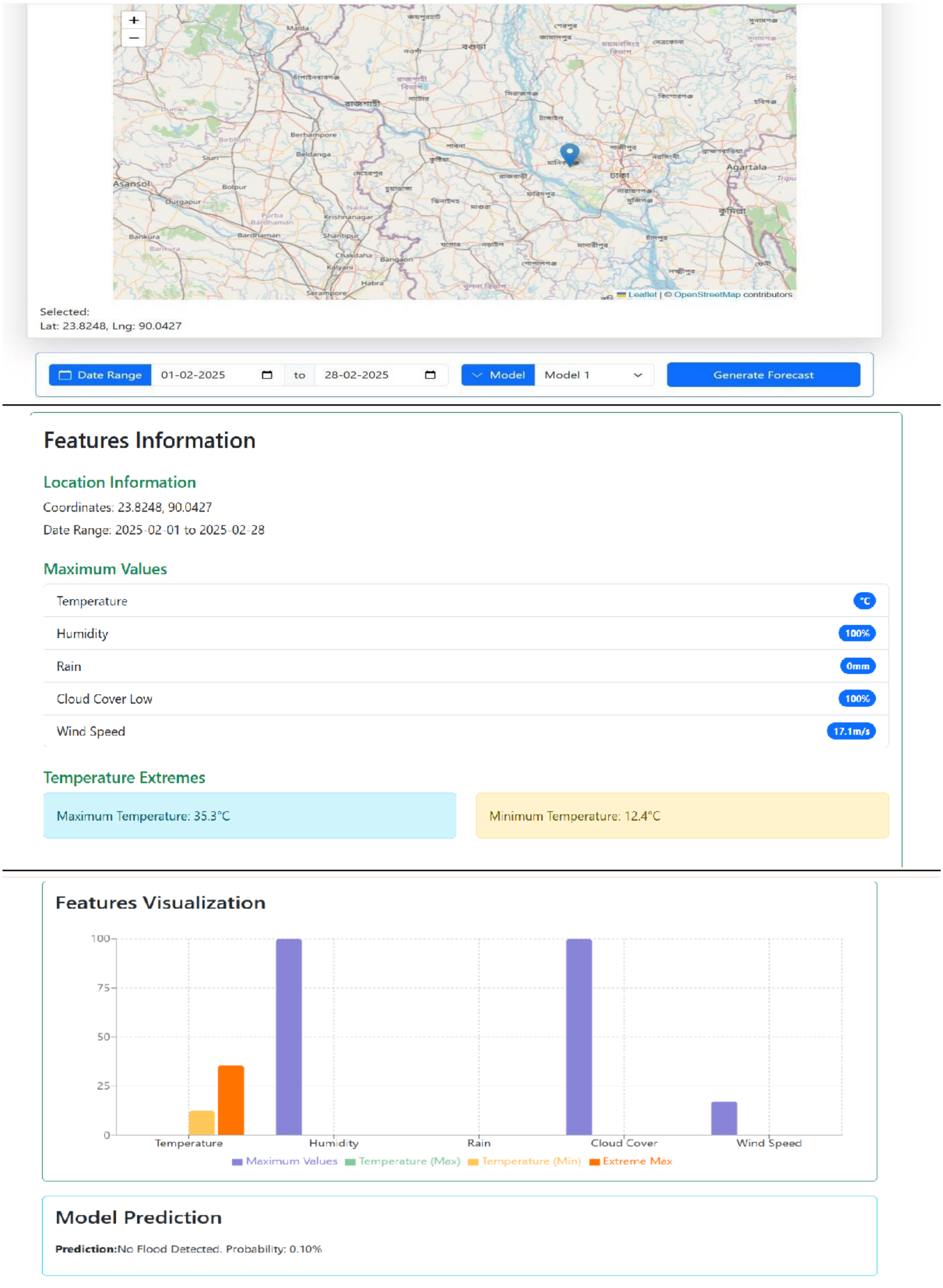


Fig-7.2(d)- results on user end:

7.3 Performance Evaluation

The system's performance was assessed using various evaluation metrics and parameters like inference time for training and testing, it helped in deciding which is better model. The tables of evaluation metrics are already provided in section7.2 . please refer to it for further information. The Inference time for training and testing time was calculated for both model Logistic Regression and neural networks. The results for which are shown below :

```
Training Time: 0.02 seconds
Inference Time: 0.0009 seconds per batch
```

Fig: 7.3(a)- Time analysis for Logistic Regression

```
Training Time: 18.71 seconds
Inference Time: 0.1741 seconds per batch
```

Fig: 7.3(b) - Time analysis for Neural Networks

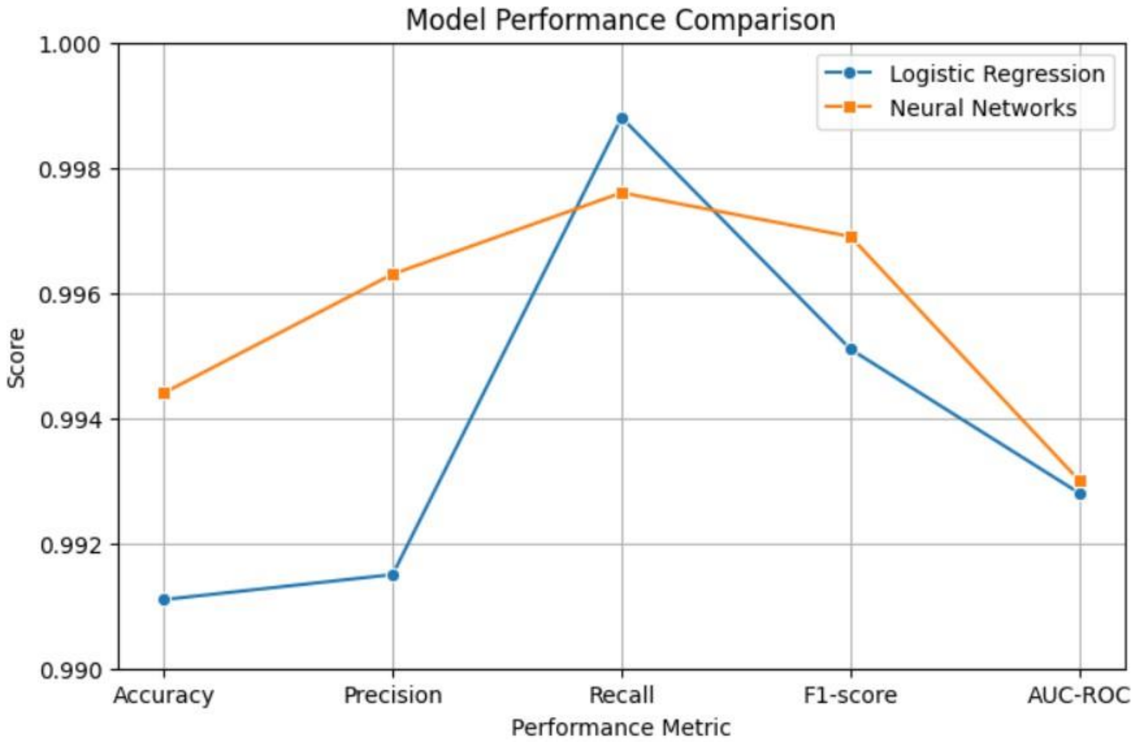


Fig: 7.3(c)- Evaluation metrices comparison for both models

7.4 Key Findings

The analysis of results led to several significant insights:

- High Predictive Accuracy: The models demonstrated strong classification performance, ensuring reliability in flood predictions, the accuracy of both model on testing data is above 95%.

- Geospatial Trends: The flood-prone regions were strongly correlated with factors such as location i.e station_name, also the temperature , and rainfall intensity, these are the factors which were playing a major role in flood preditions.

- Model Interpretability: Both models works really well but depending upon the parameters, we can choose any model. For easy deployment and less time for training and inference ,with high recall we can chose logistic regression model, but if we need a model with high precision than neural networks are giving better results as shown in fig-7.3(c).

- Scalability & Deployment Feasibility: The Hugging Face Gradio interface allowed seamless access to predictions, making the tool user-friendly for non-technical stakeholders.

- Resource Efficiency: Operated on low-end hardware (4GB RAM), ensuring accessibility in regions with limited infrastructure.

CHAPTER 8
CONCLUSION AND FUTURE SCOPE

8.1 Conclusion

This initiative has pioneered an advanced flood inundation probability mapping framework that inventively coordinating cutting-edge machine learning strategies, exactness geospatial analytics, and available web-based interfacing. The system leverages two robust predictive models, a logistic regression classifier and an artificial neural network trained on comprehensive geospatial datasets encompassing topographic elevation patterns, historical rainfall variability, and temperature fluctuations. Through deployment on Hugging Face's Gradio platform, the solution enables instantaneous flood risk visualization, transforming complex hydrological modeling into an intuitive public resource for communities, emergency responders, and policymakers.

Core Advancements and Outcomes:

<u>High-Precision Predictive Modeling</u>
The engineering illustrates extraordinary discriminative capability, accomplishing AUC-ROC scores surpassing 90% amid thorough cross-validation testing. This execution stems from orderly highlight designing of hydrologically critical factors and iterative optimization of show structures, guaranteeing dependable recognizable proof of high-risk zones beneath different climatic scenarios.

<u>Easy handling</u>
The platform's single-click operational plan dispenses with specialized boundaries through an intellectuals mapped facilitate input framework. Clients get localized surge probabilities (0-100%) by means of

intelligently maps matched with energetic chance seriousness markers, successfully bridging the hole between scholastic hydrology and community-level catastrophe preparedness.

Sustainable Innovation Framework

Developed only with open-source stack components including Python's Scikit-Learn for conventional ML, TensorFlow for profound learning usage. the framework illustrates replicability over creating locales. This approach decreases foundation costs by many folds compared to exclusive surge modeling program whereas keeping up enterprise-grade explanatory capabilities.

Strategic Impact:

By focalizing prescient analytics, geospatial insights, and cloud-based arrangement, the venture rises above ordinary hypothetical surge models that regularly stay kept to scholastic inquire about. Its real-time preparing motor adjusts to advancing climate designs through persistent information pipeline integration from meteorological APIs and fawning symbolism nourishes. This operational preparation positions the apparatus as a basic decision-support resource for urban organizers creating flood-resistant framework and calamity administration organizations optimizing crisis reaction conventions. The intrigue blend of information science and natural designing strategies builds up a modern worldview in proactive climate adjustment procedures, especially for flood-vulnerable locales missing progressed hydrological checking frameworks.

8.2 Future Scope

The system's capabilities can be significantly enhanced by expanding its geospatial coverage through training on global datasets, or we can train localized models for the locations with high flood chances and integrating high-resolution satellite imagery like Sentinel-1/2, while simultaneously improving prediction timeliness via real-time data streaming from IoT sensors such as river gauges and soil moisture probes; exploring advanced machine learning techniques including hybrid models (e.g., CNN- LSTM) coupled with uncertainty quantification would further boost prediction accuracy and reliability; developing a Progressive Web App (PWA) would ensure mobile-first accessibility even in offline conditions in remote areas, and incorporating crowdsourcing features would allow community participation in reporting flood incidents to refine model accuracy; additionally, simulating flood risks under future climate scenarios using IPCC data would aid in climate change adaptation planning, and partnering with disaster management agencies to integrate the tool into early- warning systems would maximize its policy impact and real-world utility.

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Paper Title

Interactive Flood Inundation Probability Mapping: A Web-Based Application with Machine Learning Models

Abstract

Flooding is the most common and destructive natural disaster globally, affecting millions of lives annually and causing significant economic losses. Flood forecasting is a critical aspect of disaster risk reduction and management. This study explores the application of machine learning techniques, particularly classificationbased models like logistic regression and gradient boosting algorithms (XGBoost, CatBoost), to predict flood likelihood. The research emphasizes the potential of machine learning methods to enhance flood hazard assessment and proposes the

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(57) Abstract :
The web-based flood probability prediction system combines machine learning and GIS to provide real-time flood risk predictions. The system utilizes the XGBoost algorithm with hyperparameter tuning and cross-validation to ensure accuracy. Users access the platform through a web browser to select specific locations on an interactive map and receive flood probability data alongside historical trends and risk levels. The system supports applications in urban planning, disaster management, and insurance risk assessments, enhancing decision-making and resource allocation. Its integration of real-time environmental data and a scalable, user-friendly interface make it a valuable tool for minimizing the impact of flooding on lives and property. Designed for governments, NGOs, urban planners, and individuals, the invention empowers proactive flood preparedness and mitigation efforts globally.

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