

RISING WATERS – A MACHINE LEARNING APPROACH TO FLOOD PREDICTION

1. Introduction

Floods are among the most destructive natural disasters worldwide, causing significant damage to life, infrastructure, and the economy. Rapid urbanization, climate change, and irregular rainfall patterns have increased the frequency and severity of floods in many regions.

Traditional flood monitoring systems rely on manual observation and weather reports, which are reactive rather than predictive. These methods often result in delayed warnings and insufficient preparedness.

With advancements in Artificial Intelligence and Machine Learning, predictive analytics can analyze historical rainfall and environmental parameters to forecast flood occurrence in advance.

This project focuses on developing a **Machine Learning-based Flood Prediction System** that classifies flood risk based on rainfall and climate parameters. The system provides instant prediction results through a web-based interface.

2. Project Overview

The objective of this project is to design and develop an AI-powered flood prediction system using classification algorithms.

The system consists of two major components:

- Machine Learning Model
- Web Application Interface

The ML model is trained using classification algorithms such as:

- Random Forest
- XGBoost

The web application allows users to:

- Enter rainfall and environmental parameters
- Submit data
- Receive prediction result (Flood / No Flood)

Key highlights:

- Use of ensemble learning techniques
- Real-time prediction
- Flask-based backend
- Responsive frontend interface
- Model performance evaluation

3. Architecture

The architecture is divided into three main layers:

1. Frontend Layer
2. Backend Layer
3. Data Layer

Frontend Architecture

The frontend is designed using **HTML, CSS, and Bootstrap**. It provides a clean, responsive, and user-friendly interface tailored for flood risk prediction.

The UI includes the following elements:

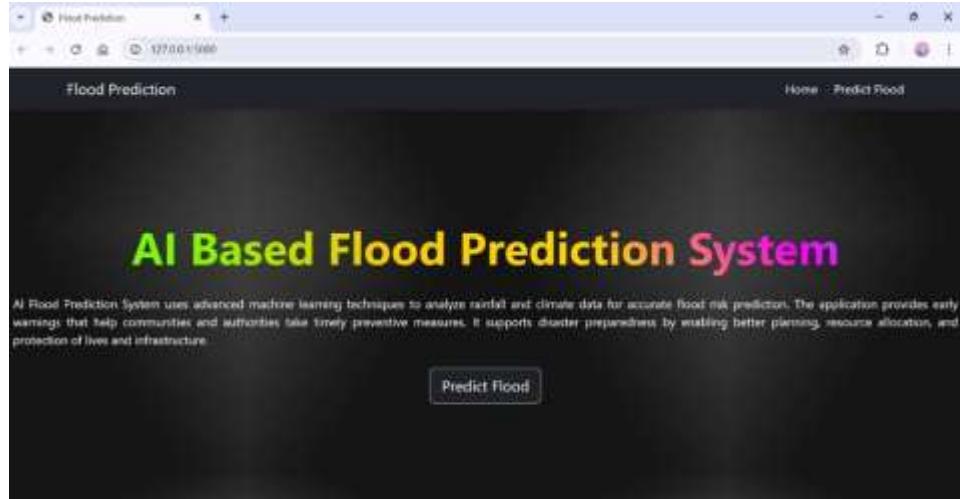
- Responsive input form for rainfall and climate parameters
- Styled cards for displaying prediction results
- Alert-based output display (Flood / No Flood)
- Clean dashboard layout
- Input validation messages
- Simple and intuitive design for ease of use

The frontend handles user interactions such as:

- Entering rainfall and environmental parameters
- Submitting prediction request
- Displaying classification results

Once the user submits the input values, the form sends a **POST request** to the Flask backend server for processing and prediction.

The design follows a responsive layout to ensure compatibility across:
Desktop, Laptop, Tablet, Mobile devices



Backend Architecture

The backend is developed using **Flask**, a lightweight Python web framework.

It performs the following tasks:

- Loads the trained Machine Learning model (.pkl file)
- Loads the scaler file for preprocessing
- Validates user input
- Applies feature scaling
- Runs classification prediction
- Sends prediction results back to frontend

Preprocessing Steps:

1. Receive user input parameters
2. Convert input values into numerical format
3. Transform data into NumPy array
4. Apply StandardScaler (feature scaling)
5. Pass processed data to trained ML model

The model outputs classification result:

- 0 → No Flood
- 1 → Flood

The final result is returned and displayed to the user through the web interface.



```
app.py
Project Files > app.py
1  from flask import Flask, render_template, request
2  import numpy as np
3  import joblib
4
5  app = Flask(__name__)
6
7  model = joblib.load("xg_flood_model.pkl")
8  xg_scaler = joblib.load("xg_scaler.pkl")
9
10 @app.route('/')
11 def home():
12     return render_template('index.html')
13
14 @app.route('/predict_page')
15 def predict_page():
16     return render_template('predict.html')
17
18 @app.route('/predict', methods=['POST'])
19 def predict():
20
21     data = [
22         float(request.form['cloud']),
23         float(request.form['annual']),
24         float(request.form['janfeb']),
25         float(request.form['marchmay']),
26         float(request.form['junsep'])
27     ]
28
29     df = np.array([data])
30     scaled = xg_scaler.transform(df)
31     pred = model.predict(scaled)[0]
32
33     result = "Flood Expected" if pred == 1 else "No Flood"
34
35     return render_template('predict.html', prediction=result)
36
37 if __name__ == "__main__":
38     app.run(debug=True)
```

Data Layer

- Flood dataset (CSV)
- Trained ML model
- Scaler file

Data Flow:

User → Web Form → Flask Backend → ML Model → Prediction → Display Result

4. Setup Instructions

4.1 Prerequisites

- Python 3.8+
- pip
- Flask
- Scikit-learn
- XGBoost
- Pandas
- NumPy

4.2 Installation Steps

Step 1: Clone repository

Step 2: Create virtual environment

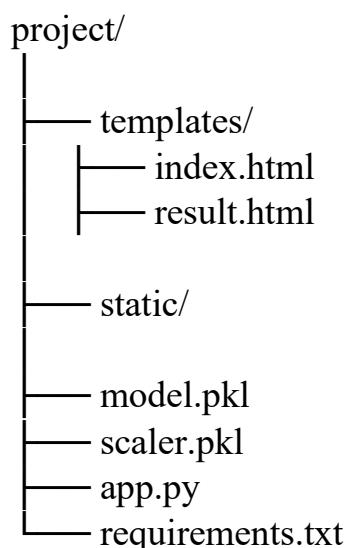
Step 3: Install dependencies

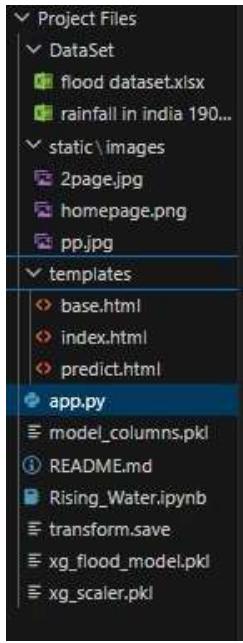
pip install -r requirements.txt

Step 4: Place trained model file (.pkl)

Step 5: Run python app.py

5. Folder Structure





6. Running the Application

- Activate virtual environment
- Run python app.py
- Open browser
- Navigate to http://127.0.0.1:5000
- Enter rainfall inputs
- View prediction

```
PS C:\Users\lalit\Desktop\APSDH-AIR_1784\Project Files> python app.py
c:/users/lalit/anaconda3\lib/pickle.py:1268: userWarning: [13:17:58] WARNING: c:\actions-runner\_work\xgboost\xgboost\src\gbm\../common/error_msg.h:83: If you are loading a serialized model (like pickle in Python, RDS in R) or
configuration generated by an older version of xgboost, please export the model by calling
'm booster.save model' from that version first, then load it back in current version. See:
https://xgboost.readthedocs.io/en/stable/tutorials/saving_model.html

for more details about differences between saving model and serializing.

setstate(state)
* Serving Flask app "app"
* Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on http://127.0.0.1:5000
Press CTRL+C to quit
* Restarting with watchdog (windowsapi)
C:\Users\lalit\anaconda3\lib/pickle.py:1268: userWarning: [13:18:02] WARNING: c:\actions-runner\_work\xgboost\xgboost\src\gbm\../common/error_msg.h:83: If you are loading a serialized model (like pickle in Python, RDS in R) or
configuration generated by an older version of xgboost, please export the model by calling
'm booster.save model' from that version first, then load it back in current version. See:
https://xgboost.readthedocs.io/en/stable/tutorials/saving_model.html

for more details about differences between saving model and serializing.

setstate(state)
* Debugger is active!
* debugger PID: 668-462-095
127.0.0.1 - - [20/Feb/2026 13:18:16] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [20/Feb/2026 13:18:16] "GET /static/images/pp.jpg HTTP/1.1" 200 -
127.0.0.1 - - [20/Feb/2026 13:18:16] "GET /favicon.ico HTTP/1.1" 404 -
```

7. API Documentation

GET /

Loads homepage.

POST /predict

Accepts input parameters:

- Rainfall
- Temperature
- Humidity
- Other features

Returns:

- Flood / No Flood

8. Testing

Functional Testing

- Input validation
- Prediction accuracy
- UI testing

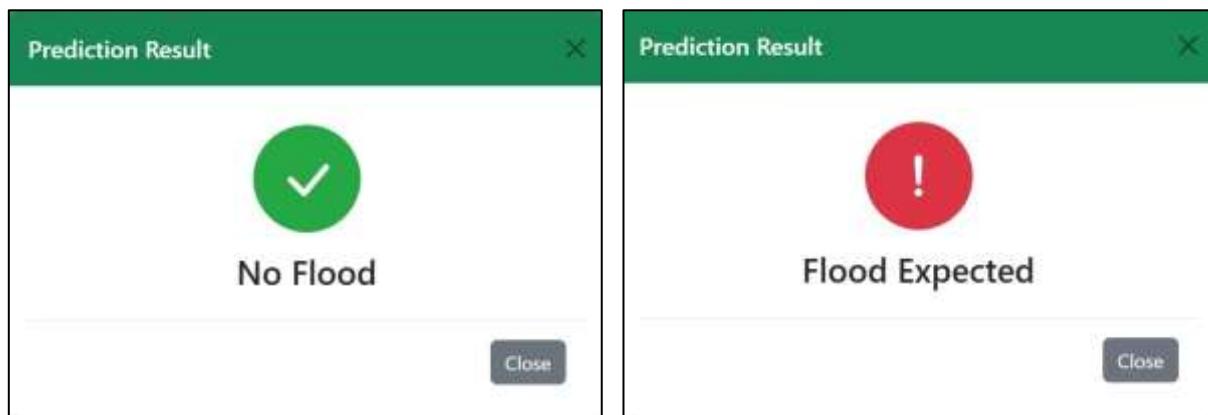
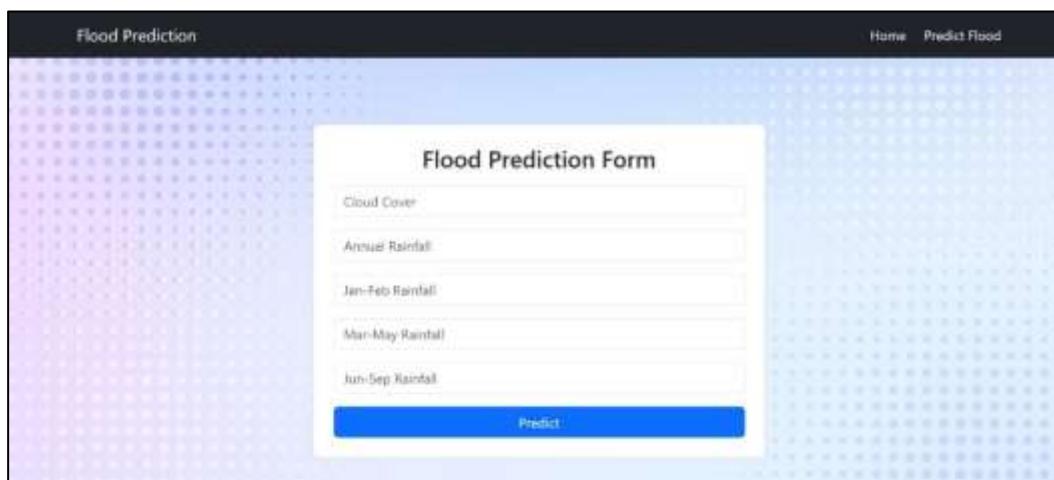
Model Testing

- Accuracy score
- Precision
- Recall
- Confusion matrix

Performance Testing

- Response time < 2 seconds
- Model loading speed

9. Results



10. Known Issues

- Depends on dataset quality
- Local deployment only
- No real-time weather API
- Cloud integration not implemented

11. Future Enhancements

- Real-time weather API integration
- SMS flood alerts
- AWS deployment
- Dashboard visualization
- Mobile application version

12. Conclusion

The Rising Waters Flood Prediction System demonstrates the real-world application of Machine Learning in disaster management. By integrating classification algorithms with a web interface, the system provides early flood risk prediction and supports proactive planning.

With further improvements and cloud deployment, the system can be scaled for large-scale disaster management usage.