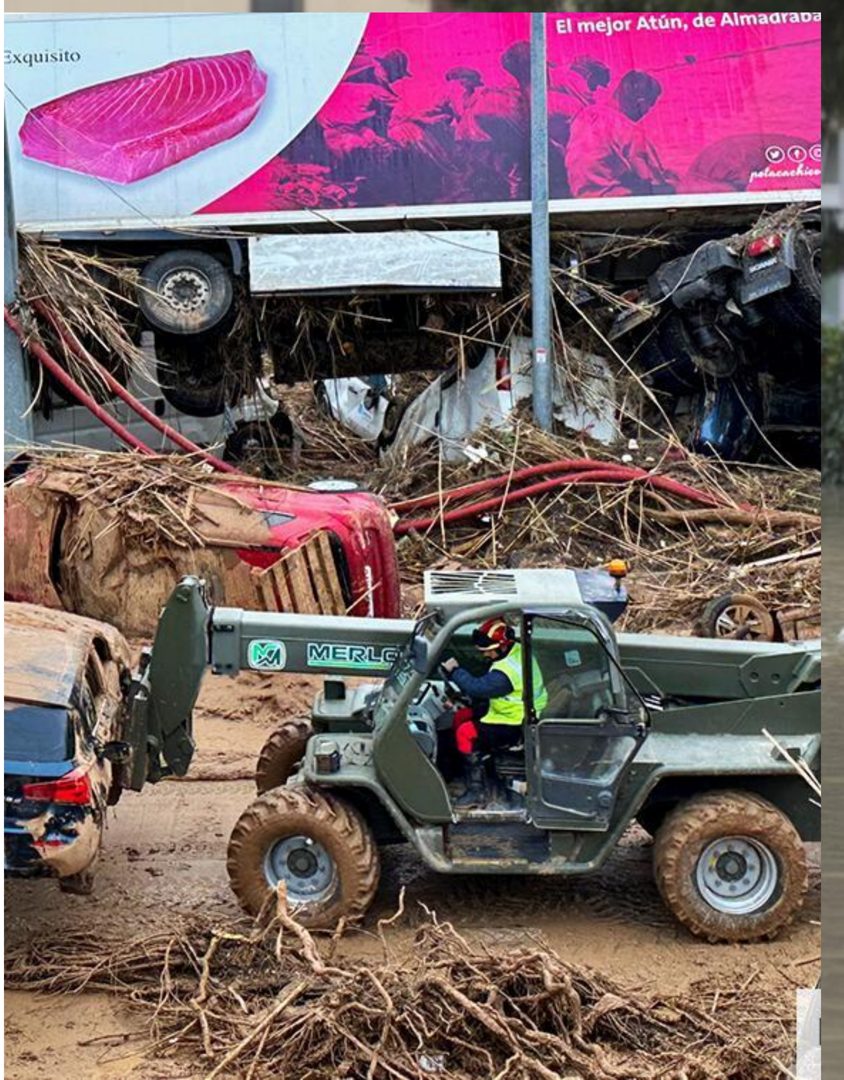
Securing *Tomorrow*: Machine Learning in Flood Risk Mitigation

Team 10
Xiaolin(Jessica) Xu, Patrick Richey, Surosh Kumar, Esther Abel

Reliable Flood Prediction Supports Resources Allocation

- Global Flood Risk Exposure: Approximately 1.47 billion people, or nearly 20% of the global population, are currently exposed to flood risks, including river, coastal, and urban flooding.
- High-Risk Populations: Over one-third of these individuals face potentially devastating flooding, with severe consequences for communities, economies, and lives.
- Economic Vulnerability: Many of the people at risk are located in low- and middle-income countries, where flood resilience and response infrastructure are often insufficient, increasing vulnerability.

Reference：https://blogs.worldbank.org/en/climatechange/147-billion-people-face-flood-risk-worldwide-over-third-it-could-be-devastating



Conceptual_Model

This conceptual machine-learning model leverages meteorological data to enhance flood prediction and management, focusing on flood accuracy. Using a dataset of different variables such rainfall,temperature, humidity, wind_speed,climate_change Index, urbanization, the model identifies patterns and relationships that impact flood risk. By employing logistic, decision tree, SVM, and Neural Networks, the model captures both spatial and temporal dynamics to improve the accuracy of flood occurrence predictions.

Outputs support decision-makers by enabling timely preventive actions, optimized resource allocation, and resilient infrastructure planning, aiming to protect communities, save lives, and minimize flood-related damage.

Business_Problem

Objective

Develop reliable flood prediction models for proactive response.

Target Users - this dataset looks at Bangladesh

Ideally support local governments and emergency management agencies.

Key Benefits:

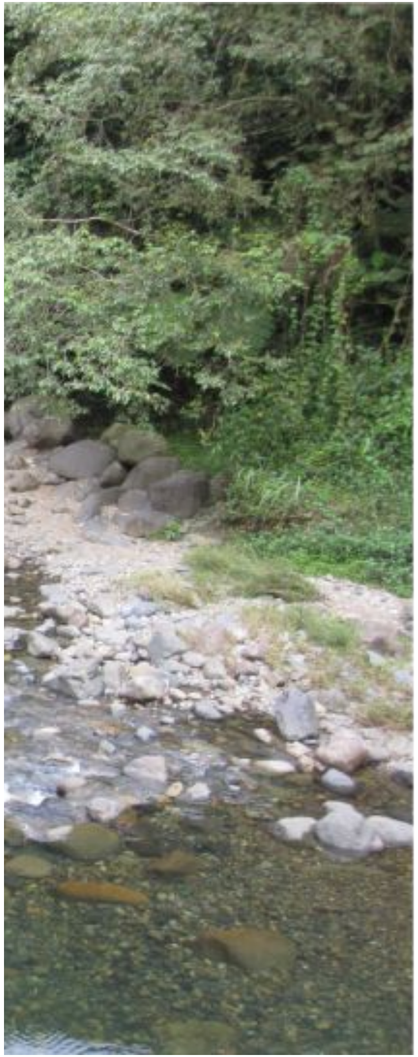
- Enhanced Public Safety
- Resource Allocation
- Infrastructure Protection
- Economic Impact Reduction
- Community Resilience
- Cost Efficiency

Outcome

Reduced human and financial impacts of flooding events through precise, actionable flood forecasts.

Machine Learning Problem

1. **Binary Classification Problem**
   - Predicts flood occurrence: **Yes** or **No**
   - Assesses flood risk levels based on historical trends.
2. **Historical Data Analysis**
   - Leverages past weather, river data, and soil metrics.
3. **Modeling Complex Relationships**
   - Factors include **rainfall**, **river discharge**, **soil moisture**, and **land use**.



Type of Learning

Supervised Learning Approach

- Uses historical flood data for training.

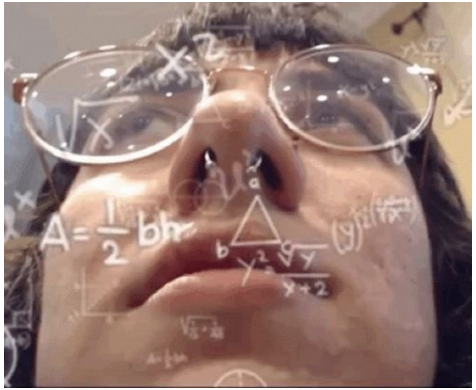
Target Variable

- *Flood Prediction (Yes/No)*

Data-Driven Prediction

- Relies on labeled data to identify flood patterns.

ML Task Model



Primary ML Tasks

- **Classification**: Determines if a flood event will occur (Yes/No)

ML Models to test

- **Logistic** for baseline
- **Decision Tree** (tree)
- **Support Vector Machine** (kernel)
- **Neural Networks** (deep learning)

Use metrics like

- Accuracy
- Precision
- Recall
- F1-score-AUC

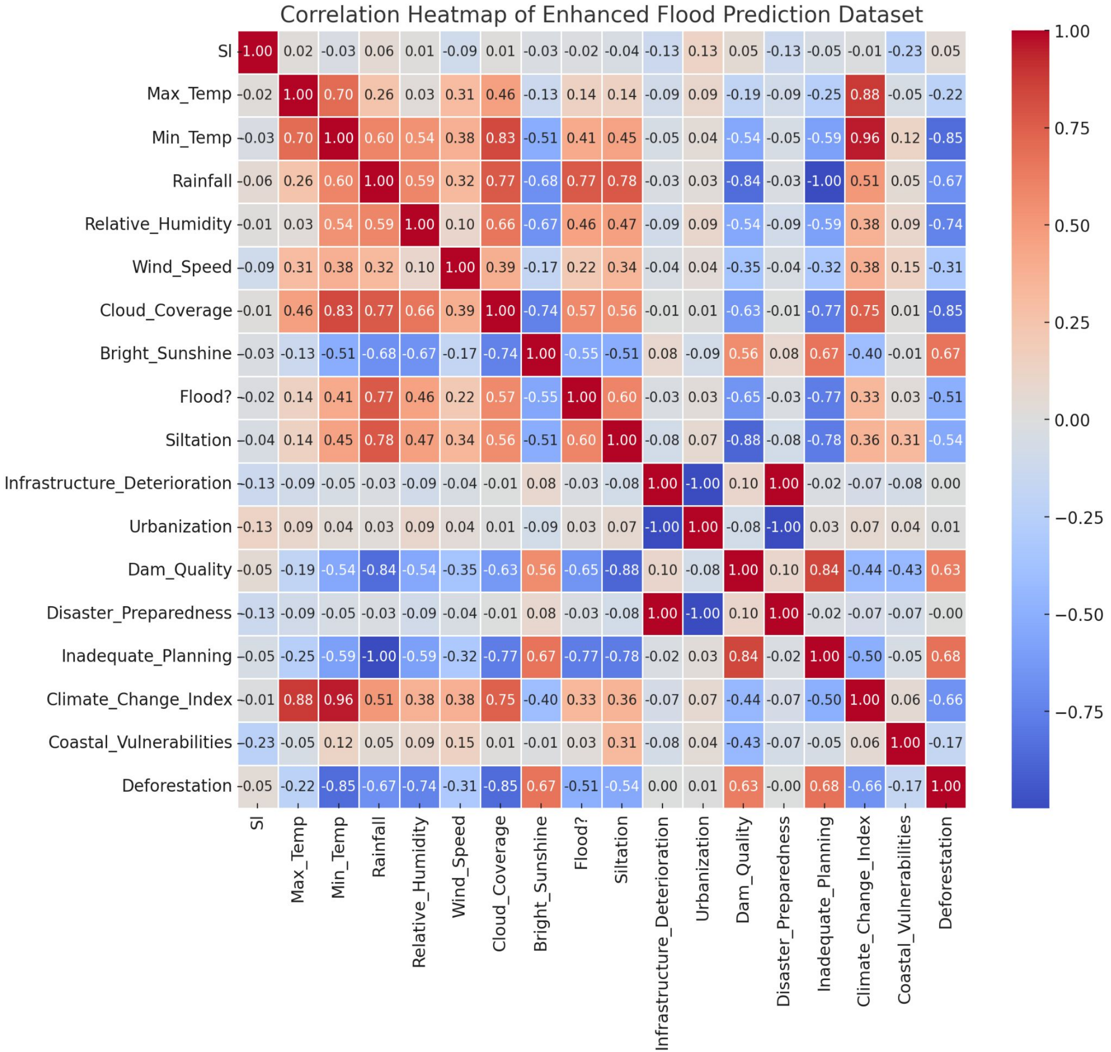
sample_data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Sl	Station_Na	Year	Month	Max_Temp	Min_Temp	Rainfall	Relative_H	Wind_Spee	Cloud_Cov	Bright_Sun	Station_Nu	X_COR	Y_COR	LATITUDE	LONGITUD	ALT	Period	Flood?
2	0	Barisal	1949	1	29.4	12.3	0	68	0.453704	0.6	7.831915	41950	536809.8	510151.9	22.7	90.36	4	1949.01	0
3	1	Barisal	1949	2	33.9	15.2	9	63	0.659259	0.9	8.314894	41950	536809.8	510151.9	22.7	90.36	4	1949.02	0
4	2	Barisal	1949	3	36.7	20.2	8	59	1.085185	1.5	8.131915	41950	536809.8	510151.9	22.7	90.36	4	1949.03	0
5	3	Barisal	1949	4	33.9	23.9	140	71	1.772222	3.9	8.219149	41950	536809.8	510151.9	22.7	90.36	4	1949.04	0
6	4	Barisal	1949	5	35.6	25	217	76	1.703704	4.1	7.046809	41950	536809.8	510151.9	22.7	90.36	4	1949.05	0
7	5	Barisal	1949	6	34.4	25.7	512	80	1.631481	5.6	4.07234	41950	536809.8	510151.9	22.7	90.36	4	1949.06	1
8	6	Barisal	1949	7	33.4	25.8	575	85	1.57037	5.4	3.738298	41950	536809.8	510151.9	22.7	90.36	4	1949.07	1
9	7	Barisal	1949	8	33.5	25.7	349	86	1.32963	5.6	4.27234	41950	536809.8	510151.9	22.7	90.36	4	1949.08	1
10	8	Barisal	1949	9	34.8	25.7	252	83	0.937037	4.8	4.823404	41950	536809.8	510151.9	22.7	90.36	4	1949.09	0
11	9	Barisal	1949	10	34	24.7	128	78	0.490741	3.1	7	41950	536809.8	510151.9	22.7	90.36	4	1949.1	0
12	10	Barisal	1949	11	31.5	17.4	41	68	0.312963	0.9	7.851064	41950	536809.8	510151.9	22.7	90.36	4	1949.11	0
13	11	Barisal	1949	12	29.7	12.5	0	66	0.337037	0.3	7.725532	41950	536809.8	510151.9	22.7	90.36	4	1949.12	0
14	12	Barisal	1950	1	30	14.1	0	77	0.453704	0.8	7.831915	41950	536809.8	510151.9	22.7	90.36	4	1950.01	0
15	13	Barisal	1950	2	31.7	16.6	90	76	0.659259	1.7	8.314894	41950	536809.8	510151.9	22.7	90.36	4	1950.02	0
16	14	Barisal	1950	3	36.1	20.5	13	70	1.085185	2.9	8.131915	41950	536809.8	510151.9	22.7	90.36	4	1950.03	0
17	15	Barisal	1950	4	37.2	24.2	66	75	1.772222	3.3	8.219149	41950	536809.8	510151.9	22.7	90.36	4	1950.04	0
18	16	Barisal	1950	5	36.1	25.5	87	78	1.703704	4.8	7.046809	41950	536809.8	510151.9	22.7	90.36	4	1950.05	1
19	17	Barisal	1950	6	33.9	26	476	87	1.631481	7.2	4.07234	41950	536809.8	510151.9	22.7	90.36	4	1950.06	1
20	18	Barisal	1950	7	32.2	25.9	546	89	1.57037	6.8	3.738298	41950	536809.8	510151.9	22.7	90.36	4	1950.07	1
21	19	Barisal	1950	8	32.8	25.6	337	90	1.32963	7.4	4.27234	41950	536809.8	510151.9	22.7	90.36	4	1950.08	1
22	20	Barisal	1950	9	33.9	26.4	187	84	0.937037	6.5	4.823404	41950	536809.8	510151.9	22.7	90.36	4	1950.09	0
23	21	Barisal	1950	10	33.3	24.5	339	85	0.490741	5.8	7	41950	536809.8	510151.9	22.7	90.36	4	1950.1	1
24	22	Barisal	1950	11	32.9	18.6	98	73	0.312963	2.9	7.851064	41950	536809.8	510151.9	22.7	90.36	4	1950.11	0
25	23	Barisal	1950	12	30.1	14	0	68	0.337037	1.5	7.725532	41950	536809.8	510151.9	22.7	90.36	4	1950.12	0
26	24	Barisal	1951	1	28.2	12.3	0	77	0.453704	0.6	7.831915	41950	536809.8	510151.9	22.7	90.36	4	1951.01	0
27	25	Barisal	1951	2	32.3	16	0	76	0.659259	0.6	8.314894	41950	536809.8	510151.9	22.7	90.36	4	1951.02	0
28	26	Barisal	1951	3	35.6	21.5	67	70	1.085185	4	8.131915	41950	536809.8	510151.9	22.7	90.36	4	1951.03	0
29	27	Barisal	1951	4	36.7	24.3	137	75	1.772222	4.6	8.219149	41950	536809.8	510151.9	22.7	90.36	4	1951.04	0

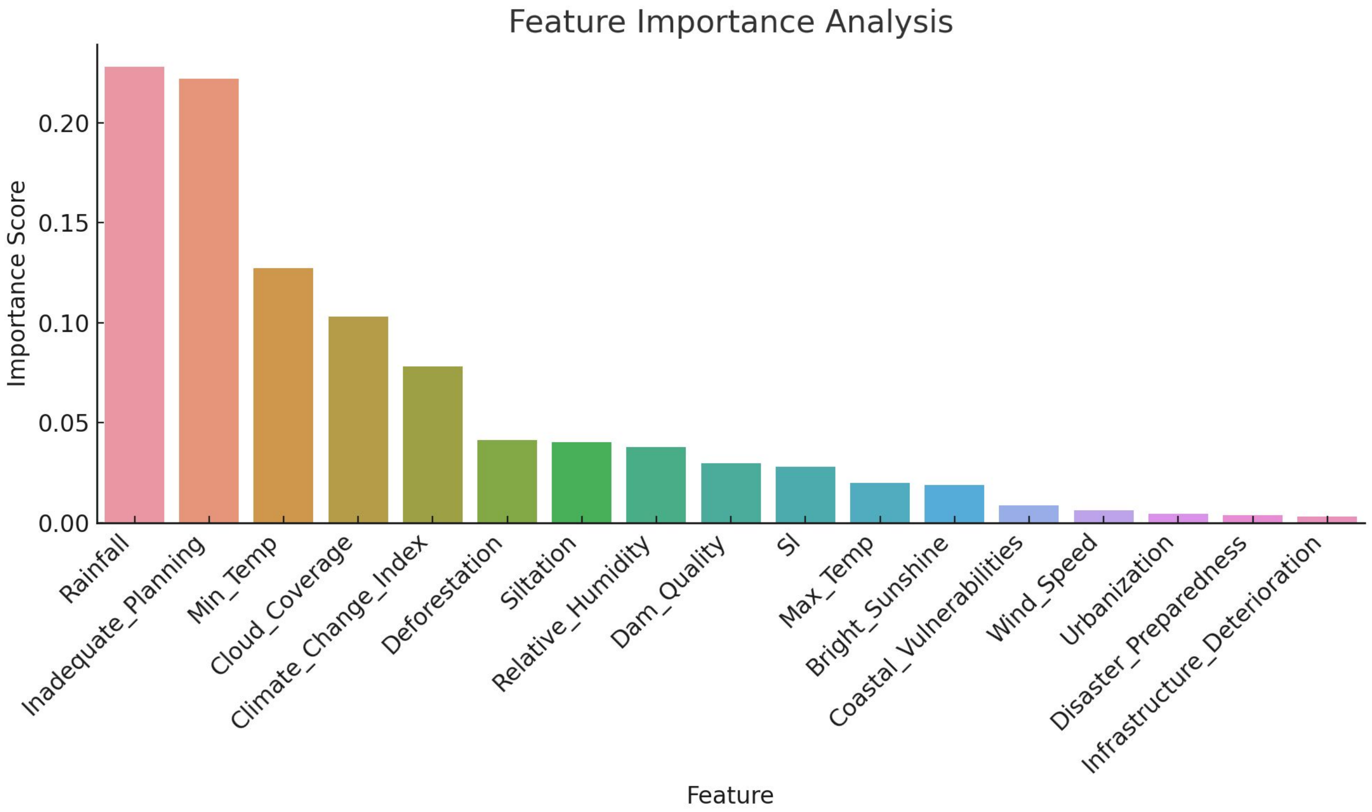
Target_variable = flood?

Key Insights

- **Climate Change Index** and **Flood Occurrence** = strong positive correlation, indicating a significant relationship.
- **Urbanization** and **Inadequate Planning** are highly correlated, which is logical given their conceptual overlap.
- **Dam Quality** and **Disaster Preparedness** show negative correlations with flood occurrence, suggesting they help mitigate flood risks.
- **Siltation**, **Deforestation**, and **Coastal Vulnerabilities** also have moderate to strong correlations with flooding.



Useful_Features



business _value?

Industries impacted (some)

- Agriculture
- Insurance
- Construction and Real Estate
- Logistics and Transportation
- Utilities and Energy
- Governments and Emergency Services
- Finance and Investments
- Tourism and Hospitality
- Environmental Conservation
- Manufacturing

- Risk Mitigation
- Operational continuity
- Insurance optimization and investment protection
- Disaster response

Conclusion / Advancement opportunities (room for improvement)

Accurate and timely warnings are critical for mitigating flood risks

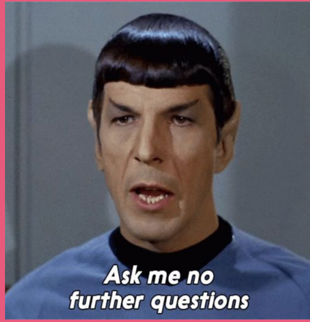
Logistic vs Decision Tree vs SVM vs Neural Networks

Future Plans?

- **Enhanced Prediction Reliability**: Achieve high reliability in forecasting extreme riverine events, particularly in **ungauged watersheds**, with up to a **five-day lead time**—matching or surpassing current nowcast (zero-day lead time) performance.
- **Expanded Flood Warning Coverage**: Provide **earlier and more extensive flood warnings**, especially for **large-scale and impactful events** in ungauged basins, improving risk mitigation in vulnerable areas.
- **Integration with Public Early Warning Systems**: Incorporate the model into an **operational, real-time forecasting system** that offers **free and open access** to flood predictions, serving over **80 countries** and supporting global disaster preparedness.

QUESTIONS?


can we skip this
question please


Ask me no
further questions