Flood Probability Regression with a Hybrid Ensemble w/ Uncertainty Quantification

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Problem Statement and Motivation

Goal: Develop a predictive, robust model(s) for determining the likelihood of a flood (percent chance of an area to flood)

Motivation: Flood frequency and severity has been rising due to climate change. Reliable systems that can predict these events in advance can help communities plan and mitigate disasters.

Understanding Uncertainty in Predictions

- Machine Learning models make predictions, but how **confident** are they?
    - A prediction of **80% flood risk** means something entirely different if the model is highly confident vs. uncertain
- **Types of Uncertainty:**
    - **Aleatoric Uncertainty (Data Uncertainty):** Noise in the data; Inherent to the task
    - **Epistemic Uncertainty (Model Uncertainty):** How much the model doesn't know due to a lack of training data.
- **Why does it matter?**
    - **High-confidence predictions ->** Trust the model's output
    - **High-uncertainty predictions ->** Need more investigation, can't take results for face value
- **Proposed Approach:** Compute uncertainty estimates using **Monte Carlo Dropout** & **Bootstrap Variance** in Ensemble Learning

Dataset Source & Description

- **Source:** Kaggle Flood Dataset
- **Key Details:** Dataset consists of 1.12m instances and 21 features, all numerical.
- **Key Features:**
  - **Environmental Factors:** Monsoon intensity, watershed count.
  - **Geographic & Infrastructure:** Drainage systems, river management.
  - **Human Impact Factors:** Urbanization, deforestation.
- **Target Variable:** Flood Probability (Continuous values from 0 to 1)
- **Data Preprocessing:**
  - Feature Scaling: Standardized using z-score normalization.
  - Outliers: Removed using IQR

Ensemble Learning: Deep Neural Network (DNN)

Architecture:

- **Input Layer:** 21 features
- **Hidden Layers:** 2 Dense Layers (64->32 neurons)
- **Activation:** ReLU
- **Dropout Layers:** 30% dropout to improve generalization
- **Output Layer:** Single neuron (linear activation) -> **Flood Probability (0-1)**

Uncertainty Estimation: Monte Carlo Dropout:

- Run Model **T** times
- Randomly drop neurons each run, giving slightly different outputs

Mean Prediction:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} \hat{y}_t$$

Uncertainty (Variance) Prediction:

$$\sigma^2 = \frac{1}{T} \sum_{t=1}^{T} (\hat{y}_t - \hat{y})^2$$

If predictions **vary a lot**, uncertainty is **high**. If they are **stable,** uncertainty is **low.**

Ensemble Learning: Gradient Boosting Machine (GBM)

How GBM Works:

- Uses **decision trees** to repeatedly improve weak models.
- Each tree focuses on correcting errors from the last one.
- Outputs a **weighted sum of trees.**

Uncertainty Estimation: Bootstrapped Variance:

- Train multiple GBM models on different randomized subsets of the data
- Collect predictions from all the models and compute:

Mean

$$\hat{y}_{GBM} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_{GBM}^{(i)}$$

Variance

$$\sigma^2_{GBM} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}GBM^{(i)} - \hat{y}GBM)^2$$

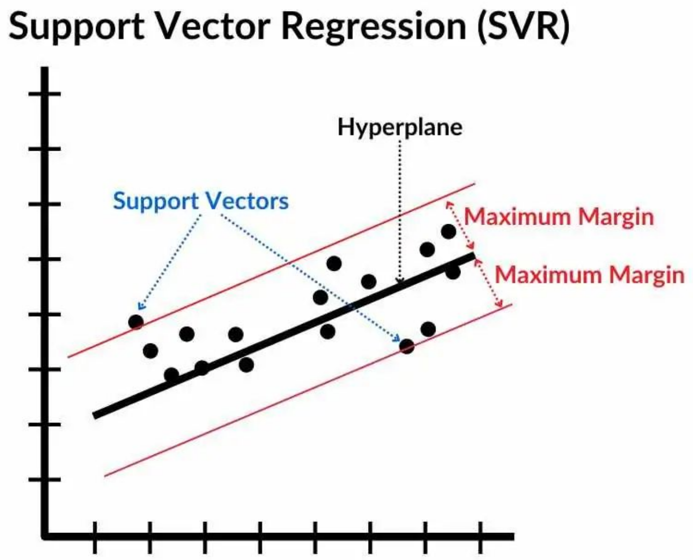
Ensemble Learning: Support Vector Regression (SVR)

How SVRs work:

- Find the best hyperplane that fits the flood probability
- Uses kernel trick to capture non-linearity

Uncertainty Estimation: Bootstrap Sampling

- Train multiple SVR models on different resampled datasets
- Use variance across models as uncertainty estimate



Model Aggregation

Each model provides a prediction + uncertainty estimate.

Uncertainty-Weighted Averaging:

More confident models **(lower variance)** contribute more:

$$\mathrm{w}_i = min(\frac{1}{max(\sigma_i,\epsilon)}, \delta), \epsilon = 1e-15, \delta = 1e15$$

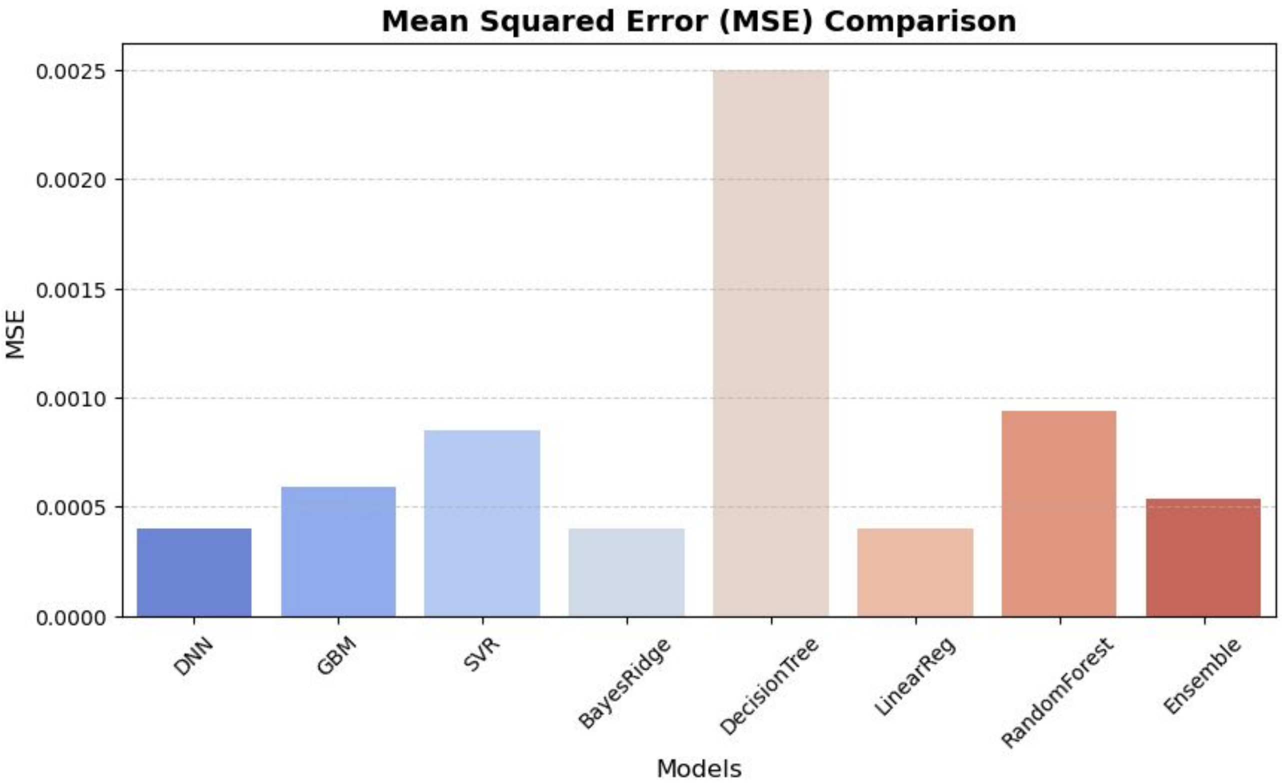
Final prediction:

$$\mathrm{p}_{ensemble} = \sum w_i p_i$$

Performance Comparison

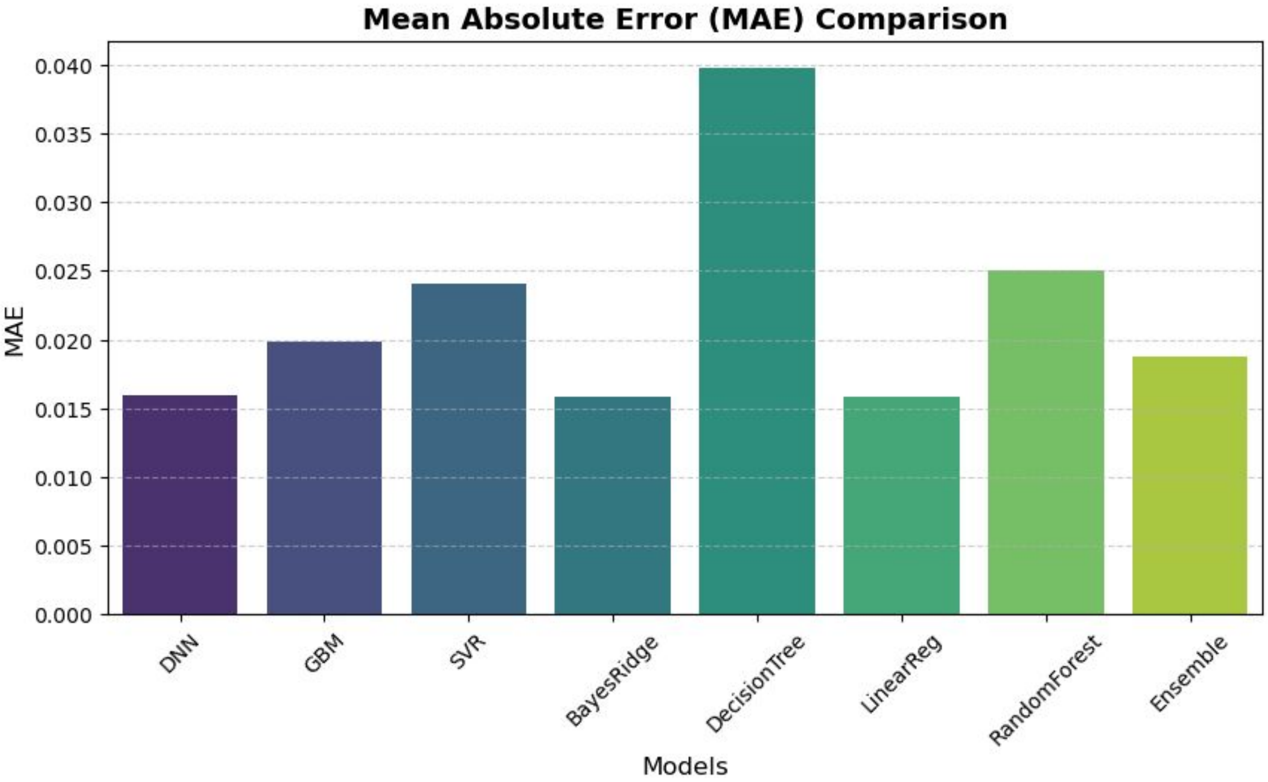
	MSE	MAE	R2 Score
DNN	0.00040	0.01595	0.84504
GBM	0.00059	0.01987	0.77274
SVR	0.00085	0.02409	0.67283
BayesRidge	0.00040	0.01580	0.84434
DecisionTree	0.00250	0.03979	0.03739
LinearReg	0.00040	0.01580	0.84434
RandomForest	0.00094	0.02503	0.63808
Ensemble	0.00054	0.01877	0.79343

Results



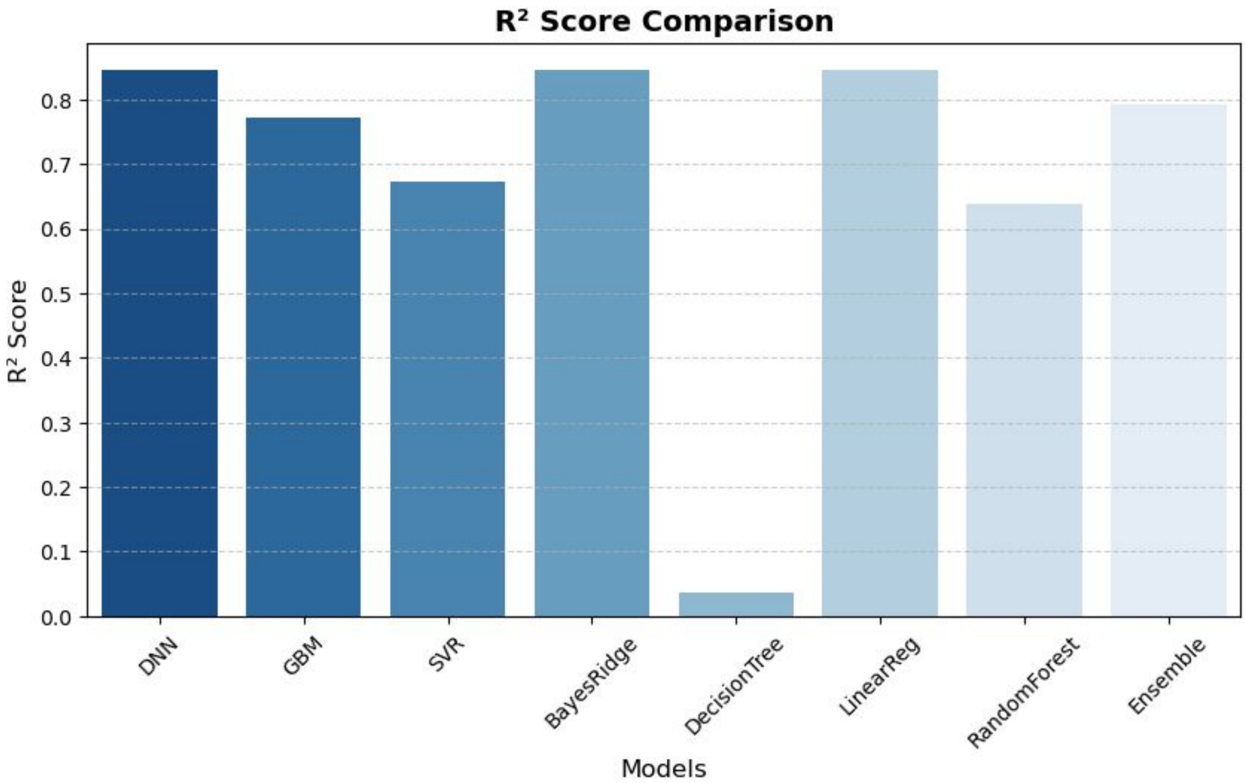
Mean Squared Error (MSE) Comparison
MSE
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
DNN
GBM
SVR
BayesRidge
DecisionTree
LinearReg
RandomForest
Ensemble
Models

Results



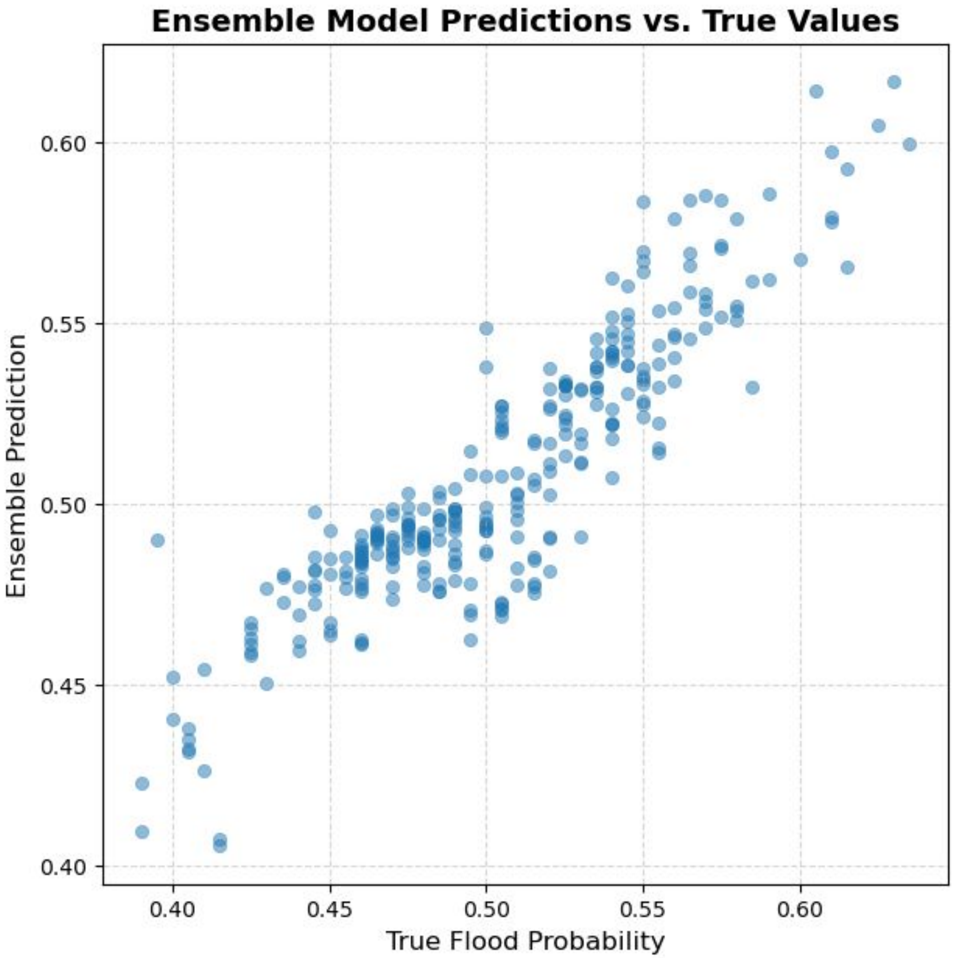
Mean Absolute Error (MAE) Comparison
MAE
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
DNN
GBM
SVR
BayesRidge
DecisionTree
LinearReg
RandomForest
Ensemble
Models

Results



R² Score Comparison
R² Score
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
DNN
GBM
SVR
BayesRidge
DecisionTree
LinearReg
RandomForest
Ensemble
Models

Results


Ensemble Model Predictions vs. True Values
Ensemble Prediction
True Flood Probability
0.40
0.45
0.50
0.55
0.60

Thanks!