BDM 1034 - Application Design for Big Data

Report

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GitHub link:

https://github.com/Andressanta09/Project_Aplication_Designe

Project Board: **https://github.com/users/Andressanta09/projects/1**

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1. Introduction

Objective:

- This project integrates real-time and static data sources for comprehensive analysis and visualization.
- It combines weather API data and accident history to predict accident severity.

Scope:

- The integration of real-time data with static datasets enables actionable insights into traffic safety and
- weather-related impacts. The interactive visualizations and predictions aim to assist decision-making.

Dataset Sources:

- - Real-Time Data: OpenWeatherMap API for live weather conditions.
- - Static Data: US Accidents dataset from Kaggle, containing accident records from 2016 to 2021.

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2. Data Pipeline Architecture

Overview:

The architecture integrates real-time API data with historical accident data. Key stages include:

- Real-time data retrieval from OpenWeatherMap API.

- Cloud storage for processed data.

- Preprocessing, modeling, and real-time prediction pipelines.

- Deployment using Streamlit for UI integration.

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3. Data Collection

Real-Time Data:

API: OpenWeatherMap API

URL: https://api.openweathermap.org/data/2.5/weather

Parameters: city, latitude, longitude, API key

Example Raw Data:

{

"coord": {"lon": -123.26, "lat": 44.56},

"weather": [{"description": "light rain", "main": "Rain"}],

"main": {"temp": 290.15, "pressure": 1013, "humidity": 80},

"visibility": 10000,

"wind": {"speed": 4.12, "deg": 120}

}

Static Data:

Dataset: US Accidents dataset from Kaggle.

Size: 1.5 million records.

Time Range: 2016-2021.

Preprocessing:

- Removed irrelevant columns.

- Handled missing values with statistical imputation.

- Normalized numerical features.

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4. Data Preprocessing and Engineering

Steps:

1. Cleaning: Removed duplicates and handled missing values using SimpleImputer.

2. Transformation: Encoded categorical columns using LabelEncoder and normalized numerical features

using StandardScaler.

3. Feature Engineering: Derived accident severity levels based on visibility and wind speed thresholds.

Libraries/Tools:

Pandas, NumPy, PySpark, Scikit-learn.

Sample Code:

```
from sklearn.preprocessing import StandardScaler, LabelEncoder

scaler = StandardScaler()

data['scaled_temp'] = scaler.fit_transform(data[['temp']])

le = LabelEncoder()

data['city_encoded'] = le.fit_transform(data['city'])
```

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5. Modeling

Model Selection Explanation:

Purpose

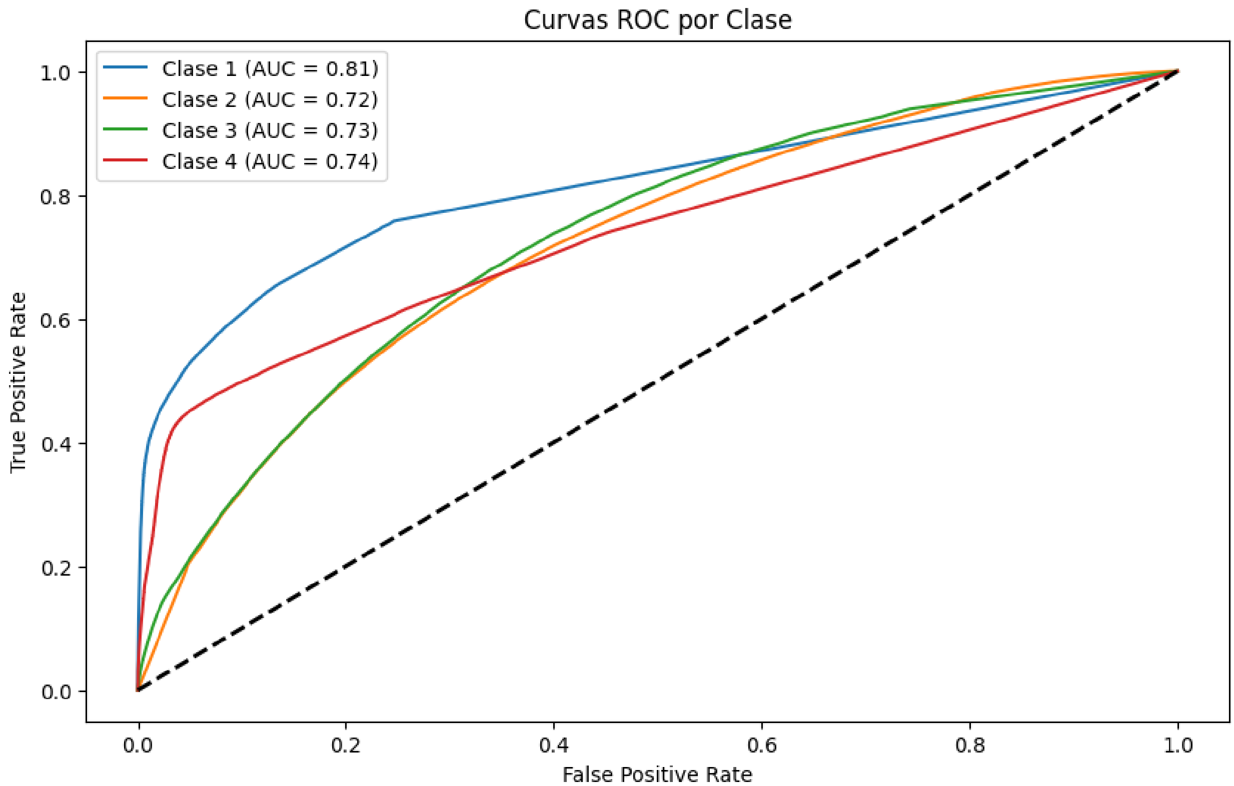
The project evaluated multiple machine learning models to predict accident severity effectively. The selection process aimed to balance accuracy, interpretability, and computational efficiency.

Chosen Models

1. Random Forest Classifier:

• Why Chosen: Random Forest is robust, interpretable, and handles feature importance well. It's ideal for datasets with mixed types of features.

- **Accuracy:** 84.5%
- **Explanation:**
    - The ensemble nature of Random Forest reduces overfitting compared to individual decision trees.
    - Strong performance is seen in predicting dominant classes (e.g., Class 2), but the model struggles with minority classes, leading to a low macro-average F1-score.
    - Feature importance suggests `Pressure(in)` and `Humidity(%)` are key predictors, likely because these weather conditions significantly impact severity.



• Best For: Baseline predictions with insights into feature importance.

2. Gradient Boosting:

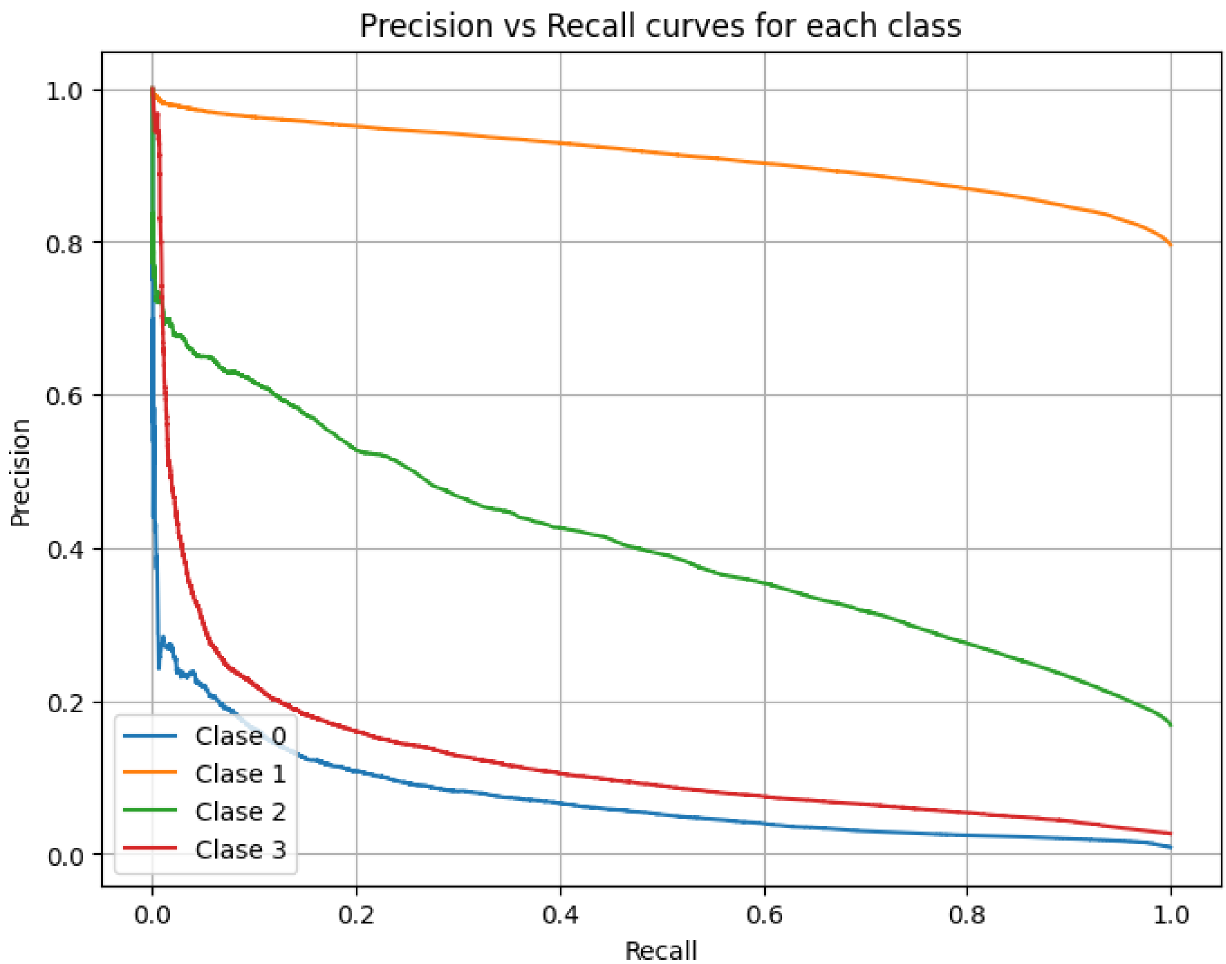
• Why Chosen: Gradient Boosting excels in handling complex feature interactions and provides higher accuracy than Random Forest with fine-tuned hyperparameters.

• Performance:

• Accuracy: 0.80140831311029

Explanation:

- XGBoost optimizes performance by correcting errors made by previous iterations, making it robust for both linear and non-linear patterns.
- High interpretability of feature importance highlights `Humidity(%)` and `Temperature(F)` as critical contributors.



• Best For: High-accuracy predictions where overfitting is controlled.

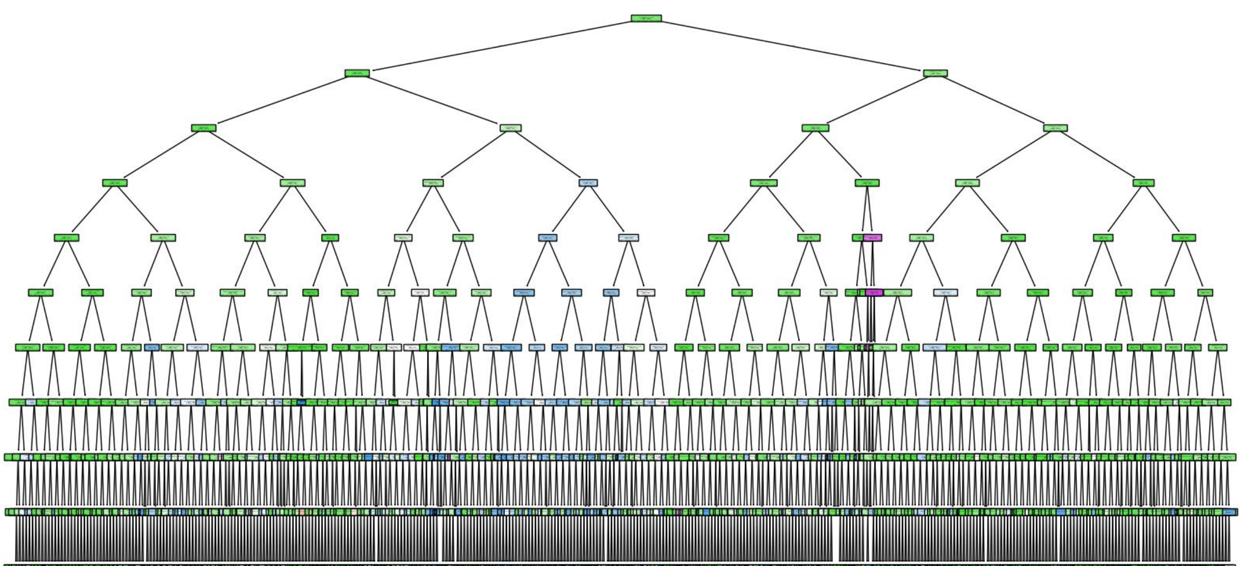
Decision tree Classifier:

The **Decision Tree Classifier** achieved an accuracy of **80.02%**. Here's the explanation for this result:

Performance Insights

- **Accuracy (80.02%):**
  - Moderate accuracy indicates that the Decision Tree is fitting the dataset to some extent but may not generalize well to unseen data.
  - Decision Trees tend to overfit the training data, especially when the tree depth is not constrained.
- **Strengths:**
  - Simple and interpretable model.
  - Captures non-linear relationships between features and target variables.
- **Weaknesses:**
  - Prone to overfitting, especially in datasets with high feature variance or noise.
  - Struggles with class imbalance, likely leading to biased predictions favoring dominant classes.

Decision Tree



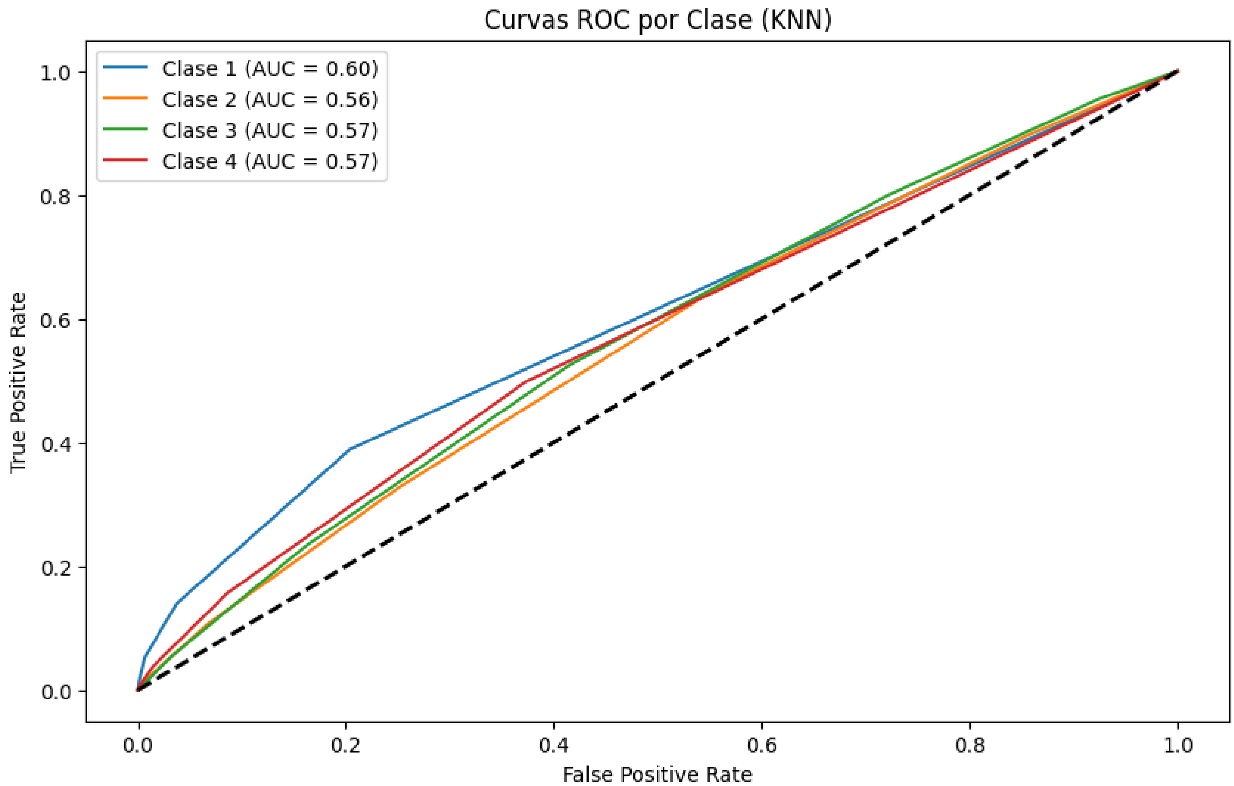
K-Nearest Neighbors (KNN)

Overall Metrics:

- **Accuracy: 46%** (not ideal, close to random guessing for imbalanced classes).
- **Macro Average:** (Average across classes):
    - Precision: **34%**, Recall: **30%**, F1-score: **30%**.
    - Indicates poor generalization across all classes.
- **Weighted Average:** (Weighted by class sizes):
    - Precision: **44%**, Recall: **46%**, F1-score: **44%**.
    - Skewed towards better performance on majority classes (2 and 3).

Analysis

1. **Class Imbalance:**
    a. Classes 1 and 4 are underrepresented in the dataset, leading to poor recall and F1-scores for these classes.
2. **KNN Limitations:**
    a. KNN is sensitive to imbalanced datasets, as it relies on majority voting in the neighborhood.
    b. Performance depends heavily on the choice of k (number of neighbors) and feature scaling.



6. Deployment

Cloud Hosting:

The app was deployed on Streamlit Cloud, enabling public access and demonstrating the scalability of the solution.

Real-Time Predictions:

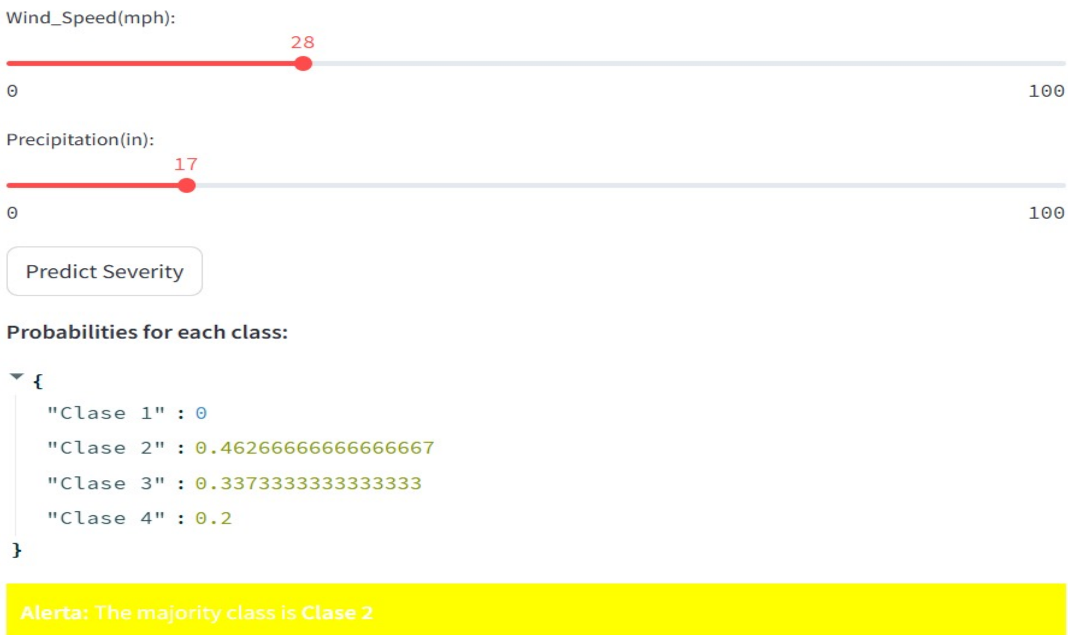
- Weather data fetched in real-time is passed to trained models for severity predictions.

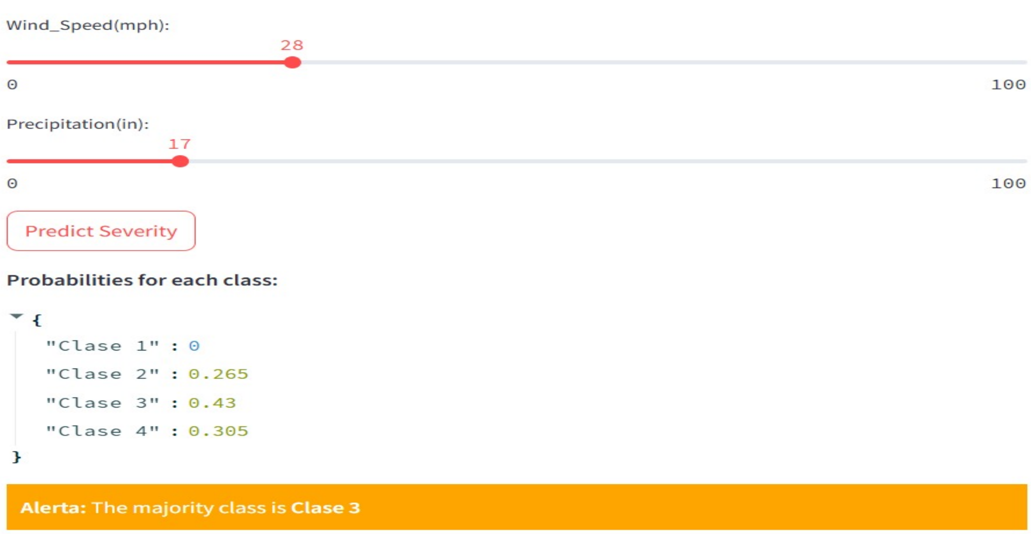
Integration:

- Streamlit app connects to the Flask API for visualizations and predictions.

1. Deployment Overview :The application was deployed online using Streamlit Cloud, a platform designed for hosting Python-based web applications. This ensured the

application was accessible via a public URL, allowing seamless interaction with the predictive models developed during the project.





Key Features

1. Prediction Functionality:

• Users input features (e.g., Wind Speed and Precipitation) using sliders and dropdown menus.

• Upon clicking the “Predict Severity” button, the app uses the trained Random Forest Classifier to predict the severity of traffic accidents.

2. Output Probabilities:

• The app provides class probabilities for each severity level, ensuring transparency in predictions.

• **Example probabilities:**

• Class 1: 0.265

• Class 2: 0.243

• Class 3: 0.397 (majority class, highlighted)

• Class 4: 0.095

Key Benefits of Deployment

• Accessibility: The online deployment eliminates the need for users to set up local environments, making the app easily accessible on any device with an internet connection.
• Usability: The intuitive interface ensures that users with minimal technical expertise can interact with the application.

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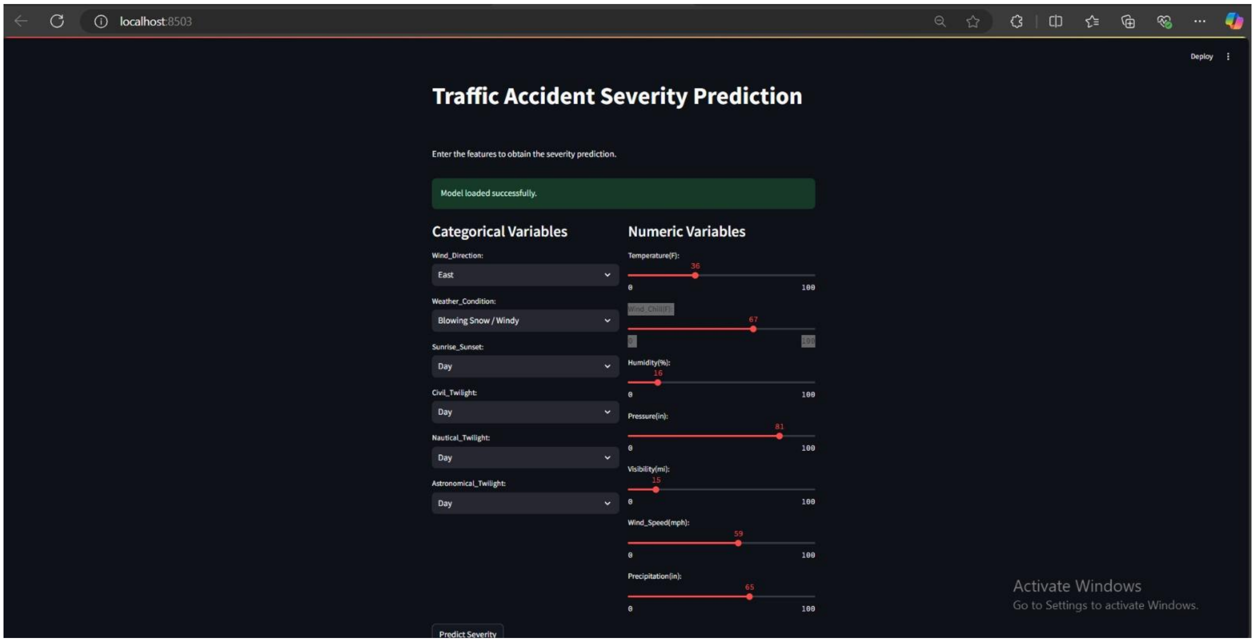
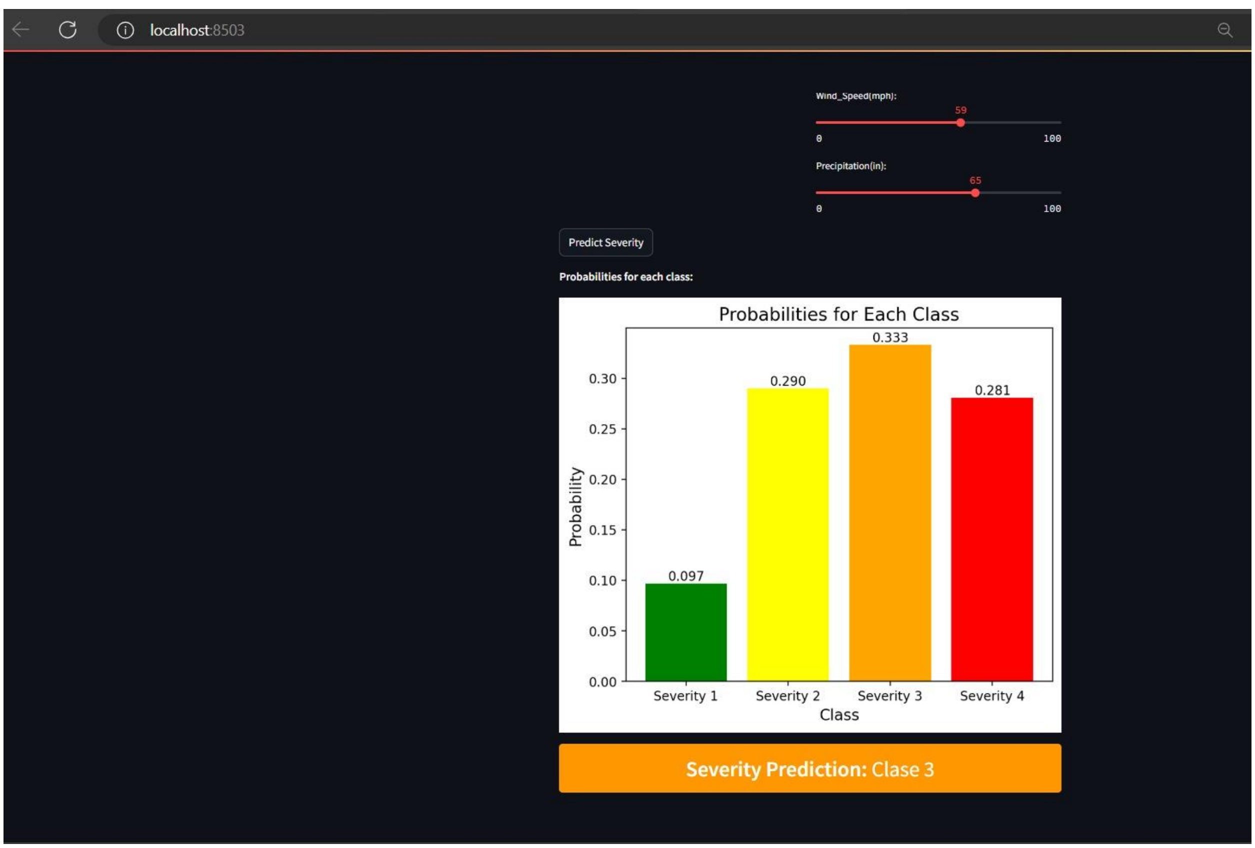
7. Visualization and UI





The UI is designed to prioritize user interaction and visualization:

• Features are organized into categorical and numerical sections.

• Probabilities for each class are displayed in a graphical format.

• Alerts highlight critical information, such as the predicted severity class.

8. challenges and learnings:

Challenges:

- Managing API rate limits and handling missing data in real-time streams.

- Optimizing cloud deployment for low-latency predictions.

Learnings:

- Real-time data integration significantly enhances analysis.

- Scalable architecture is crucial for handling high-frequency data streams.

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9. Conclusion

This project successfully integrated real-time and static data for predictive analysis and visualization.

Future enhancements include adding traffic and demographic data, improving model interpretability,

and optimizing deployment for scalability.

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10. References

1. OpenWeatherMap API documentation.

2. US Accidents dataset on Kaggle: https://www.kaggle.com/datasets/sobhanmoosavi/us-accidents/data

3. Libraries: Pandas, NumPy, Scikit-lea