Crash and Weather Data Modeling Project

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Overview

This project analyzes crash and weather data to build a predictive model evaluating the likelihood of injuries during motor vehicle accidents. The workflow includes data preprocessing, dataset integration, machine learning model implementation, optimization, and documentation. The goal is to derive meaningful predictive power with at least 75% classification accuracy or an R-squared value of 0.80, aligning weather conditions with crash patterns.

Tools and Technologies Used

Python: Programming language.

Keras-Tuner: For hyperparameter optimization.

TensorFlow: Neural network model implementation.

Scikit-learn: Random Forest classifier and preprocessing utilities.

Pandas and NumPy: Data manipulation and analysis.

Matplotlib: Data visualization.

Potential Use by Insurers

01   Price policies more accurately based on risk factors.

02   Manage claims more effectively by predicting spikes in weather-related incidents.

03   Promote safety measures to reduce accidents in hazardous weather.

04   Enhance customer service by offering weather-specific advice and coverage options.

Deep Neural Network

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Inputs (feature set)	Temperature, visibility, humidity, wind speed, weather description, borough, zip code, contributing factor, vehicle type
Output (target variable)	Number of persons injured
Hidden layers	2 layers with 8 and 5 nodes
Activation functions	ReLU for hidden layers, Sigmoid for output
Loss function	Binary Crossentropy
Optimizer	Adam
Validation accuracy	59.7%
Optimization	Best model hyperparameters with validation accuracy of 59.3%

Data Visualization

Categorized the vehicle:

- <u>Passenger Vehicle</u> - Sedan, 4 dr sedan, Station Wagon/Sport Utility Vehicle, Convertible, Taxi, 3-Door
- <u>Commercial Vehicles</u> - Pick-up Truck, Box Truck, Dump, Flat Bed, Garbage or Refuse, Tanker, Tractor Truck Diesel, Tractor Truck Gasoline, Van, Carry All
- <u>Emergency Vehicles</u> - Ambulance
- <u>Two-Wheelers</u> - Motorcycle, Bike, E-Bike, Moped, E-Scooter, MOTOR SCOO
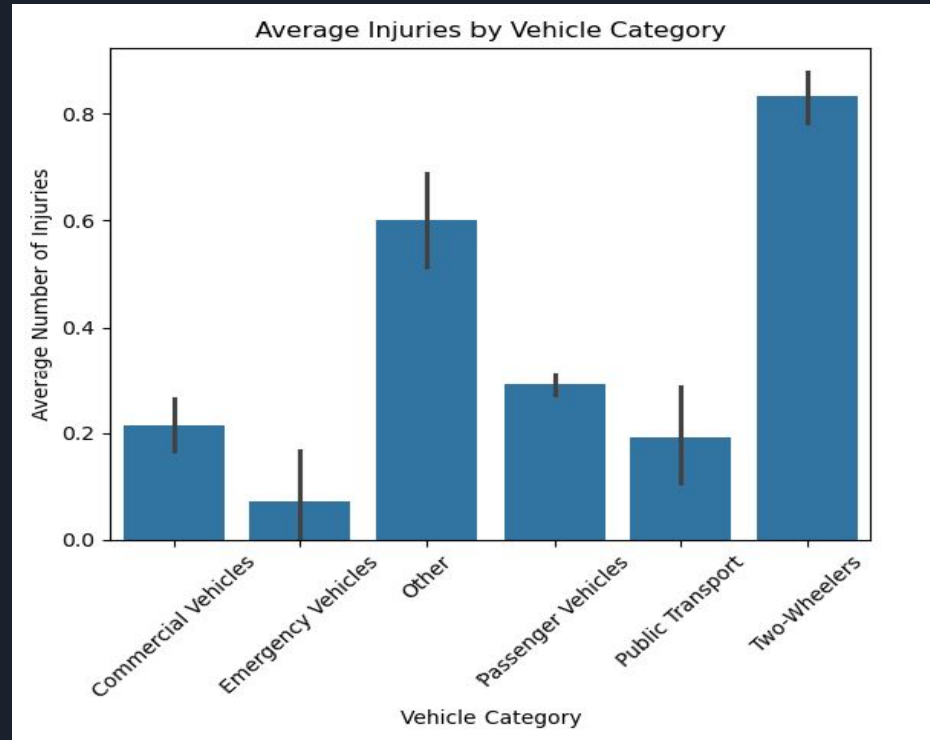- <u>Other</u> - Unspecified or Blank
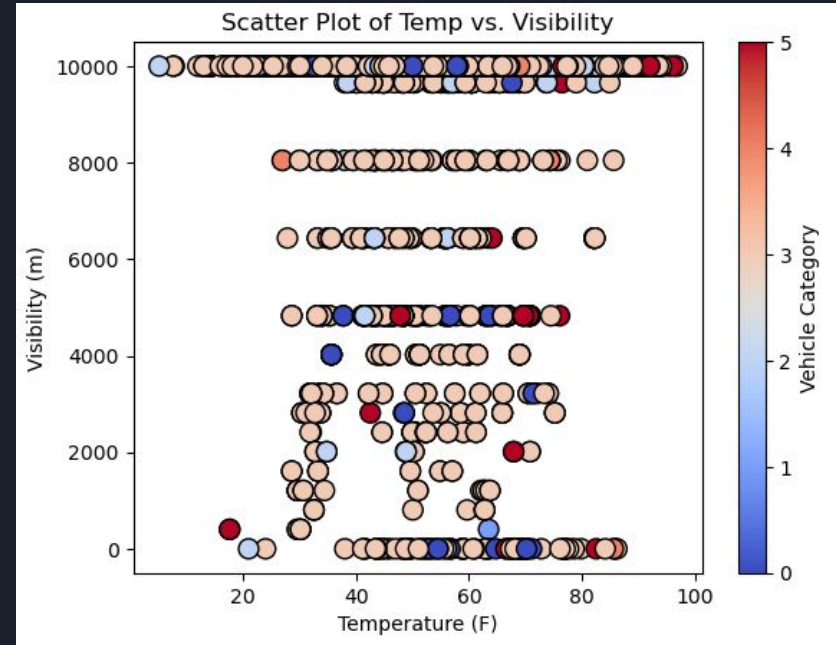
Commercial Vehicles: 0, Emergency Vehicles: 1, Other: 2, Passenger Vehicles: 3, Public Transport: 4, Two-Wheelers: 5

Box Plot
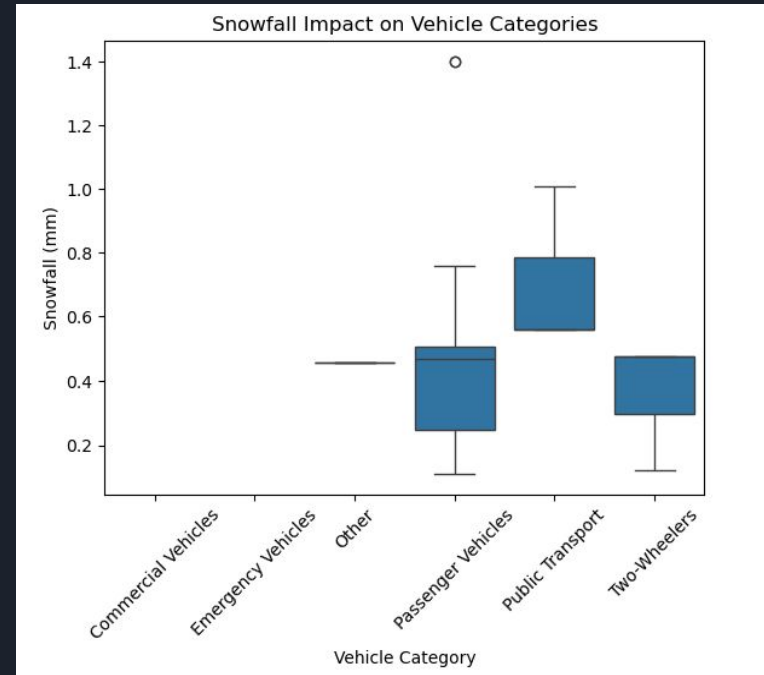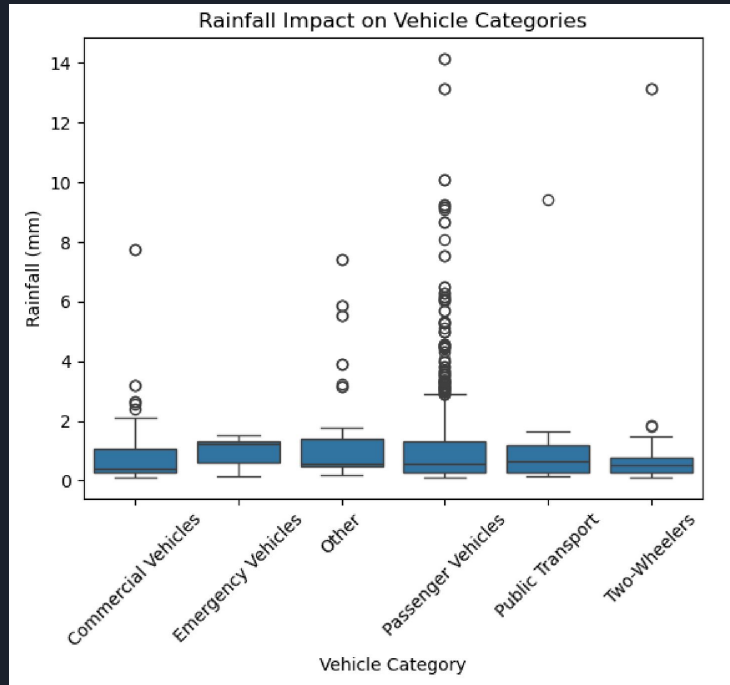
Average Injuries

Data Cleaning and Random Forest

- Filtering by distance
- Accuracy: 96.8%
- Advantages
    - Can model complex relationships
    - Combining predictions of many trees leads to more generalized results

```python
# Ensure merged_data_cleaned is a standalone DataFrame
merged_data_cleaned = merged_data_cleaned.copy()

# Apply the distance calculation
merged_data_cleaned.loc[:, 'distance'] = merged_data_cleaned.apply(calculate_distance, axis=1)

# Drop rows with invalid distances
merged_data_cleaned = merged_data_cleaned.dropna(subset=['distance'])

# Filter by proximity threshold
merged_data_filtered = merged_data_cleaned[merged_data_cleaned['distance'] <= 10000]
```

```python
# Reshape y if it's already a NumPy array
y = y.ravel()

# Using Random Forest
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a model
clf = RandomForestClassifier()
clf.fit(X_train, y_train)

# Predict and evaluate
y_pred = clf.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
```
```
Accuracy: 0.9682866961217477
```

Results and Observations

Neural Network:

- Validation accuracy: 59.7%.
- Keras Tuner was useful for exploring hyperparameter configurations but required significant runtime (11 minutes for 60 trials).
- Neural network accuracy was limited due to the structured nature of the data.

Random Forest:

- Test accuracy: 96.8%.
- Performed significantly better than the neural network, demonstrating the suitability of ensemble methods for this dataset.

Challenges and Considerations

01 Ensuring precise alignment of crash and weather data required careful datetime normalization.

02 Filtering rows by proximity using geodesic distances helped improve the quality of the merged data.

03 Missing or mismatched coordinates were handled through cleaning and filtering steps.

Future Improvements

01 Expand Data Sources: Incorporate additional datasets, such as traffic density or road conditions, to improve model robustness.

02 Experiment with Advanced Models: Explore gradient boosting techniques such as XGBoost or LightGBM for further performance gains.

03 Refine Feature Engineering: Investigate additional derived features to enhance predictive accuracy.

Thank you!