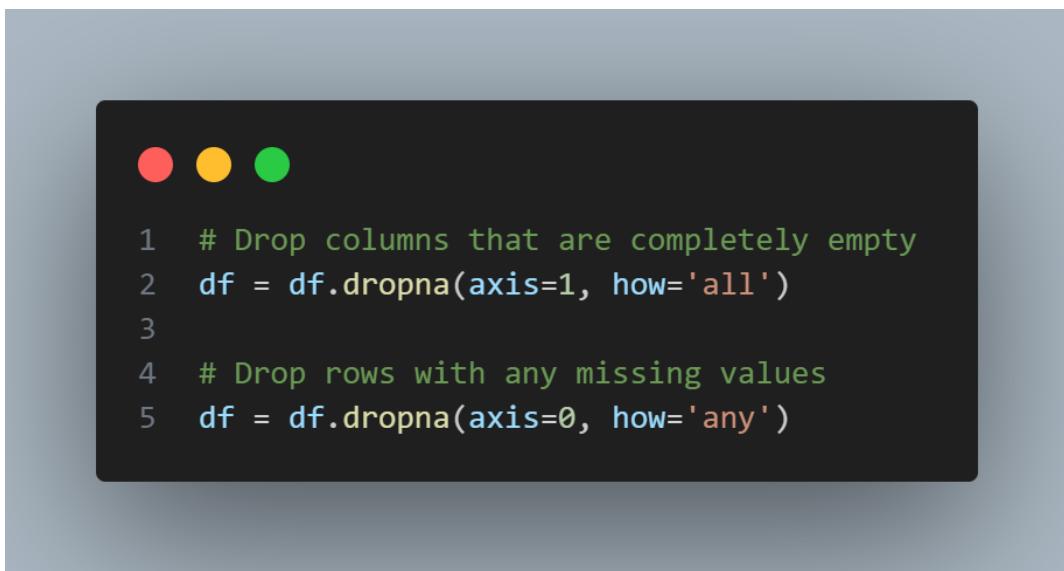


# Data Science Lab1

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## CLASSIFICATION

### 1 DATA CLEANING



The screenshot shows a Jupyter Notebook cell with a dark theme. At the top left are three colored circular icons: red, yellow, and green. The cell contains the following Python code:

```
1 # Drop columns that are completely empty
2 df = df.dropna(axis=1, how='all')
3
4 # Drop rows with any missing values
5 df = df.dropna(axis=0, how='any')
```

Figure 1: Dropping all empty variables and all records with missing values.

```

1 # PREPROCESSING: Encode categorical target to numeric BEFORE discarding non-numeric columns
2 # This converts text labels to numbers, making the target "numeric"
3 if target_column in df.columns and df[target_column].dtype == 'object':
4     print(f"\nEncoding categorical target '{target_column}' to numeric...")
5     le = LabelEncoder()
6     df[target_column] = le.fit_transform(df[target_column])
7     print(f" Classes: {list(le.classes_)}")
8     print(f" Encoded as: {dict(zip(le.classes_, range(len(le.classes_))))}")
9
10 # Keep only numeric columns (now includes the encoded target)
11 numeric_cols = df.select_dtypes(include=[np.number]).columns
12 df = df[numeric_cols]

```

Figure 2: Discard all non-numeric data excluding the target variable.

## 2 RESULTS

### 2.1 Model Performance Summary

Table 1: Performance Metrics - Traffic Accidents Dataset

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	0.823	0.863	0.823	0.813
Logistic Regression	0.821	0.864	0.821	0.811
KNN	0.811	0.822	0.811	0.806
Decision Tree	0.829	0.859	0.829	0.821
Multi-layer Perceptron	0.829	0.859	0.829	0.821

Table 2: Performance Metrics - Combined Flights 2022 Dataset

<b>Model</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-Score</b>
Naïve Bayes	0.968	0.943	0.968	0.955
Logistic Regression	0.970	0.971	0.970	0.956
KNN	0.970	0.954	0.970	0.956
Decision Tree	0.971	0.962	0.971	0.960
Multi-layer Perceptron	0.970	0.970	0.970	0.956

## 2.2 Best Hyperparameters

Table 3: Optimal Hyperparameters - Traffic Accidents

<b>Model</b>	<b>Best Hyperparameters</b>
Naïve Bayes	var_smoothing: 0.001
Logistic Regression	C: 0.01, solver: lbfgs, max_iter: 500
KNN	n_neighbors: 7, weights: uniform, metric: euclidean
Decision Tree	criterion: gini, max_depth: 5, min_samples_split: 10, min_samples_leaf: 1
Multi-layer Perceptron	hidden_layer_sizes: (50,), activation: relu, alpha: 0.0001, learning_rate: adaptive

Table 4: Optimal Hyperparameters - Combined Flights 2022

<b>Model</b>	<b>Best Hyperparameters</b>
Naïve Bayes	var_smoothing: 1e-10
Logistic Regression	C: 0.01, solver: lbfgs, max_iter: 500
KNN	n_neighbors: 7, weights: uniform, metric: euclidean
Decision Tree	criterion: gini, max_depth: 10, min_samples_split: 2, min_samples_leaf: 4
Multi-layer Perceptron	hidden_layer_sizes: (100,), activation: relu, alpha: 0.0001, learning_rate: adaptive

## 2.3 Naïve Bayes

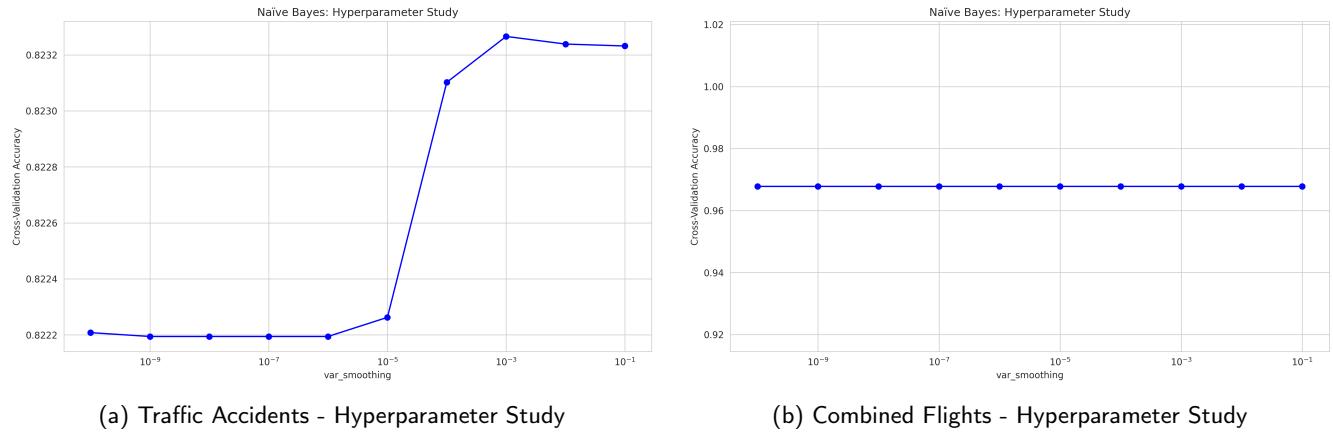


Figure 3: Naïve Bayes: Hyperparameter Tuning Results

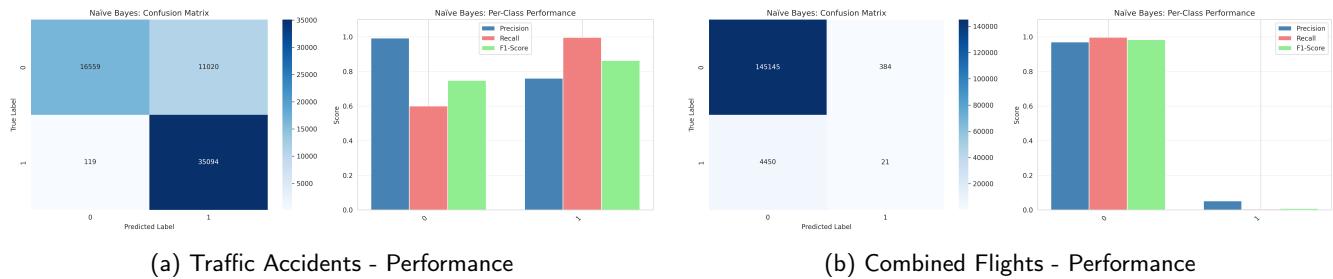


Figure 4: Naïve Bayes: Model Performance

## 2.4 Logistic Regression

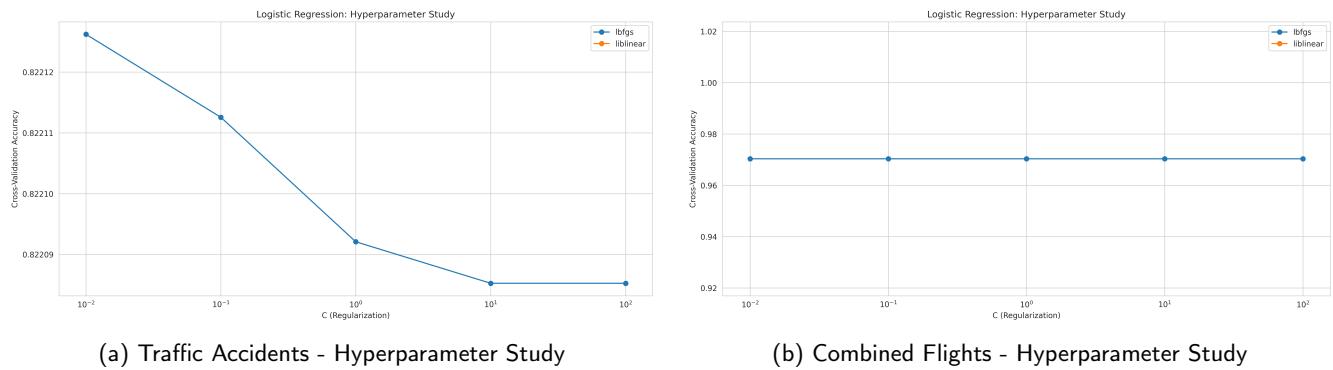


Figure 5: Logistic Regression: Hyperparameter Tuning Results

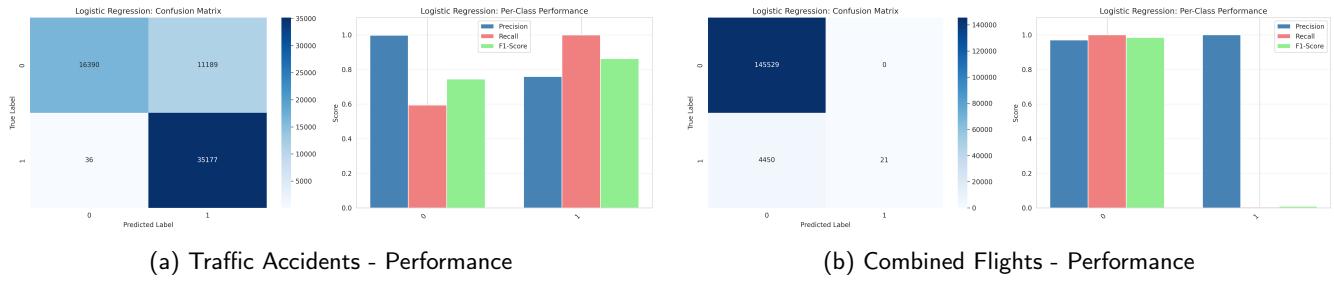


Figure 6: Logistic Regression: Model Performance

## 2.5 K-Nearest Neighbors (KNN)

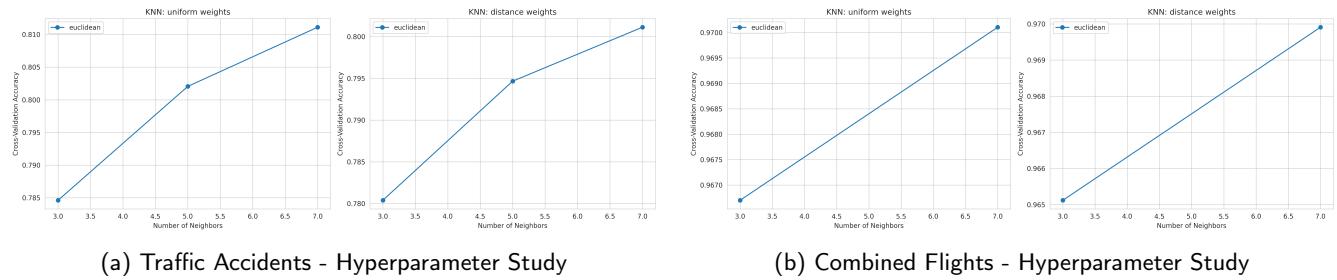


Figure 7: KNN: Hyperparameter Tuning Results

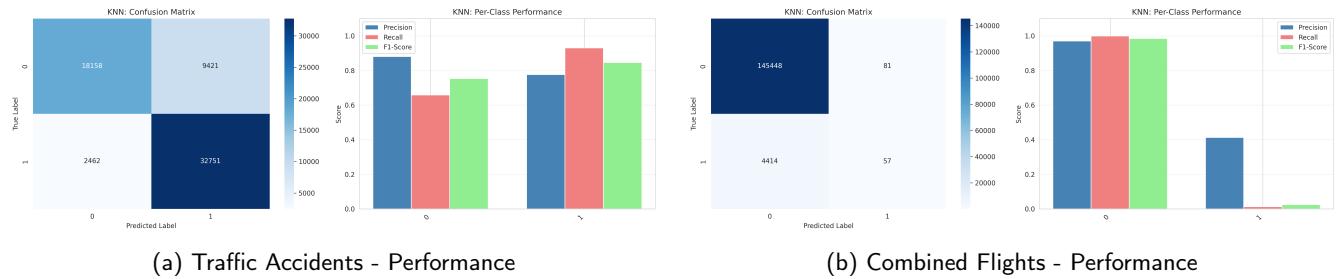


Figure 8: KNN: Model Performance

## 2.6 Decision Tree

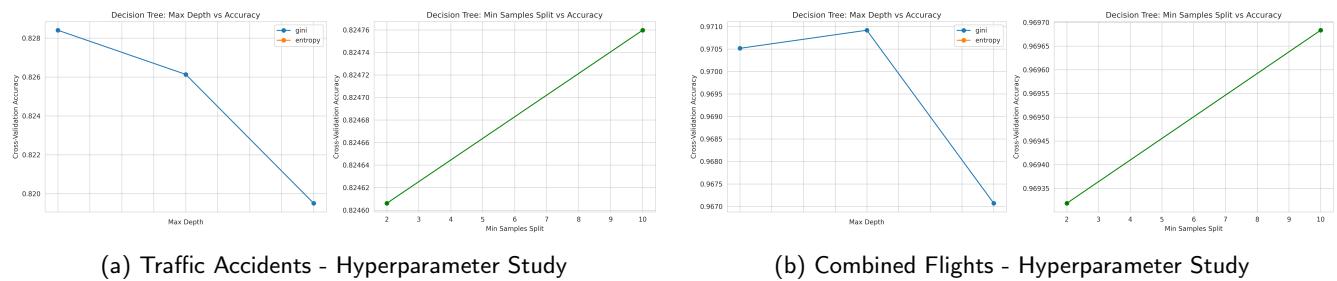


Figure 9: Decision Tree: Hyperparameter Tuning Results

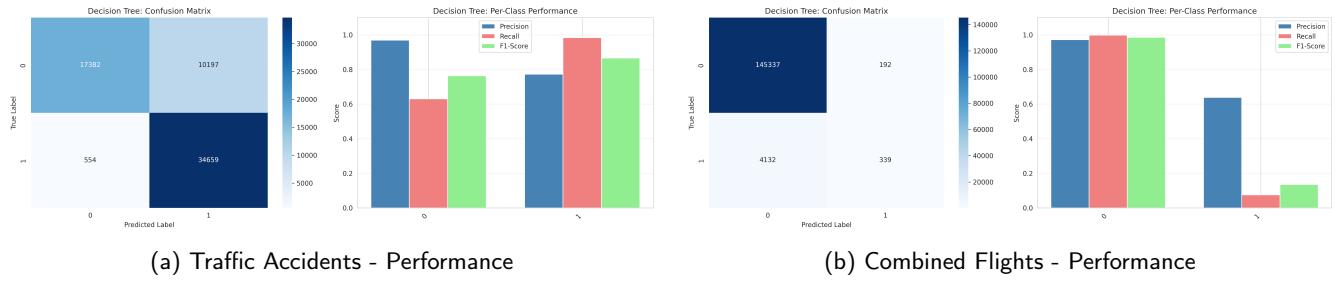


Figure 10: Decision Tree: Model Performance

## 2.7 Multi-layer Perceptron

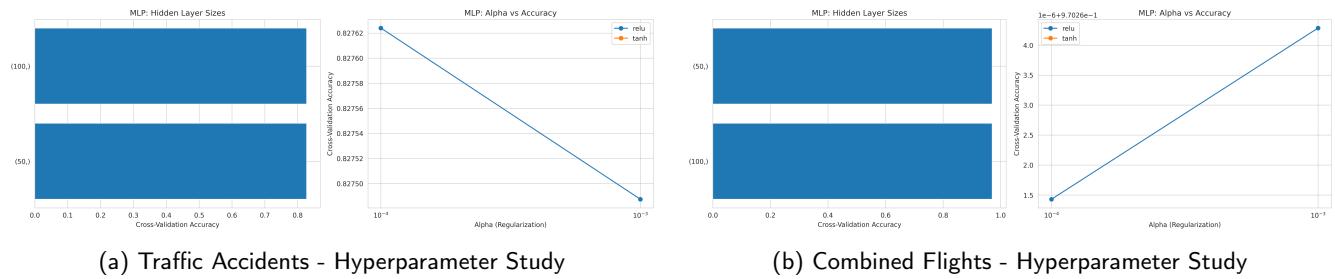


Figure 11: Multi-layer Perceptron: Hyperparameter Tuning Results

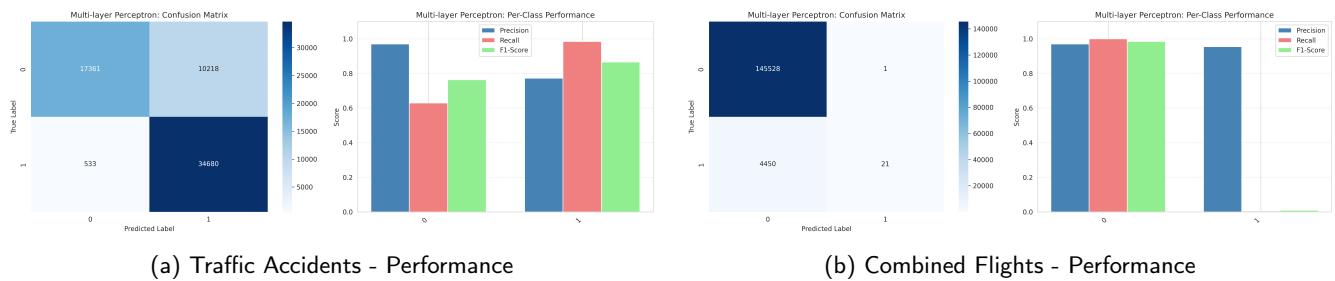


Figure 12: Multi-layer Perceptron: Model Performance

## 2.8 Overall Model Comparison

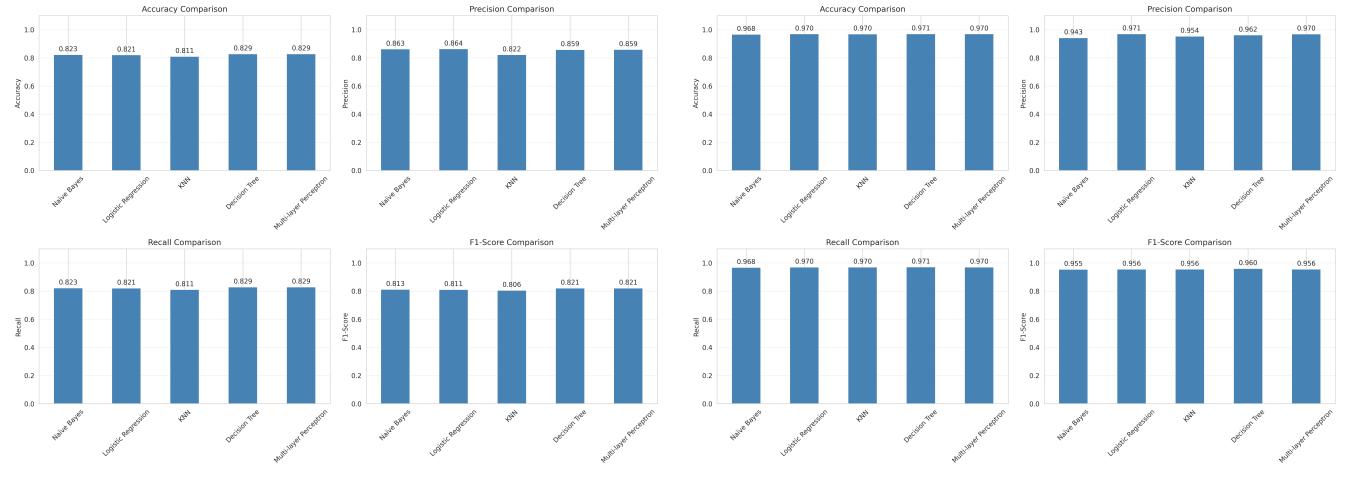


Figure 13: Overall Performance Comparison Across All Models