Analyzing Bird strike Incidents

"This project focuses on analyzing bird strike incidents to gain insights into patterns and trends, and to predict the impact of future incidents on aircraft safety."

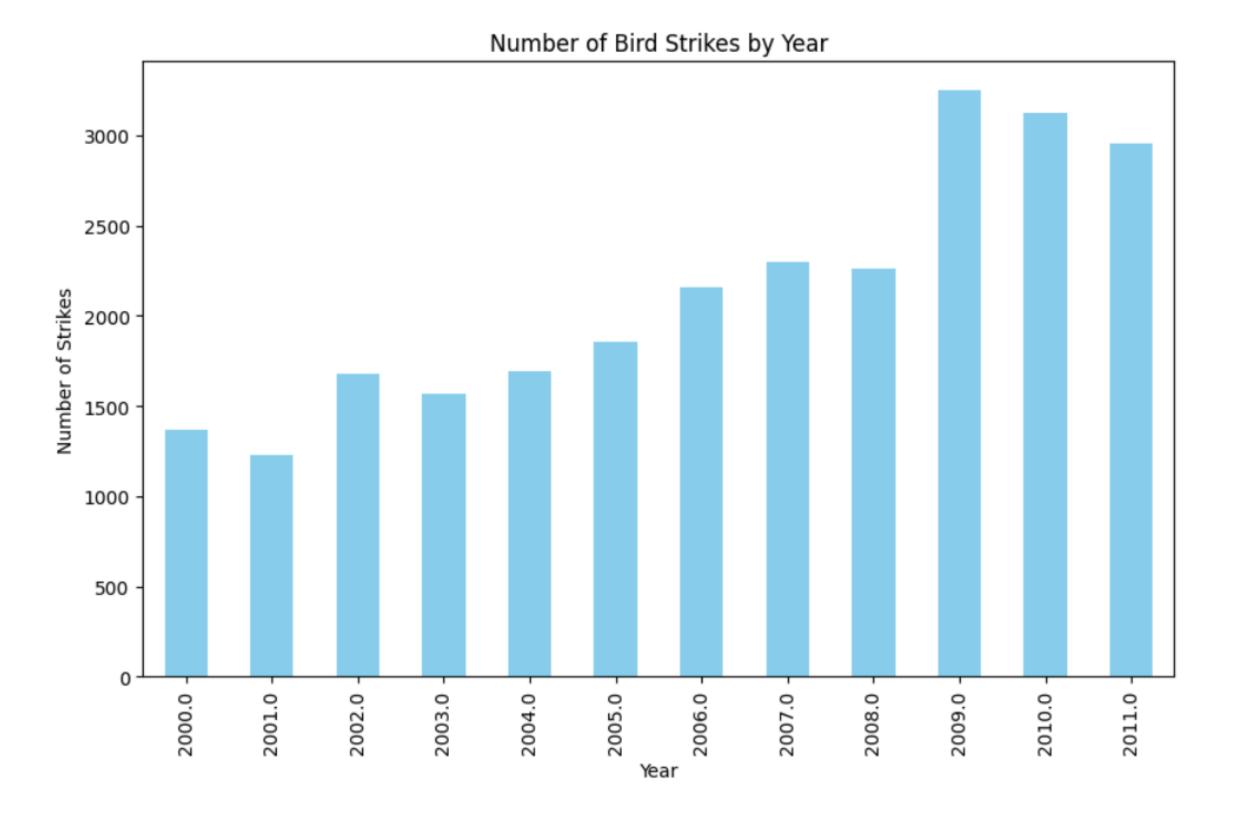
A bar chart showing bird strikes over time from 2000-2011.

The chart shows a steady increase in bird strikes over the years. This suggests that bird strike incidents have become more frequent, especially from 2000 to 2011. In particular, the period between 2007 and 2011 exhibits a noticeable rise.

Some years show sudden spikes in bird strikes, such as 2006, 2009, and 2010. These peaks could indicate important changes or external factors influencing the frequency of incidents. Possible reasons for these spikes include:

Airport Expansion or Traffic Growth Growing Wildlife Populations

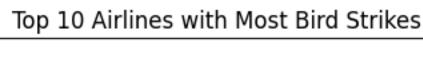
"Yearly Trend of Bird Strikes"

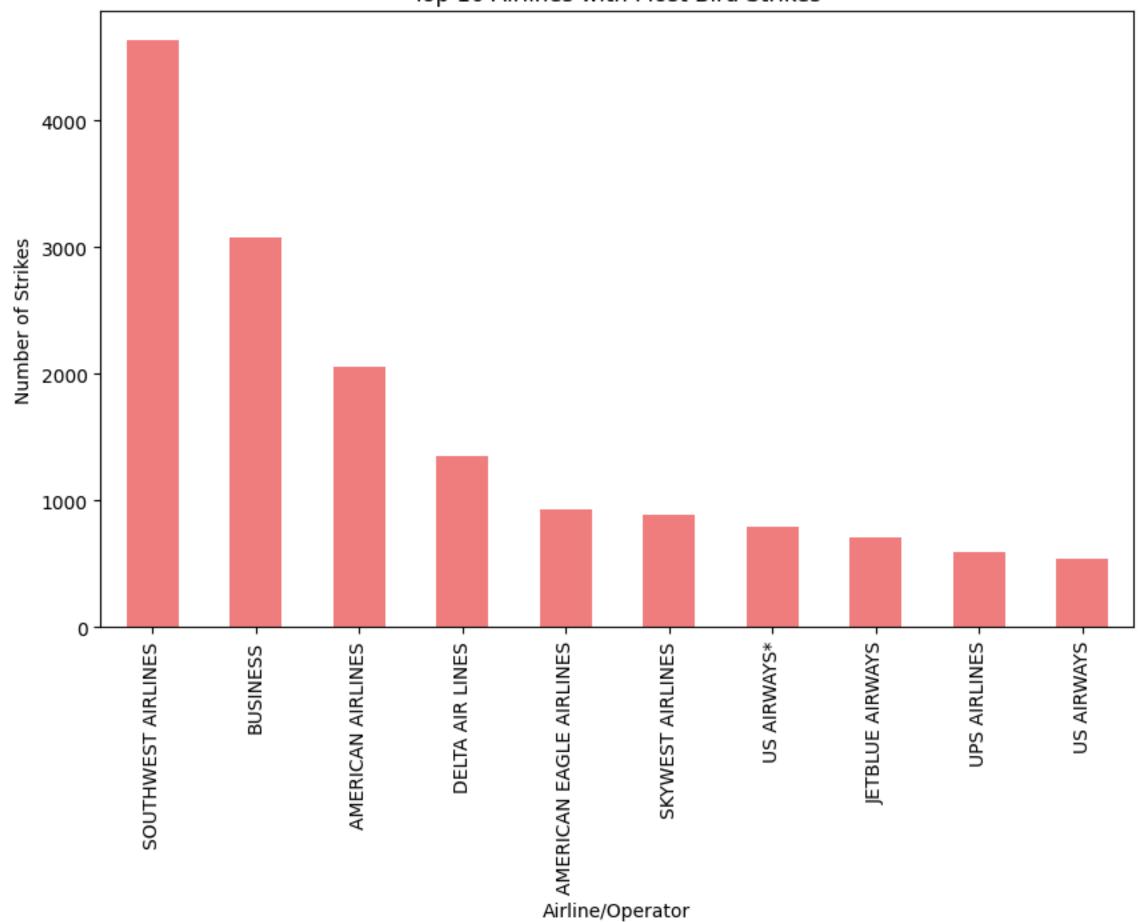


This bar chart highlights the top 10 airlines that have experienced the highest number of bird strikes.

This bar chart displays the top 10 airlines with the highest number of bird strikes. The disparities in incidents suggest that airlines operating in regions with high bird activity or with larger fleets experience more frequent strikes. Understanding these patterns enables airlines to implement targeted strategies to reduce bird strike risks, enhancing both safety and operational efficiency.

"Airlines Most Affected by Bird Strikes"





The heatmap shows the frequency of bird strikes across different altitude bins (e.g., below and above 1000 ft) and phases of flight (e.g., takeoff, cruise, landing). Darker areas indicate more bird strikes, while lighter areas show fewer.

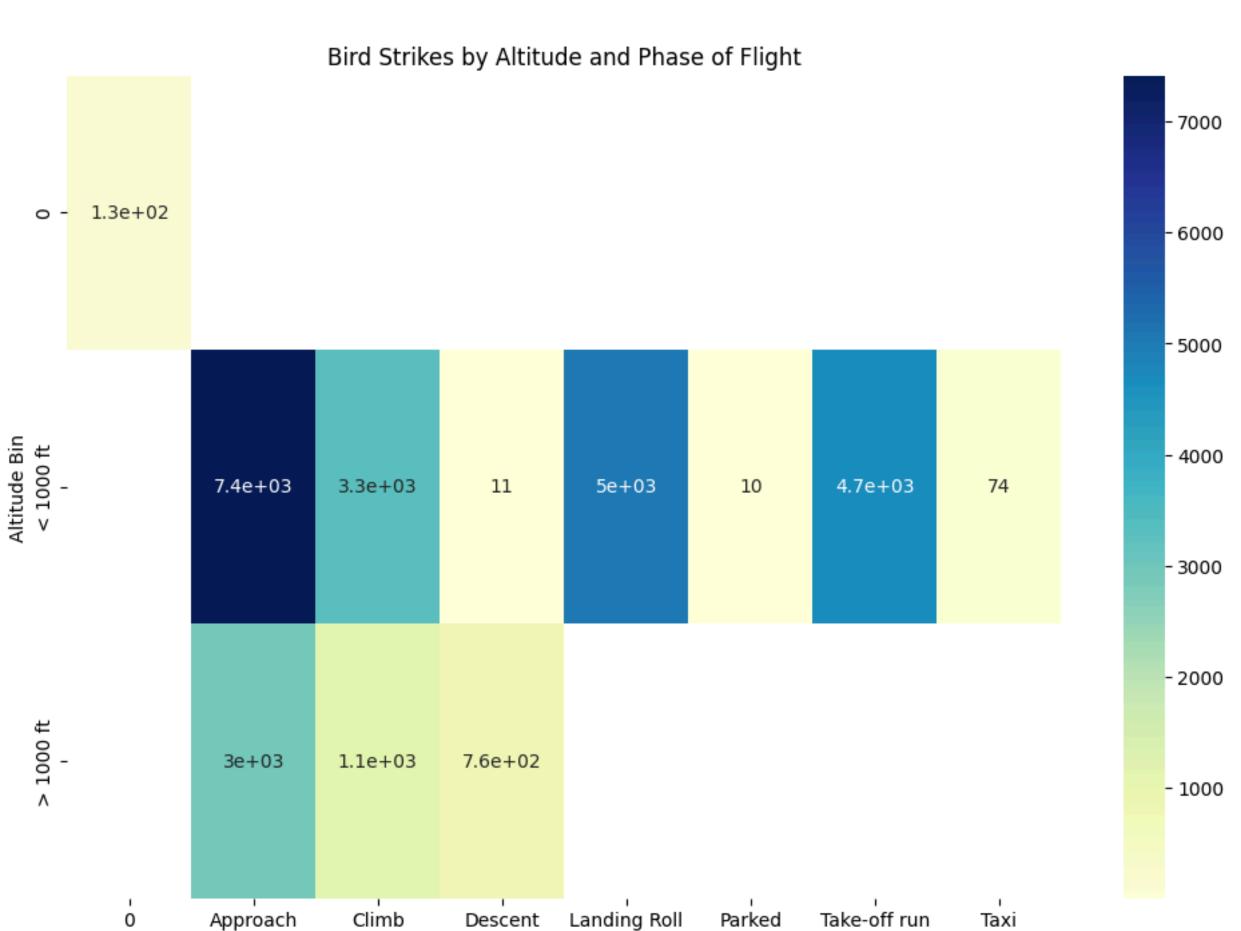
Higher Risk During Takeoff and Landing (Below 1000 ft):

 Most bird strikes occur at lower altitudes during takeoff and landing, where aircraft are closer to the ground and birds.

Lower Risk at Higher Altitudes (> 1000 ft):

 Bird strikes are significantly less common at higher altitudes and during cruise.

"Bird Strikes by Altitude and Flight Phase"



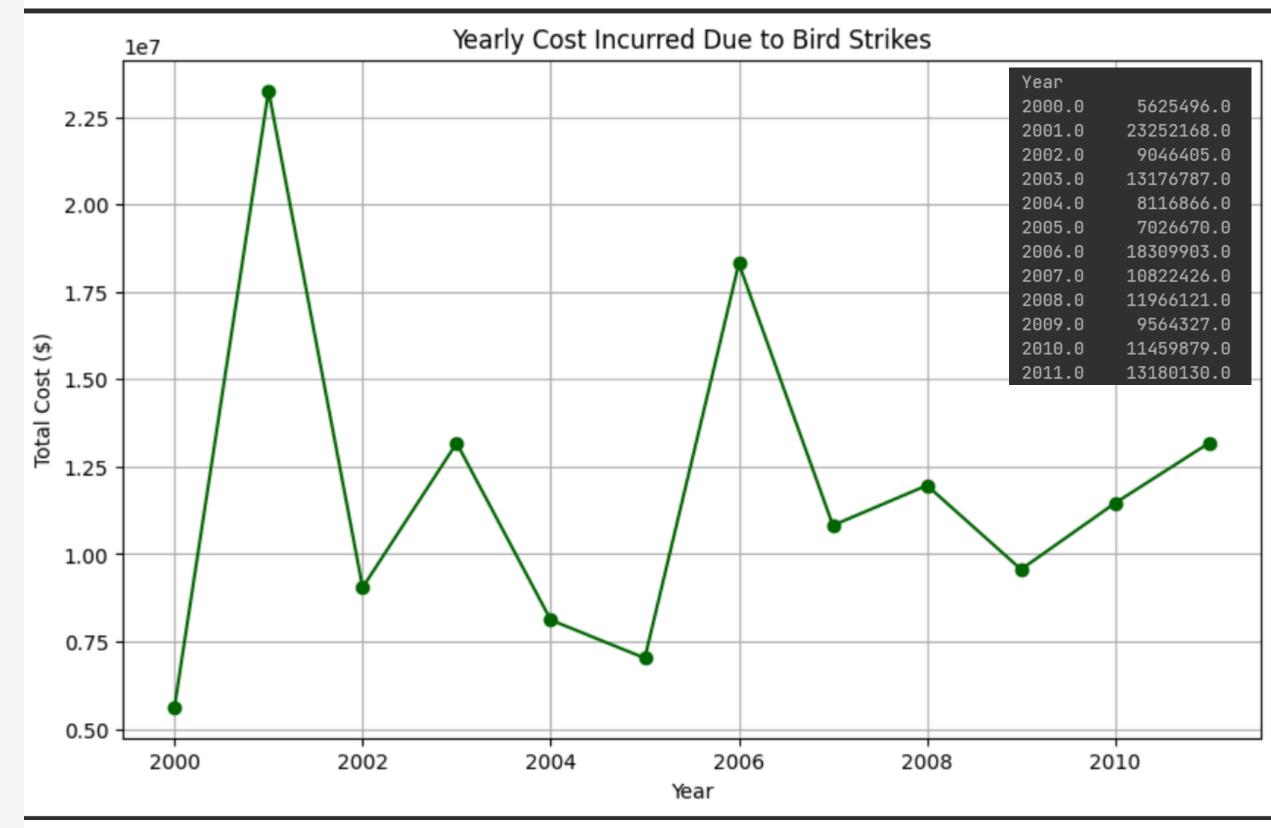
Phase of Flight

This line graph visualizes the total financial cost incurred due to bird strikes from 2000 to 2011. The graph's x-axis represents the years, while the y-axis represents the total cost in USD.

- General Trend: Costs generally increased over time, with spikes in specific years like 2001 and 2006.
- 2001 & 2006 Spikes: These years saw higher costs, likely due to severe incidents that involved larger aircraft or critical damage (e.g., engine failure).

The fluctuating costs reflect the severity of bird strikes and factors like wildlife patterns and aircraft size. This underscores the need for effective risk management to minimize financial impact.

"Yearly Trend of Bird Strikes"



Problems Solutions

Predicting Bird Strike Severity:

The model predicts the potential severity of bird strike damage based on environmental and operational factors, enabling early intervention and accident prevention.

Reducing Aviation Risk:

Accurate predictions help the airline industry develop mitigation strategies, such as adjusting flight paths or enhancing bird detection during high-risk phases like low-altitude approaches.

Optimizing Resource Allocation:

Insights from the model guide airports in focusing bird control efforts on high-risk areas and times, improving safety and efficiency.

Model Explanation

Model Accuracy: 0.92

Key Steps in the Model

Uses multiple decision trees for robust accuracy. Ideal for classifying bird strike severity.

Feature Selection:

Factors like altitude, phase of flight, sky conditions, bird size, and financial cost were used to predict severity.

One-Hot Encoding:

Converted categorical variables into a numeric format for model training.

Train/Test Split:

70% training, 30% testing ensures model generalization.

Model Accuracy:

Achieved 92% accuracy in predicting severity.

```
# Step 1: Handle missing values
                                                                    # For numeric columns, fill with the median
                                                                    numeric cols = df.select dtypes(include=['float64', 'int64']).columns
predictions, reducing overfitting and improving df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].median())
                                                                    # For categorical columns, fill with the mode
                                                                    categorical_cols = df.select_dtypes(include=['object']).columns
                                                                    df[categorical_cols] = df[categorical_cols].fillna(df[categorical_cols].mode().iloc[0])
                                                                    # Step 2: Feature selection (you can add or modify based on your understanding)
                                                                    # Here we assume 'Severity' is the target variable and select some features
                                                                    features = ['Altitude bin', 'When: Phase of flight', 'Conditions: Sky', 'Wildlife: Size', 'Cost: Total $']
                                                                    target = 'Effect: Indicated Damage' # Assuming this is related to severity or effect on flight
                                                                    # Step 3: Encode categorical variables
                                                                   X = df[features]
                                                                   y = df[target]
                                                                   X = pd.get dummies(X) # Convert categorical variables into dummy/indicator variables
                                                                    # Step 4: Split data into training and test sets
                                                                   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
                                                                    # Step 5: Train the Random Forest Classifier
                                                                    model = RandomForestClassifier(n_estimators=100, random_state=42)
                                                                    model.fit(X_train, y_train)
                                                                    # Step 6: Predict on test data
                                                                   y_pred = model.predict(X_test)
                                                                    # Step 7: Evaluate the model
                                                                    accuracy = accuracy_score(y_test, y_pred)
                                                                    print(f"Model Accuracy: {accuracy:.2f}")
```

Impact & Insights from Bird Strike Predictions

Outcomes of the Model:

High prediction accuracy (92%) for determining the severity of bird strikes.

Helps airlines and airports focus on high-risk phases and altitudes for bird strikes.

How It Solves the Problem:

Proactive Safety Measures: Predicts when and where severe bird strikes are likely, allowing for earlier intervention.

Resource Allocation: Guides airports in focusing bird control efforts during critical flight phases (e.g., take-off and landing).

Feature Importance: Highlights the most influential factors (e.g., altitude and phase of flight), aiding in safety protocol adjustments.

Future Benefits:

Enhanced Flight Safety: Helps reduce the risk of severe bird strikes by identifying high-risk conditions.

Data-Driven Decisions: Assists aviation authorities in making informed decisions about flight paths and safety regulations.