Risk Assessment of Aircraft for Commercial and Private Operations

1. Business Understanding

Project Goal

To analyze National Transportation Safety Board that includes aviation accident data from 1962 to 2023 about civil aviation accidents and selected incidents in the United States and international waters.To determine which aircraft are the lowest risk for the company, translate the findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

Data source

The NTSB aviation accident database contains information from 1962 and later about civil aviation accidents and selected incidents within the United States, its territories and possessions, and in international waters.

Key Questions:

1. Which aircraft type have the lowest accident rates?
2. Are there specific manufacturers associated with higher safety standards?
3. How do accident severities vary across aircraft types and manufacturers?
4. Are there specific times, places, or circimstances under which the risk is heightened for certain aircraft types?

Success Criteria:

1. Identify aircraft that have a low accident frequency and severity history
2. Provide actionable recommendations on model of aircaft that fit the company's operational needs.

2. Data Understanding

In [1]:

```
#import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [2]:

```
# Load the dataset.

df = pd.read_csv('AviationData.csv', engine='python')
df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	NaN
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN

5 rows × 31 columns

In [3]:
```
# checking the tail of the data
df.tail()
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Ai
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	

5 rows × 31 columns

In [4]:
```
# Summary statistics of the numeric columns
df.describe()
```

Out[4]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.000000
mean	1.146585	0.647855	0.279881	0.357061	5.325440
std	0.446510	5.485960	1.544084	2.235625	27.913634
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000	1.000000
75%	1.000000	0.000000	0.000000	0.000000	2.000000
max	8.000000	349.000000	161.000000	380.000000	699.000000

In [5]:
```
# Size of the data
df.shape
```

Out[5]:
```
(88889, 31)
```

In [6]:

```
# Summary of the Data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

3. Data Preparation

Data Cleaning

In [7]:

```
# Checking the numner of missing values in each column
df.isna().sum()
```

Out[7]:

```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38640
Airport.Name              36099
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1317
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7077
```

In [8]:

```
# I am going to drop columns that have roughly more than 25% of their data missing
# More columns which are not important for my analysis, i drop for easier halnding of the data
columns_to_drop = ['Latitude', 'Longitude', 'Airport.Code','Accident.Number', 'Registration.Number',
                   'Amateur.Built', 'Publication.Date', 'Report.Status', 'Engine.Type',
                   'Airport.Name','Aircraft.Category', 'FAR.Description', 'Schedule',
                   'Air.carrier', 'Broad.phase.of.flight']
df_clean = df.drop(columns=columns_to_drop)
```

In [9]:
```
df_clean.columns
```

Out[9]:
```
Index(['Event.Id', 'Investigation.Type', 'Event.Date', 'Location', 'Country',
       'Injury.Severity', 'Aircraft.damage', 'Make', 'Model',
       'Number.of.Engines', 'Purpose.of.flight', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition'],
      dtype='object')
```

In [10]:
```
# Rename some columns in the DataFrame
rename_columns = {
        'Event.Id':'ID', 'Investigation.Type': 'Type', 'Event.Date': 'Date',
        'Injury.Severity': 'Injury_severity', 'Aircraft.damage': 'Damage_type',
        'Number.of.Engines': 'Engines', 'Purpose.of.flight': 'Flight_Purpose',
        'Total.Fatal.Injuries': 'Fatal_Injuries','Total.Serious.Injuries': 'Serious_Injuries',
        'Total.Minor.Injuries': 'Minor_Injuries', 'Total.Uninjured': 'Uninjured',
        'Weather.Condition': 'Weather'}
df_clean.rename(columns=rename_columns, inplace=True)
```

In [11]:
```
df_clean.head()
```

Out[11]:

	ID	Type	Date	Location	Country	Injury_severity	Damage_type	Make	Model	Engines	Flight_Purpos
0	20001218X45444	Accident	1948-10-24	MOOSE CREEK, ID	United States	Fatal(2)	Destroyed	Stinson	108-3	1.0	Person
1	20001218X45447	Accident	1962-07-19	BRIDGEPORT, CA	United States	Fatal(4)	Destroyed	Piper	PA24-180	1.0	Person
2	20061025X01555	Accident	1974-08-30	Saltville, VA	United States	Fatal(3)	Destroyed	Cessna	172M	1.0	Person
3	20001218X45448	Accident	1977-06-19	EUREKA, CA	United States	Fatal(2)	Destroyed	Rockwell	112	1.0	Person
4	20041105X01764	Accident	1979-08-02	Canton, OH	United States	Fatal(1)	Destroyed	Cessna	501	NaN	Person

In [12]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ID                88889 non-null  object 
 1   Type              88889 non-null  object 
 2   Date              88889 non-null  object 
 3   Location          88837 non-null  object 
 4   Country           88663 non-null  object 
 5   Injury_severity   87889 non-null  object 
 6   Damage_type       85695 non-null  object 
 7   Make              88826 non-null  object 
 8   Model             88797 non-null  object 
 9   Engines           82805 non-null  float64
 10  Flight_Purpose    82697 non-null  object 
 11  Fatal_Injuries    77488 non-null  float64
 12  Serious_Injuries  76379 non-null  float64
 13  Minor_Injuries    76956 non-null  float64
 14  Uninjured         82977 non-null  float64
 15  Weather           84397 non-null  object 
dtypes: float64(5), object(11)
memory usage: 10.9+ MB
```

In [13]:
```
df_clean.isna().sum()
```

Out[13]:
```
ID                     0
Type                   0
Date                   0
Location              52
Country              226
Injury_severity     1000
Damage_type         3194
Make                  63
Model                 92
Engines             6084
Flight_Purpose      6192
Fatal_Injuries     11401
Serious_Injuries   12510
Minor_Injuries     11933
Uninjured           5912
Weather             4492
dtype: int64
```

In [14]:
```
# Standsrdize the Injury_severity & Fatal_injuries
# The columns provide the same information
# Drop Fatal_Injuries column

df_clean.drop('Injury_severity', axis=1 , inplace=True)
df_clean.head()
```

Out[14]:

	ID	Type	Date	Location	Country	Damage_type	Make	Model	Engines	Flight_Purpose	Fatal_Injuries
0	20001218X45444	Accident	1948-10-24	MOOSE CREEK, ID	United States	Destroyed	Stinson	108-3	1.0	Personal	2.C
1	20001218X45447	Accident	1962-07-19	BRIDGEPORT, CA	United States	Destroyed	Piper	PA24-180	1.0	Personal	4.C
2	20061025X01555	Accident	1974-08-30	Saltville, VA	United States	Destroyed	Cessna	172M	1.0	Personal	3.C
3	20001218X45448	Accident	1977-06-19	EUREKA, CA	United States	Destroyed	Rockwell	112	1.0	Personal	2.C
4	20041105X01764	Accident	1979-08-02	Canton, OH	United States	Destroyed	Cessna	501	NaN	Personal	1.C

Exploratory Data Analysis (EDA)

In [15]:
```
# correlation
df_clean.corr()
```

Out[15]:

	Engines	Fatal_Injuries	Serious_Injuries	Minor_Injuries	Uninjured
Engines	1.000000	0.098505	0.046157	0.098162	0.406058
Fatal_Injuries	0.098505	1.000000	0.135724	0.073559	-0.015214
Serious_Injuries	0.046157	0.135724	1.000000	0.326849	0.052869
Minor_Injuries	0.098162	0.073559	0.326849	1.000000	0.147770
Uninjured	0.406058	-0.015214	0.052869	0.147770	1.000000

In [16]:
```
# Plot a heatmap
plt.figure(figsize=(12,8))
sns.heatmap(df_clean.corr(),annot=True, cmap='coolwarm')
```

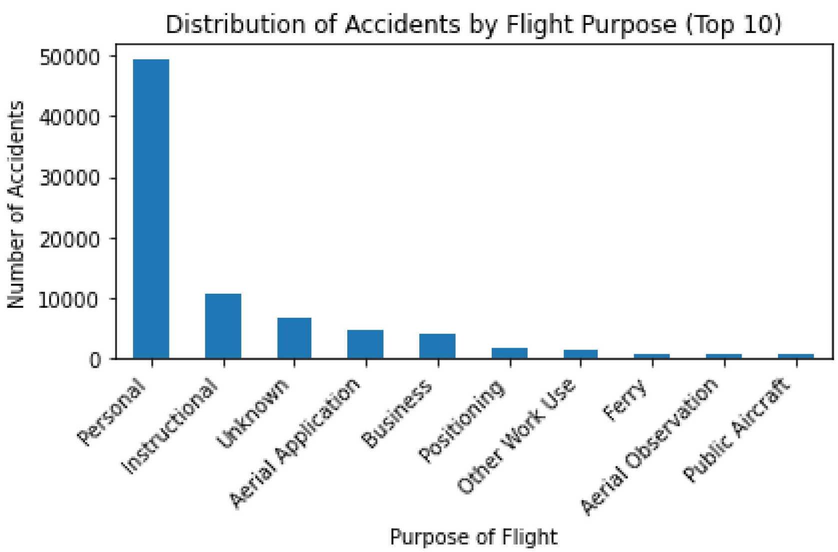
Out[16]: <AxesSubplot:>

Observations

1. Positive correlation: Engines and minor_injuries there is a strong postive correlation between these two variables by suggeting that as the number of engines increases the number of of minor injuries tends to increase.
2. Negative correlations: Engines and Uninjured show a moderate negative correlation as the number of engines increases, number of uninjured individuals tends to decrease.

The heatmap suggests that there might be a relationship between the number of eingine systems and likelihood of accidents and injuries.

In [23]:
```
# Exploring the purpose of flights involved in accidents

top_10_purposes = df_clean['Flight_Purpose'].value_counts().nlargest(10).sort_values(ascending=False)


plt.figure(figsize=(6, 4))
top_10_purposes.plot(kind='bar')
plt.title('Distribution of Accidents by Flight Purpose (Top 10)')
plt.xlabel('Purpose of Flight')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()


plt.show()
# Significant number of personal flights are responsible for aviation accidents
```



In [25]:

```
# The relationship between Makes, Models and engine types with accidents
make_model_accident_counts = df_clean.groupby(['Make', 'Model']).size().reset_index(name='AccidentCount',
make_model_accident_counts = make_model_accident_counts.sort_values(by='AccidentCount', ascending=False)
make_model_accident_counts
```

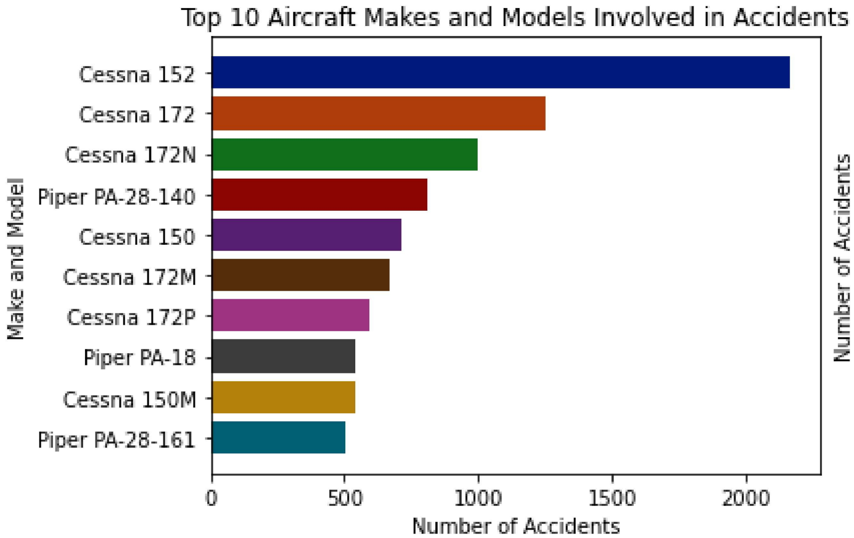
Out[25]:

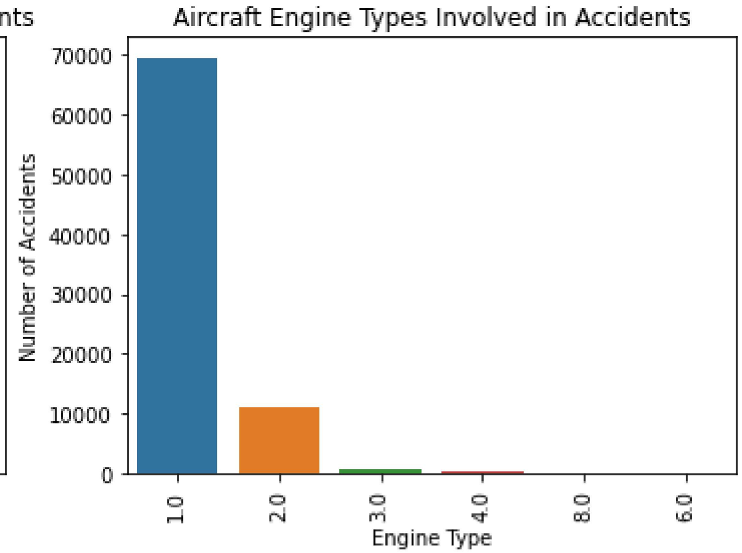
	Make	Model	AccidentCount
5745	Cessna	152	2168
5767	Cessna	172	1254
5811	Cessna	172N	996
15079	Piper	PA-28-140	812
5720	Cessna	150	716
...	...	...	...
8312	Engineering & Research	ERCOUPE 415-CD	1
8314	Engineering and Research	415C	1
8315	Engleman	PITTS S1	1
8316	English	PIETENPOL AIRCAMPER	1
20135	unknown	kit	1

20136 rows × 3 columns

In [28]:

```
# Exploring what Make, Model and engine type involved in more accidents

df_clean['Engines'] = df_clean['Engines'].replace(0.0, np.nan) # some values in Engine column are 0. I am
# I am not sure if we have any aircraft with 0 engine. So I treat them as missing values

fig, axes = plt.subplots(1, 2, figsize=(12, 4))


top_10_make_model = make_model_accident_counts.head(10)
colors = sns.color_palette("dark", len(top_10_make_model))
axes[0].barh(top_10_make_model['Make'] + ' ' + top_10_make_model['Model'], top_10_make_model['AccidentCour
axes[0].set_xlabel('Number of Accidents')
axes[0].set_ylabel('Make and Model')
axes[0].set_title('Top 10 Aircraft Makes and Models Involved in Accidents')
axes[0].invert_yaxis()


axes[1].set_xticks([])
sns.countplot(data=df_clean, x='Engines', order=df_clean['Engines'].value_counts().index, ax=axes[1])
axes[1].set_title('Aircraft Engine Types Involved in Accidents')
axes[1].set_ylabel('Number of Accidents')
axes[1].set_xlabel('Engine Type')
axes[1].tick_params(axis='x', rotation=90)
axes[1].set_xlabel('Engine Type')

plt.show()
```



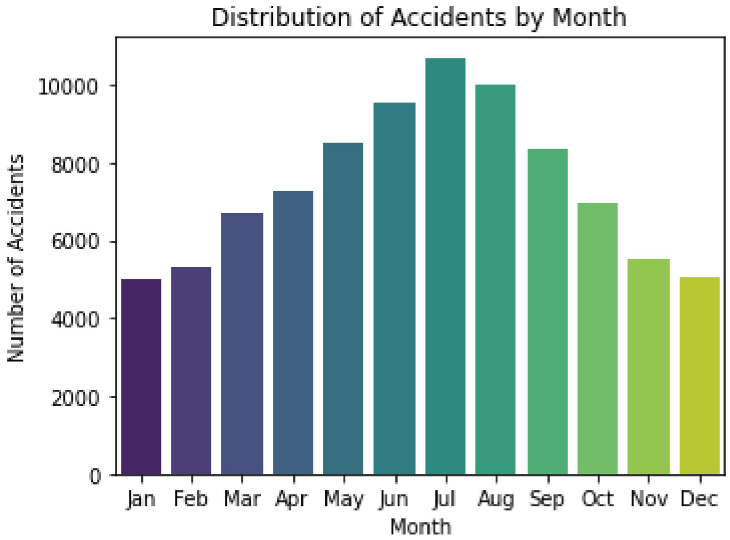


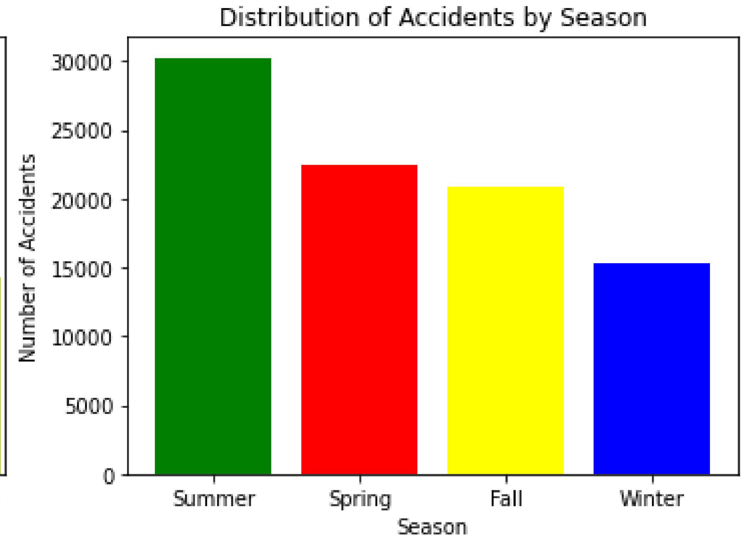
In [31]:

```
# changing date type to the appropriate format and creating a column for seasons
df_clean['Date'] = pd.to_datetime(df_clean['Date'], format='%Y-%m-%d')
df_clean['Month'] = df_clean['Date'].dt.month
seasons = {
    12: 'Winter', 1: 'Winter', 2: 'Winter',
    3: 'Spring', 4: 'Spring', 5: 'Spring',
    6: 'Summer', 7: 'Summer', 8: 'Summer',
    9: 'Fall', 10: 'Fall', 11: 'Fall'
}

df_clean['Season'] = df_clean['Month'].map(seasons)
```

In [39]:

```
# Plot distribution of accidents by months and seasons

fig, axes = plt.subplots(1, 2, figsize=(12, 4))


sns.countplot(data=df_clean, x='Month', palette='viridis', ax=axes[0])
axes[0].set_title('Distribution of Accidents by Month')
axes[0].set_xlabel('Month')
axes[0].set_ylabel('Number of Accidents')


month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
axes[0].set_xticks(range(12))
axes[0].set_xticklabels(month_order)


season_colors = {
    'Winter': 'blue',
    'Spring': 'red',
    'Summer': 'green',
    'Fall': 'yellow'
}


seasonal_accident_counts = df_clean['Season'].value_counts()


axes[1].bar(seasonal_accident_counts.index, seasonal_accident_counts, color=[season_colors.get(season, 'ta
axes[1].set_title('Distribution of Accidents by Season')
axes[1].set_xlabel('Season')
axes[1].set_ylabel('Number of Accidents')
plt.show()

# Most accidents happen in the summer
```





4. Recommendations

Personal flights are responsible for a high percentage of aviation accidents. In the area of personal flights, detailed education and training courses should be encouraged for pilots. The safety-first culture has to be nourished within the community of personal aviation. Minimizing the occurrence of accidents in personal flights depends on how safety is considered the priority in every personal flying activity. Whichever the weather condition, pilots must be very prepared and informed of the possible risks to be taken in personal aviation.

Most accidents occur in summer. In good weather, pilots may become overly confident and feel there is less risk than in poor weather conditions. This can result in a casual approach toward safety procedures and / or unsafe behavior, like flying low, going too fast, or using aerobatics, which raise the accident risk. The remedy is to encourage responsible flying practices and avoid taking unnecessary risks by proper training and awareness. It is also a re-emphasis on flying inside the safety envelope to avert accidents.

Aircraft makes and models, and engine types, in accidents. The Cessna 152 is the highest aircraft model in the number of accidents, followed by the Cessna 172. The opposite is observed in the case of the type of engine: the "1.0" type is dominant, while all others have much lower accident numbers. These findings might indicate that higher accident rates are related to models Cessna 152 and 172, combined with engine type "1.0.". Recommendations include: (1) Targeted safety investigations into these specific models and engine types to identify potential design flaws or operational issues; (2) Increased pilot training and education for these aircraft to address any recurring factors contributing to accidents; (3) Regular maintenance and inspections of these models and engines to ensure their continued airworthiness.