PROJECT PHASE 1

AVIATION ACCIDENTS ANALYSIS

1. Introduction.

In line with Our plans to diversify portfolios, by taking interest in purchase and operating aircrafts,for commercial and private enterprises.I have taken dataset from National Transportation Safety Board (NTSB) that has aviation accidents data from 1962 to 2023. Its all about civil aviation accidents and incidents in USA nad International waters.

Import Standard Libraries

In [24]:
```
#import standard libraries to use throught out.
#alias is key here
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.cm as cm
```

Load dataset into dataframe

In [25]:
```
#read dataset from where its stored.
#  loading is critical to ensure its accessibility.
df = pd.read_csv('data/Aviation_Data.csv', low_memory = False)
```

Data Exploration and preparation

In [26]:
```
#getting to know the data
#data knowledge will enable to make clearer analysis
df.head()
```

Out[26]:

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

5 rows × 31 columns

In [27]:
```
#overview of the data
#get to know the number of entries and number of objects
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      90348 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            50132 non-null  object 
 9   Airport.Name            52704 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     87507 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             81793 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           82505 non-null  object 
 30  Publication.Date        73659 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

In [28]:
```
#how about finding the columns the data has
#insight into categorization used i.e data columns
df.columns
```

Out[28]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.Description',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [29]:
```
#lets get the summary statics of the data
df.describe()
```

Out[29]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tot
count	82805.000000	77488.000000	76379.000000	76956.000000	8
mean	1.146585	0.647855	0.279881	0.357061	
std	0.446510	5.485960	1.544084	2.235625	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	
75%	1.000000	0.000000	0.000000	0.000000	
max	8.000000	349.000000	161.000000	380.000000	

Data cleaning and Data handling

In [30]:
```
#getting to know about missing values
#will assist to eliminate to ensure we get most inform from data with more informat
#check the number of missing values
df.isna().sum()
```

Out[30]:
```
Event.Id                  1459
Investigation.Type           0
Accident.Number           1459
Event.Date                1459
Location                  1511
Country                   1685
Latitude                 55966
Longitude                55975
Airport.Code             40216
Airport.Name             37644
Injury.Severity           2459
Aircraft.damage           4653
Aircraft.Category        58061
Registration.Number       2841
Make                      1522
Model                     1551
Amateur.Built             1561
Number.of.Engines         7543
Engine.Type               8555
FAR.Description          58325
Schedule                 77766
Purpose.of.flight         7651
Air.carrier              73700
Total.Fatal.Injuries     12860
Total.Serious.Injuries   13969
Total.Minor.Injuries     13392
Total.Uninjured           7371
Weather.Condition         5951
Broad.phase.of.flight    28624
Report.Status             7843
Publication.Date         16689
dtype: int64
```

In [31]:
```
#check the columns inorder to choose what is irrelevant
df.columns
```

Out[31]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.Description',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [32]:
```
#I think there are many columns which are not important for my analysis.
#  I drop these columns for easier handling of data and clearer analysis
# I am going to drop columns that have roughly more than 25% of their data missing.
columns_to_drop = ['Accident.Number','Registration.Number','Amateur.Built','Publica
'Engine.Type','Latitude','Longitude','Airport.Code','Airport.Name','Aircraft.Catego
'Schedule','Air.carrier','Broad.phase.of.flight','Report.Status']
df = df.drop(columns=columns_to_drop)
```

```
#see columns left and find any similarities
df.head(2)
```

Out[32]:

	Event.Id	Investigation.Type	Event.Date	Location	Country	Injury.Severity
0	20001218X45444	Accident	1948-10-24	MOOSE CREEK, ID	United States	Fatal(2)
1	20001218X45447	Accident	1962-07-19	BRIDGEPORT, CA	United States	Fatal(4)

When exploring the data,I noticed Injury.Severity and Total.fatal.injuries return same data.But Total.FataL.Injuries has many missing data, thus we are going to drop it.We can use Injury.Severity.It will give us more of data neeeded for our analysis.

In [33]:
```
#drop the column that has similar data but more missing values
columns_to_drop = ['Total.Fatal.Injuries']
df = df.drop(columns=columns_to_drop)
```

From the data set provided,we want to find the country featuring alot.This will help select country to focus this analysis.

In [34]:
```
#find out country with most dataset entries
df['Country'].value_counts()
```

Out[34]:
```
Country
United States                      82248
Brazil                               374
Canada                               359
Mexico                               358
United Kingdom                       344
                                   ...
Seychelles                             1
Palau                                  1
Libya                                  1
Saint Vincent and the Grenadines       1
Turks and Caicos Islands               1
Name: count, Length: 219, dtype: int64
```

We going to focus on United States since its way above 80 % of the dataset.This gives an deeper and better analysis.

Going to change event date to be featuring the year only for better analysis.

In [35]:
```
#we going to select United states only
```

In [36]:
```
df = df = df[df['Country'] == 'United States']
df.reset_index(drop=True, inplace=True)
```

In [37]:
```
#changing event.date to year only
df['Event.Date'] = pd.to_datetime(df['Event.Date'], format='%Y-%m-%d')
```

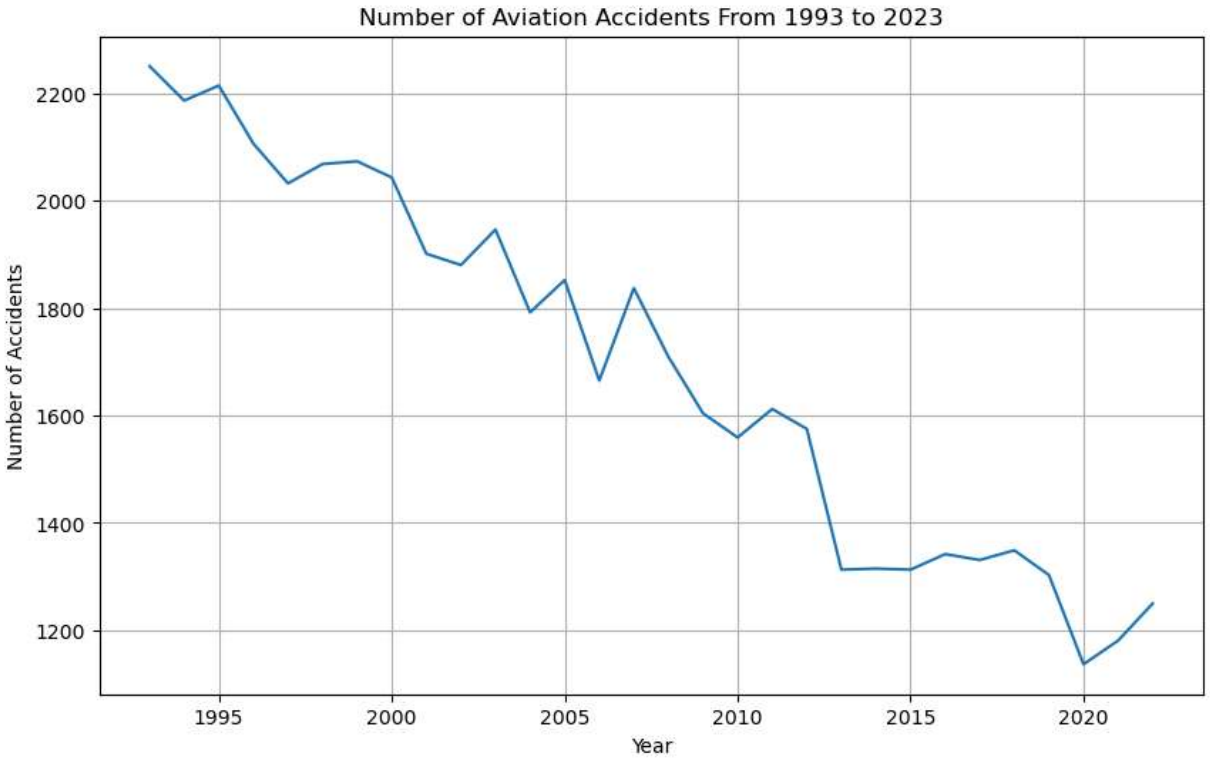
```
df['Year'] = df['Event.Date'].dt.year
```

In [38]:
```
df = df[df['Year'] >= 1993]
accidents_by_year = df['Year'].value_counts().sort_index()
```

Data Visualization

We can have a look at aviation accidents over years.Full narrative descriptions were not much available for dates before 1993,cases under revision and where NTSB didn't have primary investigative obligation.

In [39]:
```
#Line plot for aviation accidents from 1993 to 2023
df = df[df['Year'] >= 1993]
accidents_by_year = df['Year'].value_counts().sort_index()
x = accidents_by_year.index
y =  accidents_by_year.values
plt.figure(figsize=(10, 6))
plt.plot(x, y, linestyle= '-')
plt.title('Number of Aviation Accidents From 1993 to 2023')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.grid(True)

plt.show()
```



We can look at the top ten states with accidents.

In [40]:
```
# I create new columns using Location for future geographical analysis and visualis
#This was easier on Jupyter notebook by pip install us & import us, but it did not
# So I ended up creating a list of valid US states codes
```

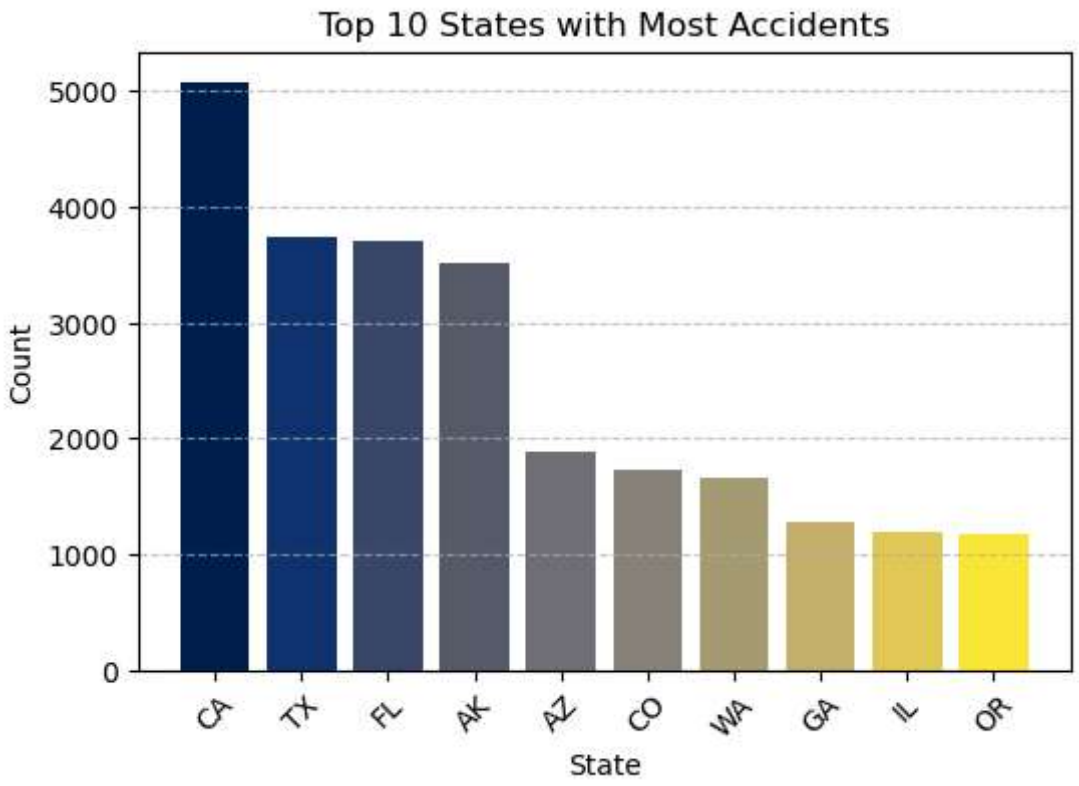
```
valid_state_codes = [
    'AL', 'AK', 'AZ', 'AR', 'CA', 'CO', 'CT', 'DE', 'FL', 'GA',
    'HI', 'ID', 'IL', 'IN', 'IA', 'KS', 'KY', 'LA', 'ME', 'MD',
    'MA', 'MI', 'MN', 'MS', 'MO', 'MT', 'NE', 'NV', 'NH', 'NJ',
    'NM', 'NY', 'NC', 'ND', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC',
    'SD', 'TN', 'TX', 'UT', 'VT', 'VA', 'WA', 'WV', 'WI', 'WY'
]

def extract_city_state(location):
    if pd.notna(location):
        location = location.strip()
        last_two_chars = location[-2:].upper()
        if last_two_chars in valid_state_codes:
            return location[:-3].strip(), last_two_chars
        else:
            return location, "Not Applicable" # Some accidents have not happend in
    else:
        return np.nan, np.nan

df[['City', 'State']] = df['Location'].apply(extract_city_state).apply(pd.Series)
```

In [41]:
```
# getting rid of trailing commas in City column
df['City'] = df['City'].str.rstrip(',')
```

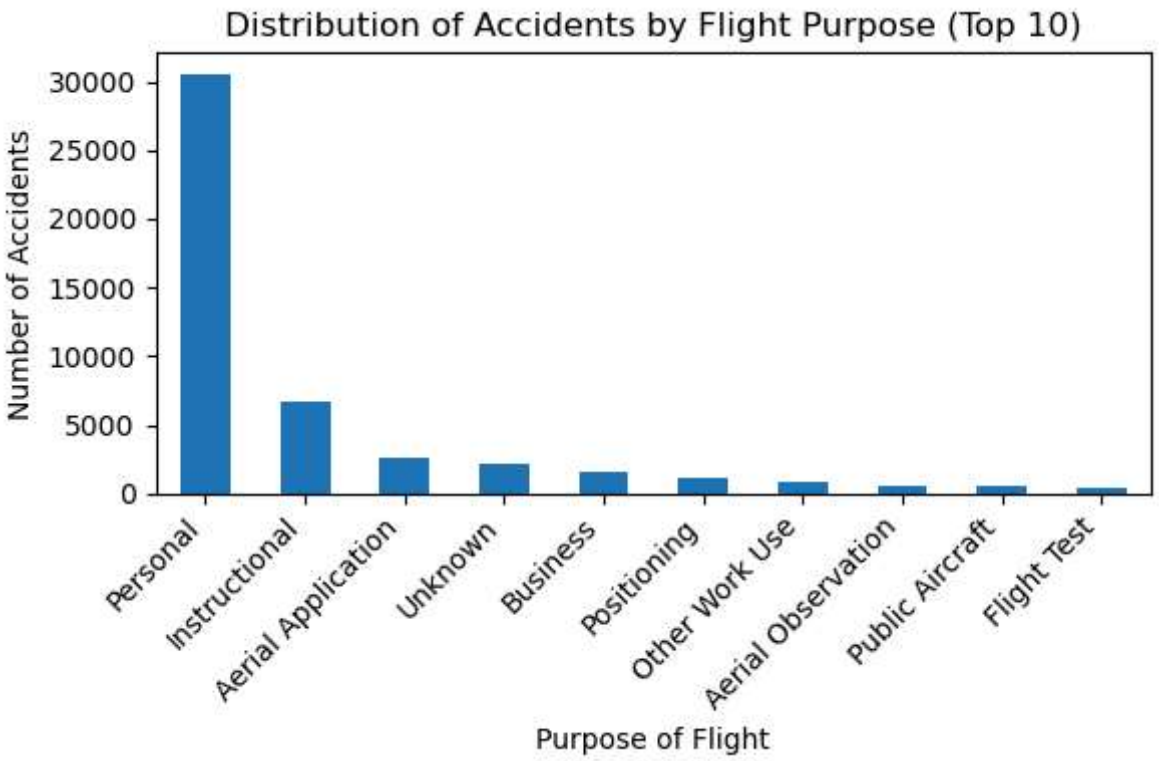
In [42]:
```
# having devided Location and Date columns, now we can drop these as well
df.drop(columns=['Event.Date', 'Location'], inplace=True)
```

In [43]:
```
# Let's have a look at top ten states with most accidents
top_10_states = df['State'].value_counts().head(10)


cmap = cm.get_cmap('cividis', len(top_10_states))
colors = cmap(range(len(top_10_states)))
x = top_10_states.index
y = top_10_states.values
plt.figure(figsize=(6, 4))
bars = plt.bar(x, y, color=colors)
plt.xlabel('State')
plt.ylabel('Count')
plt.title('Top 10 States with Most Accidents')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_16024\1327370354.py:5: MatplotlibDepreca
tionWarning: The get_cmap function was deprecated in Matplotlib 3.7 and will be remo
ved in 3.11. Use ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()
`` or ``pyplot.get_cmap()`` instead.
  cmap = cm.get_cmap('cividis', len(top_10_states))
```



In [44]:
```
# Exploring the purpose of flights involved in accidents

top_10_purposes = df['Purpose.of.flight'].value_counts().nlargest(10).sort_values(a


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
```



Try to see relationship between Makes,models and engines types in regard to accidents.

In [45]:
```
# Trying to see the relationship between Makes, Models and engine types with accide
make_model_accident_counts = df.groupby(['Make', 'Model']).size().reset_index(name=
make_model_accident_counts = make_model_accident_counts.sort_values(by='AccidentCou
make_model_accident_counts
```

Out[45]:

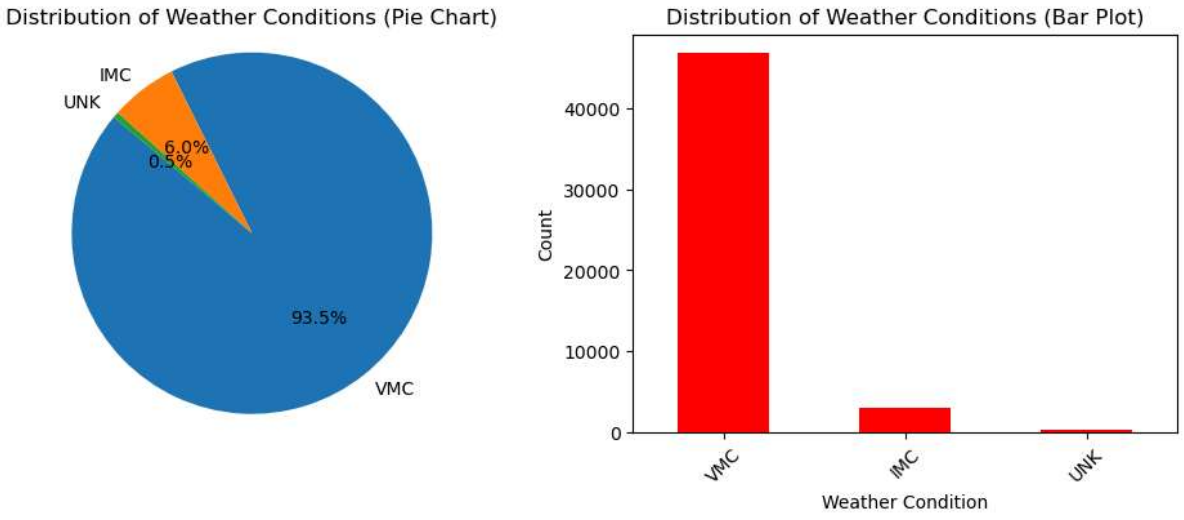
	Make	Model	AccidentCount
4118	Cessna	152	820
4133	Cessna	172	599
4164	Cessna	172N	508
3442	CESSNA	172	410
10877	Piper	PA-28-140	359
...	...	...	...
6075	FAUNCE	PA-11	1
6076	FDR601 LLC	ZODIAC 601XL	1
6077	FECHTNER	KR-2	1
6078	FEDERSEN WALTER	LANCAIR IVP	1
14587	unknown	kit	1

14588 rows × 3 columns

There is more accidents for the cessna model but this could be due to popularity of these models.

We can explore if there is relationship between weather conditions and accidents.

In [46]:
```
# I would like to explore if there is a meaningful relationship between wheather co

# in Weather column'Unknown' value was writen in both upper and lower cases and it
df['Weather.Condition'] = df['Weather.Condition'].str.upper()


weather_counts_updated = df['Weather.Condition'].value_counts()

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


axes[0].pie(weather_counts_updated, labels=weather_counts_updated.index,autopct='%1
axes[0].set_title('Distribution of Weather Conditions (Pie Chart)')
axes[0].axis('equal')



weather_counts_updated.plot(kind='bar', color='red', ax=axes[1])
axes[1].set_title('Distribution of Weather Conditions (Bar Plot)')
axes[1].set_xlabel('Weather Condition')
axes[1].set_ylabel('Count')
axes[1].tick_params(axis='x', rotation=45)

plt.show()
```



From the above, most accidents occur in VMC weather condition whic more favourable for pilots.Thus more flights are in opretion during this time.

CONCLUSION

Its clear there has been a decrease in accident since 1993 thus encouraging to venture in the industry.There are still states like California and Texas still reporting high accidents.Regular

reviews and updates of measure like safety protocols ,regulations and procudures will keep you afloat.

Most accidents occur in good weather conditions,meaning most Pilots could be less vigilant and also drop there guard.There could be incidents of laxity,excessive speed and less observation of safety protocols.To cater for this,I recommend refresher training and creating awarenes to remind Pilots of safety protocls during good weather conditions.

Personal flights is cause for mst accidents.Thus venturing in commercial flights gives as an edge of less accidents.Due to safety protocols and regular trainings We are guaranteed to avoid such.

Finally purchase should be focused on model with less accidents.It will be cost effective and less cost on repairs or replacements