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WASHINGTON, DC

THE ANALYSIS OF AVIATION ACCIDENTS

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ABSTRACT

Aviation accidents pose significant risks to human life and the aviation industry. Understanding their causes and contributing factors is crucial for enhancing safety and preventing future incidents. This abstract provides an overview of aviation accident analysis, its importance, methods employed, and desired outcomes.

Aviation accident analysis involves systematic investigation to determine causes and contributing factors. It employs methodologies such as accident scene investigation, data analysis, human factors analysis, and simulation modeling. These approaches analyze technical malfunctions, human errors, environmental conditions, and organizational factors.

The primary goal of aviation accident analysis is to identify root causes and develop effective safety recommendations. It enhances safety standards, improves operational procedures, and implements necessary changes. Insights gained help understand complex interactions between humans, technological systems, and organizations. Valuable lessons learned lead to improved training programs, enhanced aircraft design, and regulatory enhancements.

Accident analysis also contributes to safety research and the development of new technologies. It refines predictive models, establishes proactive safety measures, and improves safety regulations, standards, and practices.

In conclusion, aviation accident analysis plays a critical role in enhancing safety. By investigating accidents, identifying root causes, and implementing safety recommendations, it prevents future incidents and improves overall safety in the aviation industry. Continued investment in accident analysis research and collaboration between stakeholders is essential for ongoing improvement.

INTRODUCTION

Aviation accidents are complex events that require meticulous analysis to identify contributing factors and enhance safety measures. In this project, we delve into the captivating world of aviation accident analysis, with a particular focus on investigating the influence of weather conditions. The aim is to determine whether weather acts as a determinant factor in aviation accidents, shedding light on its potential impact on flight safety.

With an extensive dataset comprising 88,889 observations and 31 features, we embark on a comprehensive examination of aviation accidents spanning various contexts. However, recognizing the importance of quality and accuracy, we diligently cleaned and refined the dataset, resulting in a robust sample of approximately 75,000 observations.

By exploring the relationship between weather conditions and aviation accidents, we hope to uncover patterns, correlations, and potential risk factors that can aid in the development of proactive safety measures. The findings of this analysis will provide valuable insights for aviation professionals, regulators, and researchers, enabling them to make informed decisions and enhance safety protocols.

Join us as we delve into the rich tapestry of aviation accident data, employing advanced analytical techniques, including an interactive app for users to choose their preferences for visualization, to uncover the role of weather in these critical incidents. By doing so, we strive to contribute to the continuous improvement of aviation safety, paving the way for a safer and more secure future in the skies.

DATA PRE-PROCESSING

Beginning with the initial dataset containing 88,889 observations and 31 features, we undertook modifications by eliminating certain features and introducing new ones. Consequently, the shape of the original dataset transformed to retain the same number of observations, but with 27 features. Additional features such as Year, Month, and Day were incorporated by extracting information from the Event.Date column. These new features enabled the categorization of our time series dataset based on days, months, and years, which follows the default categorization scheme.

```
         Event.Id Investigation.Type  ...   Report.Status Publication.Date
0  20001218X45444           Accident  ...  Probable Cause              NaN
1  20001218X45447           Accident  ...  Probable Cause       19-09-1996
2  20061025X01555           Accident  ...  Probable Cause       26-02-2007
3  20001218X45448           Accident  ...  Probable Cause       12-09-2000
4  20041105X01764           Accident  ...  Probable Cause       16-04-1980

[5 rows x 31 columns]
There are 88889 and 27 columns observations in the original dataset
========================================================
```

Fig 1

Following that, we began examining the dataset for cleanup purposes. Initially, we identified columns with missing values, as shown below:

```
============================================
Event_Date                      0
Year                            0
Month                           0
Day                             0
Investigation_Type              0
Location                       52
Country                       226
Airport_Name                36099
Injury_Severity              1000
Aircraft_damage              3194
Aircraft_Category           56602
Make                           63
Model                          92
Amateur_Built                 102
Number_of_Engines            6084
Engine_Type                  7077
FAR_Description             56866
Purpose_of_flight            6192
Air_carrier                 72241
Total_Fatal_Injuries            0
Total_Serious_Injuries          0
Total_Minor_Injuries            0
Total_Uninjured                 0
Weather_Condition            4492
Broad_phase_of_flight       27165
Report_Status                6381
Number_of_passengers            0
dtype: int64
============================================
```

Fig 2

Figure 2 displays that our target variable, Weather_Condition, initially contained 4,492 missing values. By removing the corresponding rows with null values and making necessary adjustments to the dataset, we successfully reduced this count to 692. Subsequently, we proceeded to eliminate the remaining missing values specifically from the Weather_Condition column, resulting in a count of 0. The figure below shows the cleaned dataset:

```
=========================================================
There are 75751 observations and 17 columns in the cleaned up dataset, which is enough to carry out our analysis
=========================================================
Event_Date                0
Year                      0
Month                     0
Day                       0
Investigation_Type        0
Country                   0
Injury_Severity           0
Aircraft_damage           0
Amateur_Built             0
Number_of_Engines         0
Engine_Type               0
Total_Fatal_Injuries      0
Total_Serious_Injuries    0
Total_Minor_Injuries      0
Total_Uninjured           0
Weather_Condition         0
Number_of_passengers      0
dtype: int64
=========================================================
```

Fig 3

Upon completion of the dataset cleaning process, we obtained a total of 75,751 observations and 17 features, which included our target variable. This dataset size was deemed sufficient for conducting our analysis. To further refine the dataset and identify the continuous variables, we proceeded to modify the data types. The figure below illustrates the changes made before and after this process.

```
=========================================
Event_Date                 datetime64[ns]
Year                                int64
Month                              object
Day                                object
Investigation_Type                 object
Country                            object
Injury_Severity                    object
Aircraft_damage                    object
Amateur_Built                      object
Number_of_Engines                  object
Engine_Type                        object
Total_Fatal_Injuries               object
Total_Serious_Injuries             object
Total_Minor_Injuries               object
Total_Uninjured                    object
Weather_Condition                  object
Number_of_passengers              float64
dtype: object
=========================================
```

```
=========================================
Event_Date                 datetime64[ns]
Year                                int64
Month                              object
Day                                object
Investigation_Type                 object
Country                            object
Injury_Severity                    object
Aircraft_damage                    object
Amateur_Built                      object
Number_of_Engines                   int64
Engine_Type                        object
Total_Fatal_Injuries                int64
Total_Serious_Injuries              int64
Total_Minor_Injuries                int64
Total_Uninjured                     int64
Weather_Condition                  object
Number_of_passengers              float64
dtype: object
=========================================
```

Fig 4

Following the completion of dataset cleaning, our next step involved outlier detection. The resulting numbers outlining the detected outliers are presented in the figure below:

```
=========================================================
Number of outliers for Total_Fatal_Injuries is 111
Number of outliers for Total_Serious_Injuries is 298
Number of outliers for Total_Minor_Injuries is 243
Number of outliers for Total_Uninjured is 715
=========================================================
```

Fig 5

Given the characteristics of our dataset, it is expected that the outliers will primarily consist of extremely high values or zero values for the number of passengers. This aspect is crucial for obtaining accurate results. The presence of such outliers can be justified by the possibility of commercial airlines with larger aircraft accommodating a substantial number of passengers, while smaller aircraft might have fewer passengers on board. Additionally, columns with zero as an outlier likely indicate that the corresponding numbers are present in other columns. This implies that air crash incidents involving passengers with fatal injuries may not have any uninjured passengers, and vice versa.

Subsequently, we proceeded with conducting PCA analysis and determined that by removing one component, we could account for 95% of the variance in the data. This component was likely to be associated with the "Number_of_passengers" column, which is not essential for our analysis purposes. However, due to the nature of our dataset, it is necessary to retain this column to differentiate between private, chartered, and commercial aircraft, as it aids in comprehending certain results. Displayed below are the numerical findings and graph derived from our PCA analysis:

Numerical Results:

```
==========================================================
Number of components to be removed: 1
Explained variance ratio of original feature space: [3.46846634e-01 2.14933651e-01 1.67867671e-01 1.60292642e-01
 1.10059402e-01 2.84691135e-30]
Explained variance ratio of reduced feature space: [0.34684663 0.21493365 0.16786767 0.16029264 0.1100594 ]
Singular values: [3.97043922e+02 3.12551810e+02 2.76218869e+02 2.69914741e+02
 2.23657458e+02 1.13751408e-12]
Condition number: 349045280118988.9
==========================================================
```

Fig 6

Graph:

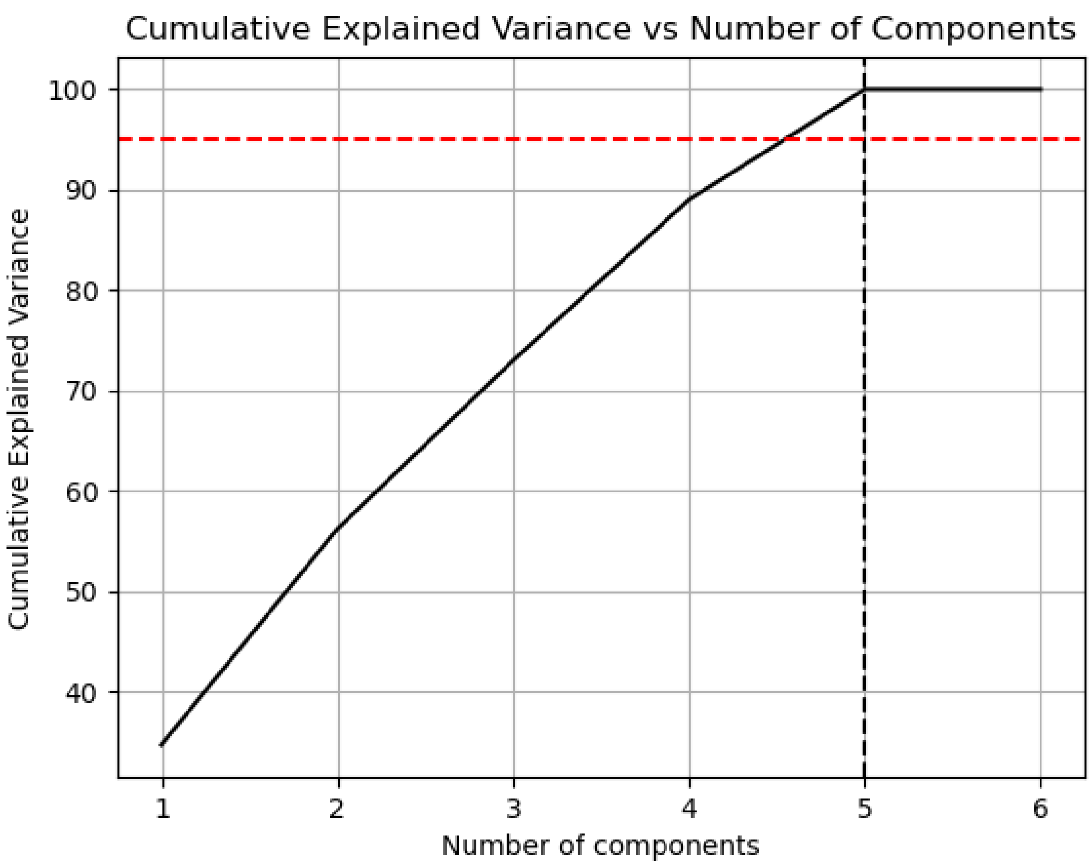

Fig 7

Subsequently, we conducted a D'Agostino's K^2 test, which indicated that our numerical datasets did not follow a normal distribution. This observation aligns with the nature of the dataset we are handling. Consequently, we made the decision to retain the dataset in its current form, as each data point within it holds significance, and altering the distribution may lead to a loss of valuable information. The image below depicts the test performed in the console:

```
==================================================
da_k_squared test: Total_Fatal_Injuries dataset: statistics= 251611.92 p-value = 0.00
da_k_squared test : Total_Fatal_Injuries dataset does not look Normal
==================================================
==================================================
da_k_squared test: Total_Serious_Injuries dataset: statistics= 267284.47 p-value = 0.00
da_k_squared test : Total_Serious_Injuries dataset does not look Normal
==================================================
==================================================
da_k_squared test: Total_Minor_Injuries dataset: statistics= 211768.34 p-value = 0.00
da_k_squared test : Total_Minor_Injuries dataset does not look Normal
==================================================
==================================================
da_k_squared test: Total_Uninjured dataset: statistics= 149086.91 p-value = 0.00
da_k_squared test : Total_Uninjured dataset does not look Normal
==================================================
```

Fig 8

Correlation Matrix

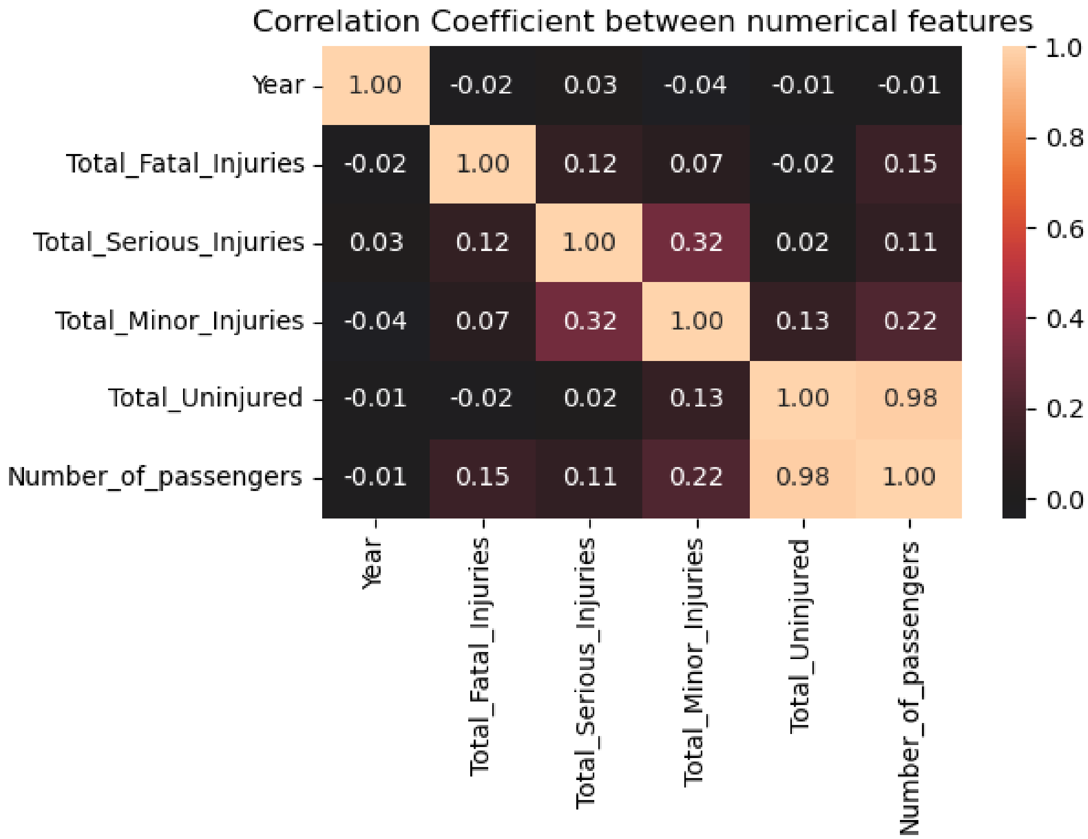

Fig 9

The correlation matrix presented above (Fig 9) highlights notable relationships within the dataset. The strongest positive correlation is observed between "Total Uninjured" and "Number of passengers" (r = 0.98). This indicates that in aviation accidents, a higher number of uninjured passengers is often associated with a larger passenger count. Conversely, the data reveals the strongest negative correlation between "Year" and "Total Minor Injuries" (r = -0.04). This suggests that over the years, there has been a slight decrease in the number of minor injuries in aviation accidents. It is worth noting that the correlation between year and total minor injuries is very weak, indicating that the relationship is not substantially strong.

PLOTS

LINE PLOTS:

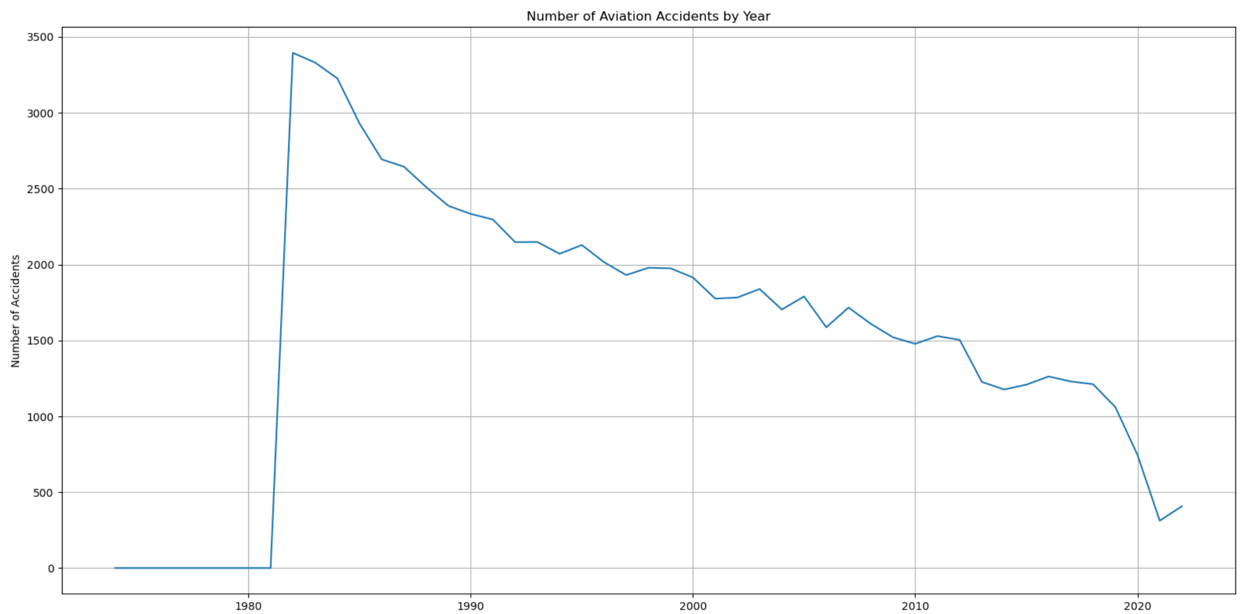

Fig 10

The depicted plot illustrates the frequency of aviation accidents over a span of 48 years. Within the timeframe covered by this dataset, there is a noticeable and noteworthy decline in the number of aviation accidents. This trend signifies a positive development, indicating the ongoing endeavors of the aviation industry to enhance safety measures and mitigate the occurrence of accidents.

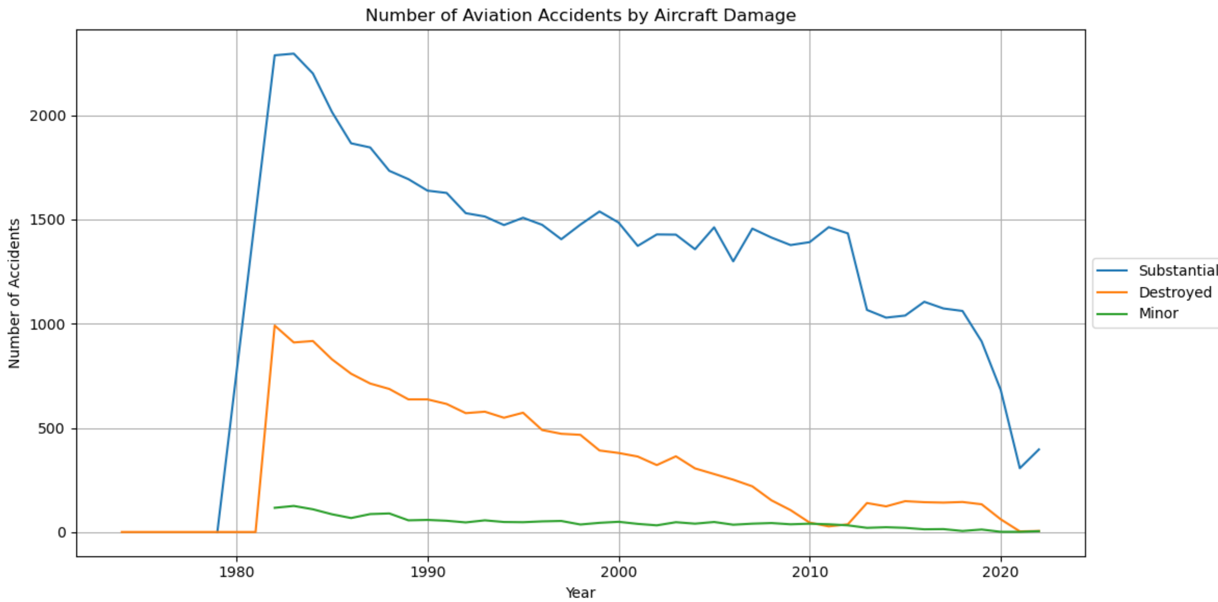

Fig 11

The presented plot illustrates the trend of aircraft damages over the years. It is evident that a majority of aircraft experienced substantial damages, while a smaller portion was completely destroyed. The observed decrease in these figures indicates that the aviation industry has implemented significant precautions or that rapid technological advancements have contributed to this decline.

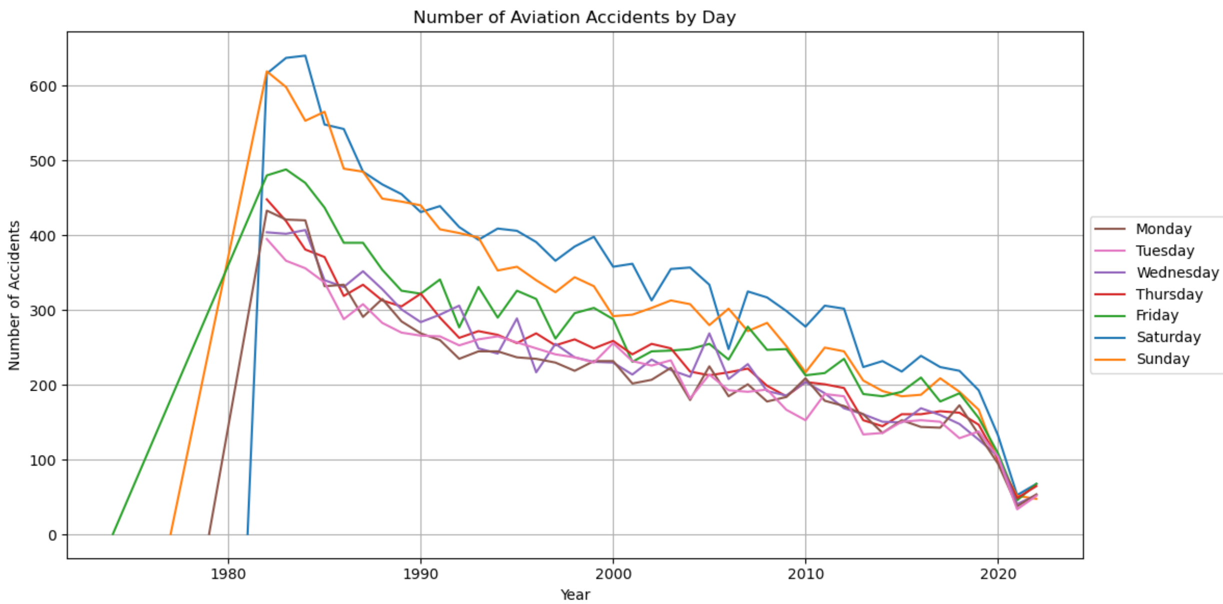

Fig 12

The displayed plot depicts the frequency of aviation crashes for each day of the week spanning from 1974 to 2022. It is notable that Saturday consistently exhibits the highest number of crashes throughout the years, with a decline observed around 2020, likely influenced by the impact of the pandemic during that period. Conversely, Tuesday stands out as the day with the lowest probability of aviation crashes. Therefore, the likelihood of being involved in an aviation crash on Tuesdays is relatively lower compared to other days of the week.

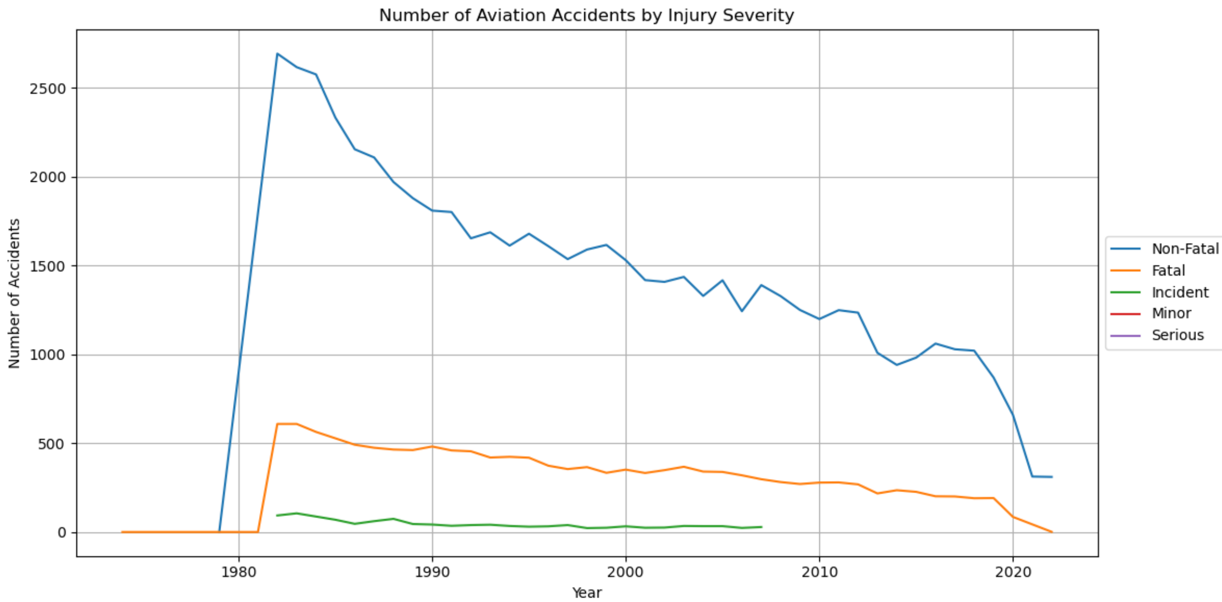

Fig 13

The presented plot showcases the frequency of aviation crashes categorized by the severity of injuries spanning from 1974 to 2022. Notably, non-fatal injuries consistently account for the highest number of crashes throughout the years, with a decline observed around 2020, potentially influenced by the effects of the pandemic during that time. On the other hand, it is worth mentioning that most of the plane crashes that occurred during this period did not result in serious injuries.

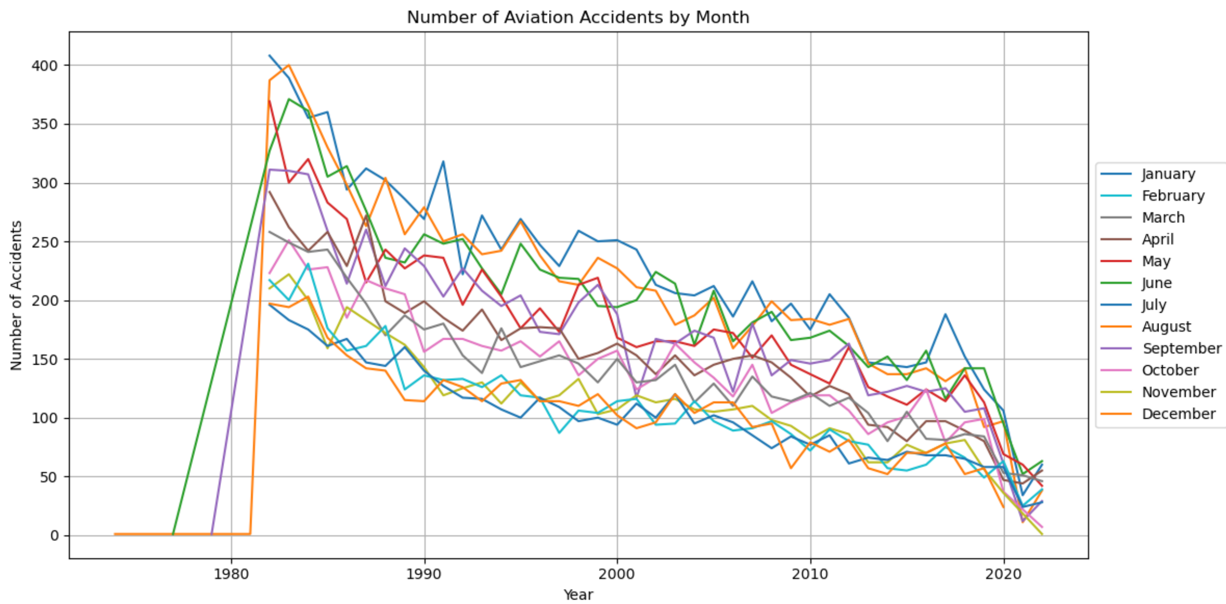

Fig 14

The plot presented illustrates the frequency of aviation crashes across each month of the year from 1974 to 2022. Notably, July and August consistently demonstrate the highest number of crashes throughout the years, with a decline observed around 2020, potentially influenced by the impact of the pandemic during that period. In contrast, January and December emerge as the months with the lowest probability of aviation crashes. Consequently, the likelihood of being involved in an aviation crash during December or January is relatively lower compared to other months of the year.

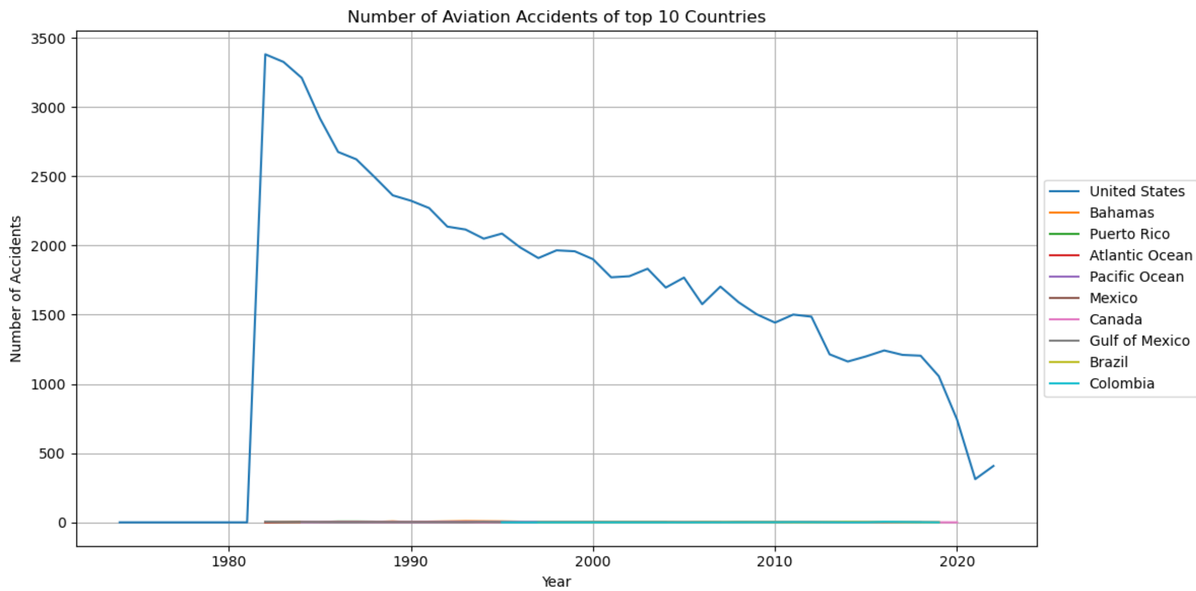

Fig 15

The presented plot depicts the number of aviation accidents across ten countries. It is evident that the United States has a considerably higher number of crashes compared to the other countries. Moreover, there appears to be a declining trend in the number of accidents over the years. In contrast, the remaining countries exhibit significantly lower numbers of aviation accidents in comparison to the US.

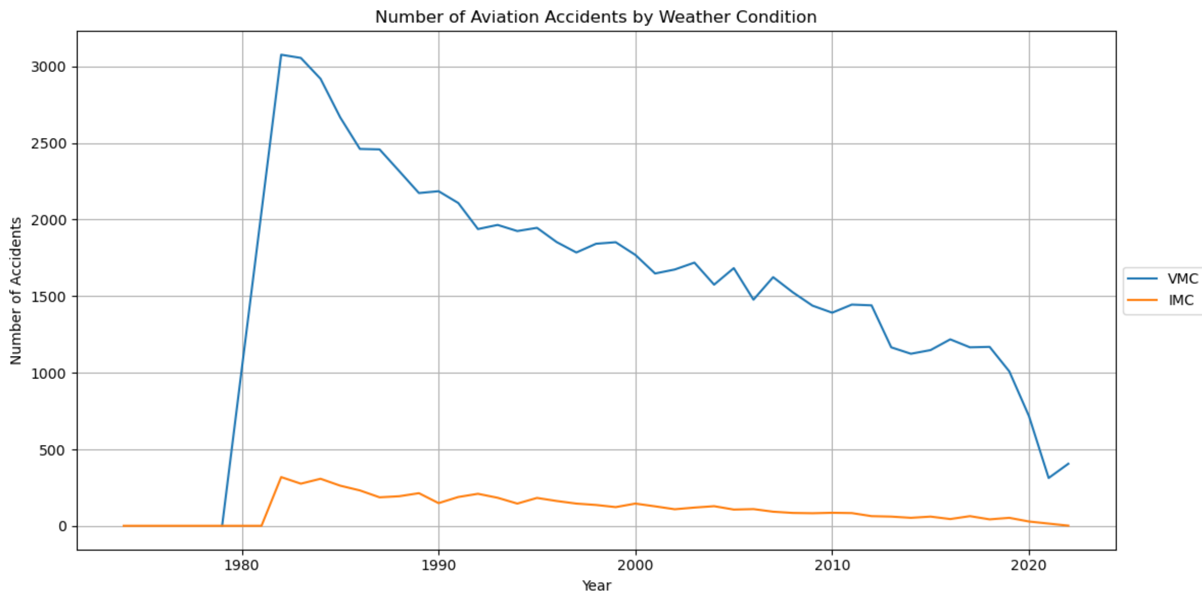

Fig 16

The displayed plot represents the variable we are attempting to predict as a potential cause of aviation accidents. Examining the weather conditions depicted in the plot, we observe that VMC (Visual Meteorological Conditions) weather has a higher frequency of aviation accidents compared to IMC (Instrument Meteorological Conditions) weather. This finding suggests that weather conditions may not be a significant contributing factor to aviation accidents, as VMC typically indicates clear skies and favorable weather conditions, while IMC signifies adverse weather. Given the higher occurrence of crashes in VMC conditions in this plot, it indicates that more accidents happen in good weather rather than in poor weather conditions.

BAR PLOTS:

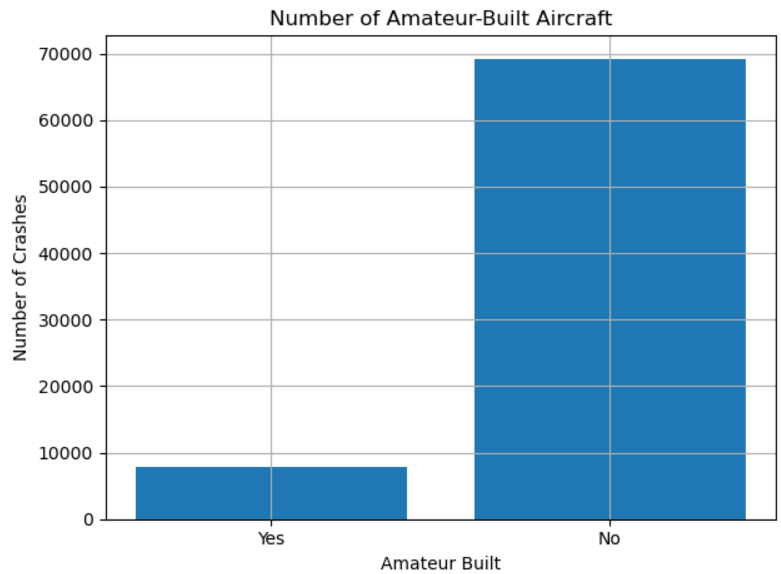

Fig 17

The presented bar plot showcases the number of aircraft in the dataset categorized as either "Amateur Built" or "Non-Amateur Built." "Amateur Built" refers to aircraft constructed privately, while "Non-Amateur Built" indicates those built by industries. It is evident from the plot that a majority of the aircraft involved in aviation accidents are categorized as "Non-Amateur Built," implying that accidents primarily involve aircraft constructed by industry professionals rather than privately built ones.

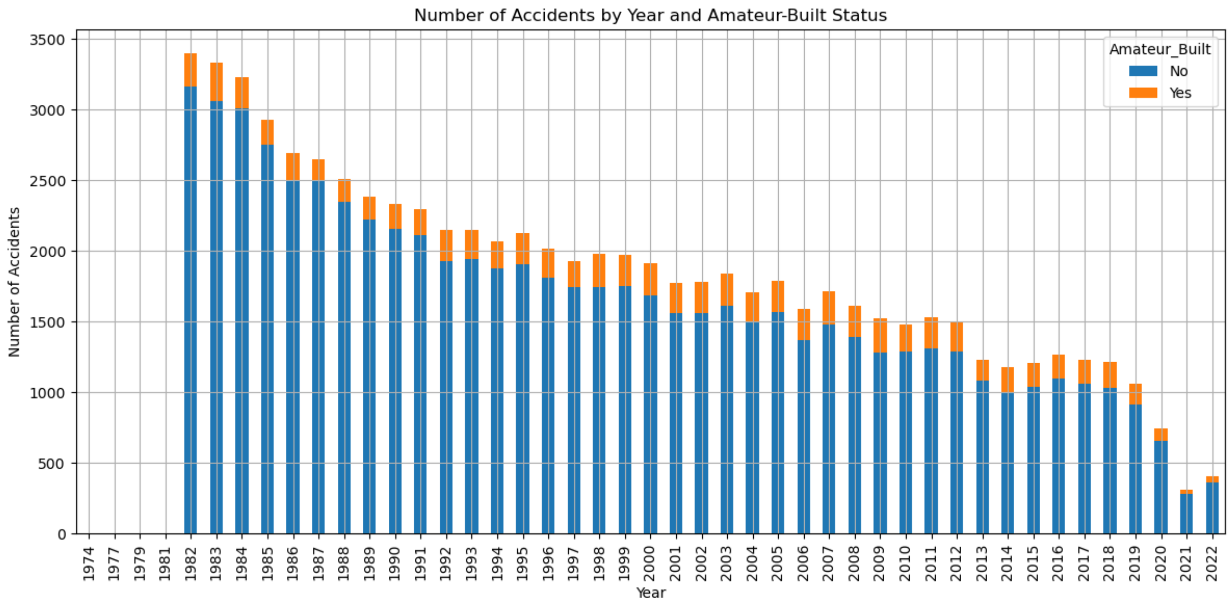

Fig 18

The plot presented above provides a similar representation as in Figure 17 but specifically focuses on the involvement of amateurly built and non-amateurly built aircraft in aviation accidents over the past 48 years.

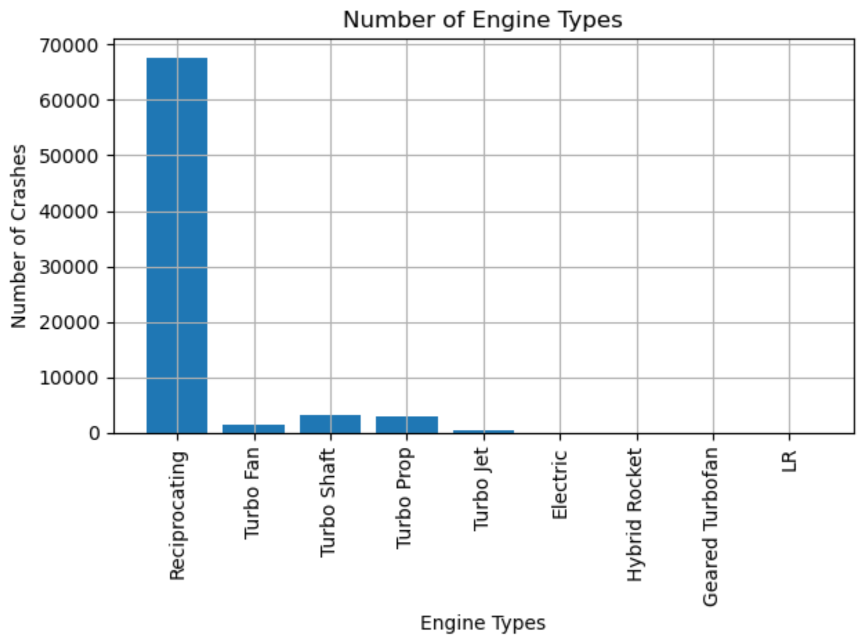

Fig 19

Upon examining the plot above, it becomes evident that reciprocating type aircraft are accountable for the majority of aviation accidents. This observation implies that there might be specific characteristics or factors related to reciprocating engines that render them more susceptible to accidents.

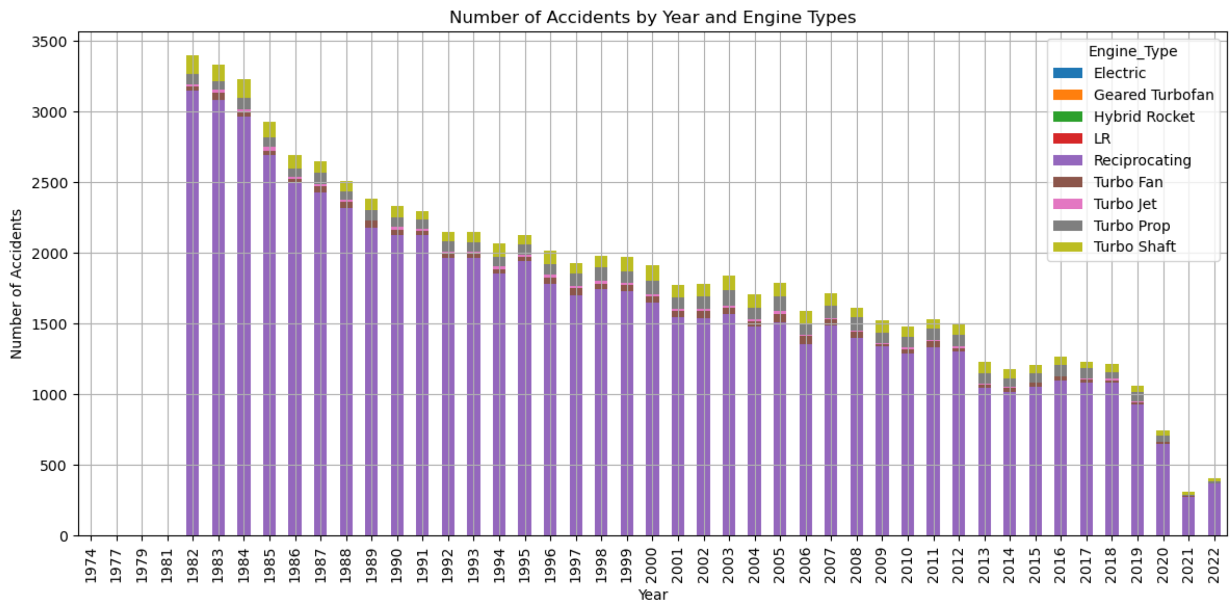

Fig 20

The plot above offers a comparable visualization to Figure 19, focusing on the role of engine types in aviation accidents over the past 48 years.

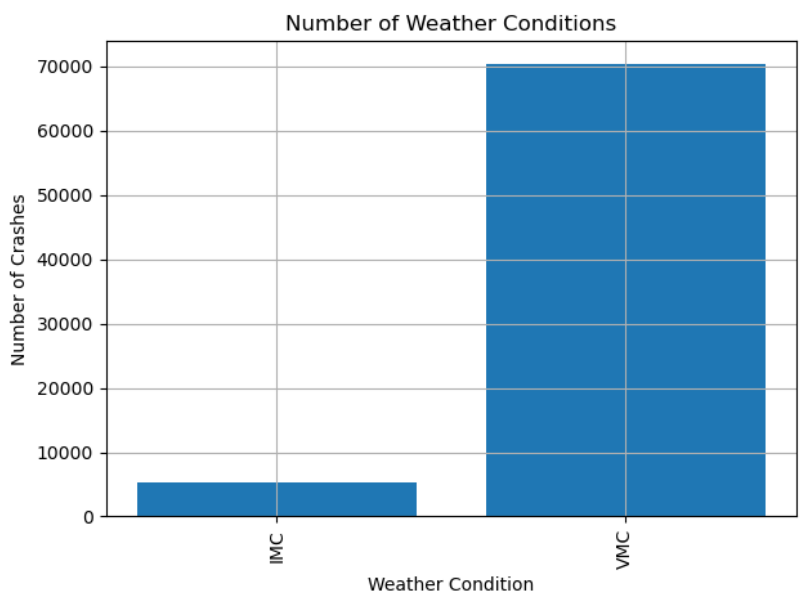

Fig 21

Based on the depicted plot, it becomes apparent that VMC (Visual Meteorological Conditions) conditions are accountable for the majority of aviation accidents. This observation suggests the presence of specific factors associated with VMC conditions that render them more susceptible to accidents. For instance, pilots may experience a heightened sense of confidence and potentially take more risks in VMC conditions, thereby contributing to the occurrence of accidents.

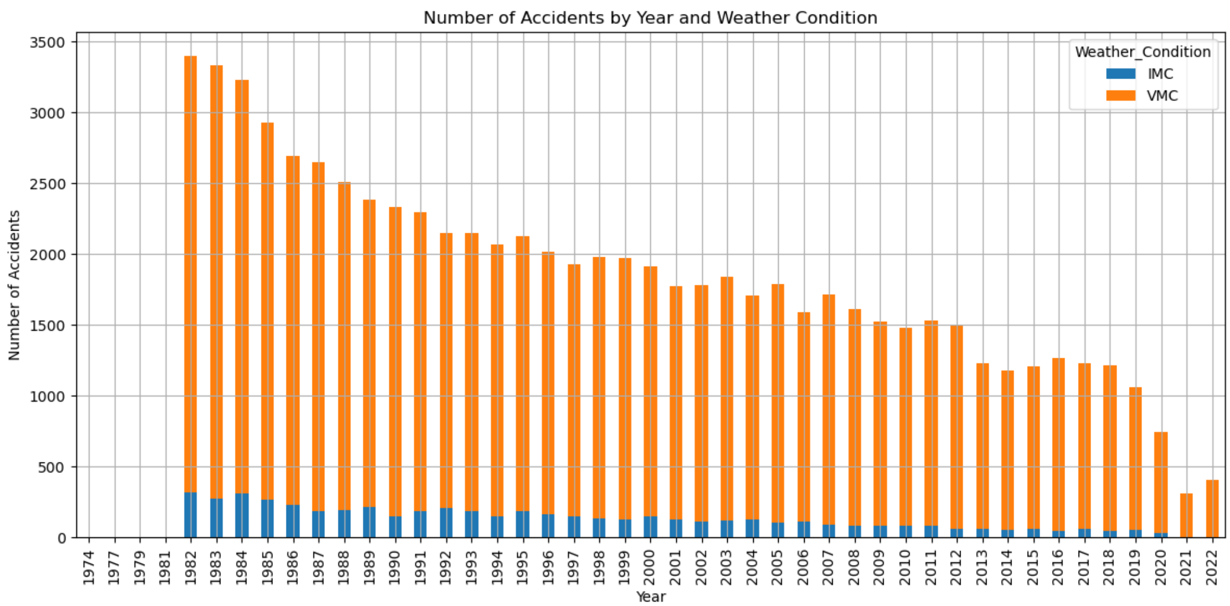

Fig 22

The presented plot provides a similar visual representation as Figure 21, specifically highlighting the influence of weather conditions on aviation accidents over the past 48 years.

COUNT PLOT:

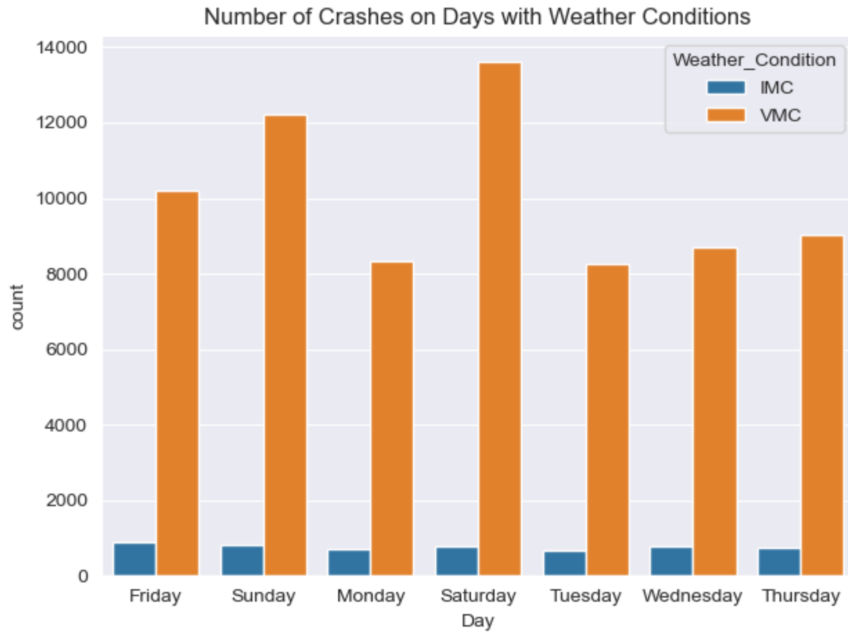

Fig 23

The plot presented illustrates the number of aviation accidents that occur each day of the week, considering the corresponding weather conditions. It is apparent that the highest number of aviation accidents happens on Saturdays, particularly in clear weather conditions (VMC). Conversely, the lowest accident count is observed between Tuesday and Monday. From this plot, it appears that weather does not have a significant impact on aviation accidents, as there is no clear relationship between weather conditions and accident frequency.

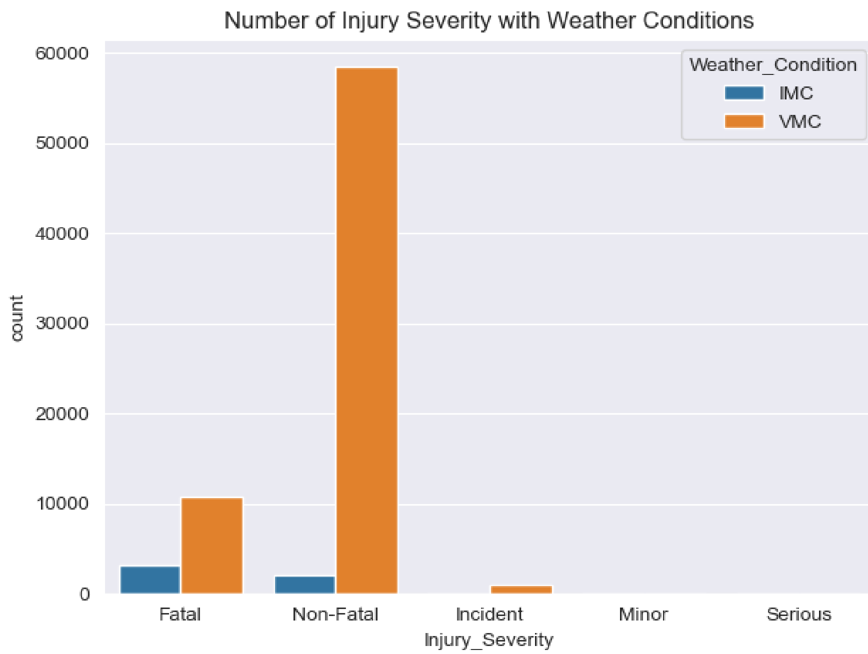

Fig 24

The presented plot depicts the count of injury severity in aviation accidents, considering the influence of weather conditions. Notably, the plot suggests that weather does not appear to play a significant role in fatalities during aviation accidents.

PIE CHARTS:

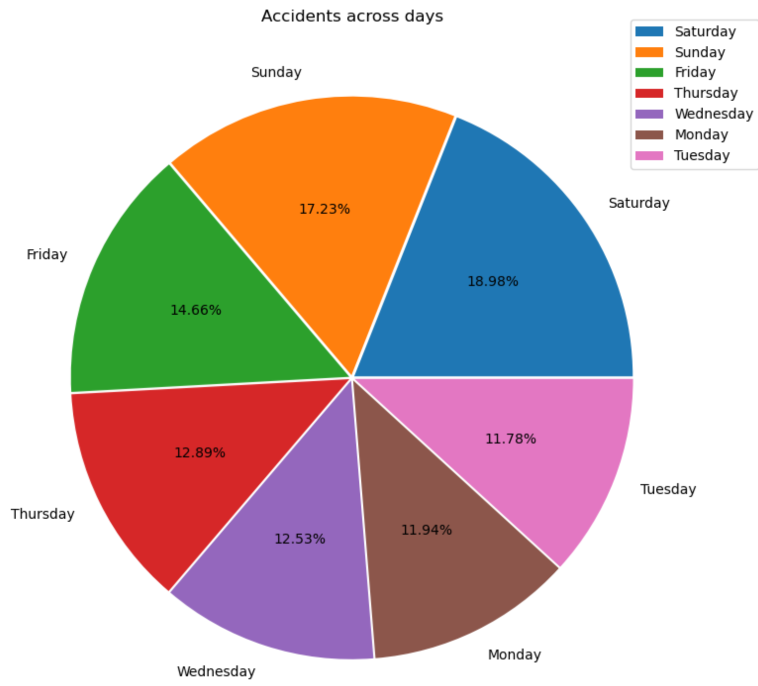

Fig 25

The chart reveals a distinct variation in the percentage of aviation accidents across different days of the week. Saturdays stand out with the highest percentage, accounting for approximately 19% of all accidents. Several potential factors could contribute to this elevated accident rate on Saturdays. For instance, Saturdays tend to be characterized by increased air travel activity, with a greater number of flights and passengers compared to other days. Furthermore, there may be a higher proportion of recreational or private flights on Saturdays, which could potentially be more susceptible to accidents when compared to commercial flights.

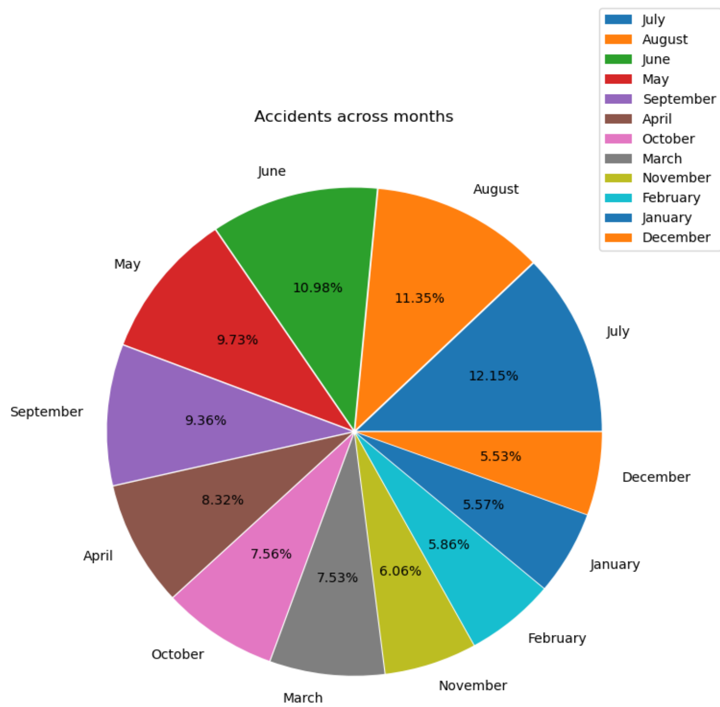

Fig 26

The chart clearly displays a distinct variation in the percentage of aviation accidents across different months. Notably, July stands out with the highest percentage, accounting for over 12% of all accidents. Several potential factors could contribute to this elevated accident rate in July. For instance, July is commonly a bustling travel month, with numerous individuals embarking on vacations or business trips. Additionally, July is often accompanied by summer storms and adverse weather conditions, which may heighten the risk of accidents.

CAT PLOT:

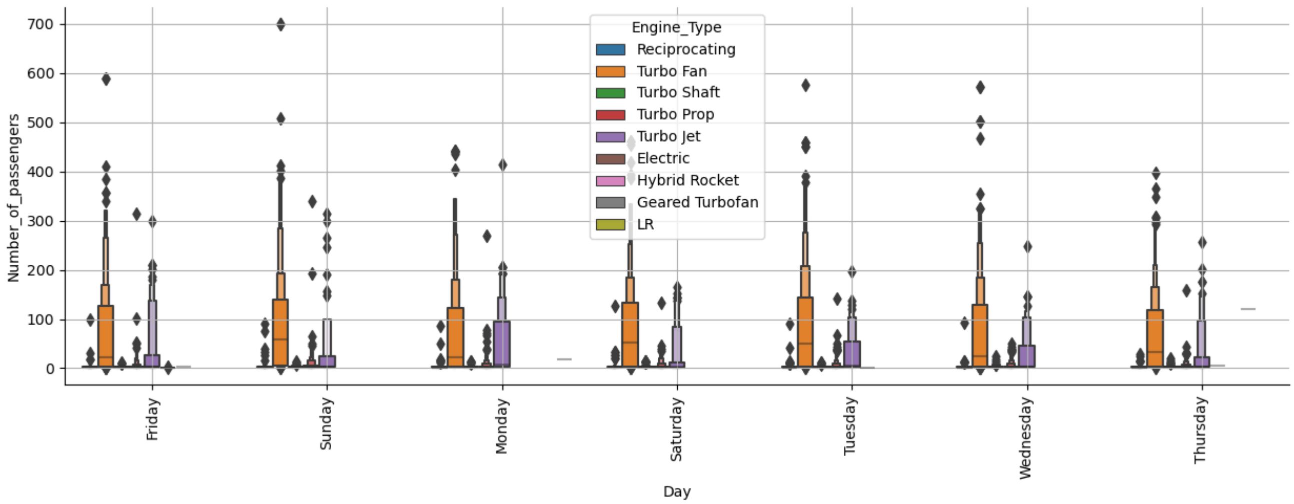

Fig 27

The presented plot indicates that a majority of passengers involved in aviation accidents are aboard aircraft equipped with Turbo fan engines with most people flying on Sunday. This observation is likely attributed to the fact that commercial aircraft typically accommodate a significantly higher number of passengers compared to chartered or private aircraft.

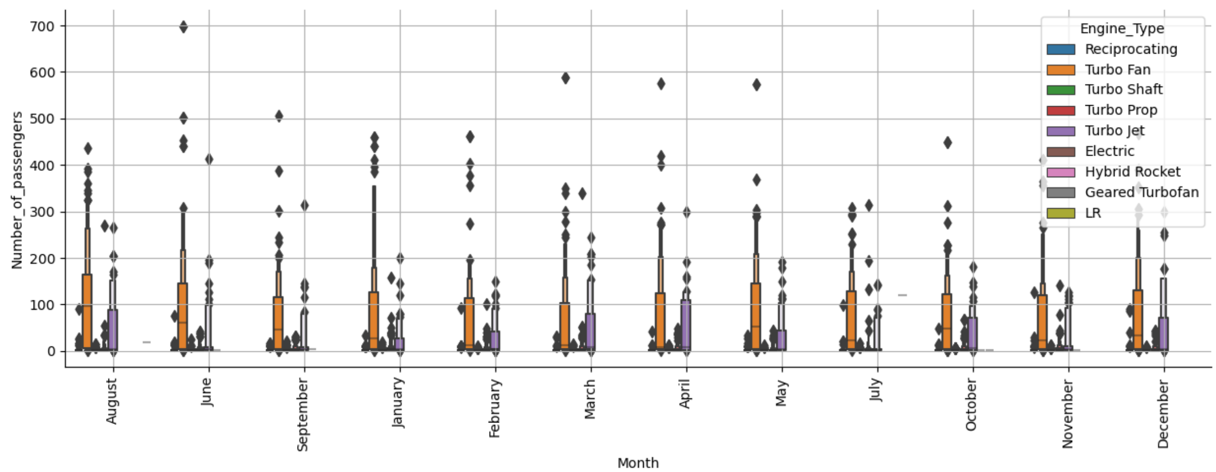

Fig 28

The plot above reveals that a significant proportion of passengers involved in aviation accidents are onboard aircraft equipped with Turbo fan engines, and there is a notable concentration of accidents occurring in the month of June. This pattern is likely influenced by the higher passenger capacity of commercial aircraft, as they generally accommodate a larger number of individuals compared to chartered or private aircraft.

DISPLOT:

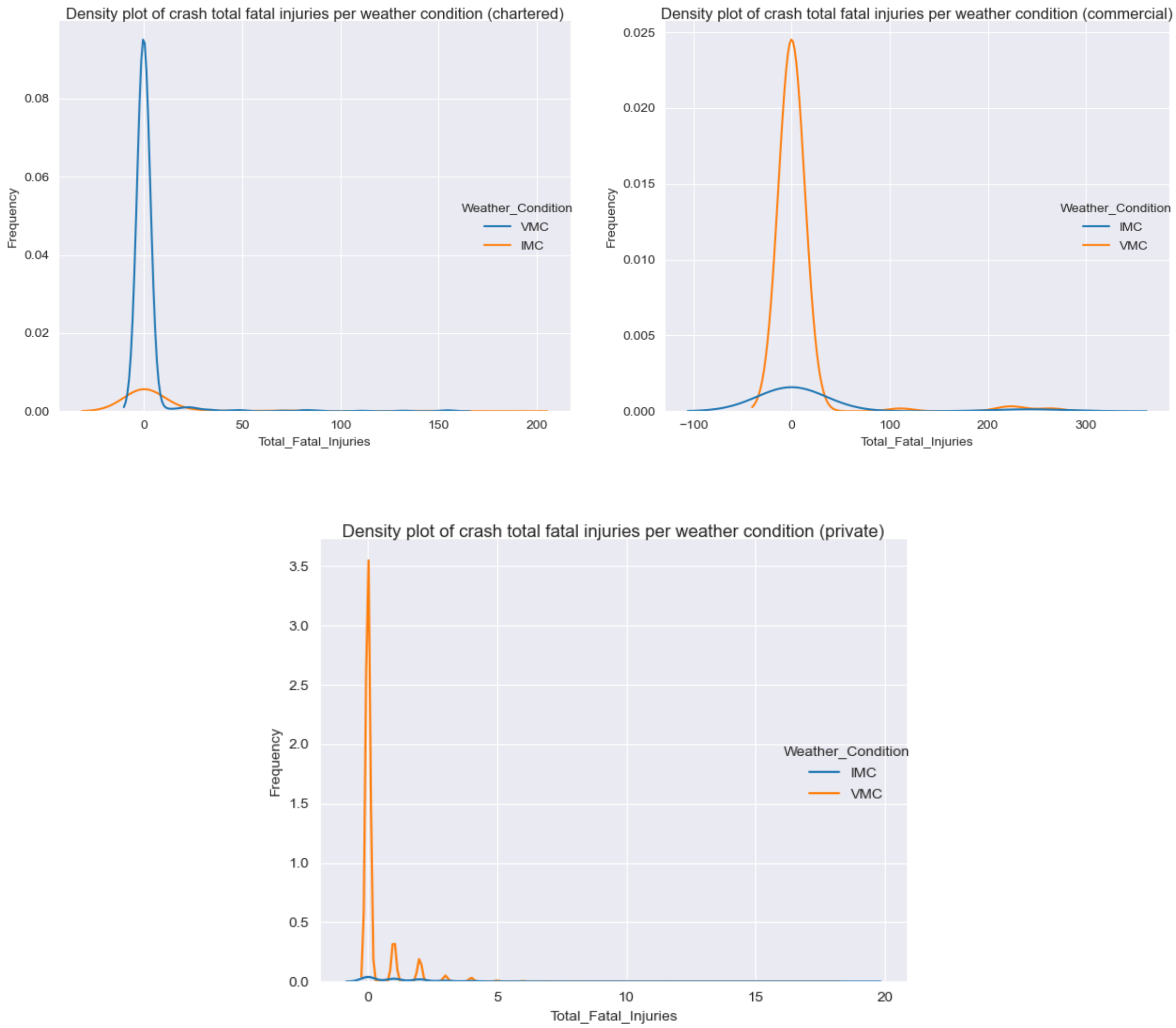

Fig 29

The plots presented in Figure 29 depict the distribution of fatal injuries in commercial, private, and chartered aircraft, categorized according to different weather scenarios. Notably, the majority of the plots indicate a prevalence of zero fatal injuries. This observation suggests that weather conditions do not strongly determine the occurrence of fatal injuries in aviation accidents.

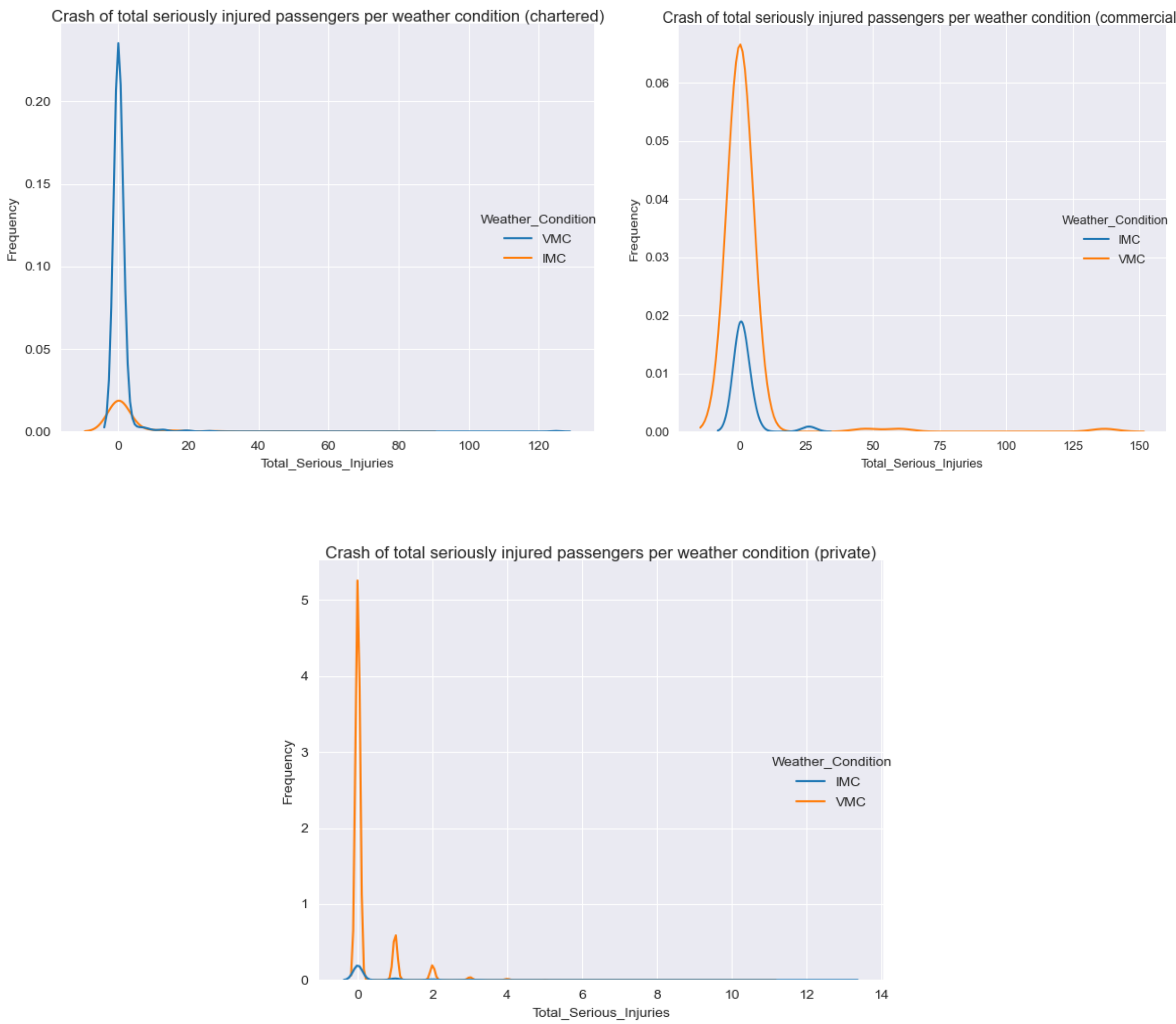

Fig 30

The plots showcased in Figure 30 illustrate the distribution of serious injuries in commercial, private, and chartered aircraft, categorized by different weather scenarios. Significantly, most of the plots exhibit a dominant occurrence of zero serious injuries. This finding indicates that weather conditions do not exert a substantial influence on the likelihood of serious injuries in aviation accidents.

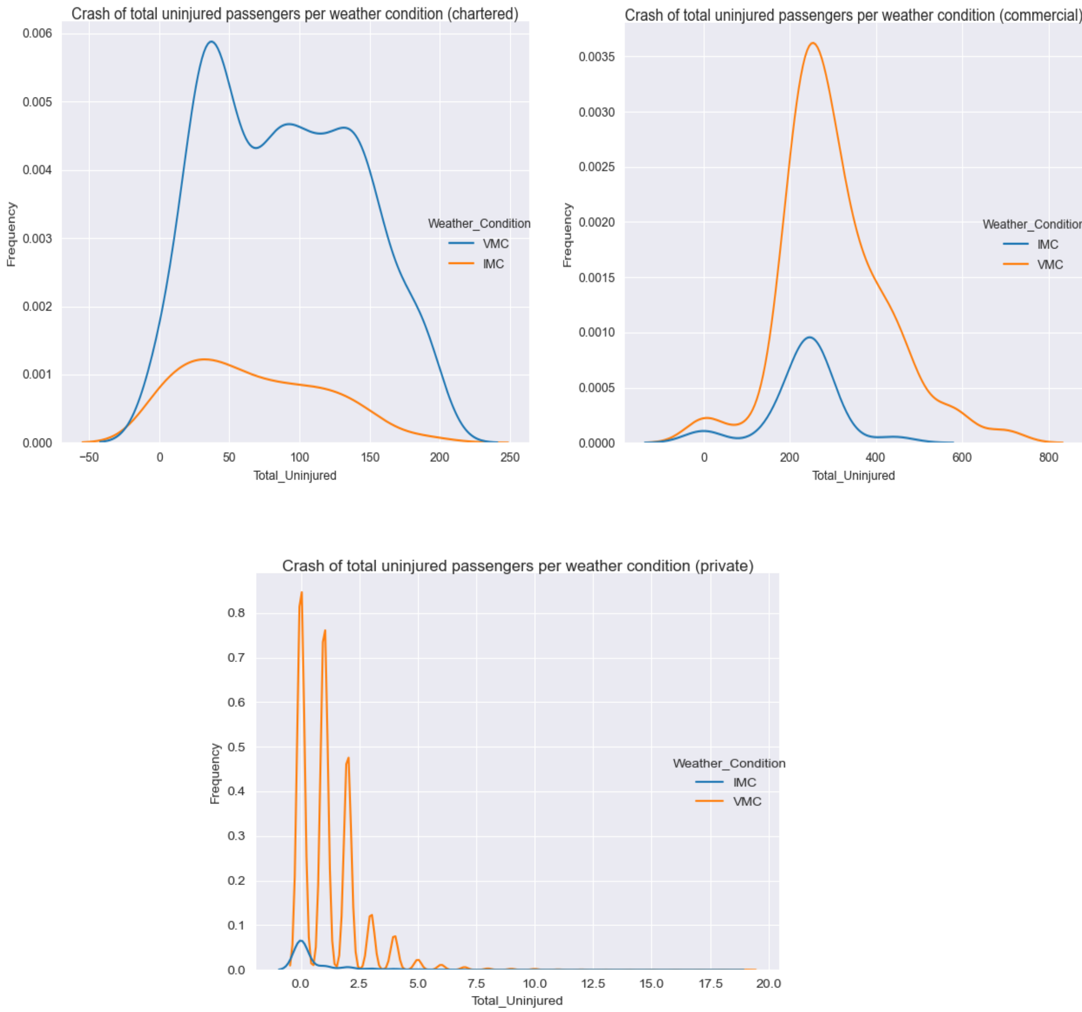

Fig 31

The presented plot illustrates the frequency of uninjured passengers across commercial, private, and chartered aircraft, categorized by different weather scenarios. Interestingly, there is an indication that adverse weather conditions may play a role in aviation accident injuries. Across all the plots, it is evident that a majority of uninjured passengers were involved in accidents that occurred in good weather conditions. However, it is important to note that this does not imply weather as a direct determinant of aviation crashes, but rather suggests that weather may influence the severity of injuries sustained in such accidents.

KDE PLOT:

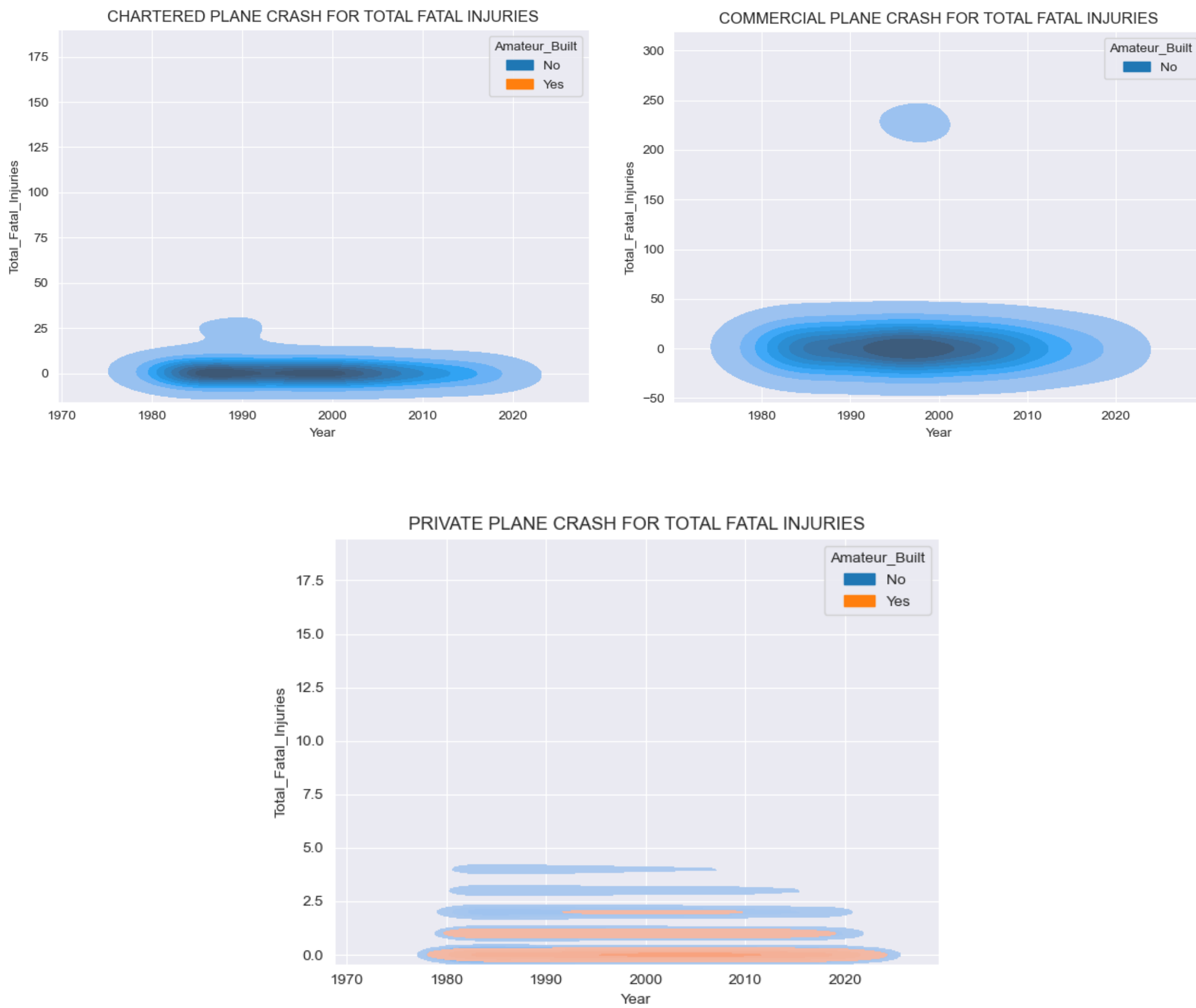

Fig 32

In this section of the presentation, we observe three Kernel density estimate plots that provide insights into different segments of aviation. The first graph pertains to commercial airlines, revealing a low occurrence of fatal injuries and a lack of amateurly built aircraft. Similarly, the second graph focuses on chartered planes, indicating a similar trend with few fatal injuries and a majority of non-amateurly built aircraft. However, the third graph presents insights on private planes, demonstrating a nearly equal chance of passengers sustaining fatal injuries. Several factors contribute to this observation:

- Pilot experience: Private pilots typically have less experience compared to commercial pilots, as they fly less frequently and may receive less comprehensive training.
- Aircraft maintenance: Private planes may not adhere to the same rigorous maintenance standards as commercial planes due to fewer regulations governing their maintenance.
- Size and technological advancements: Private planes are often smaller and less advanced than commercial aircraft, potentially rendering them more susceptible to accidents and crashes.
- Presence of amateurly built aircraft: The higher proportion of amateurly built aircraft in the private plane segment increases the likelihood of aviation accidents.

Collectively, these factors contribute to the higher chances of fatal injuries in the private plane segment, highlighting the differences in pilot experience, aircraft maintenance, and overall characteristics between private and commercial aviation.

QQ PLOT:

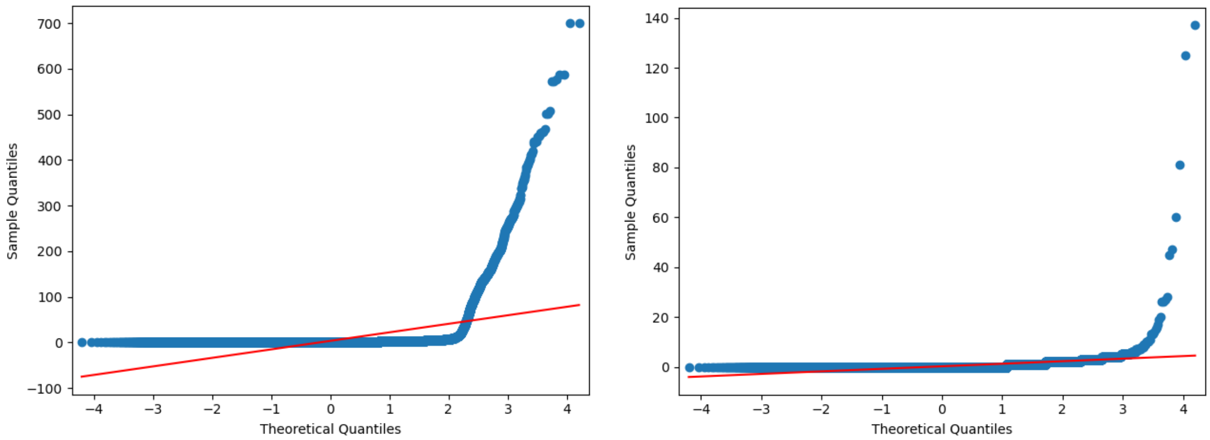

Fig 33

The QQ plots provided depict Total_Serious_Injuries on the left and Number_of_Passengers on the right. The left graph exhibits noticeable deviations from the straight line, primarily due to the presence of outliers in Total_Serious_Injuries, as expected. Conversely, the QQ plot for Number_of_Passengers on the right largely adheres to the straight line, indicating a close alignment with the theoretical distribution.

SCATTERED PLOT:

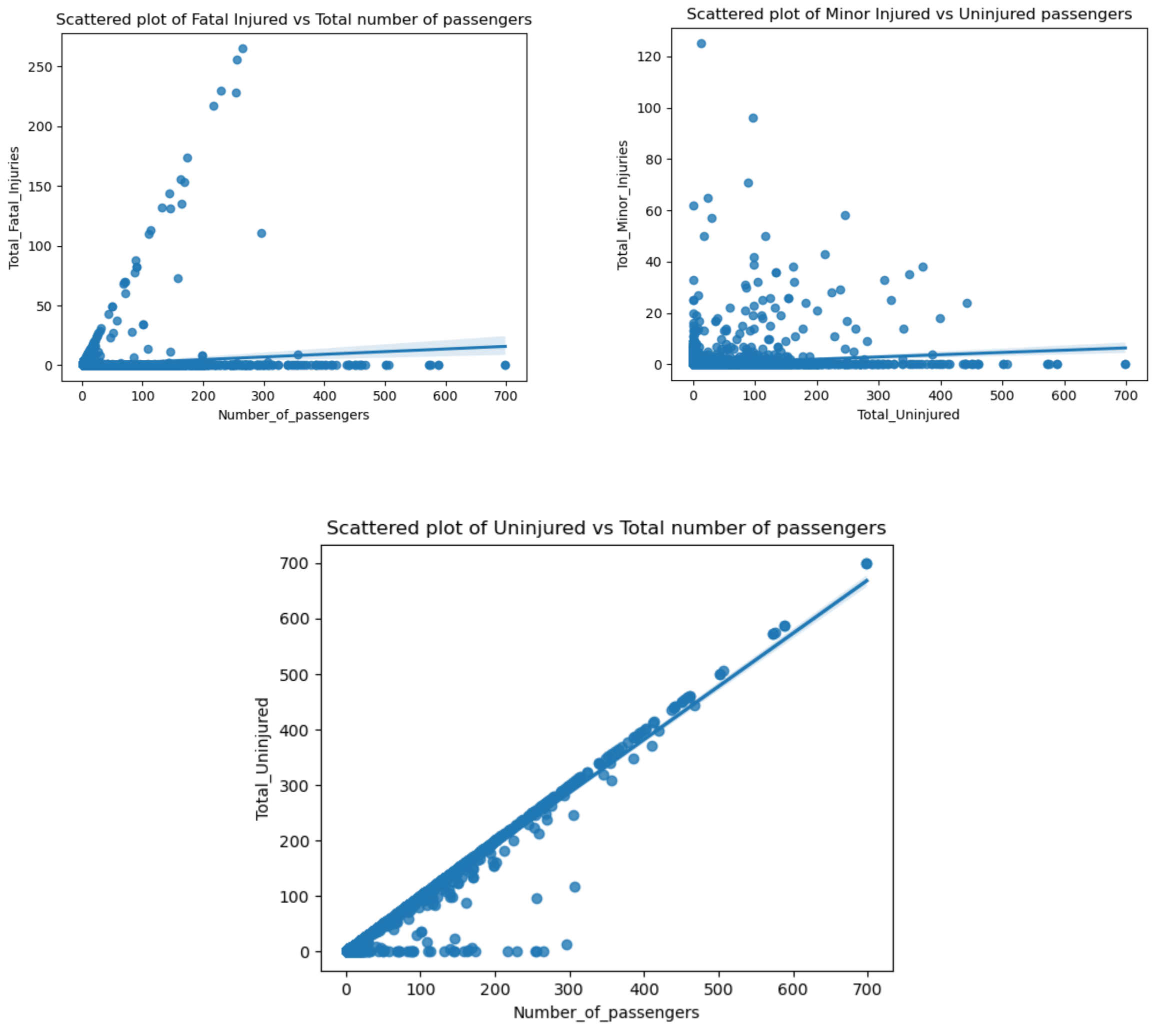

Fig 34

The figure above displays scatter plots depicting the relationships between Number_of_passengers and Total_Fatal_Injuries, Number_of_passengers and Total_Uninjured, as well as Total_Uninjured and Total_Minor_Injuries. Notably, we observe that as the number of passengers increases, there is a corresponding increase in the number of uninjured passengers. However, the other two scatter plots do not exhibit strong relationships between the variables.

BOX PLOTS:

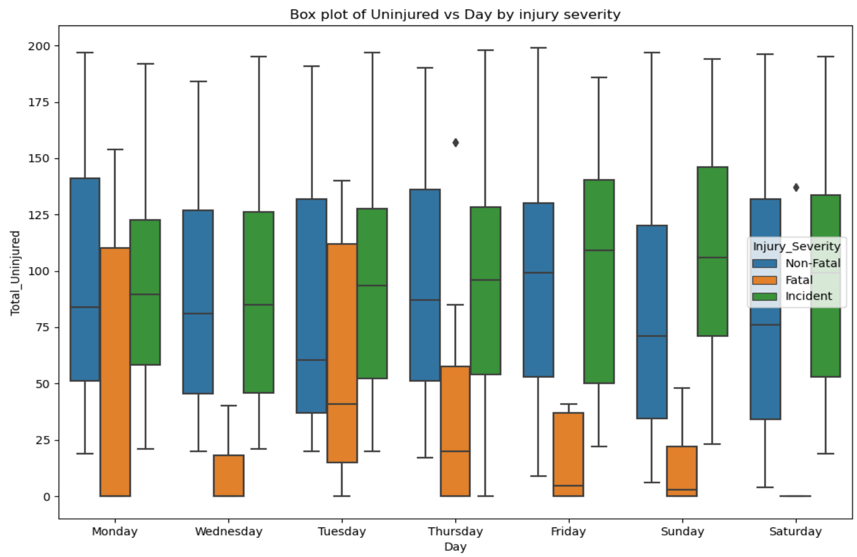

Fig 35

This graph illustrates the relationship between the number of uninjured passengers and the days on which aviation accidents occurred. It reveals that in cases where aviation accidents result in fatal injuries, the likelihood of having passengers who remained uninjured is significantly lower.

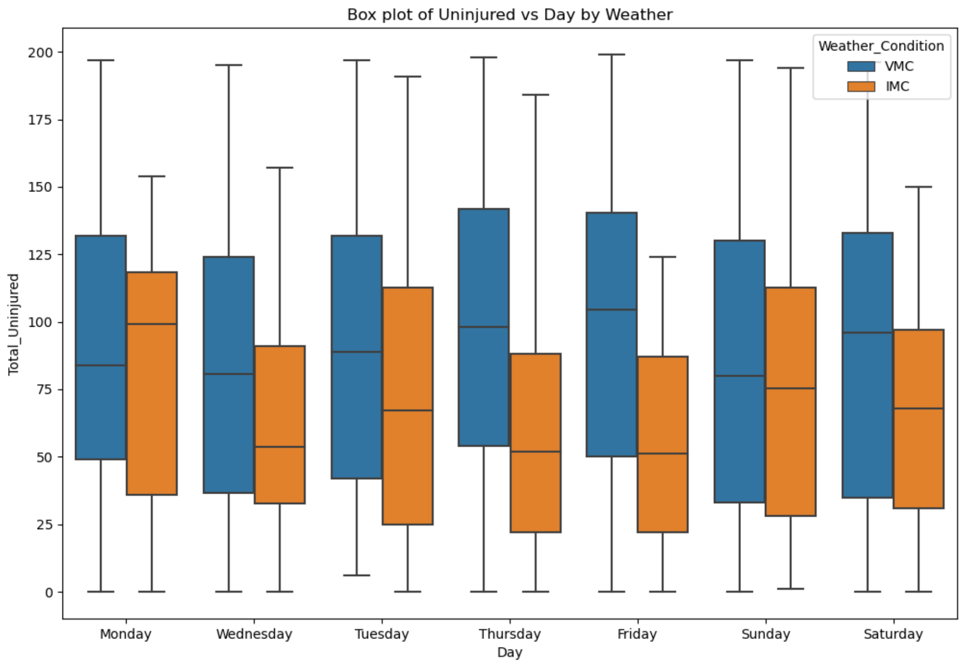

Fig 36

This graph depicts the relationship between the number of uninjured passengers and the days on which aviation accidents occurred. It suggests that weather conditions may indeed impact the survival rate of uninjured passengers. Notably, Wednesday, Tuesday, Thursday, Friday, and Saturday exhibit noticeable differences in the mean between the two weather categories. This implies that aviation accidents on these days are more likely to be associated with adverse weather conditions. The dataset specifically focuses on uninjured passengers in chartered planes, which are potentially less equipped to handle inclement weather compared to commercial aircraft.

PAIR PLOT:

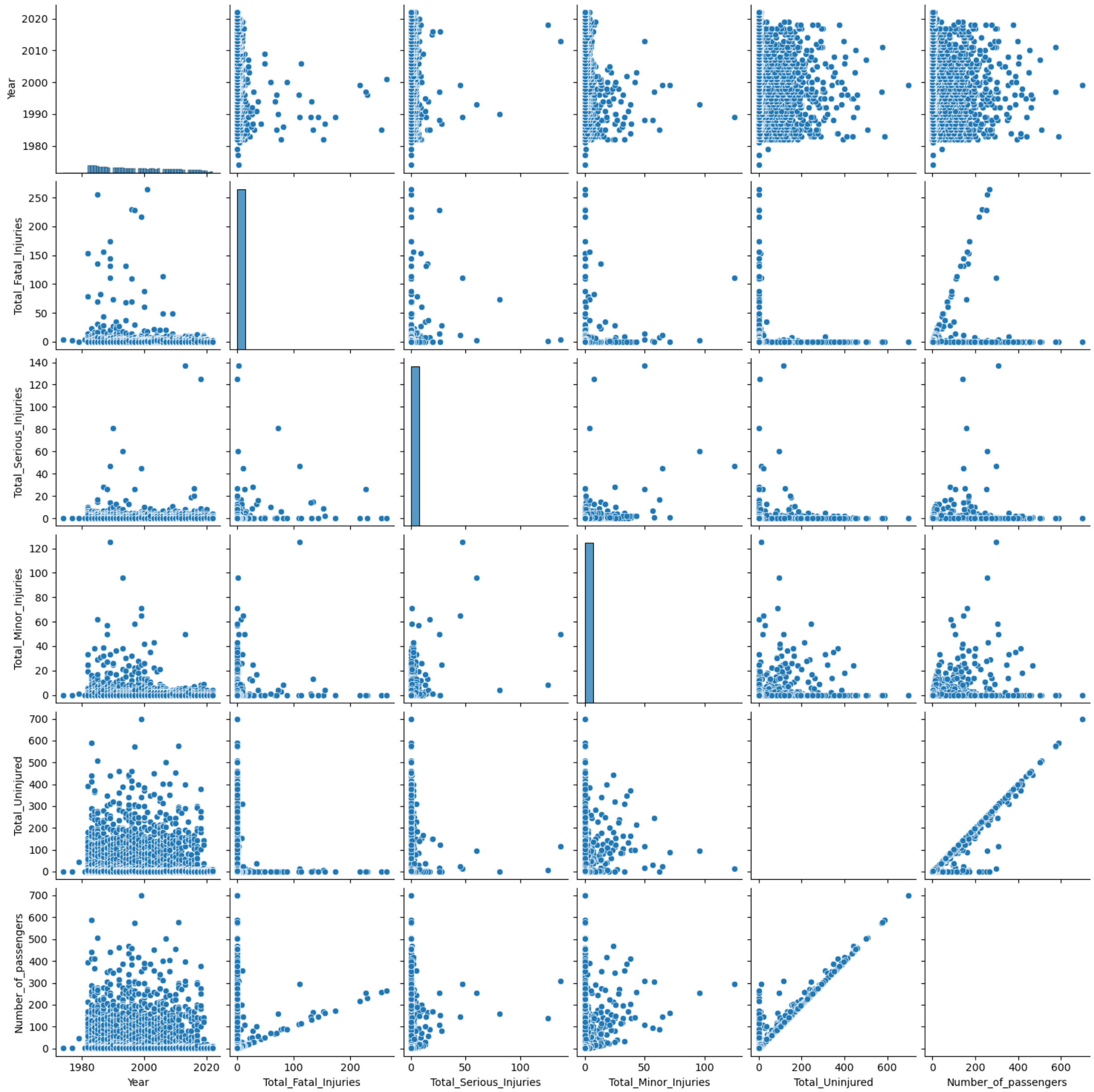

Fig 37

Based on the pair plot shown above, we observe a correlation between the number of uninjured passengers and the total number of passengers involved in aviation accidents. This suggests that in the majority of cases, most passengers in aviation accidents tend to escape without any injuries.

VIOLIN PLOT:

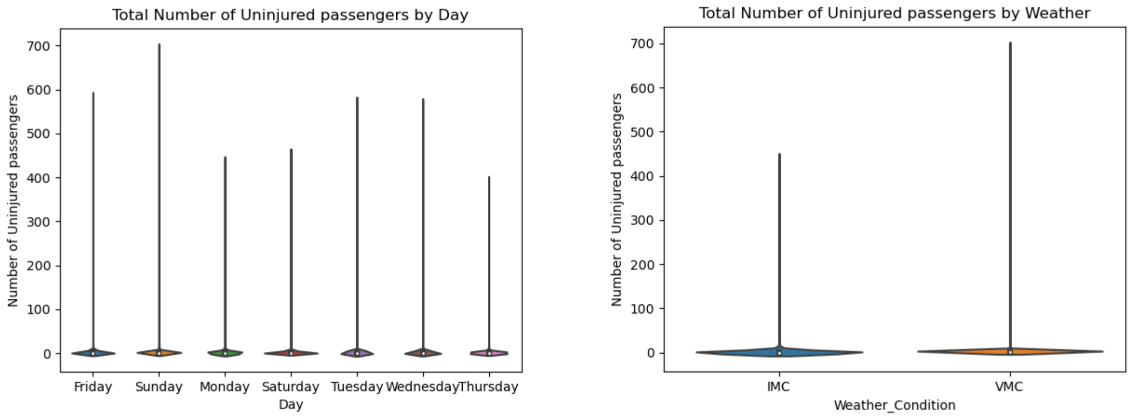

Fig 38

The above plots depict violin plots representing the relationship between days and the number of uninjured passengers, as well as weather conditions and the number of uninjured passengers. It is apparent that there is an anomaly present in our dataset, which aligns with our expectations considering the nature of the dataset we are analyzing.

SUBPLOT

LINE SUBPLOT:

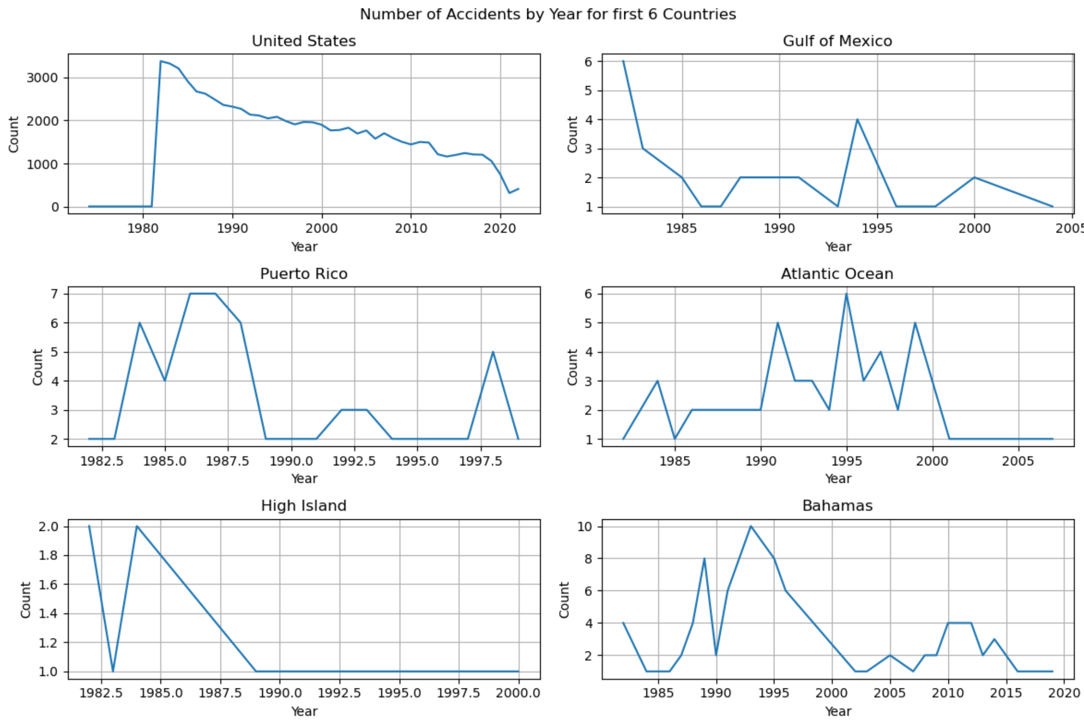

Fig 39

The line subplot presented illustrates the varying trends in aviation accidents across five distinct countries and the Atlantic Ocean. It is evident that the United States experiences a higher number of accidents compared to all other countries in the plot.

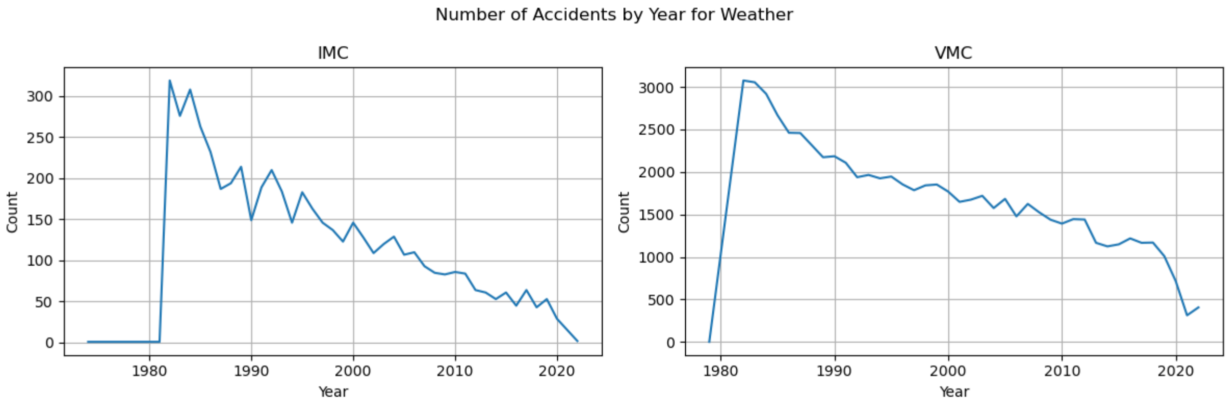

Fig 40

The provided line subplot depicts the trend of aviation accidents over the years in both Instrument Meteorological Conditions (IMC) representing bad weather and Visual Meteorological Conditions (VMC) representing good weather. Notably, it is observed that a greater number of accidents occur during good weather. As a result, we can deduce that weather does not emerge as a significant contributing factor to aviation accidents.

DASHBOARD: Here is the link for my dashboard:

https://dashapp-rh2aehd25a-ue.a.run.app/

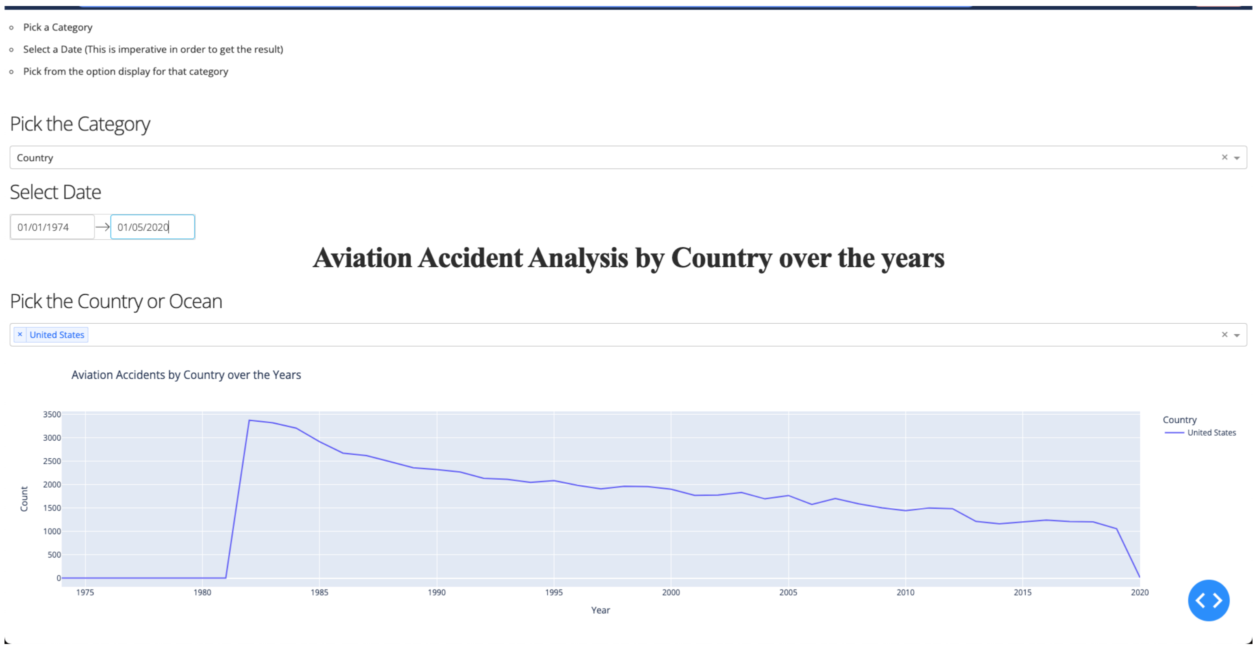

Fig 41

The line tab facilitates the creation of line plots. To generate a graph, you must first choose a category and select a date. Subsequently, you can utilize the options associated with the chosen category to customize your plot. Selecting a date is crucial, as certain date ranges may not display any data if no information is available.

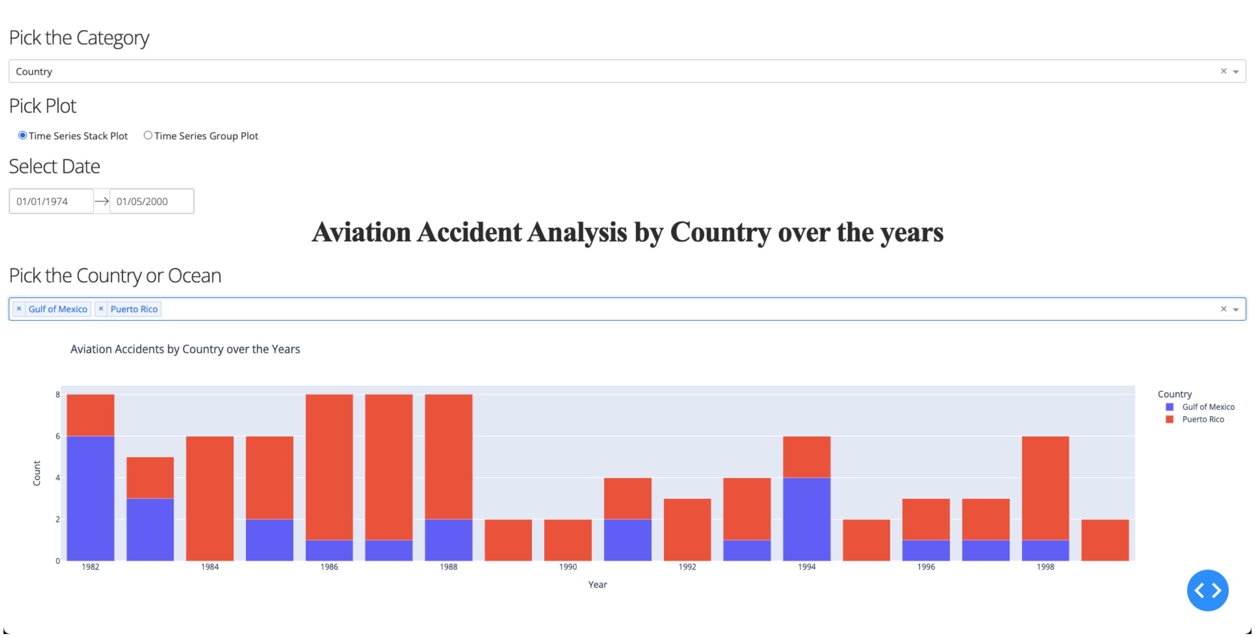

Fig 42

The bar tab enables the generation of bar plots. To create a graph, you need to start by selecting a category, choosing the plot type (either stacked or grouped), and specifying a date. Afterwards, you can utilize the available options related to the selected category to customize your plot. Remember that selecting a date is vital, as some date ranges may not display any data if there is no available information.

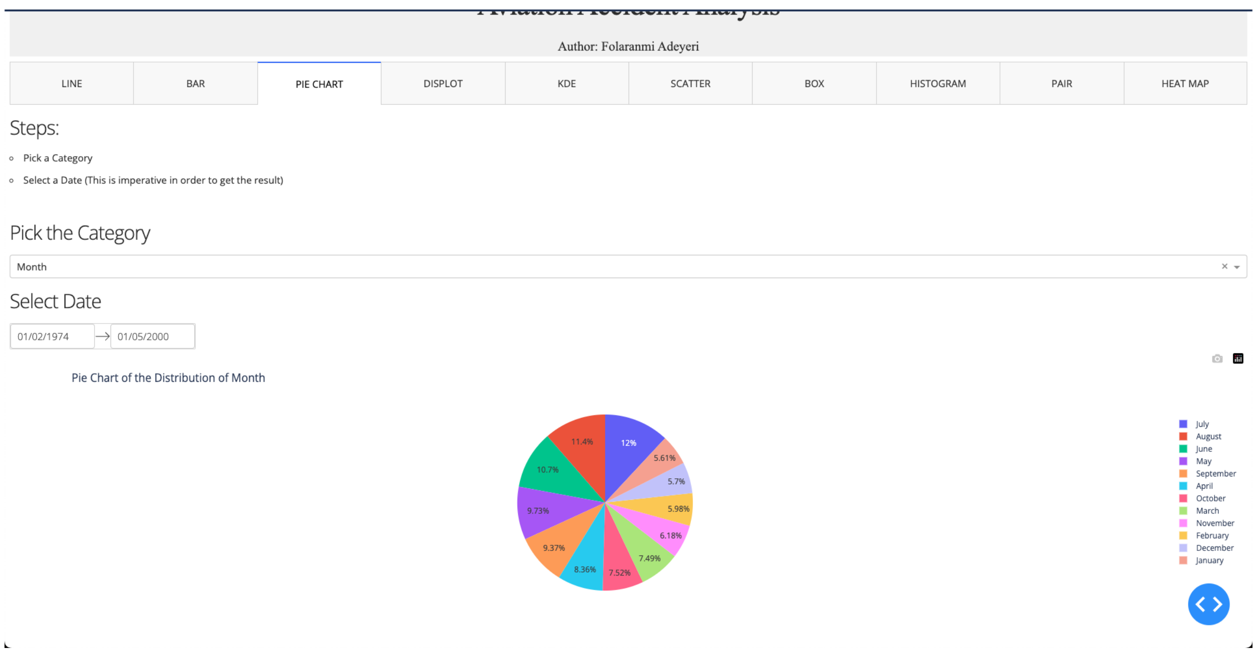

Fig 43

The pie chart tab enables the creation of pie charts. To generate a graph, you need to begin by selecting a category and specifying a date. It is important to select a date, as certain date ranges may not show any data if there is no information available.

Fig 44

The displot tab allows for the generation of distribution plots. To create a graph, you need to start by selecting an incident and indicating the specific type of aircraft you wish to analyze. Then, you can choose a category and specify a date. Remember that selecting a date is essential, as certain date ranges may not display any data if no information is available.

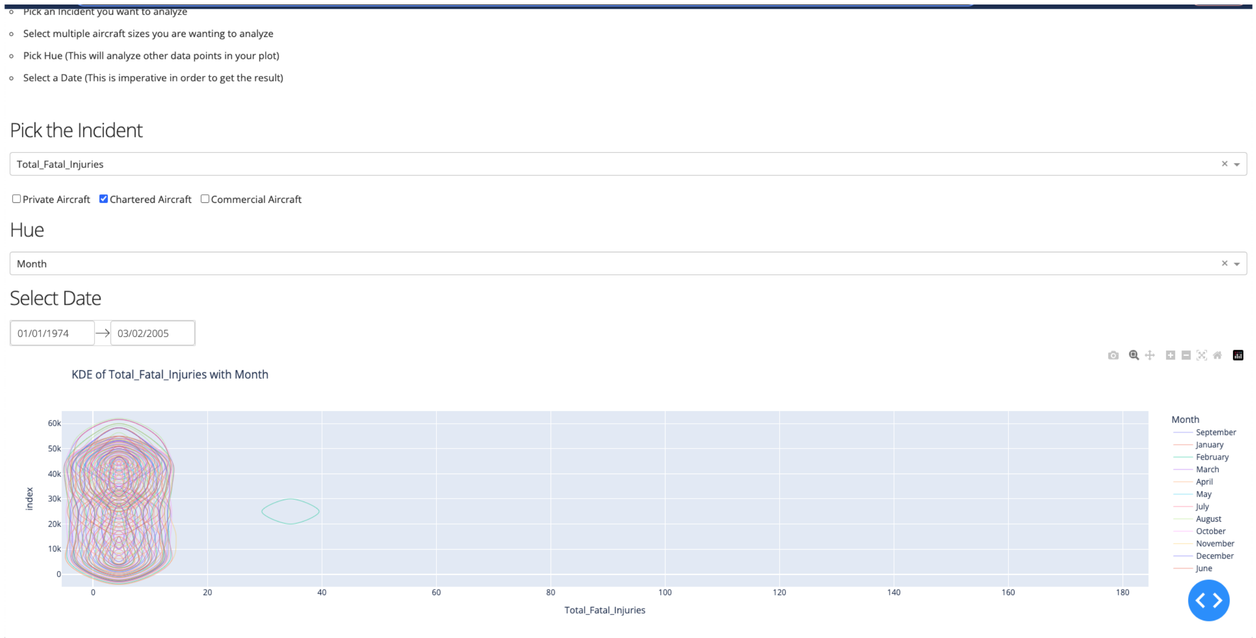

Fig 45

The KDE tab enables the creation of density plots. To generate a graph, you need to begin by selecting an incident and specifying the particular type of aircraft you wish to analyze. Then, you can choose a hue and select a date. It is important to select a date, as certain date ranges may not display any data if there is no information available.

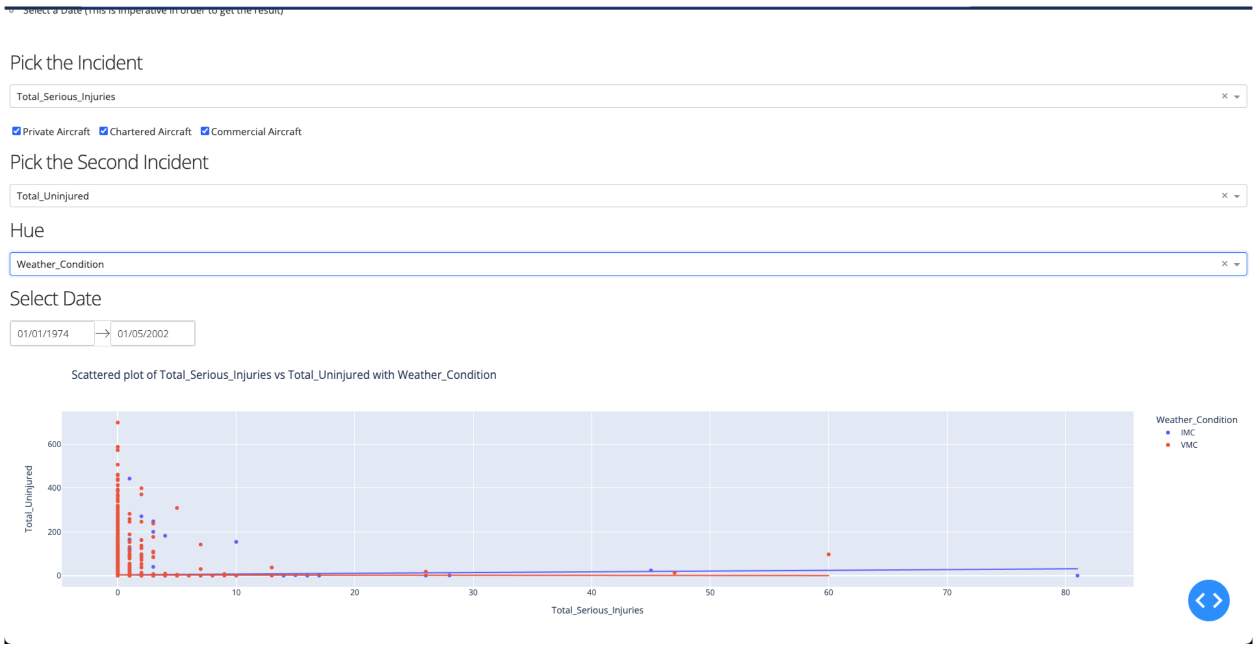

Fig 46

The Scatter tab enables the creation of scatter plots. To generate a graph, you need to start by selecting an incident and specifying the type of aircraft you wish to analyze. Next, you choose the second incident to plot against, followed by selecting a hue and specifying a date. Remember that selecting a date is crucial, as certain date ranges may not display any data if there is no available information.

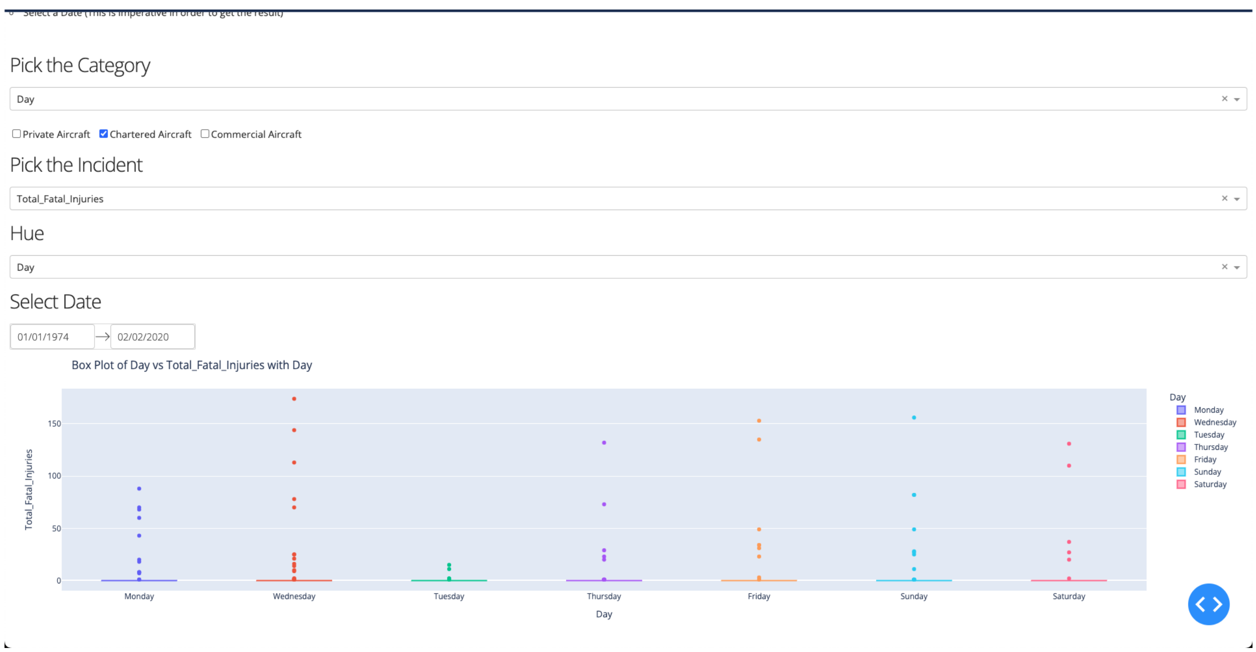

Fig 47

The Box tab enables the creation of box plots. To generate a graph, you need to start by selecting a category and specifying the type of aircraft you wish to analyze. Next, choose an incident to plot against, followed by selecting a hue and specifying a date. Remember that selecting a date is crucial, as certain date ranges may not display any data if there is no available information.

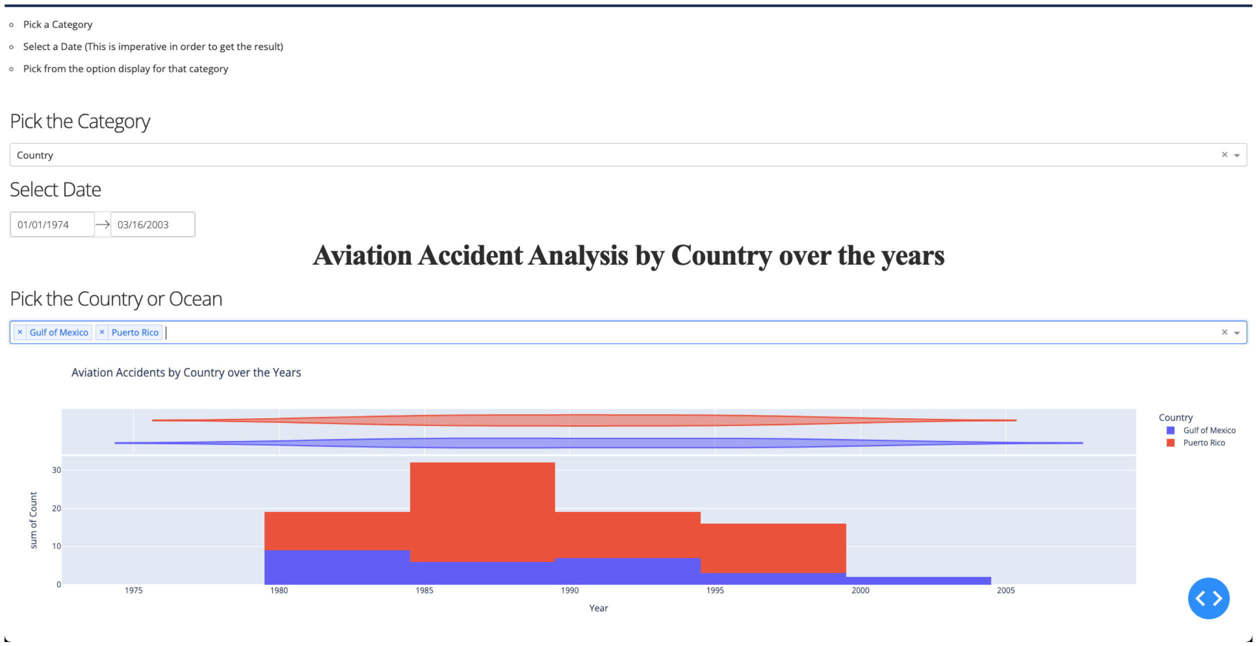

Fig 48

The histogram tab enables the creation of histogram plots. To generate a graph, you need to start by selecting a category and specifying a date. Afterwards, you can customize your plot using the options related to the chosen category. It is important to select a date, as certain date ranges may not display any data if there is no available information.

Fig 49

The pair tab enables the creation of pair plots. To generate a graph, you need to begin by selecting the categories you want to pair plot and specifying a date. Afterwards, you have the option to adjust the width and height of the graph according to your preference. Remember that selecting a date is crucial, as certain date ranges may not display any data if there is no available information.

Fig 50

The heat tab enables the creation of heat map plots. To generate a graph, you need to start by selecting the incidents you wish to plot and specifying a date. It is important to select a date, as certain date ranges may not display any data if there is no information available.

RECOMMENDATIONS

Over time, there has been a notable decrease in aviation accidents, which is a reassuring trend. This decline can be attributed to the implementation of stricter regulatory policies, ongoing advancements in aircraft technology that aim to minimize accidents, and significant enhancements made to aircraft engines.

Furthermore, it is evident that aviation accidents primarily occur during the summer vacation period (June-August). Consequently, it is advisable to choose alternative travel times for a safer journey. This spike in accidents during the summer months could be attributed to the heightened air traffic volume experienced during this period.

Additionally, it is worth mentioning that our analysis indicates that weather conditions, specifically Instrument Meteorological Conditions (IMC) and Visual Meteorological Conditions (VMC), do not appear to significantly influence the occurrence of aviation accidents. This suggests that even during challenging weather conditions, appropriate safety measures and protocols are in place to mitigate the risks and ensure the safety of air travel.

REFERENCES

- **https://en.wikipedia.org/wiki/Visual_meteorological_conditions**
- **https://en.wikipedia.org/wiki/Instrument_meteorological_conditions**