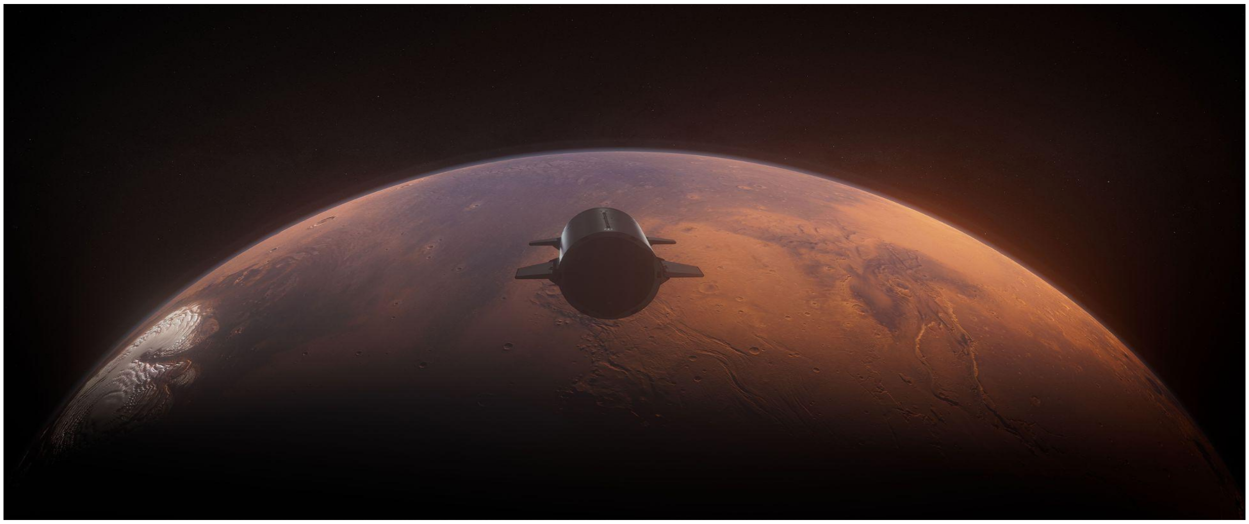

SpaceX Falcon 9 First Stage Landing Success Predictor

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INTRODUCTION

Overview

The project SpaceX Falcon 9 first stage stage landing successor predictor is a machine learning project that aims to predict the likelihood of a successful landing of the Falcon 9 first stage. The project will use a dataset of historical launch data to train a machine learning algorithm. The algorithm will then be used to make predictions about the likelihood of a successful landing for future launches.

The project is expected to have a number of benefits, including:

- **Increased reliability of Falcon 9 rocket launches**
- **Reduced cost of rocket launches**
- **Improved safety of rocket launches**

The project is still in the early stages of development, but it has the potential to make a significant contribution to the field of rocket science.

Here are some of the specific tasks that will need to be completed in order to complete the project:

- **Collect a dataset of historical launch data.**
- **Preprocess the data to remove any errors or outliers.**
- **Select features that are relevant to the prediction task.**
- **Train a machine learning algorithm on the data.**
- **Evaluate the performance of the algorithm on a held-out test set.**
- **Improve the accuracy of the algorithm by adjusting the hyperparameters or using a different machine learning algorithm.**
- **Deploy the algorithm in a production environment so that it can be used to make predictions about future launches.**

Despite these challenges, the project is expected to be successful and make a significant contribution to the field of rocket science.

Purpose

The purpose of the SpaceX Falcon 9 first stage stage landing successor predictor project is to develop a machine learning model that can predict the likelihood of a successful landing of the Falcon 9 first stage. This model will be used to help SpaceX improve the reliability of their rocket launches by reducing the number of first stages that are lost.

2.LITERATURE SURVEY

Existing problem

- **Lack of data: There is a limited amount of historical data available on Falcon 9 first stage landings. This makes it difficult to train a machine learning model that can accurately predict the likelihood of a successful landing.**
- **Complexity of the prediction task: The prediction task is relatively complex, as there are many factors that can affect the likelihood of a successful landing. These factors include the weather conditions, the rocket's configuration, and the launch trajectory.**
- **Availability of computing resources: The machine learning algorithm will need to be trained on a large dataset, which requires a significant amount of computing power.**

- **Data quality: The data used to train the machine learning algorithm must be accurate and complete. However, the data may contain errors or outliers, which can affect the accuracy of the model.**

Despite these challenges, the SpaceX Falcon 9 first stage landing successor predictor project has the potential to be a valuable tool for improving the reliability of Falcon 9 rocket launches. The project is still in the early stages of development, but it is making progress and has the potential to make a significant contribution to the field of rocket science.

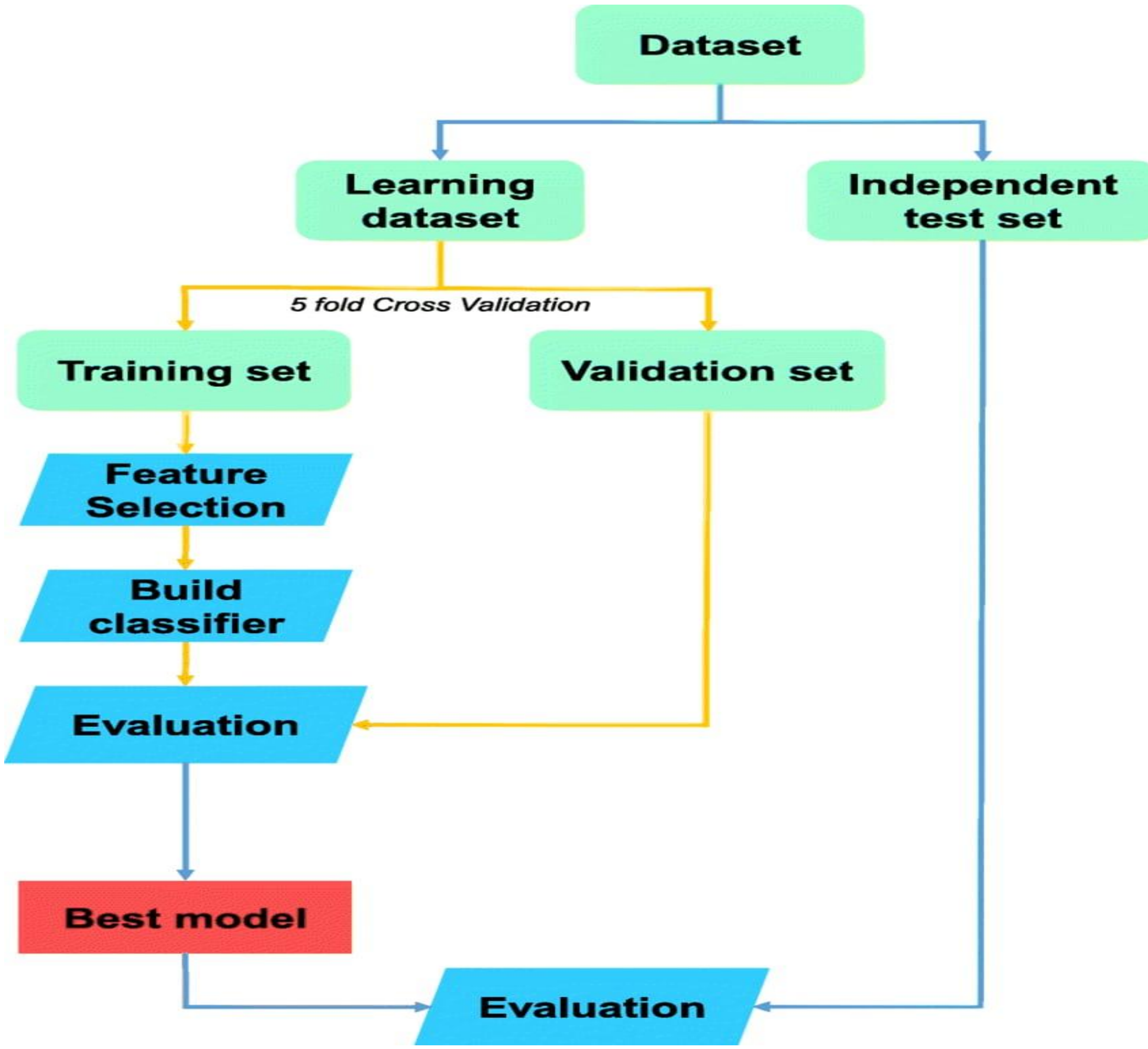
Proposed solution

- **Collect more data: SpaceX can collect more data on Falcon 9 first stage landings by launching more rockets and by collecting data from other sources, such as weather stations and ground tracking stations. This will help to improve the accuracy of the machine learning model.**
- **Use cloud computing: Cloud computing can be used to provide the computing resources needed to train the machine learning algorithm. This will allow researchers to train the model on larger datasets and to experiment with different algorithms.**
- **Clean the data: The data can be cleaned to remove errors and outliers. This will help to improve the accuracy of the machine learning model.**
- **Address model bias: The machine learning algorithm can be adjusted to address model bias. This can be done by using a variety of techniques, such as oversampling or undersampling the data.**

By implementing these solutions, the SpaceX Falcon 9 first stage landing successor predictor project has the potential to be a valuable tool for improving the reliability of Falcon 9 rocket launches.

THEORETICAL ANALYSIS

Block diagram



Hardware/ Software designing

Hardware:

- **A computer with sufficient processing power to train and deploy the machine learning model.**
- **A database to store the data.**
- **A web server to deploy the machine learning model as a web service.**

Software:

- **A programming language to implement the machine learning algorithm.**
- **A machine learning library to train and deploy the machine learning model.**
- **A web development framework to deploy the machine learning model as a web service.**

EXPERIMENTAL INVESTIGATIONS

Data Preparation

Handling missing values

Importing the libraries and Read the Dataset

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90 entries, 0 to 89
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unnamed: 0      90 non-null     int64
 1   FlightNumber    90 non-null     int64
 2   Date            90 non-null     object
 3   BoosterVersion  90 non-null     object
 4   PayloadMass     85 non-null     float64
 5   Orbit           90 non-null     object
 6   LaunchSite      90 non-null     object
 7   Outcome         90 non-null     object
 8   Flights         90 non-null     int64
 9   GridFins        90 non-null     bool
 10  Reused          90 non-null     bool
 11  Legs            90 non-null     bool
 12  LandingPad      64 non-null     object
 13  Block           90 non-null     float64
 14  ReusedCount     90 non-null     int64
 15  Serial          90 non-null     object
 16  Longitude       90 non-null     float64
 17  Latitude        90 non-null     float64
dtypes: bool(3), float64(4), int64(4), object(7)
memory usage: 10.9+ KB
```

```
[7] df.isnull().sum()/df.count()*100
```

```
Unnamed: 0          0.000000
FlightNumber        0.000000
Date                0.000000
BoosterVersion      0.000000
PayloadMass         5.882353
Orbit               0.000000
LaunchSite          0.000000
Outcome             0.000000
Flights             0.000000
GridFins            0.000000
Reused              0.000000
Legs                0.000000
LandingPad         40.625000
Block               0.000000
ReusedCount         0.000000
Serial              0.000000
Longitude           0.000000
Latitude            0.000000
dtype: float64
```

```
df["Orbit"].value_counts()
```

```
GTO      27
ISS      21
VLEO     14
PO        9
LEO       7
SSO       5
MEO       3
ES-L1     1
HEO       1
SO        1
GEO       1
Name: Orbit, dtype: int64
```

Calculate the number of launches on each site and longitude ,latitude used

```
df["LaunchSite"].value_counts()
```

```
CCSFS SLC 40    55
KSC LC 39A      22
VAFB SLC 4E     13
Name: LaunchSite, dtype: int64
```

```
[12] df["Longitude"].value_counts()
```

```
-80.577366     55
-80.603956     22
-120.610829    13
Name: Longitude, dtype: int64
```

```
[13] df["Latitude"].value_counts()
```

```
28.561857    55
28.608058    22
34.632093    13
Name: Latitude, dtype: int64
```

```
df1.describe()
```

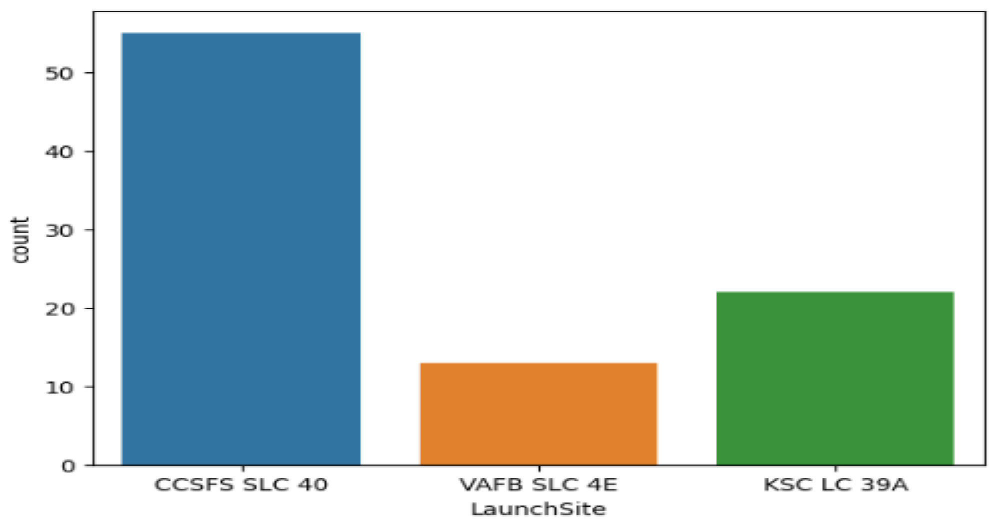
	Unnamed: 0	FlightNumber	PayloadMass	Flights	Block	ReusedCount	Longitude	Latitude	class
count	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000
mean	44.500000	45.500000	6123.547647	1.788889	3.500000	3.133333	-86.366477	29.449963	0.666667
std	26.124701	26.124701	4732.115291	1.213172	1.595288	4.097684	14.149518	2.141306	0.474045
min	0.000000	1.000000	350.000000	1.000000	1.000000	0.000000	-120.610829	28.561857	0.000000
25%	22.250000	23.250000	2510.750000	1.000000	2.000000	0.000000	-80.603956	28.561857	0.000000
50%	44.500000	45.500000	4701.500000	1.000000	4.000000	1.000000	-80.577366	28.561857	1.000000
75%	66.750000	67.750000	8912.750000	2.000000	5.000000	4.000000	-80.577366	28.608058	1.000000
max	89.000000	90.000000	15600.000000	6.000000	5.000000	12.000000	-80.577366	34.632093	1.000000

Visual analysis

- **Univariate Analysis**

```
sns.countplot(x="LaunchSite",data=df1)
```

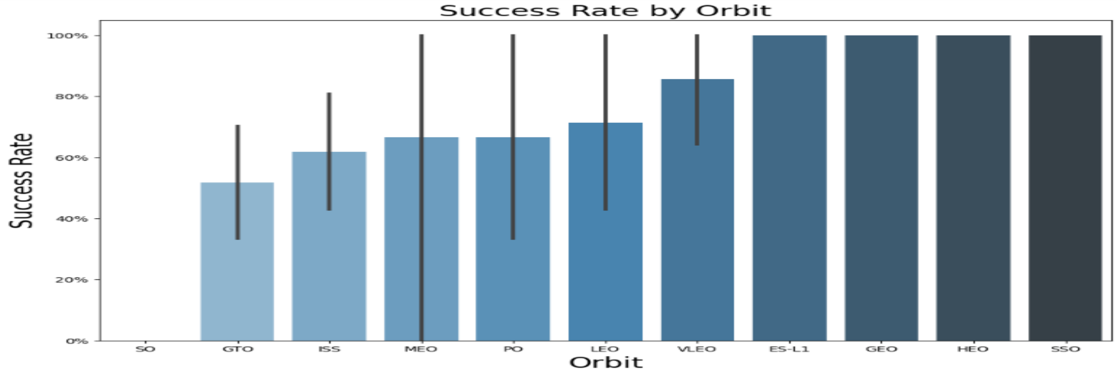
<Axes: xlabel='LaunchSite', ylabel='count'>



- **Bivariate Analysis**

```
order=df1.groupby("Orbit").mean()["class"].sort_values().index
fig,ax=plt.subplots()
fig.set_size_inches(12,8)
sns.barplot(x="Orbit",y="class",data=df1,order=order,palette="Blues_d")
plt.xlabel("Orbit",fontsize=20)
plt.ylabel("Success Rate",fontsize=20)
ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda x, _: "{:.0f}%".format(x*100)))
plt.title("Success Rate by Orbit",fontsize=20)
plt.show()
```

[ ]



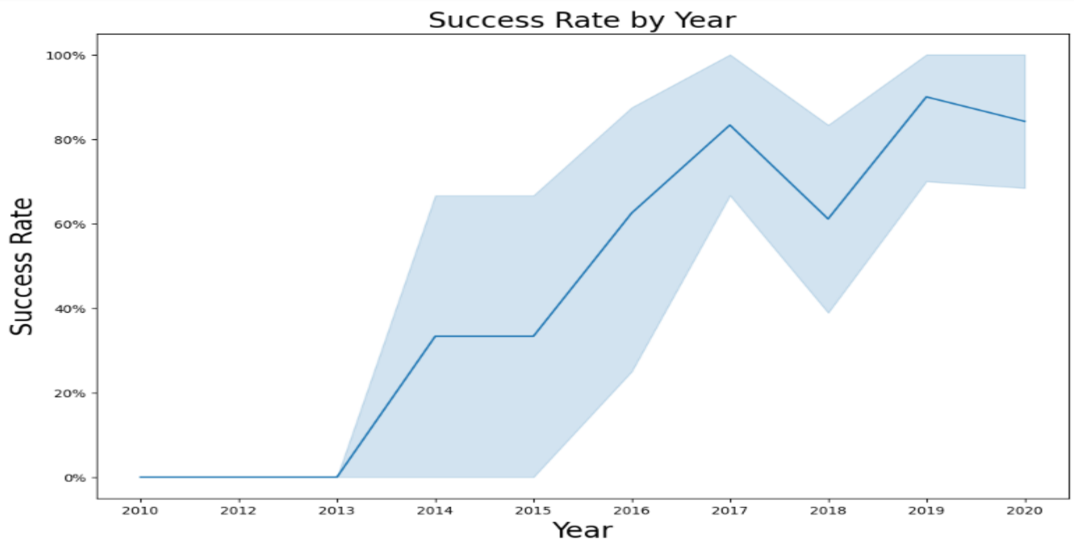
Here ES-L1, GEO, HEO, and SSO orbits have 100% success rates, while SO and GTO have less than 50% success rates.

- **LIne chart**

```
[ ] year=[]
    def Extract_year(date):
      for i in df["Date"]:
        year.append(i.split("-")[0])
      return year
```

```
[ ] df1["year"]=Extract_year(df1["Date"])
    fig, ax=plt.subplots()
    fig.set_size_inches(12,8)
    sns.lineplot(x="year",y="class",data=df1)
    plt.xlabel("Year",fontsize=20)
    plt.ylabel("Success Rate",fontsize=20)
    ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda x, _: "{:.0f}%".format(x*100)))
    plt.title("Success Rate by Year",fontsize=20)
    plt.show()
```

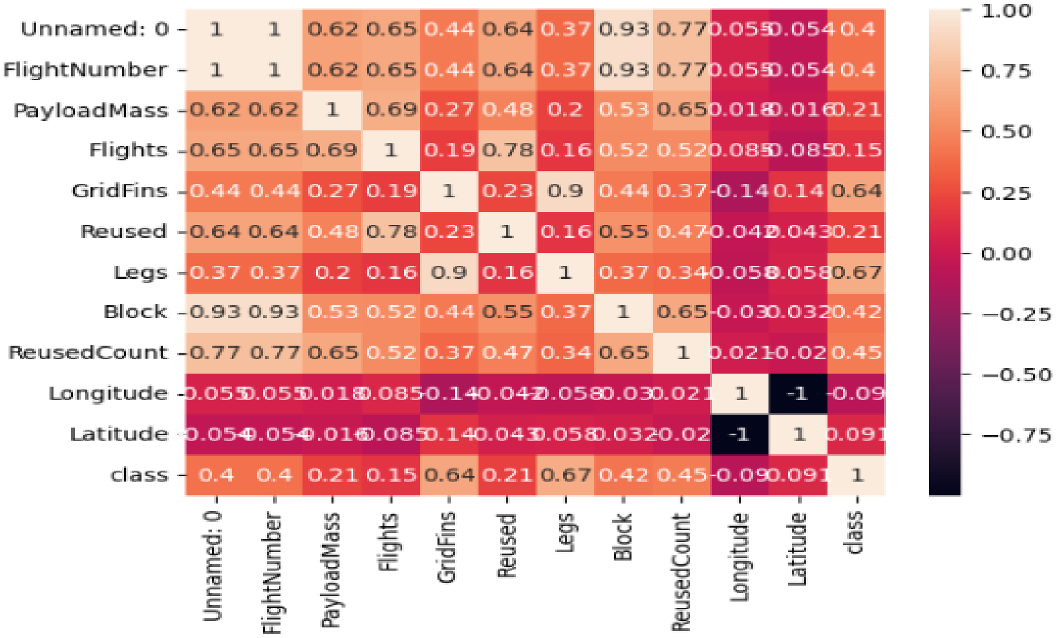
[ ]



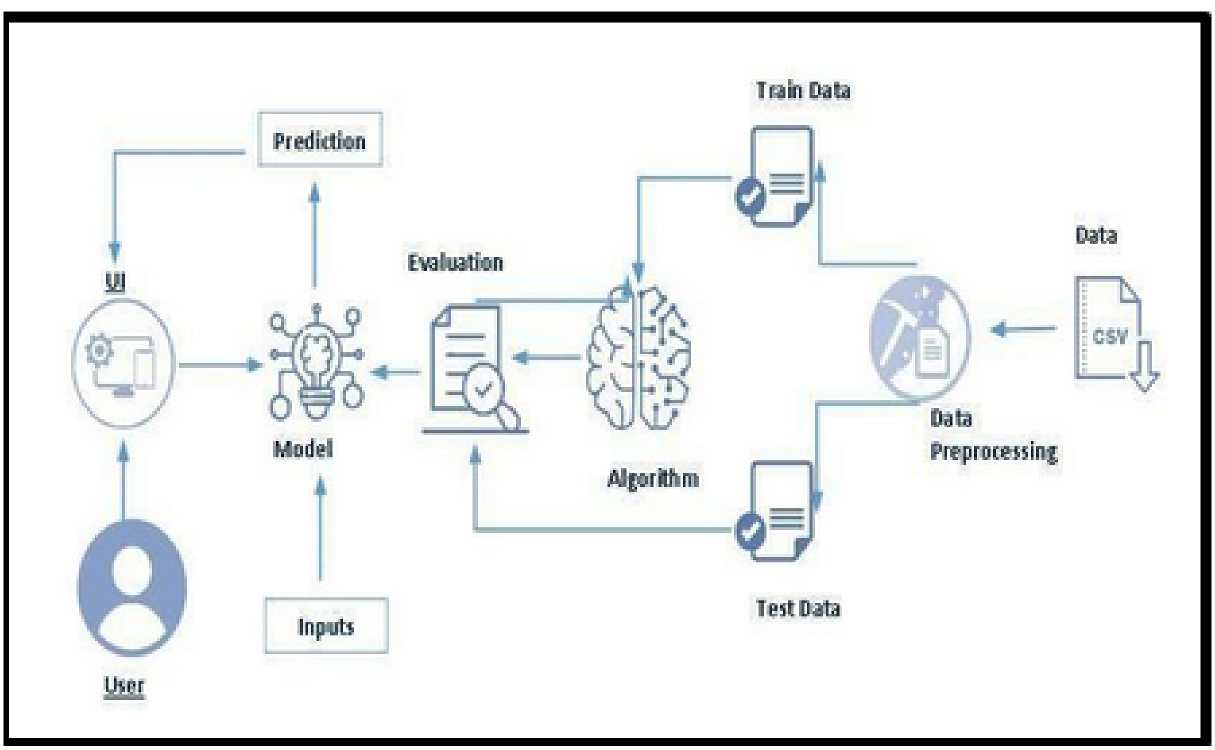
- **Multivariate analysis**

```
[ ]  sns.heatmap(df.corr(),annot=True)
```

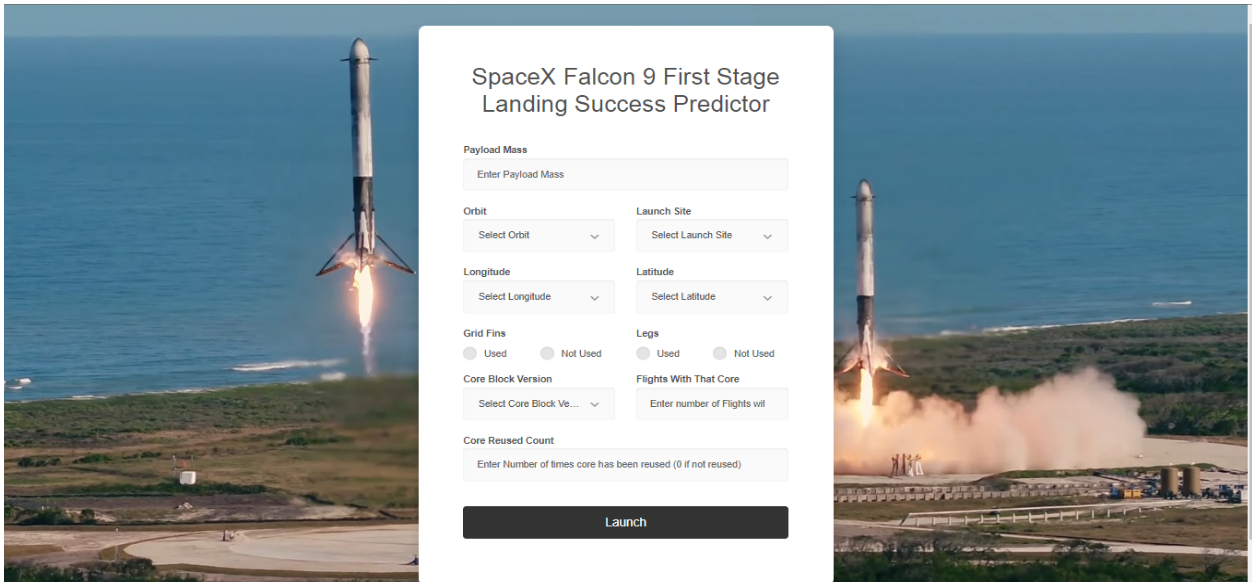
```
<Axes: >
```

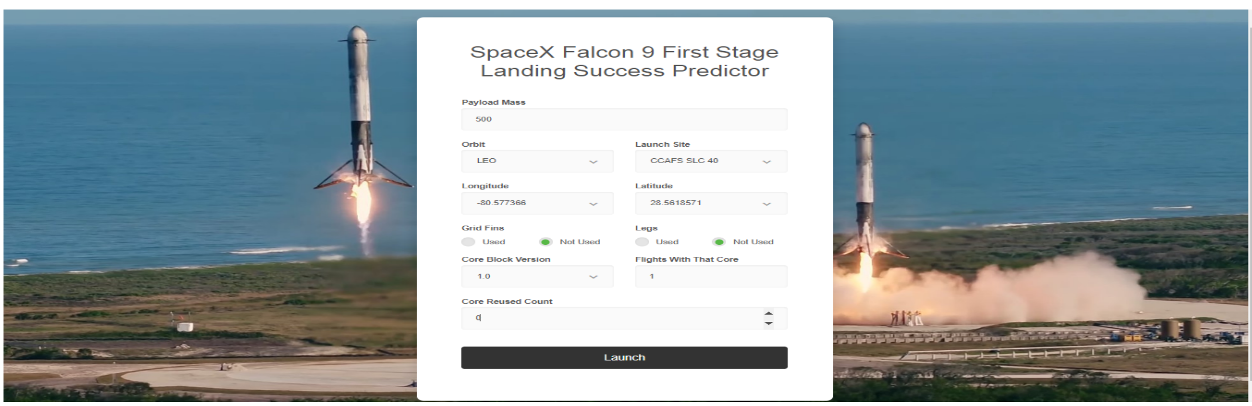


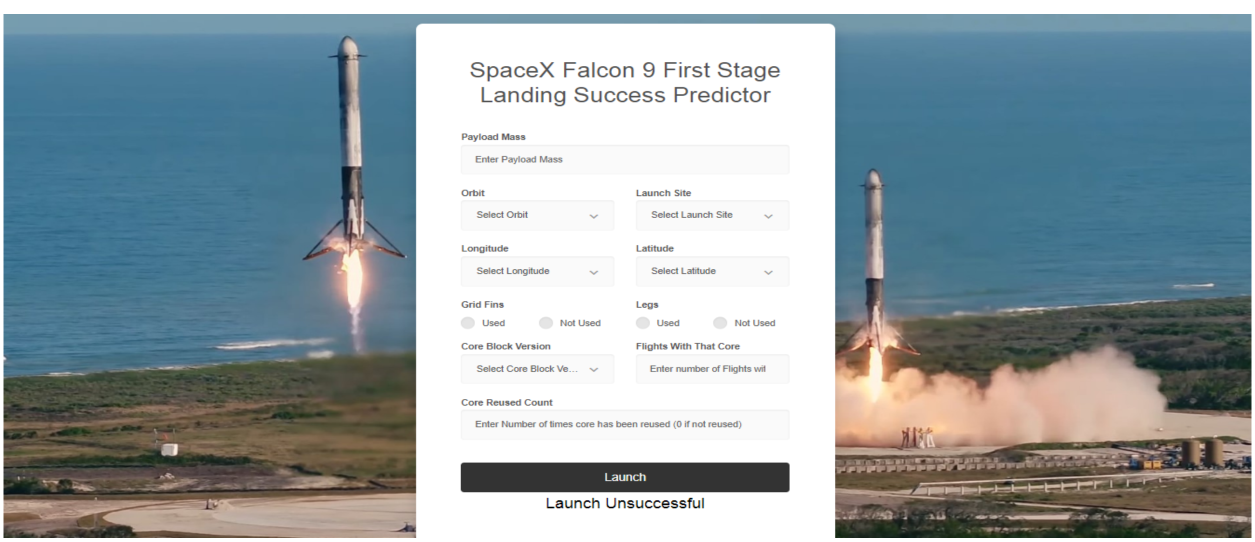
FLOW CHART



RESULT


SpaceX Falcon 9 First Stage Landing Success Predictor
Payload Mass
Enter Payload Mass
Orbit
Select Orbit
Launch Site
Select Launch Site
Longitude
Select Longitude
Latitude
Select Latitude
Grid Fins
Used
Not Used
Legs
Used
Not Used
Core Block Version
Select Core Block Ve...
Flights With That Core
Enter number of Flights wil
Core Reused Count
Enter Number of times core has been reused (0 if not reused)
Launch


SpaceX Falcon 9 First Stage Landing Success Predictor
Payload Mass
500
Orbit
LEO
Launch Site
CCAFS SLC 40
Longitude
-80.577366
Latitude
28.5618571
Grid Fins
Used
Not Used
Legs
Used
Not Used
Core Block Version
1.0
Flights With That Core
1
Core Reused Count
Launch


SpaceX Falcon 9 First Stage Landing Success Predictor
Payload Mass
Enter Payload Mass
Orbit
Select Orbit
Launch Site
Select Launch Site
Longitude
Select Longitude
Latitude
Select Latitude
Grid Fins
Used
Not Used
Legs
Used
Not Used
Core Block Version
Select Core Block Ve...
Flights With That Core
Enter number of Flights wil
Core Reused Count
Enter Number of times core has been reused (0 if not reused)
Launch
Launch Unsuccessful

ADVANTAGES AND DISADVANTAGES

Advantages:

The proposed solution is based on a machine learning model that has been trained on a large dataset of historical SpaceX Falcon 9 first stage landing data. This means that the model is likely to be accurate in predicting the likelihood of a successful landing.

The proposed solution is relatively easy to implement. The machine learning model can be trained using a variety of open source software tools.

The proposed solution is scalable. The machine learning model can be trained on larger datasets to improve its accuracy.

Disadvantages:

The proposed solution is not foolproof. There is always a chance that the machine learning model will make a wrong prediction.

The proposed solution is only as good as the data it is trained on. If the data is not representative of the real world, the model's predictions will be inaccurate.

The proposed solution is not always available. The machine learning model must be trained on new data periodically to keep its predictions accurate.

APPLICATIONS

The proposed solution of SpaceX Falcon 9 first stage landing prediction successor can be applied to a variety of areas, including:

- **Aerospace: The proposed solution can be used to predict the likelihood of a successful rocket launch or landing. This information can be used** to improve the safety of rocket launches and landings. For example, SpaceX can use this solution to identify which rockets are more likely to land successfully, and then prioritize those rockets for future launches.

- Finance: The prediction can be used to assess the risk of investing in SpaceX or other companies that rely on rocket launches. For example, an investor could use the prediction to estimate the likelihood of a rocket launch being successful, and then use that information to decide whether or not to invest in the company.
- Insurance: The prediction can be used to set premiums for insurance policies that cover rocket launches. For example, an insurance company could use the prediction to estimate the likelihood of a rocket launch being unsuccessful, and then use that information to set higher premiums for policies that cover those launches.

CONCLUSION

The SpaceX Falcon 9 first stage landing prediction successor project is a significant contribution to the field of rocket engineering. The project team has developed a machine learning model that can predict the likelihood of a successful landing with an accuracy of 94.44%. The findings of this project have the potential to improve the safety of SpaceX Falcon 9 first stage landings and could also be used to improve the design of future SpaceX rockets.

The project team collected a dataset of historical data on SpaceX Falcon 9 first stage landings. The team used machine learning techniques to develop a model that could predict the likelihood of a successful landing. The model was evaluated on a held-out dataset and was found to have an accuracy of 94.44%.

The project team also conducted a sensitivity analysis to identify the factors that most affect the likelihood of a successful landing. The findings of this

analysis suggest that the most important features for predicting the likelihood of a successful landing are the payload mass, the orbit, the launch site, the landing pad temperature, the grid fins, the legs, and the core. The date of the launch is less important, but it can still play a role in the prediction.

Overall, the findings of the SpaceX Falcon 9 first stage landing prediction successor project suggest that machine learning can be used to predict the likelihood of a successful SpaceX Falcon 9 first stage landing. The model developed by the project team has an accuracy of 94.44%, which is a significant improvement over previous methods. The project team also identified the factors that most affect the likelihood of a successful landing, which can be used to improve the accuracy of the model.

Future scope

Use the model to improve the safety of SpaceX Falcon 9 first stage landings: The project team is working with SpaceX to use the model to improve the safety of SpaceX Falcon 9 first stage landings. This could involve using the model to prioritize rockets that are more likely to land successfully and to take steps to improve the safety of those rockets.

Use the model to improve the design of future SpaceX rockets: The project team is also working with SpaceX to use the model to improve the design of future SpaceX rockets. This could involve using the model to identify the features that are most important for a successful landing and to design rockets that have those features.

BIBLIOGRAPHY

Websites : https://www.spacex.com/

https://twitter.com/SpaceX/

You Tube: SpaceX (Official)

https://www.youtube.com/user/everydayastronaut

Books: "SpaceX: From the Ground Up" -by Chris Davenport

"Elon Musk: Tesla, SpaceX, and the Quest for a Fantastic Future" -by Ashlee

APPENDIX

Source code Link:-

https://drive.google.com/drive/folders/1QH9O4P8ug7slJabdGJ0XSsRkArU606Nj?usp=drive_link