#### STARTUP PROPHET

#### AN INDUSTRY ORIENTED MINI REPORT

Submitted to

### JAWAHARLAL NEHRU TECNOLOGICAL UNIVERSITY, HYDERABAD

In partial fulfillment of the requirements for the award of the degree of

#### **BACHELOR OF TECHNOLOGY**

In

#### **COMPUTER SCIENCE AND ENGINEERING(DS)**

Submitted By

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#### **DEPARTMENT OF**

## COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

#### **VAAGDEVI ENGINEERING COLLEGE(WARANGAL)**



### <u>CERTIFICATE OF COMPLETION</u> INDUSTRY ORIENTED MINI PROJECT

This is to certify that the UG Project Phase-1 entitled "STARTUP PROPHET" is being submitted by SAHAS SALLA(21UK1A6704), GK MANI(21UK1A6758), AKARAPU JYOTHI(21UK1A6743), SUDHATI KIRAN(21UK1A6753) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science & Engineering to Jawaharlal Nehru Technological University Hyderabad during the academic year 2023- 2024.

Project Guide
Dr.K. SHARMILA REDDY

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**EXTERNAL** 

#### **ACKNOWLEDGEMENT**

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Finally, we express our sincere thanks and gratitude to my family members, friends for their encouragement and outpouring their knowledge and experience throughout the thesis.

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#### **ABSTRACT**

The dynamic landscape of startup ventures poses significant challenges for entrepreneurs, investors, and stakeholders in predicting the success of new enterprises. "Startup Prophet" is a predictive analytics application developed to address this challenge by leveraging machine learning techniques to forecast the success probability of startups. This web-based application utilizes a machine learning model trained on diverse datasets containing historical data on startup performance, market conditions, and various other influential factors.

Startup Prophet serves as a valuable tool for entrepreneurs seeking to assess their venture's potential, investors looking to make informed funding decisions, and analysts interested in market trends. By integrating sophisticated machine learning techniques with an accessible platform, Startup Prophet aims to demystify the startup success prediction process and foster informed decision-making in the entrepreneurial ecosystem.

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#### **CHAPTER 1**

#### **INTRODUCTION**

#### 1.1 OVERVIEW:

A startup or start-up is a company or project begun by an entrepreneur to seek, develop, and validate a scalable economic model. While entrepreneurship refers to all new businesses, including self-employment and businesses that never intend to become registered, startups refer to new businesses that intend to grow large beyond the solo founder. Startups face high uncertainty and have high rates of failure, but a minority of them do go on to be successful and influential. Startups play a major role in economic growth. They bring new ideas, spur innovation, create employment thereby moving the economy. There has been an exponential growth in startups over the past few years. Predicting the success of a startup allows investors to find companies that have the potential for rapid growth, thereby allowing them to be one step ahead of the competition.

The objective is to predict whether a startup which is currently operating turns into a success or a failure. The success of a company is defined as the event that gives the company's founders a large sum of money through the process of M&A (Merger and Acquisition) or an IPO (Initial Public Offering). A company would be considered as failed if it had to be shut down.

#### 1.2 PURPOSE:

The purpose of this project is to predict the startup prophet on machine learning model classification using the support vector machine algorithm and random forest model by this we can be capable to predict the startup prophet classification.

#### **CHAPTER 2:**

#### LITERATURE SURVEY

#### 2.1 EXISTING PROBLEM

India is seeing a growth phase under the leadership of able people. However, there still exist many challenges that need to be addressed. To solve these challenges and problems, the country as a whole must be engaged, and talent must be brought from outside the government domain, especially where domain knowledge or entrepreneurial leadership is required. People who are passionate create great things, and companies that aspire to solve bigger problems do much better than those who just look around for funding and money. A combination of talent and diverse experiences backed by strong political will are the key ingredients to coming up with out-of-the-box solutions to address the many challenges we face as a developing country. We look at some of the real issues in India that startups can aim to address.

Instant access to healthcare One of the most critical needs today is access to good healthcare. Billions around the world, particularly people in the Indian subcontinent, struggle because they do not get proper access to healthcare. Even those with access have a sour experience. That exists apps that let us book movie tickets and seats in a jiffy or even find that perfect restaurant! However, finding doctors is still unbelievably tough. Patient records are either maintained in fat files or if they are online, they are often not accessible or understandable. Doctors do not usually have the time to go through all the reports and this may lead to a compromise on the health front. Health-based startups can address a lot of issues plaguing instant access to healthcare in India. Healthcare is undergoing a major change and smartphones will soon replace doctors for more than 80 percent of health-related problems! Public transportation In India, the pains of a city's chaotic public transport system.

#### 2.2 PROPOSED SOLUTION:

we will prepare the data using JUPYTER notebook and we use various models to predict the output. machine learning models are used very useful in predicting outcomes for large amount datasets. We use support vector machine and random forest model machine learning algorithm to predict the startup prophet classification.

## CHAPTER 3 THEORETICAL ANALYSIS

## 3.1 BLOCK DIAGRAM

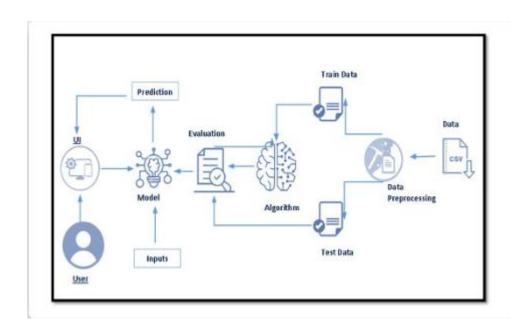


Fig 01: Flow chart

## 3.2 SOFTWARE & HARDWARE DESIGNING:

## Software Requirements

REQUIREMENTS	SPECIFICATIONS		
Anaconda Navigator	You must have anaconda installed in your device prior to begin.		
<ul> <li>Anaconda prompt, google colab, Flask, spyder</li> <li>Frame work</li> </ul>	<ul> <li>One should have anaconda prompt and google colab.</li> <li>One should install flask framework through Anaconda prompt for running their web application.</li> <li>We need to build the mode; using JUPYTER notebook with all the imported packages.</li> </ul>		
Web browser	For all Web browsers, the following must be enabled:  Cookies Java script		

## Hardware Requirements:

REQUIREMENTS	SPECIFICATIONS
Operating system	<ul><li>Microsoft windows</li><li>Unix</li><li>Linux</li></ul>
Processing	Minimum: 4 CPU cores for one user. For each deployment, a sizing exercise is highly recommended.
RAM	Minimum 8 GB.
Operating system specifications	File descriptor limit set to 8192 on UNIX and Linux
Disk space	A minimum of 7 GB of free space is required to install the software.

#### **CHAPTER 4**

#### **EXPERIMENTAL ANALYSIS**

Analysis or the investigation made while working on the solution:

While working on the solution we investigated on what is Startup prophet, visualizing and analyzing the data, data pre-processing, Machine Learning service, model building. The key role on investigation is collection of data set.

#### **DATA PRE-PROCESSING:**

As we have understood how the data is let's pre-process the collected data.

The download data set is not suitable for training the machine learning model as it might have so much of randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

- → Handling missing values
- → Handling categorical data
- → Scaling Techniques
- → Handling class imbalance
- → Splitting dataset into training and test set

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

#### **DATA SET COLLECTION:**

- → Kaggle.com
- → Machine learning repository

#### The data set contains thirteen classes:

- 1.is\_ecommerce
- 2.is\_otherstate
- 3.has\_angel
- 4.has\_roundA
- 5.has\_roundB
- 6.has\_roundC
- 7.has\_roundD
- 8.is\_top500
- 9.labels
- 10.has\_VC
- 11.funding\_rounds
- 12.relationships
- 13.milestones

## CHAPTER 5: FLOW CHART

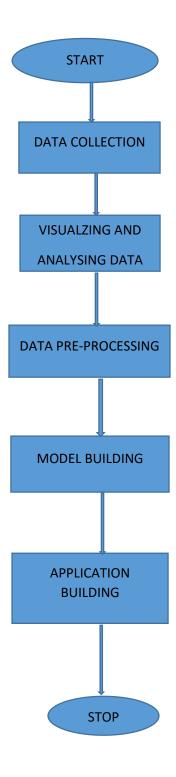
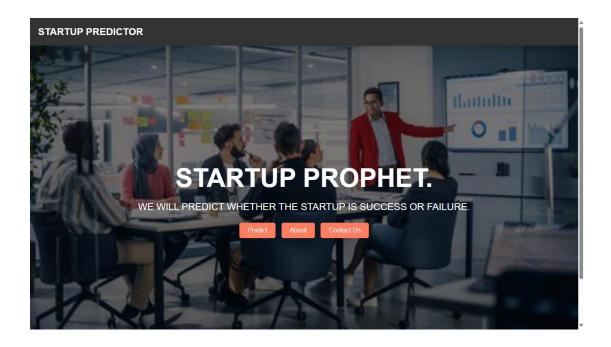


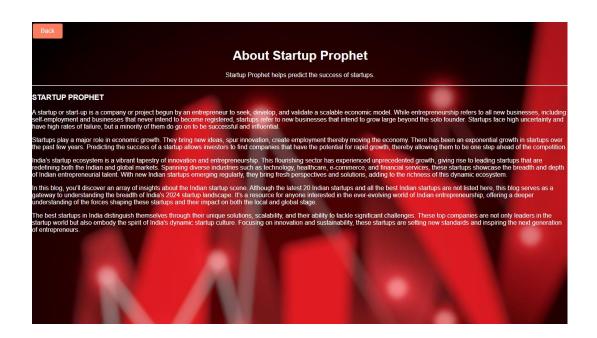
Fig 02: Flow chart of the project

## CHAPTER 6 RESULT

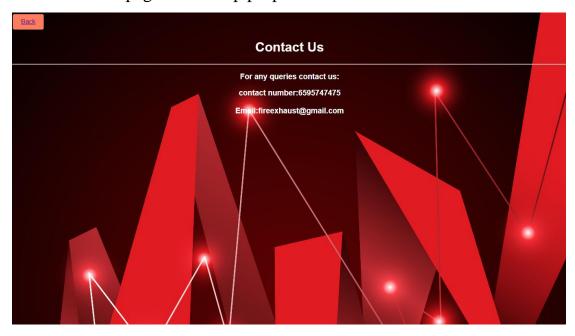
The home page will be shown as:



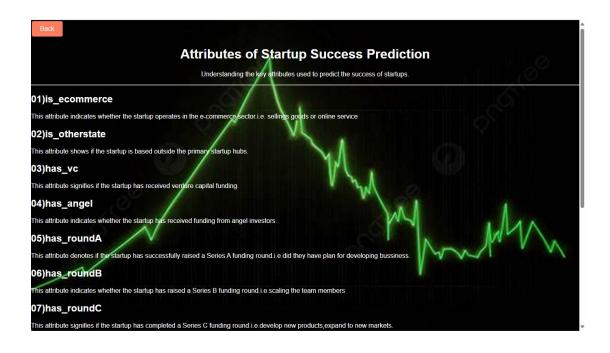
The about page about startup prophet



#### The contact us page for startup prophet



### The info page for startup prophet



## The prediction page for startup prophet





## The result page shown as





## The result page for startup prophet



## CHAPTER 7 ADVANTAGES & DISADVANTAGES

#### **ADVANTAGES:**

- Being your own boss
- Flexibility
- Financial rewards
- Opportunity to innovate
- Chance to impact your community

#### **DISADVANTAGES:**

- High costs and limited revenue
- Lack of a developed business model
- Inadequate capital to move to the next phase
- Risk of failure is high
- Long working hours are the norm

#### **CHAPTER 8**

#### APPLICATIONS

#### The areas where this solution can be used:

- → By stakeholders to predict the growth of the company.
- → By businessman to know whether the company will Is Success or failure.

#### **CHAPTER 9**

#### **CONCLUSION**

#### FROM THIS PROJECT WE HAVE CONCLUDED THAT:

- → We have Known fundamental concepts and techniques used for machine learning.
- → Gain a broad understanding about data.
- → Have knowledge on pre-processing the data/transformation techniques and some visualization techniques.

#### **CHAPTER 10**

#### **FUTURE SCOPE**

#### Enhancements that can be made in the future

- → Know fundamental concepts and techniques used for machine learning.
- → Gain a broad understanding about data.
- → Have knowledge on pre-processing the data/transformation techniques and some visualization concepts.

## CHAPTER 11 BIBILOGRAPHY

References of previous works or websites visited/books referred for analysis about the project, previous solution findings and previous STARTUP PROPHET documents.

#### **CHAPTER 12**

#### **CODE SNIPPETS**

#### **MODEL BUILDING:**

- 1)Dataset
- 2) Jupyter notebook and Spyder Application Building
  - 1. HTML file (home file, about file, predict file, submit file )
  - 1. Models in pickle format

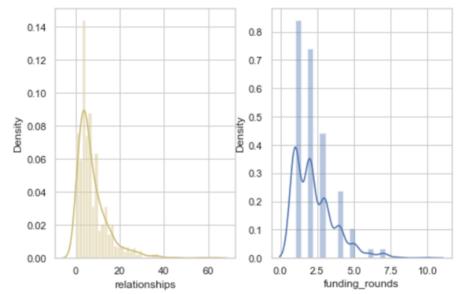
#### **CODE SNIPPETS**

#### MODEL BUILDING

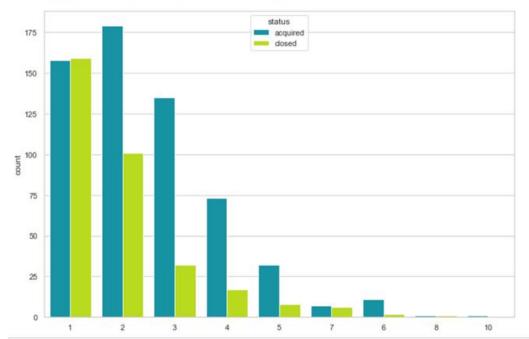
```
import pandas as pd
     import numpy as np
      #visulization
      from matplotlib import pyplot as plt
      %matplotlib inline
      import seaborn as sns
      sns.set(style="whitegrid")
      # data preprocessing
      from sklearn.model_selection import train_test_split, GridSearchCV
      from sklearn.impute import SimpleImputer
      from sklearn.preprocessing import OneHotEncoder,StandardScaler,LabelEncoder
      from sklearn.preprocessing import StandardScaler,MinMaxScaler
      # handling class imbalance
      from imblearn.over_sampling import SMOTE
      # model
      from sklearn.linear_model import LogisticRegression
      from sklearn.svm import SVC
      from sklearn.ensemble import RandomForestClassifier
      # evalution
      from sklearn.metrics import accuracy_score,classification_report, recall_score, precision_score, confusion_matrix
      import pickle
      import warnings
     warnings.filterwarnings('ignore')
In [3]: df=pd.read_csv('startup data.csv')
In [4]: df
Out[4]:
          0
                  1005
                            CA 42.358880 -71.056820
                                                     92101 c:6669 San Diego
                                                                                NaN Randsintown
                                                                                                          c:6669
                                                                                                                     0
                            CA 37.238916 -121.973718
                  204
                                                     95032 c:16283 Los Gatos
                                                                                NaN
                                                                                       TriCipher
                                                                                                         c:16283
                                                     92121 c:65620 San Diego
          2
                  1001
                            CA 32.901049 -117.192656
                                                                                                         c:65620
                                                                                                                              0
                            CA 37.320309 -122.050040
                                                                                                                              0
          3
                  738
                                                     95014 c:42668 Cupertino
                                                                                                         c:42668
                                                                   San
Francisco
                  1002
                            CA 37.779281 -122.419236
                                                      94105 c:65806
                                                                            Francisco
CA 94105
                                                                                    Inhale Digital
                                                                                                         c:65806
                                                     94107 c:21343 San
Francisco
         918
                  352
                            CA 37.740594 -122.376471
                                                                                NaN
                                                                                       CoTweet
                                                                                                         c:21343
                                                                                      Reef Point
                  721
                            MA 42.504817 -71.195611
                                                                                                         c:41747
         919
                                                      1803 c:41747 Burlington
         920
                  557
                            CA 37.408261 -122.015920
                                                      94089 c:31549 Sunnyvale
                                                                                NaN
                                                                                                         c:31549
                                                                                                                              0
         921
                  589
                            CA 37.556732 -122.288378
                                                     94404 c:33198
                                                                               NaN
                                                                                                         c:33198
                                                                                                                     0
                                                                                                                              0
                                                                                        Causata
         922
                  462
                            CA 37.386778 -121.966277
                                                     95054 c:26702
                                                                                                         c:26702
```

923 rows x 49 columns

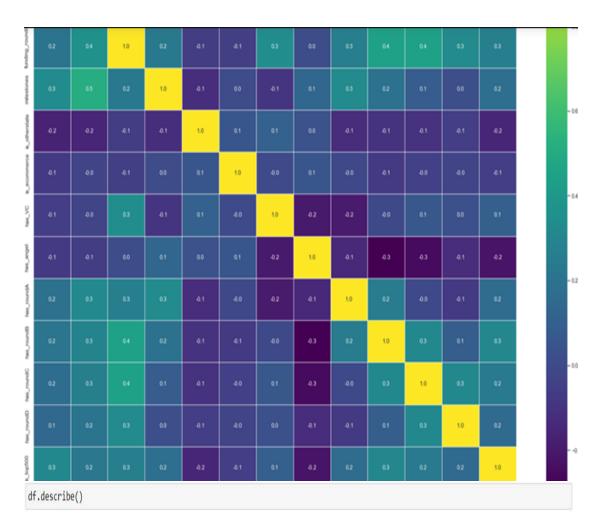
```
6]: plt.figure(figsize=(12,5))
  plt.subplot(131)
  sns.distplot(df["relationships"],color="y")
  plt.subplot(132)
  sns.distplot(df["funding_rounds"])
  plt.show()
```



']: <AxesSubplot:xlabel='funding\_rounds', ylabel='count'>



plt.figure(figsize = (25, 18))
sns.heatmap(df.corr(), annot = True, cmap = 'viridis', linewidth = 0.5, fmt = '.1f')



	Unnamed: 0	latitude	longitude	labels	age_first_funding_year	age_last_funding_year	age_first_milestone_year	age_last_milestone_year	relati
count	923.000000	923.000000	923.000000	923.000000	923.000000	923.000000	771.000000	771.000000	923
mean	572.297941	38.517442	-103.539212	0.646804	2.235630	3.931456	3.055353	4.754423	7
std	333.585431	3.741497	22.394167	0.478222	2.510449	2.967910	2.977057	3.212107	7
min	1.000000	25.752358	-122.756956	0.000000	-9.046600	-9.046600	-14.169900	-7.005500	0
25%	283.500000	37.388869	-122.198732	0.000000	0.576700	1.669850	1.000000	2.411000	3
50%	577.000000	37.779281	-118.374037	1.000000	1.446600	3.528800	2.520500	4.476700	5
75%	866.500000	40.730646	-77.214731	1.000000	3.575350	5.560250	4.686300	6.753400	10
max	1153.000000	59.335232	18.057121	1.000000	21.895900	21.895900	24.684900	24.684900	63
3 rows	× 35 columns	3							

```
5]: df.shape
 5]: (923, 49)
 5]: df.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 923 entries, 0 to 922
     Data columns (total 49 columns):
                                     Non-Null Count
          Column
                                                     Dtype
                                                     int64
                                     923 non-null
      0
          Unnamed: 0
                                                     object
                                     923 non-null
          state code
                                                     float64
      2
         latitude
                                     923 non-null
          longitude
                                                     float64
                                     923 non-null
      3
      4
          zip code
                                     923 non-null
                                                     object
      5
          id
                                     923 non-null
                                                     object
      6
          city
                                                     object
                                     923 non-null
      7
                                     430 non-null
                                                     object
          Unnamed: 6
      8
                                     923 non-null
                                                     object
          name
                                     923 non-null
          labels
                                                     int64
      10 founded at
                                     923 non-null
                                                     object
      11 closed at
                                     335 non-null
                                                     object
      12 first funding at
                                                     object
                                     923 non-null
      13 last funding at
                                     923 non-null
                                                     object
                                     923 non-null
      14 age first funding year
                                                     float64
      15 age last funding year
                                     923 non-null
                                                     float64
          age first milestone year
                                     771 non-null
                                                     float64
      16
      17 age last milestone year
                                     771 non-null
                                                     float64
      18 relationships
                                     923 non-null
                                                     int64
      19 funding rounds
                                     923 non-null
                                                     int64
      20 funding total usd
                                     923 non-null
                                                     int64
      21 milestones
                                     923 non-null
                                                     int64
      22 state_code.1
                                                     object
                                     922 non-null
                                     923 non-null
                                                     int64
      23 is CA
                                     923 non-null
                                                     int64
      24 is NY
S
```

```
8]: df.isna().sum()
8]: Unnamed: 0
                                             0
      state_code
                                             0
      latitude
                                             0
                                             0
      longitude
      zip_code
                                             0
      id
                                             0
      city
                                             0
      Unnamed: 6
                                          493
      name
                                             0
      labels
                                             0
      founded_at
                                             0
      closed_at
                                          588
      first_funding_at
                                             0
      last_funding_at
                                             0
      age_first_funding_year
                                             0
      age_last_funding_year
                                             0
      age_first_milestone_year
                                          152
      age_last_milestone_year
                                          152
      relationships
                                             0
      funding_rounds
                                             0
      funding_total_usd
                                             0
                                             0
      milestones
      state code.1
                                             1
      is CA
                                             0
      is NY
                                             0
      is MA
                                             0
      is_TX
                                             0
      is_otherstate
                                             0
                                             0
      category_code
                                             0
      is_software
      is_web
                                             0
      is_mobile
                                             0
      is_enterprise
                                             0
      is_advertising
                                             0
0]: df.drop(["status","is_othercategory","is_biotech","is_consulting","is_gamesvideo","is_advertising","is_web","is_TX","funding_total
                  df.drop(["is_enterprise","is_CA","is_NY","is_MA","age_last_funding_year","age_first_funding_year","state_code.1","city","last_funding_year","state_code.1","city","last_funding_year
            df.shape
t[28]: (923, 13)
```

```
30]: df.dtypes
30]: labels
                               int64
       relationships
                               int64
       funding rounds
                               int64
       milestones
                               int64
       is otherstate
                               int64
       is ecommerce
                               int64
       has VC
                               int64
       has angel
                               int64
       has roundA
                               int64
       has roundB
                               int64
       has roundC
                               int64
       has roundD
                               int64
       is_top500
                               int64
       dtype: object
in [32]: X = df.drop(['labels'], axis = 1)
        y = df['labels']
In [33]: sc= StandardScaler()
        x = sc.fit transform(X)
[n [34]: x
ut[34]: array([[-0.648696 , 0.49566485, 0.87613768, ..., -0.55106471,
                -0.3327311 , -2.06017431],
               [ 0.17754099, 1.21500235, -0.6368185 , ..., 1.81466891,
                 3.00542987, 0.48539582],
               [-0.37328367, -0.94301016, 0.11965959, ..., -0.55106471,
                -0.3327311 , 0.48539582],
               ...,
               [-0.37328367, -0.94301016, -0.6368185 , ..., -0.55106471,
                 3.00542987, 0.48539582],
               [ 0.59065949, -0.22367266, 0.11965959, ..., -0.55106471,
                -0.3327311 , 0.48539582],
               [-0.51098983, -0.94301016, -0.6368185 , ..., -0.55106471,
                -0.3327311 , 0.48539582]])
In [35]: x = pd.DataFrame(X)
In [36]: # Apply SMOTE to balance the classes
          smote = SMOTE(sampling_strategy='auto', random_state=42)
         x_bal, y_bal = smote.fit_resample(x, y)
  # Split the dataset into train and test sets
  X_train, X_test, y_train, y_test = train_test_split(x_bal, y_bal, test_size=0.3, random_state=42)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, recall_score, precision_score, confusion_matrix, f1_score
lg=LogisticRegression()
log=lg.fit(x_bal, y_bal)
y_pred=lg.predict(X_test)
print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test, y_pred))
[[140 30]
[54 135]]
           precision
                      recall f1-score support
                0.72
                        0.82
                                0.77
         0
                                          170
                0.82
                                0.76
                                9.77
   accuracy
                                          359
                0.77
                        0.77
                                0.77
  macro avg
                                          359
weighted avg
                0.77
                        0.77
                                0.77
                                          359
from sklearn.metrics import log_loss
logloss = log_loss(y_test,y_pred)
logloss
8.081563245391097
In [39]: from sklearn.svm import SVC
             # Train an SVM classifier on the resampled data
             svm = SVC(kernel='rbf',C=2.0, random_state=42)
             svm.fit(x bal, y bal)
             # Make predictions on the test set
             y_pred =svm.predict(X_test)
             # Print classification report , confusion matrix
             print(confusion_matrix(y_test,y_pred))
             print(classification_report(y_test, y_pred))
             [[127 43]
              [ 32 157]]
                                 precision
                                                   recall f1-score
                                                                              support
                             0
                                        0.80
                                                      0.75
                                                                    0.77
                                                                                    170
                             1
                                        0.79
                                                      0.83
                                                                    0.81
                                                                                   189
                   accuracy
                                                                    0.79
                                                                                   359
                                                                    0.79
                 macro avg
                                        0.79
                                                      0.79
                                                                                   359
```

0.79

0.79

0.79

359

weighted avg

```
In [40]: from sklearn.ensemble import RandomForestClassifier
           rf = RandomForestClassifier()
           rf.fit(x_bal, y_bal)
rftrain =rf.predict(X_train)
           rftest =rf.predict(X_test)
# Print classification report , confusion matrix
print(confusion_matrix(rftrain,y_train))
print(confusion_matrix(rftest,y_test))
print(classification_report(rftrain,y_train))
           print(classification_report(rftest,y_test))
           [[409 19]
           [ 18 389]]
[[165 9]
               5 180]]
                           precision
                                          recall f1-score
                                                                support
                                 0.96
                                            0.96
                                                       0.96
                        0
                                                                    428
                        1
                                 0.95
                                            0.96
                                                       0.95
                                                                    407
                                                        0.96
                                                                    835
                accuracy
               macro avg
                                 0.96
                                            0.96
                                                        0.96
                                                                    835
           weighted avg
                                 0.96
                                            0.96
                                                       0.96
                                                                    835
                           precision
                                          recall f1-score
                                                                support
                                 0.97
                                            0.95
                                 0.95
                                            0.97
                                                        0.96
                                                                    185
                                                        0.96
                                                                    359
                accuracy
                                 0.96
                                            0.96
                                                        0.96
                                                                    359
               macro avg
           weighted avg
                                            0.96
                                                       0.96
                                                                    359
                                 0.96
In [45]: ## Tesing
               rf.predict([[3,3,3,0,0,0,1,0,0,0,0,0]])
Out[45]: array([1], dtype=int64)
In [46]: rf.predict([[2,2,1,0,0,1,1,0,0,0,0,1]])
Dut[46]: array([0], dtype=int64)
             pickle.dump(rf,open("Randf.pkl","wb"))
```