1.Importing necessary dependencies

```
!pip install seaborn==0.11
```

```
Collecting seaborn==0.11
  Downloading seaborn-0.11.0-py3-none-any.whl (283 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 283.1/283.1 kB 4.8 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.10/dist-packages (from seaborn==0.11) (1.23
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.10/dist-packages (from seaborn==0.11) (1.11.
Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.10/dist-packages (from seaborn==0.11) (1.5
Requirement already satisfied: matplotlib>=2.2 in /usr/local/lib/python3.10/dist-packages (from seaborn==0.11) (
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.2
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.2->se
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.2-
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.2->s
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.2
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.23->seabo
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->m
Installing collected packages: seaborn
  Attempting uninstall: seaborn
    Found existing installation: seaborn 0.12.2
    Uninstalling seaborn-0.12.2:
      Successfully uninstalled seaborn-0.12.2
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This
lida 0.0.10 requires fastapi, which is not installed.
lida 0.0.10 requires kaleido, which is not installed.
lida 0.0.10 requires python-multipart, which is not installed.
lida 0.0.10 requires uvicorn, which is not installed.
Successfully installed seaborn-0.11.0
```

```
# for data reading and data manipulation
import numpy as np
import pandas as pd
import statistics as st

# for data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# for model creation and model evaluation
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
```

```
# reading data from a .csv file to a Pandas DataFrame
df = pd.read_csv('Customer_Conversion_Prediction.csv')
pd.set_option('display.max_columns',None)
df.head()
```

	age	job	marital	education_qual	call_type	day	mon	dur	num_calls	prev_outcome	y
0	58	management	married	tertiary	unknown	5	may	261	1	unknown	no

```
df.shape
```

```
(45211, 11)
```

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mon',
       'dur', 'num_calls', 'prev_outcome', 'y'],
      dtype='object')
```

```
print(f'➤ The DataFrame(df) contains {df.shape[0]} rows and {df.shape[1]} columns.')
```

```
➤ The DataFrame(df) contains 45211 rows and 11 columns.
```

2.Checking and Handling Missing Values

Checking for missing values

```
# looking for the amount of null data in the pandas dataframe
df.isnull().sum()
```

```
age               0
job               0
marital           0
education_qual    0
call_type         0
day               0
mon               0
dur               0
num_calls         0
prev_outcome      0
y                 0
dtype: int64
```

3.Data Type Correction

```
df.dtypes
```

```
age                int64
job               object
marital           object
education_qual    object
call_type         object
day                int64
mon               object
dur                int64
num_calls          int64
prev_outcome      object
y                 object
dtype: object
```

4.Analyze Categorical Columns

```
# for column "job"
df['job'].value_counts()
```

```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

```
df['job'] = df['job'].replace({'admin.':'admin'})
```

```
df['job'].value_counts()
```

```
blue-collar      9732
management       9458
technician       7597
admin            5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

```
# for column "marital"
df['marital'].value_counts()
```

```
married     27214
single      12790
divorced     5207
Name: marital, dtype: int64
```

```
# for column "education_qual"
df['education_qual'].value_counts()
```

```
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education_qual, dtype: int64
```

```
# for column "call_type"
df['call_type'].value_counts()
```

```
cellular     29285
unknown      13020
telephone     2906
Name: call_type, dtype: int64
```

```
# for column "mon"
df['mon'].value_counts()
```

```
may    13766
jul     6895
aug     6247
jun     5341
nov     3970
apr     2932
feb     2649
jan     1403
oct      738
sep      579
mar      477
dec      214
Name: mon, dtype: int64
```

```
df['mon'] = df['mon'].replace({'jul':'july','jun':'june','aug':'auguest','nov':'november','apr':'april','feb':'februa
```

```
df['mon'].value_counts()
```

```
may          13766
july          6895
auguest       6247
june          5341
november      3970
april         2932
february      2649
january       1403
october        738
september      579
march          477
december       214
Name: mon, dtype: int64
```

```
# for column "prev_outcome"
df['prev_outcome'].value_counts()
```

```
unknown    36959
failure     4901
other       1840
success     1511
Name: prev_outcome, dtype: int64
```

```
df = df.drop_duplicates()
```

```
df.shape
```

```
(45205, 11)
```

5.Data Visualization.

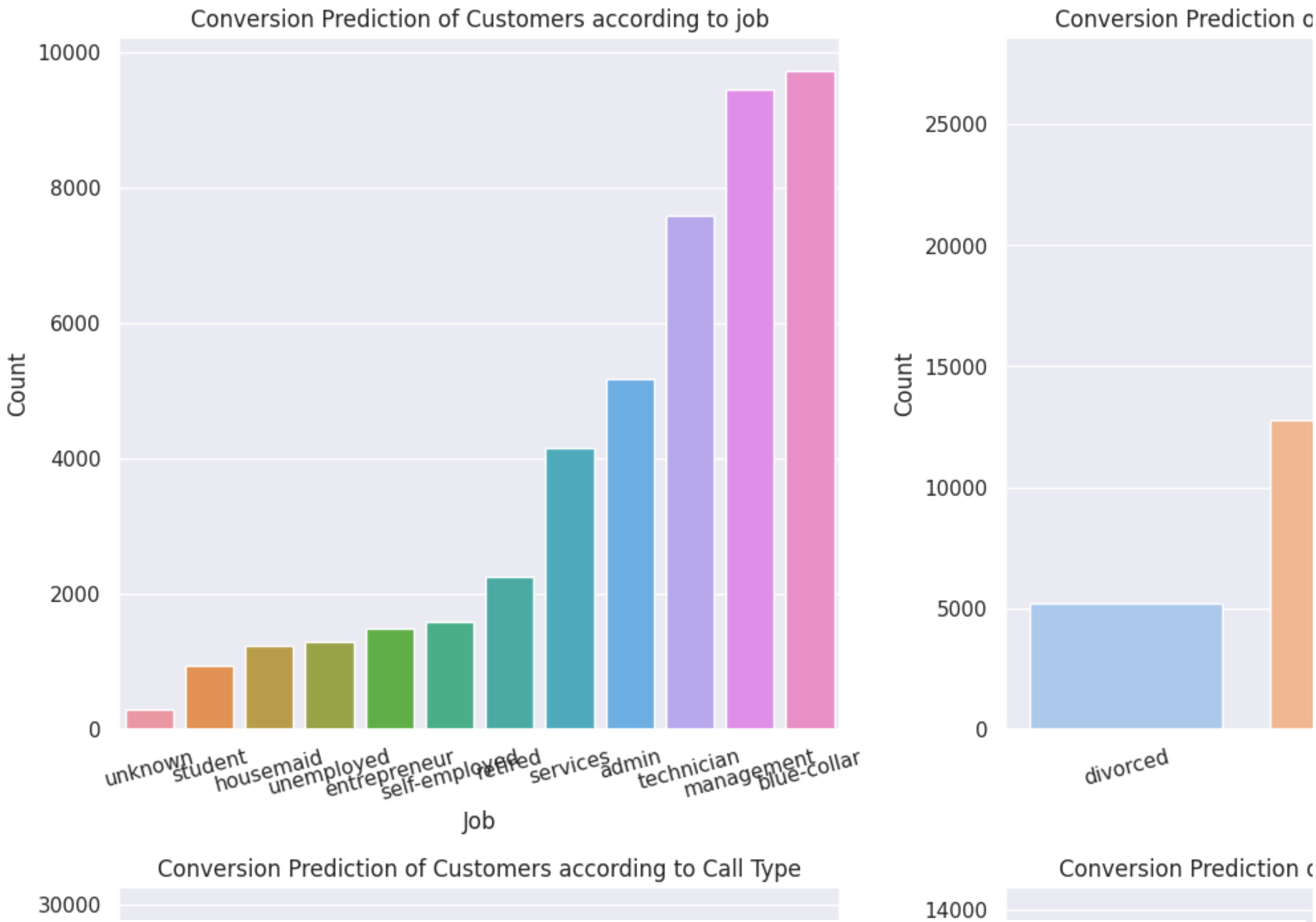
```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mon',
       'dur', 'num_calls', 'prev_outcome', 'y'],
      dtype='object')
```

5.1.Distribution of Future Plot

```
#plotting count plots for all the categorical columns
sns.set_theme(style='darkgrid',palette='pastel')


plt.figure(figsize=(20,25))
plt.subplot(431)
sns.countplot(df['job'],order=df['job'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Job')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to job')

plt.subplot(432)
sns.countplot(df['marital'],order=df['marital'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Marital')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to marital')

plt.subplot(433)
sns.countplot(df['education_qual'],order=df['education_qual'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Education Qualification')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to Education Qualification')

plt.subplot(434)
sns.countplot(df['call_type'],order=df['call_type'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Call Type')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to Call Type')

plt.subplot(435)
sns.countplot(df['mon'],order=df['mon'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Month')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to Month')

plt.subplot(436)
sns.countplot(df['prev_outcome'],order=df['prev_outcome'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Prev outcome')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to Prev outcome')


plt.subplot(436)
sns.countplot(df['y'],order=df['y'].value_counts().index[::-1])
plt.xticks(rotation=15)
plt.xlabel('Customer Conversion')
plt.ylabel('Count')
plt.title('Conversion Prediction of Customers according to Target Plot')

plt.tight_layout()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
  warnings.warn(
```

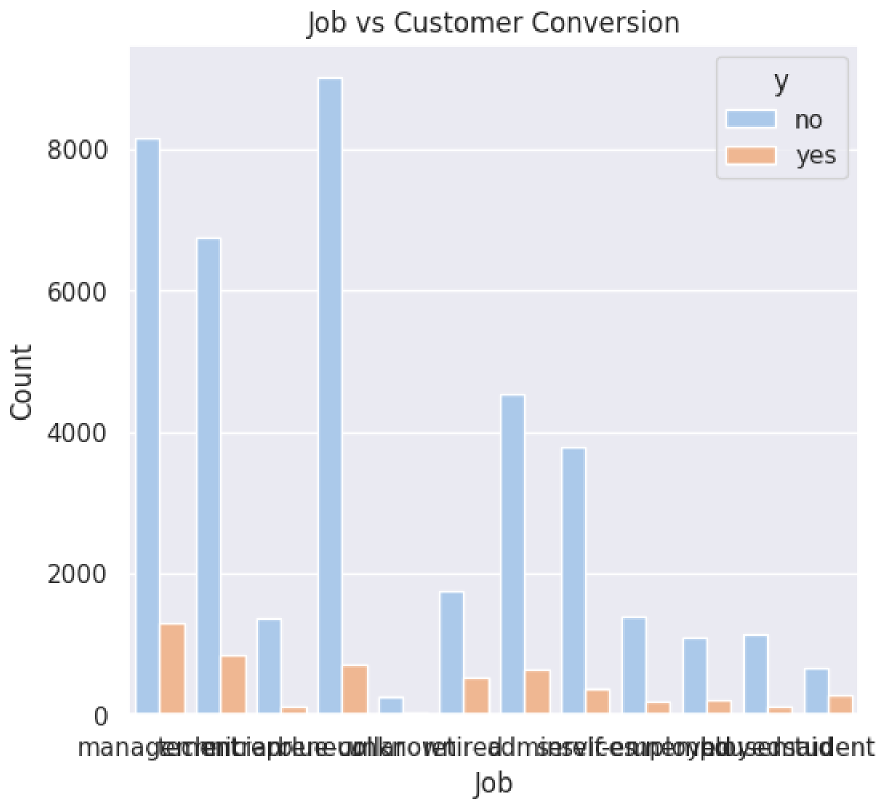


5.2.Future Vs Target Plot

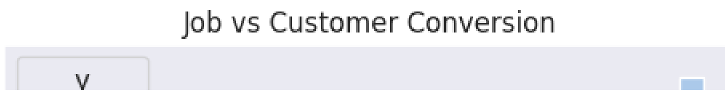
```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mon',
       'dur', 'num_calls', 'prev_outcome', 'y'],
      dtype='object')
```

```
plt.figure(figsize=(20, 25))
plt.subplot(435)
sns.countplot(data=df, x='job', hue='y')
plt.xlabel('Job')
plt.ylabel('Count')
plt.title('Job vs Customer Conversion')
plt.show()
```

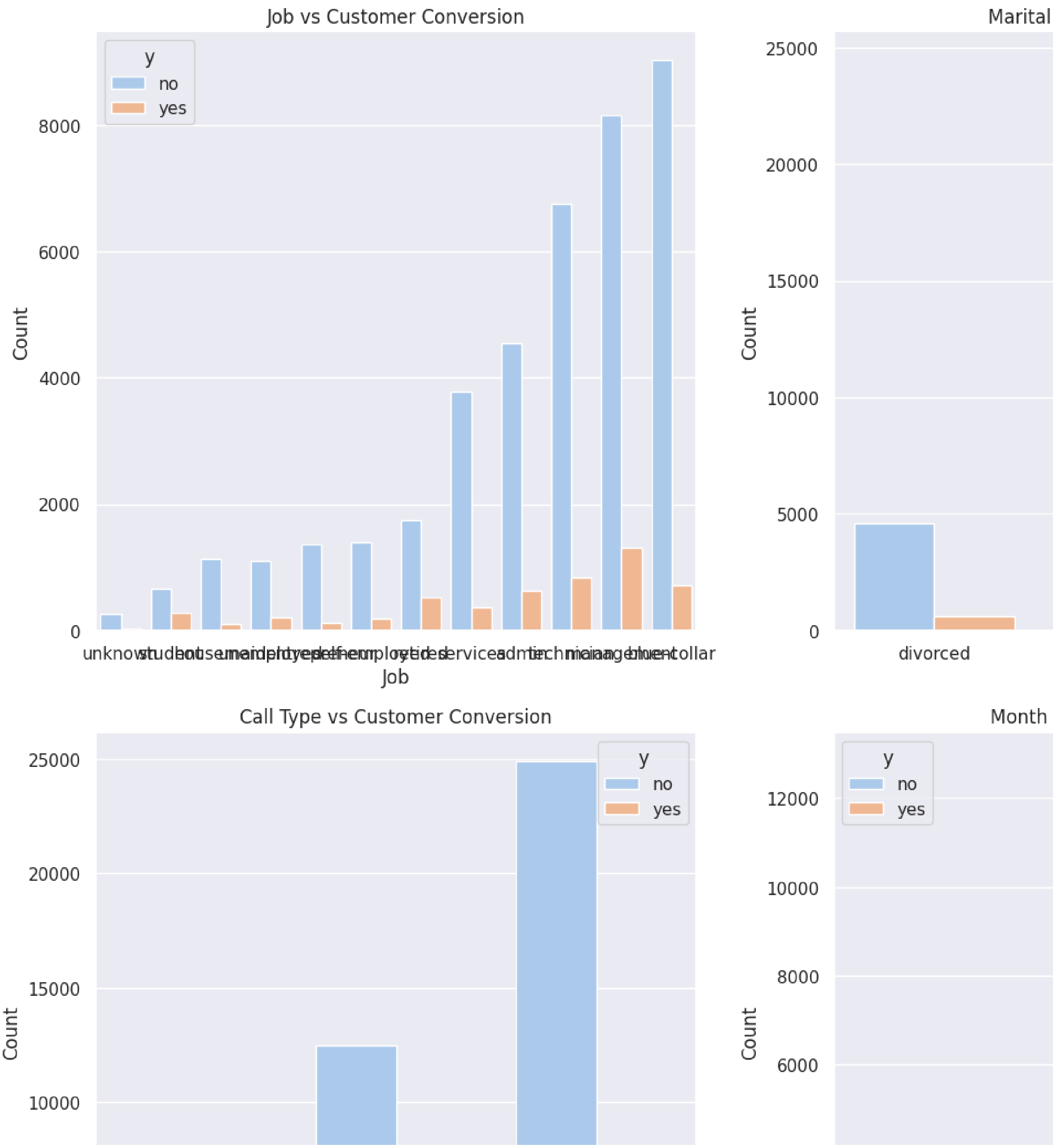



```
count_y_by_job = df.groupby('job')['y'].count().reset_index()
ordered_job_by_count = count_y_by_job.sort_values('y')['job']

plt.figure(figsize=(20, 25))
plt.subplot(431)
sns.countplot(data=df, x='job', hue='y', order=ordered_job_by_count)
plt.xlabel('Job')
plt.ylabel('Count')
plt.title('Job vs Customer Conversion')
plt.show()
```




```
#orders for all the barplots in ascending order

#Job Variable
count_y_by_job = df.groupby('job')['y'].count().reset_index()
ordered_job_by_count = count_y_by_job.sort_values('y')['job']

#marital variable
count_y_by_marital = df.groupby('marital')['y'].count().reset_index()
ordered_marital_by_count = count_y_by_marital.sort_values('y')['marital']

#education_qual Variable
count_y_by_education_qual = df.groupby('education_qual')['y'].count().reset_index()
ordered_education_qual_by_count = count_y_by_education_qual.sort_values('y')['education_qual']

#call_type Variable
count_y_by_call_type = df.groupby('call_type')['y'].count().reset_index()
ordered_call_type_by_count = count_y_by_call_type.sort_values('y')['call_type']

#month Variable
count_y_by_month = df.groupby('mon')['y'].count().reset_index()
ordered_month_by_count = count_y_by_month.sort_values('y')['mon']

#prev_outcome Variable
count_y_by_prev_outcome = df.groupby('prev_outcome')['y'].count().reset_index()
ordered_prev_outcome_by_count = count_y_by_prev_outcome.sort_values('y')['prev_outcome']


#categorical Variable


plt.figure(figsize=(20,25))

plt.subplot(431)
sns.countplot(data=df, x='job', hue='y', order=ordered_job_by_count)
plt.xlabel('Job')
plt.ylabel('Count')
plt.title('Job vs Customer Conversion')

plt.subplot(432)
sns.countplot(data=df, x='marital', hue='y', order=ordered_marital_by_count)
plt.xlabel('Marital')
plt.ylabel('Count')
plt.title('Marital vs Customer Conversion')

plt.subplot(433)
sns.countplot(data=df, x='education_qual', hue='y', order=ordered_education_qual_by_count)
plt.xlabel('Education Qualification')
plt.ylabel('Count')
plt.title('Education Qualification vs Customer Conversion')

plt.subplot(434)
sns.countplot(data=df, x='call_type', hue='y', order=ordered_call_type_by_count)
plt.xlabel('Call Type')
plt.ylabel('Count')
plt.title('Call Type vs Customer Conversion')

plt.subplot(435)
sns.countplot(data=df, x='mon', hue='y', order=ordered_month_by_count)
plt.xlabel('Month')
plt.ylabel('Count')
plt.title('Month vs Customer Conversion')
```

```
plt.subplot(436)
sns.countplot(data=df, x='prev_outcome', hue='y', order=ordered_prev_outcome_by_count)
plt.xlabel('Prev Outcome')
plt.ylabel('Count')
plt.title('Prev Outcome vs Customer Conversion')

plt.tight_layout()
```




```
#continuous variable
```

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mon',
       'dur', 'num_calls', 'prev_outcome', 'y'],
      dtype='object')
```

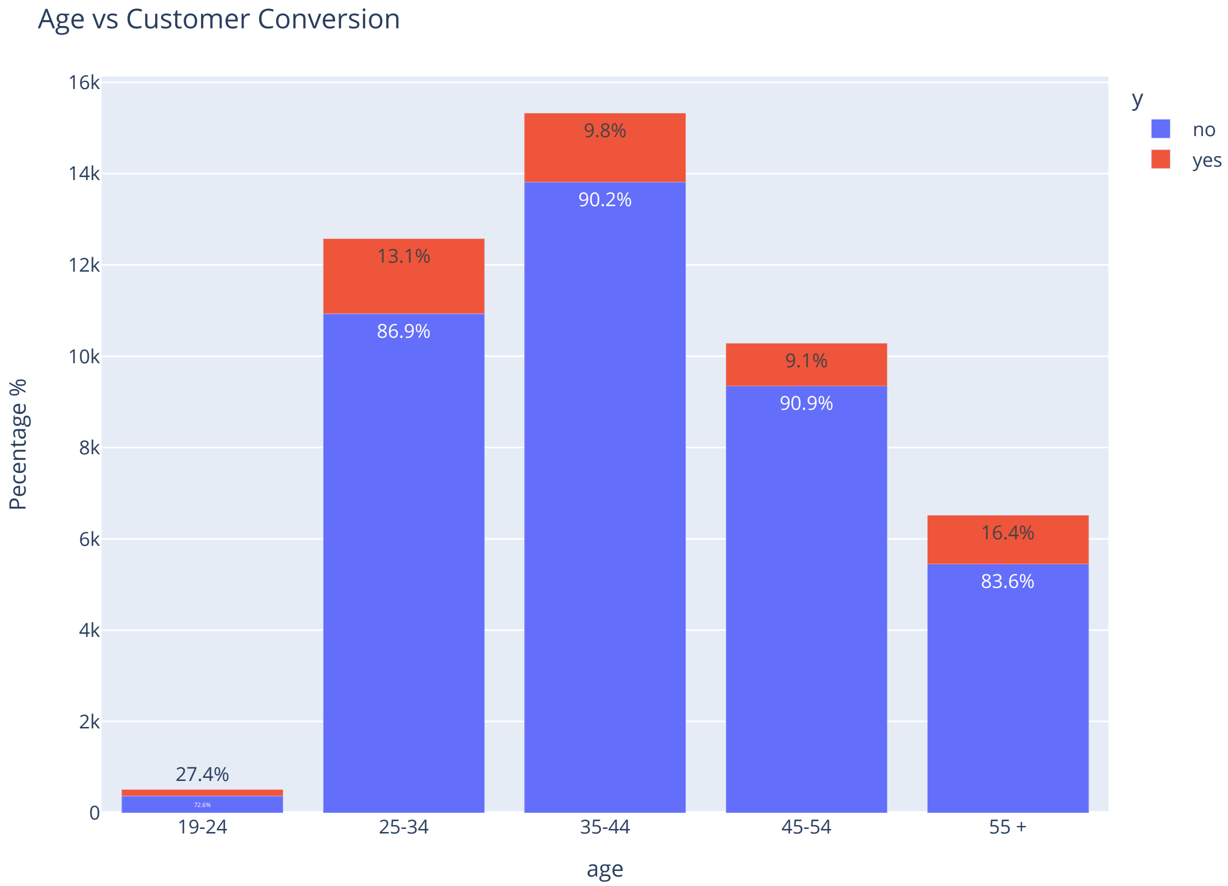
```
def group(x):

    if x <18:
        status=  "< 18"
    elif x<24:
        status = "19-24"
    elif x<34:
        status = "25-34"
    elif x<44:
        status = "35-44"
    elif x<54:
        status = "45-54"
    else:
        status = "55 +"

    return status
```

```
df['Age_group'] = df['age'].apply(group)
```

```
import pandas as pd
import plotly.express as px

def table(df, row, column, title, xaxis_title, yaxis_title):
    def bivariate_table(df, row, column):
        table = df.groupby([row, column]).size().reset_index()
        table['percentage'] = df.groupby([row, column]).size().groupby(level=0).apply(lambda x: 100 * x / float(x.sum
        table.columns = [row, column, 'Counts', 'Percentage']
        table['Percentage'] = table['Percentage'].astype(str) + '%'
        return table

    table = bivariate_table(df, row, column)

    fig = px.bar(table, x=row, y='Counts', color=column, barmode='stack', text=table['Percentage'])
    fig.update_layout(title=title, xaxis_title=xaxis_title, yaxis_title=yaxis_title, width=800, height=600)

    fig.show()

    return table
```

```
table(df,'Age_group','y','Age vs Customer Conversion', 'age', 'Pecentage %')
```

```
<ipython-input-32-4215a39c0ed2>:7: FutureWarning: Not prepending group keys to the result index of transform-like
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
  table['percentage'] = df.groupby([row, column]).size().groupby(level=0).apply(lambda x: 100 * x / float(x.sum(
```



	Age_group	y	Counts	Percentage
0	19-24	no	368	72.6%

```
def day_group(day_D):
    if day_D <= 5:
        return "<5 Days"
    elif day_D <= 10:
        return "6-10 Days"
    elif day_D <= 15:
        return "11-15 Days"
    elif day_D <= 20:
        return "16-20 Days"
    elif day_D <= 25:
        return "21-25 Days"
    else:
        return "25 + Days"

df['Day_Group'] = df['day'].apply(day_group)
df['Day_Group'] = pd.Categorical(df['Day_Group'], categories=['<5 Days', '6-10 Days', '11-15 Days', '16-20 Days', '21


table(df,'Day_Group','y','Day vs Customer Conversion', 'Day', 'Pecentage %')
```

```
<ipython-input-32-4215a39c0ed2>:7: FutureWarning:
```

```
def dur_group(dur):
    if dur <= 700:  # 700 seconds = 11 minutes 40 seconds
        return "11-23 minutes"
    elif dur <= 1400:  # 1400 seconds = 23 minutes 20 seconds
        return "23-40 minutes"
    elif dur <= 2100:  # 2100 seconds = 35 minutes
        return "40-60 minutes"
    elif dur <= 3600:  # 3600 seconds = 60 minutes (1 hour)
        return "1-2 hours"
    else:
        return "Over 2 hours"

df['Duration_Group'] = df['dur'].apply(dur_group)
df['Duration_Group'] = pd.Categorical(df['Duration_Group'],
                                     categories=['11-23 minutes', '23-40 minutes', '40-60 minutes', '1-2 hours', 'Ove
                                     ordered=True)
```

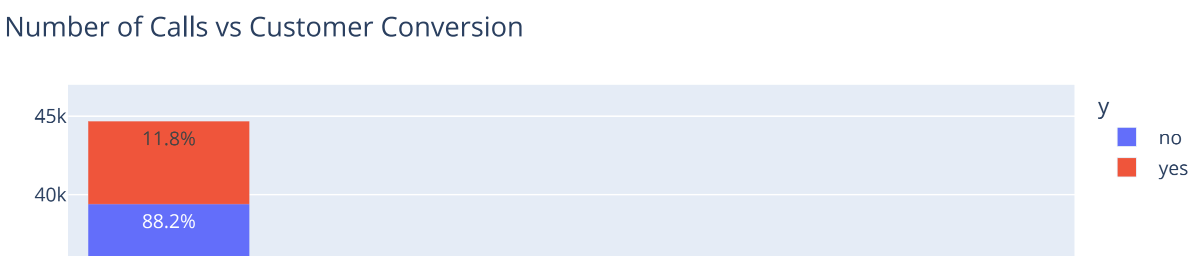
```
table(df,'Duration_Group','y','Duration of Call vs Customer Conversion', 'Duration', 'Pecentage %')
```

```
<ipython-input-32-4215a39c0ed2>:7: FutureWarning:

Not prepending group keys to the result index of transform-like apply. In the future, the group keys will be inc
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
```

```
def calls_group(num_calls):
    if num_calls <= 15:  # Grouping: 1-15 calls
        return "1-15 calls"
    elif num_calls <= 30:  # Grouping: 16-30 calls
        return "16-30 calls"
    elif num_calls <= 45:  # Grouping: 31-45 calls
        return "31-45 calls"
    elif num_calls <= 60:  # Grouping: 46-60 calls
        return "46-60 calls"
    else:
        return "Over 60 calls"

df['Calls_Group'] = df['num_calls'].apply(calls_group)
df['Calls_Group'] = pd.Categorical(df['Calls_Group'],
                                   categories=['1-15 calls', '16-30 calls', '31-45 calls', '46-60 calls', 'Over 60 ca
                                   ordered=True)
```

```
table(df,'Calls_Group','y','Number of Calls vs Customer Conversion', 'Number of Calls', 'Pecentage %')
```

```
<ipython-input-32-4215a39c0ed2>:7: FutureWarning:

Not prepending group keys to the result index of transform-like apply. In the future, the group keys will be inc
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
```



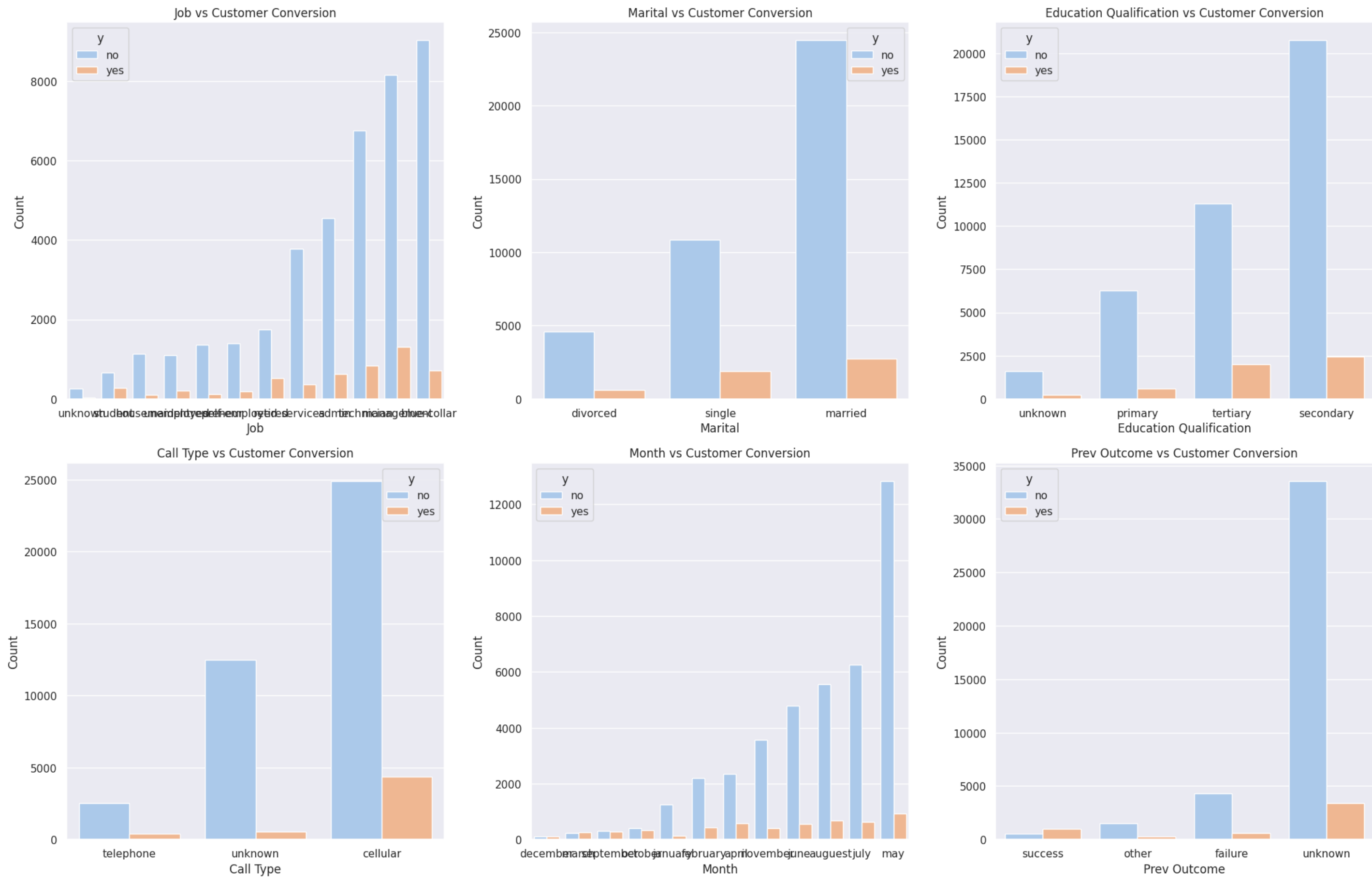
5.3.Encoding Categorical Variables

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'mon',
       'dur', 'num_calls', 'prev_outcome', 'y', 'Age_group', 'Day_Group',
       'Duration_Group', 'Calls_Group'],
      dtype='object')
```

```
df['prev_outcome'].value_counts()
```

```
unknown    36953
failure     4901
other       1840
success     1511
Name: prev_outcome, dtype: int64
```




```
df['job'] = df['job'].map({'unknown':0,'student':1,'housemaid':2,'unemployed':3,'entrepreneur':4,'self-employed':5,'r
df['marital'] = df['marital'].map({'divorced':0,'single':1,'married':2})
df['education_qual'] = df['education_qual'].map({'unknown':0,'primary':1,'tertiary':2,'secondary':3})
df['call_type'] = df['call_type'].map({'telephone':0,'unknown':1,'cellular':2})
df = pd.get_dummies(df, columns = ['mon'])
##df['mon'] = df['mon'].map({'december':0,'march':1,'september':2,'october':3,'january':4,'february':5,'april':6,'nov
df = pd.get_dummies(df, columns = ['prev_outcome'])
##df['prev_outcome'] = df['prev_outcome'].map({'success':0,'other':1,'failure':2,'unknown':3})
df['y'] = df['y'].map({'yes':0,'no':1})
```

```
df.head()
```

	age	job	marital	education_qual	call_type	day	dur	num_calls	y	Age_group	Day_Group	Duration_Group	Cal
0	58	10	2	2	1	5	261	1	1	55 +	<5 Days	11-23 minutes	
1	44	9	1	3	1	5	151	1	1	45-54	<5 Days	11-23 minutes	
2	33	4	2	3	1	5	76	1	1	25-34	<5 Days	11-23 minutes	
3	47	11	2	0	1	5	92	1	1	45-54	<5 Days	11-23 minutes	
4	33	0	1	0	1	5	198	1	1	25-34	<5 Days	11-23 minutes	

6.Splitting the data into input data and output data

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'dur',
       'num_calls', 'y', 'Age_group', 'Day_Group', 'Duration_Group',
       'Calls_Group', 'mon_april', 'mon_auguest', 'mon_december',
       'mon_february', 'mon_january', 'mon_july', 'mon_june', 'mon_march',
       'mon_may', 'mon_november', 'mon_october', 'mon_september',
       'prev_outcome_failure', 'prev_outcome_other', 'prev_outcome_success',
       'prev_outcome_unknown'],
      dtype='object')
```

```
del df['Age_group']
del df['Day_Group']
del df['Duration_Group']
del df['Calls_Group']
```

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'dur',
       'num_calls', 'y', 'mon_april', 'mon_auguest', 'mon_december',
       'mon_february', 'mon_january', 'mon_july', 'mon_june', 'mon_march',
       'mon_may', 'mon_november', 'mon_october', 'mon_september',
       'prev_outcome_failure', 'prev_outcome_other', 'prev_outcome_success',
       'prev_outcome_unknown'],
      dtype='object')
```

```
df.head()
```

	age	job	marital	education_qual	call_type	day	dur	num_calls	y	mon_april	mon_auguest	mon_december	mor
0	58	10	2	2	1	5	261	1	1	0	0	0	
1	44	9	1	3	1	5	151	1	1	0	0	0	
2	33	4	2	3	1	5	76	1	1	0	0	0	
3	47	11	2	0	1	5	92	1	1	0	0	0	
4	33	0	1	0	1	5	198	1	1	0	0	0	

```
def split (dataframe):
  x = dataframe.drop('y',axis=1)
  y = dataframe['y']
  return x,y
```

```
x,y = split(df)
```

```
x
```

	age	job	marital	education_qual	call_type	day	dur	num_calls	mon_april	mon_auguest	mon_december
0	58	10	2	2	1	5	261	1	0	0	0
1	44	9	1	3	1	5	151	1	0	0	0
2	33	4	2	3	1	5	76	1	0	0	0
3	47	11	2	0	1	5	92	1	0	0	0
4	33	0	1	0	1	5	198	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...

```
y
```

```
0        1
1        1
2        1
3        1
4        1
        ..
45206    0
45207    0
45208    0
45209    1
45210    1
Name: y, Length: 45205, dtype: int64
```

```
#splitting the data into training and testing sets with the ratio of 8:2
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.2,random_state=70)
```

```
print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

```
(36164, 24) (9041, 24) (36164,) (9041,)
```

```
X_train
```

	age	job	marital	education_qual	call_type	day	dur	num_calls	mon_april	mon_auguest	mon_december
2955	40	9	1	0	1	14	1028	2	0	0	0
18005	49	4	0	0	2	30	988	2	0	0	0
36166	45	11	2	0	2	11	306	1	0	0	0
3657	55	9	2	3	1	16	248	3	0	0	0
11307	38	5	2	3	1	18	313	2	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
21569	57	2	2	1	2	19	111	4	0	1	0
25922	54	3	2	2	2	19	394	2	0	0	0
44830	81	6	2	1	0	17	231	1	0	0	0
21624	56	9	2	3	2	19	35	4	0	1	0
23892	33	7	2	3	2	29	155	2	0	1	0

36164 rows × 24 columns

7.Building Machine Learning Model

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB

from sklearn.metrics import accuracy_score, classification_report
#Logistic Regression
#Random Forest
#Gradient Boosting (XGBoost
#K-Nearest Neighbors (KNN)
#Naive Bayes
```

7.1 Logistic Regression

```
logistic_reg = LogisticRegression()
logistic_reg.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

```
▾ LogisticRegression
LogisticRegression()
```

```
predictions_lr = logistic_reg.predict(X_test)
```

```
accuracy_lr = accuracy_score(y_test, predictions_lr)
print(f"Logistic Regression Accuracy: {accuracy_lr}")
print("Logistic Regression Classification Report:")
print(classification_report(y_test, predictions_lr))
```

```
Logistic Regression Accuracy: 0.8976883088153965
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.32      0.43      1056
           1       0.92      0.97      0.94      7985

    accuracy                           0.90      9041
   macro avg       0.77      0.65      0.68      9041
weighted avg       0.88      0.90      0.88      9041
```

7.2 Random Forest:

```
# Train the Random Forest model
random_forest = RandomForestClassifier()
random_forest.fit(X_train, y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
predictions_rf = random_forest.predict(X_test)
```

```
accuracy_rf = accuracy_score(y_test, predictions_rf)
print(f"\nRandom Forest Accuracy: {accuracy_rf}")
print("Random Forest Classification Report:")
print(classification_report(y_test, predictions_rf))
```

```
Random Forest Accuracy: 0.9029974560336246
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.45      0.52      1056
           1       0.93      0.96      0.95      7985

    accuracy                           0.90      9041
   macro avg       0.77      0.71      0.73      9041
weighted avg       0.89      0.90      0.90      9041
```

7.3 Gradient Boosting (XGBoost):

```
# Train the XGBoost model
xgboost = xgb.XGBClassifier()
xgboost.fit(X_train, y_train)
```

```
▾                                XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

```
predictions_xgb = xgboost.predict(X_test)
```

```
accuracy_xgb = accuracy_score(y_test, predictions_xgb)
print(f"\nXGBoost Accuracy: {accuracy_xgb}")
print("XGBoost Classification Report:")
print(classification_report(y_test, predictions_xgb))
```

```
XGBoost Accuracy: 0.9058732441101648
XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.49      0.55      1056
           1       0.93      0.96      0.95      7985

    accuracy                           0.91      9041
   macro avg       0.78      0.73      0.75      9041
```

```
weighted avg       0.90      0.91      0.90      9041
```

7.4 K-Nearest Neighbors (KNN):

```
# Train the KNN model
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

```
predictions_knn = knn.predict(X_test)
```

```
accuracy_knn = accuracy_score(y_test, predictions_knn)
print(f"\nK-Nearest Neighbors Accuracy: {accuracy_knn}")
print("K-Nearest Neighbors Classification Report:")
print(classification_report(y_test, predictions_knn))
```

```
K-Nearest Neighbors Accuracy: 0.8822032960955647
K-Nearest Neighbors Classification Report:
              precision    recall  f1-score   support

           0       0.49      0.23      0.31      1056
           1       0.90      0.97      0.94      7985

    accuracy                           0.88      9041
   macro avg       0.70      0.60      0.62      9041
weighted avg       0.86      0.88      0.86      9041
```

7.5 Naive Bayes

```
# Train the Naive Bayes model
naive_bayes = GaussianNB()
naive_bayes.fit(X_train, y_train)
```

```
▾ GaussianNB
GaussianNB()
```

```
predictions_nb = naive_bayes.predict(X_test)
```

```
accuracy_nb = accuracy_score(y_test, predictions_nb)
print(f"\nNaive Bayes Accuracy: {accuracy_nb}")
print("Naive Bayes Classification Report:")
print(classification_report(y_test, predictions_nb))
```

```
Naive Bayes Accuracy: 0.8816502599269992
Naive Bayes Classification Report:
              precision    recall  f1-score   support

           0       0.49      0.41      0.45      1056
           1       0.92      0.94      0.93      7985
```

```
    accuracy                           0.88      9041
   macro avg       0.71      0.68      0.69      9041
weighted avg       0.87      0.88      0.88      9041
```

7.6 Cross-validation scores

```
from sklearn.model_selection import cross_val_score

models = [logistic_reg, random_forest, xgboost, knn, naive_bayes]
model_names = ['Logistic Regression', 'Random Forest', 'XGBoost', 'K-Nearest Neighbors', 'Naive Bayes']
```

```
for model, name in zip(models, model_names):
    cv_scores = cross_val_score(model, X_train, y_train, cv=10)
    print(f"{name} - Cross Validation Score: {cv_scores.mean()} (±{cv_scores.std()})")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

```
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
```

8.F1 Score for Machine-Learning Models

```
from sklearn.metrics import f1_score
```

```
models = [logistic_reg, random_forest, xgboost, knn, naive_bayes]
model_names = ['Logistic Regression Model', 'Random Forest Model', 'XGBoost Model', 'K-Nearest Neighbors Model', 'Nai
```

```
for model, name in zip(models, model_names):
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    f1 = f1_score(y_test, predictions)
    print(f"{name} - F1 Score: {f1}")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

Logistic Regression Model - F1 Score: 0.9438406896970434
Random Forest Model - F1 Score: 0.9463780592793014
XGBoost Model - F1 Score: 0.9474334424609302
K-Nearest Neighbors Model - F1 Score: 0.9355989599080848
Naive Bayes Model - F1 Score: 0.9337050805452293
```

9.Suggestion

```
xgboost.feature_importances_
```

```
array([0.01484445, 0.01221474, 0.01210118, 0.01092021, 0.05915434,
       0.01778406, 0.05698902, 0.01287511, 0.02980603, 0.02077172,
       0.02271581, 0.03245021, 0.02717924, 0.03175417, 0.06404951,
       0.09638961, 0.0454943 , 0.03021196, 0.06405973, 0.05480836,
       0.01264754, 0.01519127, 0.22764911, 0.02793836], dtype=float32)
```

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education_qual', 'call_type', 'day', 'dur',
       'num_calls', 'y', 'mon_april', 'mon_auguest', 'mon_december',
       'mon_february', 'mon_january', 'mon_july', 'mon_june', 'mon_march',
       'mon_may', 'mon_november', 'mon_october', 'mon_september',
       'prev_outcome_failure', 'prev_outcome_other', 'prev_outcome_success',
       'prev_outcome_unknown'],
      dtype='object')
```

```
sorted_idx = xgboost.feature_importances_.argsort()
plt.figure(figsize=(10,5))
plt.barh(df.columns[sorted_idx], xgboost.feature_importances_[sorted_idx])
plt.xlabel("Extreme Gradient Boosting Feature Importance")
plt.title("Feature Importance")
plt.show()
```