Importing Libraries

In [ ]:
```
!pip install catboost
```

In [ ]:
```
!pip uninstall -y scikit-learn
!pip install scikit-learn==1.3.1
```

In [ ]:
```
!pip install imblearn
```

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix
from xgboost import XGBClassifier
from sklearn.svm import SVC
from catboost import CatBoostClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import cross_val_score
```

Reading The Dataset

In [5]:
```
# Loading the dataset
file_path = './WA_Fn-UseC_-Telco-Customer-Churn.csv'

data = pd.read_csv(file_path)
print(f'dataset contains {data.shape[0]} rows and {data.shape[1]} columns')
```

```
dataset contains 7043 rows and 21 columns
```

In [6]:
```
data.head(10)
```

Out[6]:

	customerID	gender	Senior_Citizen	Is_Married	Dependents	tenure	Phone_Service	Dual	Internet_Service	Online_Sec
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	
5	9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	
6	1452-KIOVK	Male	0	No	Yes	22	Yes	Yes	Fiber optic	
7	6713-OKOMC	Female	0	No	No	10	No	No phone service	DSL	
8	7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	
9	6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	

10 rows × 21 columns

In [7]:
```
data.tail()
```

Out[7]:

	customerID	gender	Senior_Citizen	Is_Married	Dependents	tenure	Phone_Service	Dual	Internet_Service	Online_
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	

5 rows × 21 columns

Get Information about the dataset:

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   customerID         7043 non-null   object 
 1   gender             7043 non-null   object 
 2   Senior_Citizen     7043 non-null   int64  
 3   Is_Married         7043 non-null   object 
 4   Dependents         7043 non-null   object 
 5   tenure             7043 non-null   int64  
 6   Phone_Service      7043 non-null   object 
 7   Dual               7043 non-null   object 
 8   Internet_Service   7043 non-null   object 
 9   Online_Security    7043 non-null   object 
 10  Online_Backup      7043 non-null   object 
 11  Device_Protection  7043 non-null   object 
 12  Tech_Support       7043 non-null   object 
 13  Streaming_TV       7043 non-null   object 
 14  Streaming_Movies   7043 non-null   object 
 15  Contract           7043 non-null   object 
 16  Paperless_Billing  7043 non-null   object 
 17  Payment_Method     7043 non-null   object 
 18  Monthly_Charges    7043 non-null   float64
 19  Total_Charges      7043 non-null   object 
 20  Churn              7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Coverting Some of the Object Datatype Columns to Numerical

In [9]:
```
# Total_charges column should be of numerical type
data['Total_Charges'] = data['Total_Charges'].apply(pd.to_numeric, errors='coerce') # invalid parsing will be s
```

Checking Null Values

In [10]:
```
data.isnull().sum()
```

Out[10]:

	0
customerID	0
gender	0
Senior_Citizen	0
Is_Married	0
Dependents	0
tenure	0
Phone_Service	0
Dual	0
Internet_Service	0
Online_Security	0
Online_Backup	0
Device_Protection	0
Tech_Support	0
Streaming_TV	0
Streaming_Movies	0
Contract	0
Paperless_Billing	0
Payment_Method	0
Monthly_Charges	0
Total_Charges	11
Churn	0

dtype: int64

In [11]:

```
# Check rows where Total_Charges is NaN
nan_rows = data[data['Total_Charges'].isna()]
print(nan_rows)
```

```
      customerID  gender  Senior_Citizen  Is_Married Dependents  tenure  \
488   4472-LVYGI  Female               0         Yes        Yes       0
753   3115-CZMZD    Male               0          No        Yes       0
936   5709-LVOEQ  Female               0         Yes        Yes       0
1082  4367-NUYAO    Male               0         Yes        Yes       0
1340  1371-DWPAZ  Female               0         Yes        Yes       0
3331  7644-OMVMY    Male               0         Yes        Yes       0
3826  3213-VVOLG    Male               0         Yes        Yes       0
4380  2520-SGTTA  Female               0         Yes        Yes       0
5218  2923-ARZLG    Male               0         Yes        Yes       0
6670  4075-WKNIU  Female               0         Yes        Yes       0
6754  2775-SEFEE    Male               0          No        Yes       0

     Phone_Service              Dual Internet_Service      Online_Security  \
488             No  No phone service              DSL                  Yes
753            Yes                No               No  No internet service
936            Yes                No              DSL                  Yes
1082           Yes               Yes               No  No internet service
1340            No  No phone service              DSL                  Yes
3331           Yes                No               No  No internet service
3826           Yes               Yes               No  No internet service
4380           Yes                No               No  No internet service
5218           Yes                No               No  No internet service
6670           Yes               Yes              DSL                   No
6754           Yes               Yes              DSL                  Yes

      ...    Device_Protection         Tech_Support         Streaming_TV  \
488   ...                  Yes                  Yes                  Yes
753   ...  No internet service  No internet service  No internet service
936   ...                  Yes                   No                  Yes
1082  ...  No internet service  No internet service  No internet service
1340  ...                  Yes                  Yes                  Yes
3331  ...  No internet service  No internet service  No internet service
3826  ...  No internet service  No internet service  No internet service
4380  ...  No internet service  No internet service  No internet service
5218  ...  No internet service  No internet service  No internet service
6670  ...                  Yes                  Yes                  Yes
6754  ...                   No                  Yes                   No

         Streaming_Movies  Contract Paperless_Billing  \
488                    No  Two year               Yes
753   No internet service  Two year                No
936                   Yes  Two year                No
1082  No internet service  Two year                No
1340                   No  Two year                No
3331  No internet service  Two year                No
3826  No internet service  Two year                No
4380  No internet service  Two year                No
5218  No internet service  One year               Yes
6670                   No  Two year                No
6754                   No  Two year               Yes

                 Payment_Method Monthly_Charges  Total_Charges  Churn
488   Bank transfer (automatic)           52.55            NaN     No
753                Mailed check           20.25            NaN     No
936                Mailed check           80.85            NaN     No
1082               Mailed check           25.75            NaN     No
1340    Credit card (automatic)           56.05            NaN     No
3331               Mailed check           19.85            NaN     No
3826               Mailed check           25.35            NaN     No
4380               Mailed check           20.00            NaN     No
5218               Mailed check           19.70            NaN     No
6670               Mailed check           73.35            NaN     No
6754  Bank transfer (automatic)           61.90            NaN     No

[11 rows x 21 columns]
```

In [12]:
```python
# Due to the dataset being big i decided to drop the rows

# Drop rows with NaN in the 'Total_Charges' column
data = data.dropna(subset=['Total_Charges'])
```

In [13]:
```python
data['Total_Charges'].isnull().sum()
```

Out[13]:
```
0
```

Checking Duplicates

In [14]:
```python
data_dup = data.duplicated().any()
print(data_dup)
# data.drop_duplicates()
```

```
False
```

Overall statistics about the dataset

In [15]:
```
data.describe()
```

Out[15]:

	Senior_Citizen	tenure	Monthly_Charges	Total_Charges
count	7032.000000	7032.000000	7032.000000	7032.000000
mean	0.162400	32.421786	64.798208	2283.300441
std	0.368844	24.545260	30.085974	2266.771362
min	0.000000	1.000000	18.250000	18.800000
25%	0.000000	9.000000	35.587500	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.862500	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

Splitting the Dataset into Features and a Target

In [16]:
```
X = data.iloc[:, 1:-1] # Excluding the customerid and the churn
y = data.iloc[:, -1] # Churn
```

In [17]:
```
print(X.shape)
print(y.shape)
```

```
(7032, 19)
(7032,)
```

In [18]:
```
X.head(5)
```

Out[18]:

	gender	Senior_Citizen	Is_Married	Dependents	tenure	Phone_Service	Dual	Internet_Service	Online_Security	Online
0	Female	0	Yes	No	1	No	No phone service	DSL	No	
1	Male	0	No	No	34	Yes	No	DSL	Yes	
2	Male	0	No	No	2	Yes	No	DSL	Yes	
3	Male	0	No	No	45	No	No phone service	DSL	Yes	
4	Female	0	No	No	2	Yes	No	Fiber optic	No	

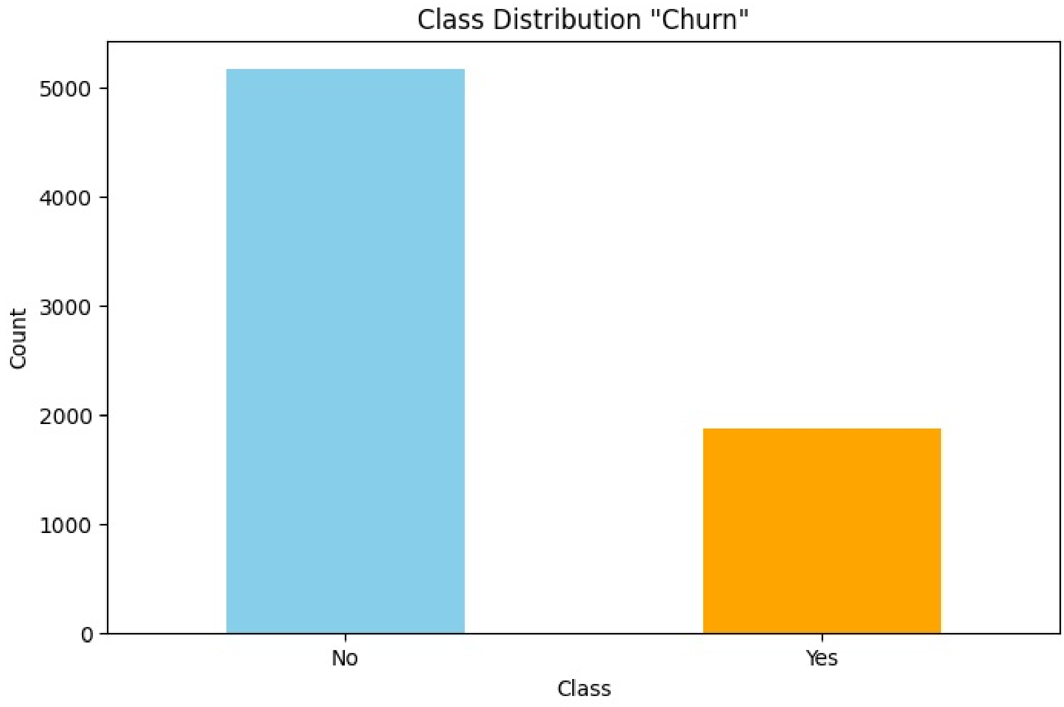
In [19]:
```
y.head(5)
```

Out[19]:

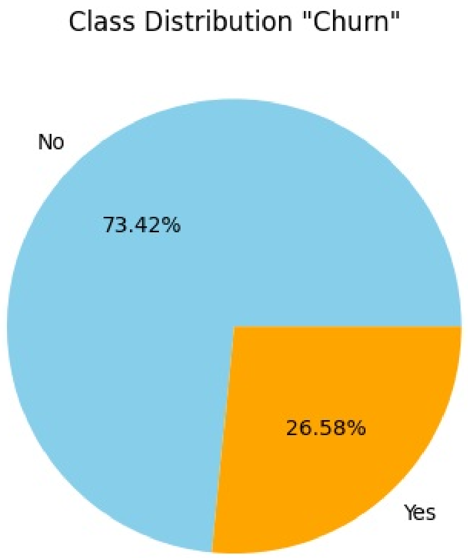
	Churn
0	No
1	No
2	Yes
3	No
4	Yes

dtype: object

In [20]:
```
# Get the count of each class
class_counts = y.value_counts() # Counts of unique values

# Plot the counts as a bar chart
plt.figure(figsize=(8, 5))
class_counts.plot(kind='bar', color=['skyblue', 'orange'])
plt.title('Class Distribution "Churn"')
plt.xlabel('Class')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```



In [21]:
```
class_counts.plot.pie(autopct='%1.2f%%', colors=['skyblue', 'orange'])
plt.title('Class Distribution "Churn"')
plt.ylabel('')
plt.show()
# Looks Like an Imbalanced Dataset
```



Encoding Categorical Data

In [22]:
```
# Checking unique values to choose which technique to apply
should_be_one_hot_encoded = []
should_be_label_encoded = []

for col in X.columns:
    if X[col].dtypes == 'object': # Exclude numerical values
        print(f'{col}: {X[col].unique()}')
        if len(X[col].unique()) > 2:
            should_be_one_hot_encoded.append(col)
        else:
            should_be_label_encoded.append(col)

print('\nOne-Hot Encoded : ', should_be_one_hot_encoded, '\n')
print('Label Encoded : ', should_be_label_encoded)
```

```
gender: ['Female' 'Male']
Is_Married: ['Yes' 'No']
Dependents: ['No' 'Yes']
Phone_Service: ['No' 'Yes']
Dual: ['No phone service' 'No' 'Yes']
Internet_Service: ['DSL' 'Fiber optic' 'No']
Online_Security: ['No' 'Yes' 'No internet service']
Online_Backup: ['Yes' 'No' 'No internet service']
Device_Protection: ['No' 'Yes' 'No internet service']
Tech_Support: ['No' 'Yes' 'No internet service']
Streaming_TV: ['No' 'Yes' 'No internet service']
Streaming_Movies: ['No' 'Yes' 'No internet service']
Contract: ['Month-to-month' 'One year' 'Two year']
Paperless_Billing: ['Yes' 'No']
Payment_Method: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']

One-Hot Encoded :  ['Dual', 'Internet_Service', 'Online_Security', 'Online_Backup', 'Device_Protection', 'Tech_
Support', 'Streaming_TV', 'Streaming_Movies', 'Contract', 'Payment_Method']

Label Encoded :  ['gender', 'Is_Married', 'Dependents', 'Phone_Service', 'Paperless_Billing']
```

Apply Label Encoding

In [23]:
```python
le = LabelEncoder()
for col in should_be_label_encoded:
    X[col] = le.fit_transform(X[col]) # Apply label encoding for each column

for col in should_be_label_encoded:
    print(f'{col}: {X[col].unique()}')
```

```
gender: [0 1]
Is_Married: [1 0]
Dependents: [0 1]
Phone_Service: [0 1]
Paperless_Billing: [1 0]
```

In [24]:
```python
# Label Encoding the Target
y = le.fit_transform(y)
print(y)
```

```
[0 0 1 ... 0 1 0]
```

Apply One-Hot Encoding

In [25]:
```python
# Get the indexes of columns to transform
hot_encode_indexes = X.columns.get_indexer(should_be_one_hot_encoded)
print(hot_encode_indexes)
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), hot_encode_indexes)], remainder='passthrough'
# Fit and transform the data
X_transformed = np.array(ct.fit_transform(X))
print(X_transformed)
```

```
[ 6  7  8  9 10 11 12 13 14 16]
[[0.0000e+00 1.0000e+00 0.0000e+00 ... 1.0000e+00 2.9850e+01 2.9850e+01]
 [1.0000e+00 0.0000e+00 0.0000e+00 ... 0.0000e+00 5.6950e+01 1.8895e+03]
 [1.0000e+00 0.0000e+00 0.0000e+00 ... 1.0000e+00 5.3850e+01 1.0815e+02]
 ...
 [0.0000e+00 1.0000e+00 0.0000e+00 ... 1.0000e+00 2.9600e+01 3.4645e+02]
 [0.0000e+00 0.0000e+00 1.0000e+00 ... 1.0000e+00 7.4400e+01 3.0660e+02]
 [1.0000e+00 0.0000e+00 0.0000e+00 ... 1.0000e+00 1.0565e+02 6.8445e+03]]
```

In [26]:
```python
# Get the feature names for the one-hot encoded columns
encoder = ct.transformers_[0][1]  # The encoder used for one-hot encoding
encoded_feature_names = encoder.get_feature_names_out(input_features=should_be_one_hot_encoded)

# Create a DataFrame with the transformed data
# Concatenate the new one-hot encoded feature names and original columns that weren't transformed
X_transformed_df = pd.DataFrame(X_transformed, columns=np.concatenate([encoded_feature_names, X.columns.differe

# Show the resulting DataFrame
print(X_transformed_df)
```

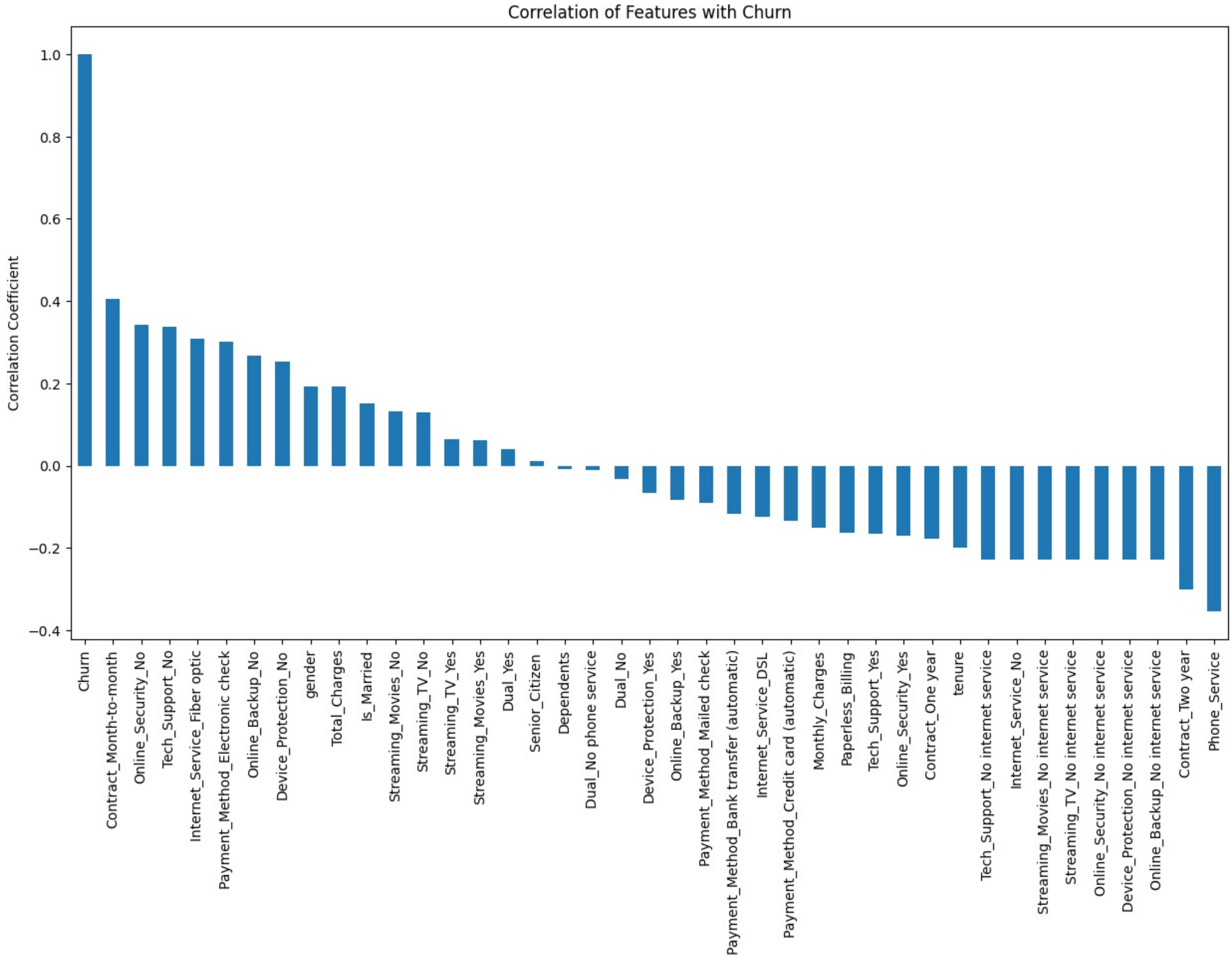
```
      Dual_No  Dual_No phone service  Dual_Yes  Internet_Service_DSL  \
0         0.0                    1.0       0.0                   1.0   
1         1.0                    0.0       0.0                   1.0   
2         1.0                    0.0       0.0                   1.0   
3         0.0                    1.0       0.0                   1.0   
4         1.0                    0.0       0.0                   0.0   
...       ...                    ...       ...                   ...   
7027      0.0                    0.0       1.0                   1.0   
7028      0.0                    0.0       1.0                   0.0   
7029      0.0                    1.0       0.0                   1.0   
7030      0.0                    0.0       1.0                   0.0   
7031      1.0                    0.0       0.0                   0.0   

      Internet_Service_Fiber optic  Internet_Service_No  Online_Security_No  \
0                              0.0                  0.0                 1.0   
1                              0.0                  0.0                 0.0   
2                              0.0                  0.0                 0.0   
3                              0.0                  0.0                 0.0   
4                              1.0                  0.0                 1.0   
...                            ...                  ...                 ...   
7027                           0.0                  0.0                 0.0   
7028                           1.0                  0.0                 1.0   
7029                           0.0                  0.0                 0.0   
7030                           1.0                  0.0                 1.0   
7031                           1.0                  0.0                 0.0   

      Online_Security_No internet service  Online_Security_Yes  \
0                                     0.0                  0.0   
1                                     0.0                  1.0   
2                                     0.0                  1.0   
3                                     0.0                  1.0   
4                                     0.0                  0.0   
...                                   ...                  ...   
7027                                  0.0                  1.0   
7028                                  0.0                  0.0   
7029                                  0.0                  1.0   
7030                                  0.0                  0.0   
7031                                  0.0                  1.0   

      Online_Backup_No  ...  Payment_Method_Mailed check  Dependents  \
0                  0.0  ...                          0.0         0.0   
1                  1.0  ...                          1.0         1.0   
2                  0.0  ...                          1.0         1.0   
3                  1.0  ...                          0.0         1.0   
4                  1.0  ...                          0.0         0.0   
...                ...  ...                          ...         ...   
7027               1.0  ...                          1.0         1.0   
7028               0.0  ...                          0.0         0.0   
7029               1.0  ...                          0.0         0.0   
7030               1.0  ...                          1.0         1.0   
7031               1.0  ...                          0.0         1.0   

      Is_Married  Monthly_Charges  Paperless_Billing  Phone_Service  \
0            0.0              1.0                0.0            1.0   
1            0.0              0.0                0.0           34.0   
2            0.0              0.0                0.0            2.0   
3            0.0              0.0                0.0           45.0   
4            0.0              0.0                0.0            2.0   
...          ...              ...                ...            ...   
7027         0.0              1.0                1.0           24.0   
7028         0.0              1.0                1.0           72.0   
7029         0.0              1.0                1.0           11.0   
7030         1.0              1.0                0.0            4.0   
7031         0.0              0.0                0.0           66.0   

      Senior_Citizen  Total_Charges  gender   tenure  
0                0.0            1.0   29.85    29.85  
1                1.0            0.0   56.95  1889.50  
2                1.0            1.0   53.85   108.15  
3                0.0            0.0   42.30  1840.75  
4                1.0            1.0   70.70   151.65  
...              ...            ...     ...      ...  
7027             1.0            1.0   84.80  1990.50  
7028             1.0            1.0  103.20  7362.90  
7029             0.0            1.0   29.60   346.45  
7030             1.0            1.0   74.40   306.60  
7031             1.0            1.0  105.65  6844.50  

[7032 rows x 40 columns]
```

Feature Selection Using Correlation

In [27]:
```
#Get Correlation of "Churn" with other variables:
plt.figure(figsize=(15,8))
y_df = pd.DataFrame(y, columns=['Churn'])

# Concatenate the feature DataFrame and the target DataFrame
```

```python
new_df = pd.concat([X_transformed_df, y_df], axis=1)

# Calculate correlations with the 'Churn' column
correlation = new_df.corr()['Churn'].sort_values(ascending=False)

# Plot the correlation of Churn with other variables
plt.figure(figsize=(15, 8))
correlation.plot(kind='bar')
plt.title("Correlation of Features with Churn")
plt.ylabel("Correlation Coefficient")
plt.show()
```

```
<Figure size 1500x800 with 0 Axes>
```

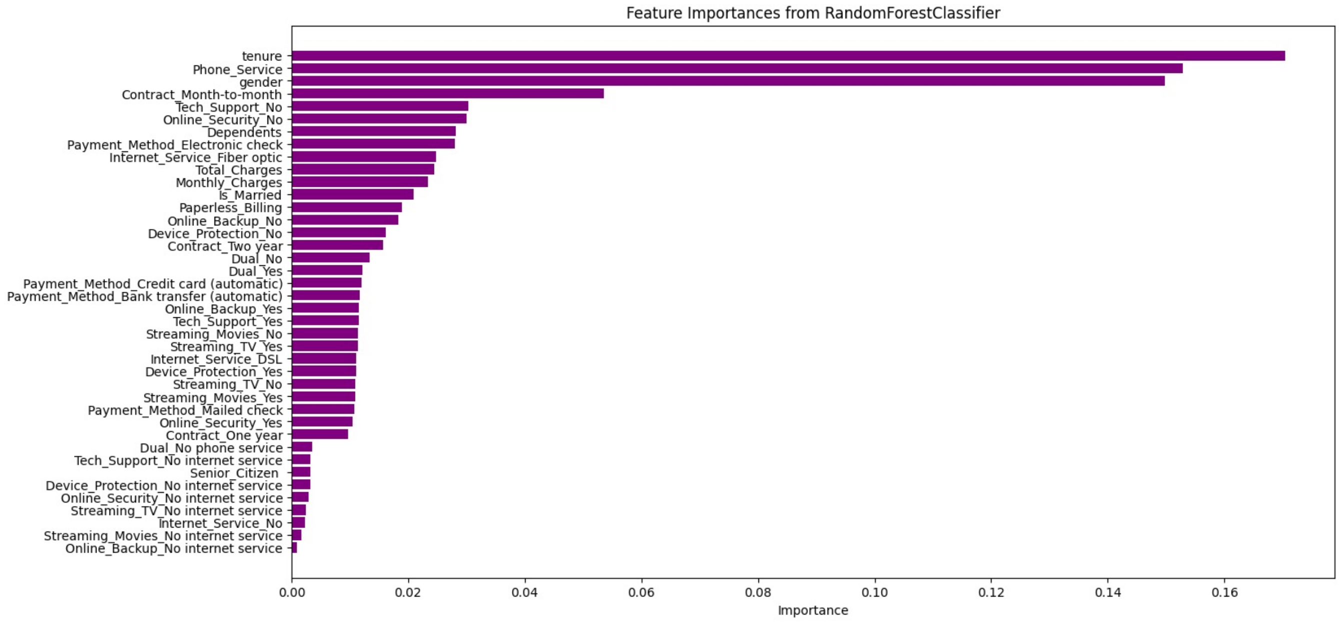


Feature Selection Using RandomForest

In [28]:

```python
# Dataset has mixed values between numerical and categorical so its best to use randomforest rather than correl
model = RandomForestClassifier()
model.fit(X_transformed, y)

# Get feature importances
importances = model.feature_importances_
print(importances)

# Create a DataFrame to store feature names and their importances
features_df = pd.DataFrame({
    'Feature': X_transformed_df.columns,
    'Importance': importances
})

# Sort the features by importance in descending order
features_df = features_df.sort_values(by='Importance', ascending=True)


# Plot the feature importances
plt.figure(figsize=(15, 8))
plt.barh(features_df['Feature'], features_df['Importance'], color='purple')
plt.xlabel('Importance')
plt.title('Feature Importances from RandomForestClassifier')
plt.show()
```

```
[0.0134645  0.00362119 0.01211903 0.01114978 0.02472343 0.00236605
 0.02996051 0.00290799 0.01045103 0.0183466  0.00095171 0.0115077
 0.01623842 0.00317968 0.01109489 0.03035744 0.00331088 0.01148571
 0.01093526 0.00247654 0.01134598 0.01143882 0.00173175 0.01090508
 0.05363645 0.00967561 0.01567628 0.01177007 0.01208563 0.02799879
 0.01081188 0.02810681 0.02097648 0.02340859 0.01894302 0.15290328
 0.00322414 0.02444555 0.14982801 0.17043944]
```



Keeping High-Correlated Features Only

In [29]:
```python
number_of_features = 15 # Take highest 15 features
filtered_features = []
for feature in features_df.tail(number_of_features).Feature:
    print(feature)
    filtered_features.append(feature)

for feature in X_transformed_df.columns:
    if feature not in filtered_features:
        X_transformed_df = X_transformed_df.drop(feature, axis=1)

print(X_transformed_df)
```

```
Online_Security_Yes
Payment_Method_Mailed check
Streaming_Movies_Yes
Streaming_TV_No
Device_Protection_Yes
Internet_Service_DSL
Streaming_TV_Yes
Streaming_Movies_No
Tech_Support_Yes
Online_Backup_Yes
Payment_Method_Bank transfer (automatic)
Payment_Method_Credit card (automatic)
Dual_Yes
Dual_No
Contract_Two year
Device_Protection_No
Online_Backup_No
Paperless_Billing
Is_Married
Monthly_Charges
Total_Charges
Internet_Service_Fiber optic
Payment_Method_Electronic check
Dependents
Online_Security_No
Tech_Support_No
Contract_Month-to-month
gender
Phone_Service
tenure
      Dual_No  Dual_Yes  Internet_Service_DSL  Internet_Service_Fiber optic  \
0         0.0       0.0                   1.0                           0.0
1         1.0       0.0                   1.0                           0.0
2         1.0       0.0                   1.0                           0.0
3         0.0       0.0                   1.0                           0.0
4         1.0       0.0                   0.0                           1.0
...       ...       ...                   ...                           ...
7027      0.0       1.0                   1.0                           0.0
7028      0.0       1.0                   0.0                           1.0
```

```
7029      0.0       0.0                   1.0                          0.0
7030      0.0       1.0                   0.0                          1.0
7031      1.0       0.0                   0.0                          1.0

      Online_Security_No  Online_Security_Yes  Online_Backup_No  \
0                    1.0                  0.0               0.0
1                    0.0                  1.0               1.0
2                    0.0                  1.0               0.0
3                    0.0                  1.0               1.0
4                    1.0                  0.0               1.0
...                  ...                  ...               ...
7027                 0.0                  1.0               1.0
7028                 1.0                  0.0               0.0
7029                 0.0                  1.0               1.0
7030                 1.0                  0.0               1.0
7031                 0.0                  1.0               1.0

      Online_Backup_Yes  Device_Protection_No  Device_Protection_Yes  ...  \
0                   1.0                   1.0                    0.0  ...
1                   0.0                   0.0                    1.0  ...
2                   1.0                   1.0                    0.0  ...
3                   0.0                   0.0                    1.0  ...
4                   0.0                   1.0                    0.0  ...
...                 ...                   ...                    ...  ...
7027                0.0                   0.0                    1.0  ...
7028                1.0                   0.0                    1.0  ...
7029                0.0                   1.0                    0.0  ...
7030                0.0                   1.0                    0.0  ...
7031                0.0                   0.0                    1.0  ...

      Payment_Method_Electronic check  Payment_Method_Mailed check  \
0                                 1.0                          0.0
1                                 0.0                          1.0
2                                 0.0                          1.0
3                                 0.0                          0.0
4                                 1.0                          0.0
...                               ...                          ...
7027                              0.0                          1.0
7028                              0.0                          0.0
7029                              1.0                          0.0
7030                              0.0                          1.0
7031                              0.0                          0.0

      Dependents  Is_Married  Monthly_Charges  Paperless_Billing  \
0            0.0         0.0              1.0                0.0
1            1.0         0.0              0.0                0.0
2            1.0         0.0              0.0                0.0
3            1.0         0.0              0.0                0.0
4            0.0         0.0              0.0                0.0
...          ...         ...              ...                ...
7027         1.0         0.0              1.0                1.0
7028         0.0         0.0              1.0                1.0
7029         0.0         0.0              1.0                1.0
7030         1.0         1.0              1.0                0.0
7031         1.0         0.0              0.0                0.0

      Phone_Service  Total_Charges  gender   tenure
0               1.0            1.0   29.85    29.85
1              34.0            0.0   56.95  1889.50
2               2.0            1.0   53.85   108.15
3              45.0            0.0   42.30  1840.75
4               2.0            1.0   70.70   151.65
...             ...            ...     ...      ...
7027           24.0            1.0   84.80  1990.50
7028           72.0            1.0  103.20  7362.90
7029           11.0            1.0   29.60   346.45
7030            4.0            1.0   74.40   306.60
7031           66.0            1.0  105.65  6844.50

[7032 rows x 30 columns]
```

Splitting the dataset into the Training and Test sets

In [30]:

```python
X_train, X_test, y_train, y_test = train_test_split(np.array(X_transformed_df), y, test_size=0.2, random_state=
```

Feature Scaling

In [31]:

```python
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Perform UnderSampling

```python
# from imblearn.under_sampling import RandomUnderSampler
```

In [32]:
```
# from imblearn.under_sampling import RandomUnderSampler
# rus = RandomUnderSampler(random_state=42)
# X_train, y_train = rus.fit_resample(X_train, y_train)
```

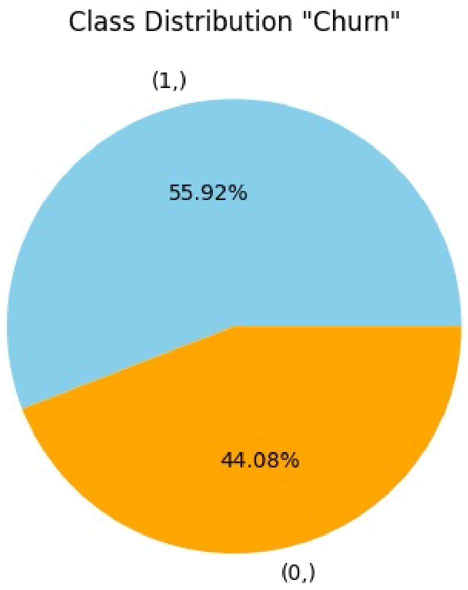
Perform OverSampling

In [33]:
```
# from imblearn.over_sampling import SMOTE
# smote = SMOTE(random_state=42)
# X_train, y_train = smote.fit_resample(X_train, y_train)
```

Perform UnderOverSampling

In [34]:
```
from imblearn.combine import SMOTEENN
smote = SMOTEENN(sampling_strategy='auto', random_state=42)
X_train, y_train = smote.fit_resample(X_train, y_train)
```

In [35]:
```
pd.DataFrame(y_train).value_counts().plot.pie(autopct='%1.2f%%', colors=['skyblue', 'orange'])
plt.title('Class Distribution "Churn"')
plt.ylabel('')
plt.show()
```



Training XGBoost on the Training set

In [36]:
```
xgb_classifier = XGBClassifier(n_estimators=194, learning_rate=0.08011727992081952, max_depth=3)
#{'n_estimators': 138, 'learning_rate': 0.2910194858724226, 'max_depth': 8}

xgb_classifier.fit(X_train, y_train)
```

Out[36]:
```
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=0.0801172799208195
2,
              max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
```

Confusion Matrix

In [37]:
```
y_pred = xgb_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[719 314]
 [ 80 294]]
```

Out[37]:
```
0.7199715707178393
```

K-Cross Validation

In [38]:
```
accuracies = cross_val_score(estimator = xgb_classifier, X = X_train, y = y_train, cv = 10) # number of folds
print(f"Accuracy: {round(accuracies.mean()*100, 2)} %")
print(f"Standard Deviation: {round(accuracies.std()*100, 2)} %") # for the variance
```

```
Accuracy: 95.65 %
Standard Deviation: 2.34 %
```

In [39]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.70      0.78      1033
           1       0.48      0.79      0.60       374

    accuracy                           0.72      1407
   macro avg       0.69      0.74      0.69      1407
weighted avg       0.79      0.72      0.74      1407
```

In [ ]:
```
!pip install optuna
```

Hyper Parameter Tuning

In [ ]:
```
import optuna
# from sklearn.metrics import accuracy_score

def objective(trial):
    params = {
        'n_estimators': trial.suggest_int('n_estimators', 50, 200),
        'learning_rate': trial.suggest_loguniform('learning_rate', 0.01, 0.3),
        'max_depth': trial.suggest_int('max_depth', 3, 9),
    }
    model = XGBClassifier(**params)
    # model.fit(X_train, y_train)
    # Evaluate on the test set
    # test_accuracy = accuracy_score(y_test, model.predict(X_test))
    # return test_accuracy
    return cross_val_score(model, X_train, y_train, cv=5, scoring='accuracy').mean()
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=50)
print(study.best_params)
```

Trying Randomized Search

In [42]:
```
# param_dist = {
#     'learning_rate': [0.01, 0.1, 0.2, 0.3],
#     'n_estimators': [50, 100, 200],
#     'max_depth': [3, 5, 7, 9],
#     'min_child_weight': [1, 3, 5],
#     'subsample': [0.6, 0.8, 1.0]
# }

# random_search = RandomizedSearchCV(xgb_classifier, param_distributions=param_dist, n_iter=10, cv=3)
# random_search.fit(X_train, y_train)
# best_accuracy = random_search.best_score_
# best_parameters = random_search.best_params_
# print(f"Best Accuracy: {round(best_accuracy*100, 2)} %")
# print(f"Best Parameters: {best_parameters}")
```

Training on CatBoost

In [43]:
```
cat_classifier = CatBoostClassifier(silent=True)
cat_classifier.fit(X_train, y_train)
```

Out[43]:
```
<catboost.core.CatBoostClassifier at 0x7db287555e10>
```

In [44]:
```
y_pred = cat_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[732 301]
 [ 83 291]]
```

Out[44]:
```
0.7270788912579957
```

In [45]:
```
accuracies = cross_val_score(estimator = cat_classifier, X = X_train, y = y_train, cv = 10) # number of folds
print(f"Accuracy: {round(accuracies.mean()*100, 2)} %")
```

```
print(f"Standard Deviation: {round(accuracies.std()*100, 2)} %") # for the variance
```

```
Accuracy: 96.63 %
Standard Deviation: 1.93 %
```

In [46]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.71      0.79      1033
           1       0.49      0.78      0.60       374

    accuracy                           0.73      1407
   macro avg       0.69      0.74      0.70      1407
weighted avg       0.79      0.73      0.74      1407
```

In [47]:
```
# import optuna
# def objective(trial):
#     # Suggest values for the hyperparameters
#     iterations = trial.suggest_categorical('iterations', [500, 1000])
#     learning_rate = trial.suggest_loguniform('learning_rate', 0.01, 0.2)
#     depth = trial.suggest_int('depth', 6, 10)
#     l2_leaf_reg = trial.suggest_float('l2_leaf_reg', 1, 5)

#     cat_classifier = CatBoostClassifier(
#         iterations=iterations,
#         learning_rate=learning_rate,
#         depth=depth,
#         l2_leaf_reg=l2_leaf_reg,
#         verbose=0
#     )
#     return cross_val_score(cat_classifier, X_train, y_train, cv=5, scoring='accuracy').mean()
# study = optuna.create_study(direction='maximize')
# study.optimize(objective, n_trials=50)
# print(study.best_params)
```

In [48]:
```
# param_dist = {
#     'iterations': [500, 1000],
#     'learning_rate': [0.01, 0.1, 0.2],
#     'depth': [6, 8, 10],
#     'l2_leaf_reg': [1, 3, 5]
# }

# random_search = RandomizedSearchCV(cat_classifier, param_distributions=param_dist, n_iter=10, cv=3)
# random_search.fit(X_train, y_train)
# best_accuracy = random_search.best_score_
# best_parameters = random_search.best_params_
# print(f"Best Accuracy: {round(best_accuracy*100, 2)} %")
# print(f"Best Parameters: {best_parameters}")
```

Training KernelSVM on the Training set

In [49]:
```
svm_classifier = SVC(kernel = 'rbf', random_state = 0)
svm_classifier.fit(X_train, y_train)
```

Out[49]:
```
▾ SVC
SVC(random_state=0)
```

In [50]:
```
y_pred = svm_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[693 340]
 [ 80 294]]
```

Out[50]:
```
0.7014925373134329
```

In [51]:
```
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = svm_classifier, X = X_train, y = y_train, cv = 10) # number of folds
print(f"Accuracy: {round(accuracies.mean()*100, 2)} %")
print(f"Standard Deviation: {round(accuracies.std()*100, 2)} %") # for the variance
```

```
Accuracy: 94.29 %
Standard Deviation: 0.9 %
```

In [52]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.67      0.77      1033
           1       0.46      0.79      0.58       374

    accuracy                           0.70      1407
   macro avg       0.68      0.73      0.68      1407
weighted avg       0.78      0.70      0.72      1407
```

In [53]:
```
# from sklearn.model_selection import GridSearchCV
# parameters = [{'C': [0.25, 0.5, 0.75, 1], 'kernel' : ['linear']},
#               {'C': [0.25, 0.5, 0.75, 1], 'kernel' : ['rbf'], 'gamma' : [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0
# grid_search = GridSearchCV(estimator = svm_classifier,
#                            param_grid = parameters,
#                            scoring = 'accuracy', # the metric with which you want to evaluate the performance
#                            cv = 10, # number of trained test polls when applying k-fold cross validation
#                            n_jobs = -1) # number of cores to use
# grid_search.fit(X_train, y_train)
# best_accuracy = grid_search.best_score_
# best_parameters = grid_search.best_params_
# print(f"Best Accuracy: {round(best_accuracy*100, 2)} %")
# print(f"Best Parameters: {best_parameters}")
```

In [54]:
```
# def objective(trial):
#     # Suggest values for the hyperparameters
#     c = trial.suggest_loguniform('C', 1e-3, 1e3)  # Loguniform for C to cover a wide range
#     kernel = trial.suggest_categorical('kernel', ['linear', 'poly', 'rbf', 'sigmoid'])
#     degree = trial.suggest_int('degree', 2, 5) if kernel == 'poly' else 3  # Degree only relevant for 'poly'
#     gamma = trial.suggest_categorical('gamma', ['scale', 'auto'])

#     # Create an SVC with suggested parameters
#     svc = SVC(C=c, kernel=kernel, degree=degree, gamma=gamma)

#     # Perform cross-validation and return the mean accuracy
#     score = cross_val_score(svc, X_train, y_train, cv=5, scoring='accuracy').mean()
#     return score

# # Create and optimize the study
# study = optuna.create_study(direction='maximize')
# study.optimize(objective, n_trials=50)
# print(study.best_params)
```

Training Logistic Regression on the Training set

In [55]:
```
from sklearn.linear_model import LogisticRegression
lr_classifier = LogisticRegression(random_state = 0)
lr_classifier.fit(X_train, y_train)
```

Out[55]:
```
▾        LogisticRegression
LogisticRegression(random_state=0)
```

In [56]:
```
y_pred = lr_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[651 382]
 [ 54 320]]
```

Out[56]:
```
0.6901208244491827
```

In [57]:
```
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = lr_classifier, X = X_train, y = y_train, cv = 10) # number of folds
print(f"Accuracy: {round(accuracies.mean()*100, 2)} %")
print(f"Standard Deviation: {round(accuracies.std()*100, 2)} %") # for the variance
```

```
Accuracy: 90.09 %
Standard Deviation: 1.16 %
```

In [58]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.63      0.75      1033
           1       0.46      0.86      0.59       374

    accuracy                           0.69      1407
   macro avg       0.69      0.74      0.67      1407
weighted avg       0.80      0.69      0.71      1407
```

In [59]:
```
# def objective(trial):
#     # Suggest values for the hyperparameters
```

```
#     c = trial.suggest_loguniform('C', 1e-3, 1e3)  # Regularization strength (log-uniform)
#     solver = trial.suggest_categorical('solver', ['liblinear', 'saga', 'lbfgs', 'newton-cg'])
#     max_iter = trial.suggest_int('max_iter', 100, 500)  # Maximum iterations
#     penalty = trial.suggest_categorical('penalty', ['l2', 'elasticnet'])  # Penalty type

#     # ElasticNet mixing parameter (only relevant if 'penalty' is 'elasticnet')
#     l1_ratio = trial.suggest_float('l1_ratio', 0.0, 1.0) if penalty == 'elasticnet' else 0.5

#     # Create Logistic Regression with suggested parameters
#     logreg = LogisticRegression(
#         C=c,
#         solver=solver,
#         max_iter=max_iter,
#         penalty=penalty,
#         l1_ratio=l1_ratio,
#         multi_class='auto',
#         random_state=42
#     )

#     # Perform cross-validation and return the mean accuracy
#     score = cross_val_score(logreg, X_train, y_train, cv=5, scoring='accuracy').mean()
#     return score

# # Create and optimize the study
# study = optuna.create_study(direction='maximize')
# study.optimize(objective, n_trials=50)
# print(study.best_params)
```

Training Random Forest on the Training set

In [60]:
```
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators= 220, max_depth=17, criterion= 'entropy', random_state= 0, 
rf_classifier.fit(X_train, y_train)
# {'n_estimators': 220, 'max_depth': 17, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'sqrt'}
```

Out[60]:
```
RandomForestClassifier

RandomForestClassifier(criterion='entropy', max_depth=17, min_samples_split=5,
                       n_estimators=220, random_state=0)
```

In [61]:
```
y_pred = rf_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[717 316]
 [ 81 293]]
```

Out[61]:
```
0.7178393745557925
```

In [62]:
```
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = rf_classifier, X = X_train, y = y_train, cv = 10) # number of folds
print(f"Accuracy: {round(accuracies.mean()*100, 2)} %")
print(f"Standard Deviation: {round(accuracies.std()*100, 2)} %") # for the variance
```

```
Accuracy: 96.43 %
Standard Deviation: 1.21 %
```

In [63]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.69      0.78      1033
           1       0.48      0.78      0.60       374

    accuracy                           0.72      1407
   macro avg       0.69      0.74      0.69      1407
weighted avg       0.79      0.72      0.73      1407
```

In [64]:
```
# import optuna
# #{'n_estimators': 220, 'max_depth': 17, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'sqrt'
# def objective(trial):
#     # Suggest values for the hyperparameters
#     n_estimators = trial.suggest_int('n_estimators', 50, 500)  # Number of trees
#     max_depth = trial.suggest_int('max_depth', 2, 20)  # Maximum depth of trees
#     min_samples_split = trial.suggest_int('min_samples_split', 2, 20)  # Minimum samples to split a node
#     min_samples_leaf = trial.suggest_int('min_samples_leaf', 1, 20)  # Minimum samples per leaf
#     max_features = trial.suggest_categorical('max_features', ['sqrt', 'log2', None])  # Number of features to

#     # Create a RandomForestClassifier with suggested parameters
#     rf = RandomForestClassifier(
#         n_estimators=n_estimators,
#         max_depth=max_depth,
#         min_samples_split=min_samples_split,
```

```
#         min_samples_leaf=min_samples_leaf,
#         max_features=max_features,
#         random_state=42
#     )

#     # Perform cross-validation and return the mean accuracy
#     score = cross_val_score(rf, X_train, y_train, cv=5, scoring='accuracy').mean()
#     return score

# # Create and optimize the study
# study = optuna.create_study(direction='maximize')
# study.optimize(objective, n_trials=50)
# print(study.best_params)
```

Building an ANN

In [76]:
```
import tensorflow as tf
from tensorflow.keras.regularizers import l2
# Building the Network

model = tf.keras.models.Sequential(
    [
        tf.keras.Input(shape=(X_train.shape[1],)),
        tf.keras.layers.Dense(units=256, activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dropout(0.3),
        tf.keras.layers.Dense(units=256, activation='relu', kernel_regularizer=l2(0.001)),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(units=128, activation='relu'),
        tf.keras.layers.Dense(units=1, activation='sigmoid')
    ]
)
```

In [77]:
```
def plot_loss_acc(history):
    '''Plots the training and validation loss and accuracy from a history object'''
    acc = history.history['accuracy']
    loss = history.history['loss']
    val_acc = history.history['val_accuracy']
    val_loss = history.history['val_loss']

    epochs = range(len(acc))

    fig, ax = plt.subplots(1,2, figsize=(12, 6))
    ax[0].plot(epochs, acc, 'b', label='Training accuracy')
    ax[0].plot(epochs, val_acc, 'r', label='Validation accuracy')
    ax[0].set_title('Training accuracy')
    ax[0].set_xlabel('epochs')
    ax[0].set_ylabel('accuracy')
    ax[0].legend()

    ax[1].plot(epochs, loss, 'b', label='Training Loss')
    ax[1].plot(epochs, val_loss, 'r', label='Validation Loss')
    ax[1].set_title('Training loss')
    ax[1].set_xlabel('epochs')
    ax[1].set_ylabel('loss')
    ax[1].legend()

    plt.show()
```

In [78]:
```
class EarlyStoppingCallback(tf.keras.callbacks.Callback):

    # Define the correct function signature for on_epoch_end method
    def on_epoch_end(self, epoch, logs={}):

        # Check if the accuracy is greater or equal to 0.98
        if (logs.get("accuracy") >= 0.94):

            # Stop training once the above condition is met
            self.model.stop_training = True

            print("\nReached 94% accuracy so cancelling training!")
```

In [79]:
```
def plot_learning_rate(history):
    """
    Plot learning rate vs loss.
    """
    # Define the learning rate array
    lrs = 1e-8 * (10 ** (np.arange(len(history.history["loss"])) / 20))

    # Set the figure size
    plt.figure(figsize=(10, 6))

    # Set the grid
    plt.grid(True)

    # Plot the loss in log scale
```

```
    plt.semilogx(lrs, history.history["loss"])

    # Increase the tickmarks size
    plt.tick_params('both', length=10, width=1, which='both')

    # Set the plot boundaries
    plt.axis([1e-8, 8e-4, 0, 50])
    plt.ylim(0, 1.0)  # This would zoom the y-axis between 0 and 1.0


    # Draw the graph on screen
    plt.xlabel('Learning Rate')
    plt.ylabel('Loss')
    plt.title('Learning Rate vs Loss')
    plt.show()
```

In [80]:

```
def tuning_learn_rate(model, X_train, y_train, optimizer, loss, batch_size=64, epochs=100):
    """
    Tunes the learning rate using an exponential increase.

    Args:
        model (tf.keras.Model): The Keras model.
        X_train (np.array): Training features.
        y_train (np.array): Training labels.
        optimizer (tf.keras.optimizers): Optimizer to use.
        loss (str or tf.keras.losses.Loss): Loss function for the model.
        epochs (int): Number of epochs to tune learning rate.
        batch_size (int): The batch size for training.

    Returns:
        history (tf.keras.callbacks.History): Training history object.
    """
    # Convert the data into a TensorFlow Dataset
    train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train))
    train_dataset = train_dataset.batch(batch_size)

    # Define the learning rate scheduler (exponential increase)
    lr_scheduler = tf.keras.callbacks.LearningRateScheduler(
        lambda epoch: 1e-8 * 10**(epoch / 20)  # Exponential growth
    )

    # Compile the model with the optimizer and loss function
    model.compile(
        optimizer=optimizer,
        loss=loss
    )

    # Fit the model with the learning rate scheduler
    history = model.fit(train_dataset, epochs=epochs, callbacks=[lr_scheduler])
    return history

# Example usage
tuned_history = tuning_learn_rate(
    model, X_train, y_train, optimizer=tf.keras.optimizers.Adam(), loss='binary_crossentropy'
)
```

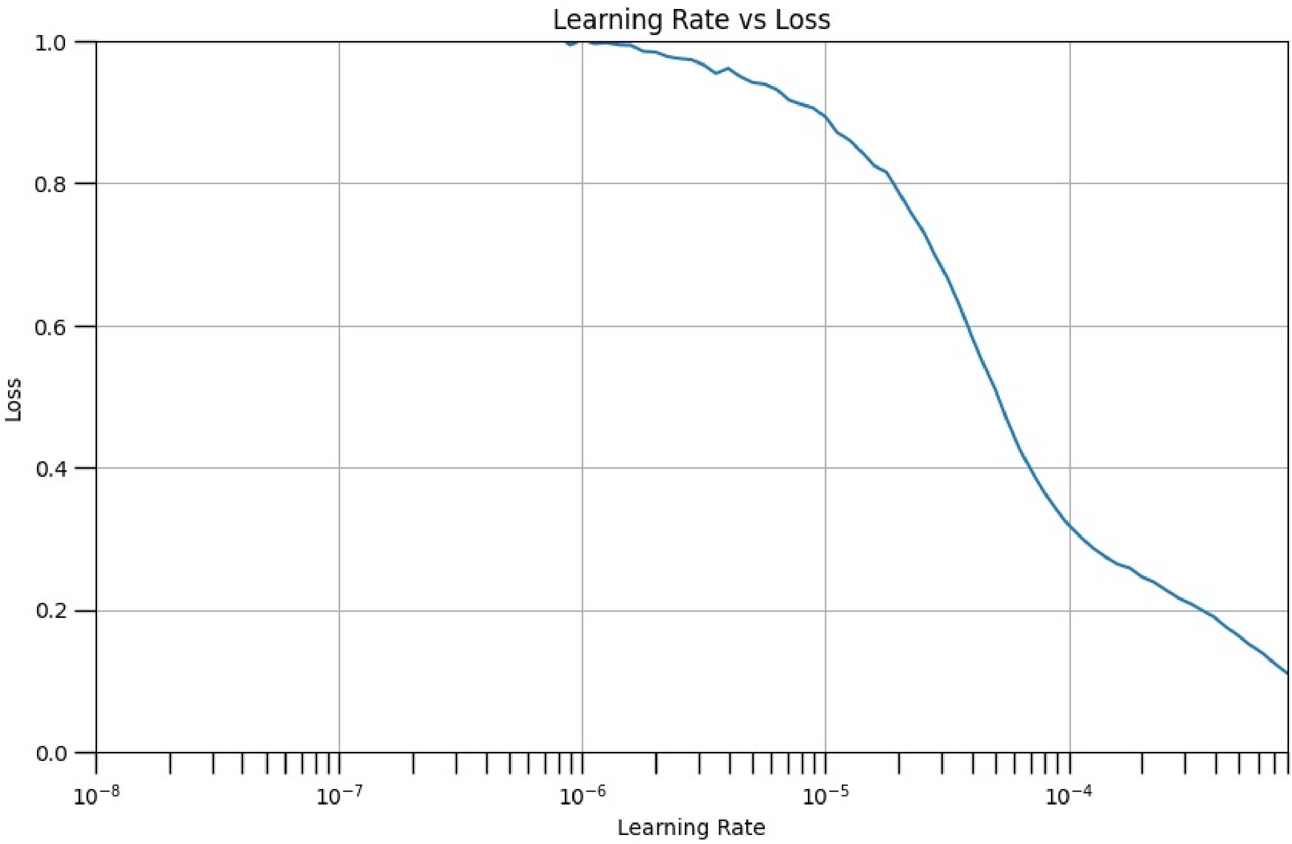
```
Epoch 1/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 6s 13ms/step - loss: 1.0233 - learning_rate: 1.0000e-08
Epoch 2/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 1.0207 - learning_rate: 1.1220e-08
Epoch 3/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0322 - learning_rate: 1.2589e-08
Epoch 4/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0249 - learning_rate: 1.4125e-08
Epoch 5/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0232 - learning_rate: 1.5849e-08
Epoch 6/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0188 - learning_rate: 1.7783e-08
Epoch 7/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0324 - learning_rate: 1.9953e-08
Epoch 8/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0155 - learning_rate: 2.2387e-08
Epoch 9/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0331 - learning_rate: 2.5119e-08
Epoch 10/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0210 - learning_rate: 2.8184e-08
Epoch 11/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0219 - learning_rate: 3.1623e-08
Epoch 12/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - loss: 1.0172 - learning_rate: 3.5481e-08
Epoch 13/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 1.0205 - learning_rate: 3.9811e-08
Epoch 14/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 1.0282 - learning_rate: 4.4668e-08
Epoch 15/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 1.0297 - learning_rate: 5.0119e-08
Epoch 16/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 1.0256 - learning_rate: 5.6234e-08
```

```
Epoch 17/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0223 - learning_rate: 6.3096e-08
Epoch 18/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 1.0132 - learning_rate: 7.0795e-08
Epoch 19/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0321 - learning_rate: 7.9433e-08
Epoch 20/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0366 - learning_rate: 8.9125e-08
Epoch 21/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0214 - learning_rate: 1.0000e-07
Epoch 22/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0249 - learning_rate: 1.1220e-07
Epoch 23/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0139 - learning_rate: 1.2589e-07
Epoch 24/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0235 - learning_rate: 1.4125e-07
Epoch 25/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0243 - learning_rate: 1.5849e-07
Epoch 26/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0291 - learning_rate: 1.7783e-07
Epoch 27/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0254 - learning_rate: 1.9953e-07
Epoch 28/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0145 - learning_rate: 2.2387e-07
Epoch 29/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0148 - learning_rate: 2.5119e-07
Epoch 30/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 1.0196 - learning_rate: 2.8184e-07
Epoch 31/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0243 - learning_rate: 3.1623e-07
Epoch 32/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0250 - learning_rate: 3.5481e-07
Epoch 33/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0286 - learning_rate: 3.9811e-07
Epoch 34/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0345 - learning_rate: 4.4668e-07
Epoch 35/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0233 - learning_rate: 5.0119e-07
Epoch 36/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0232 - learning_rate: 5.6234e-07
Epoch 37/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0181 - learning_rate: 6.3096e-07
Epoch 38/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0299 - learning_rate: 7.0795e-07
Epoch 39/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0230 - learning_rate: 7.9433e-07
Epoch 40/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0220 - learning_rate: 8.9125e-07
Epoch 41/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0297 - learning_rate: 1.0000e-06
Epoch 42/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0267 - learning_rate: 1.1220e-06
Epoch 43/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0297 - learning_rate: 1.2589e-06
Epoch 44/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0242 - learning_rate: 1.4125e-06
Epoch 45/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0324 - learning_rate: 1.5849e-06
Epoch 46/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0323 - learning_rate: 1.7783e-06
Epoch 47/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.0356 - learning_rate: 1.9953e-06
Epoch 48/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0256 - learning_rate: 2.2387e-06
Epoch 49/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0206 - learning_rate: 2.5119e-06
Epoch 50/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0333 - learning_rate: 2.8184e-06
Epoch 51/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0158 - learning_rate: 3.1623e-06
Epoch 52/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.0163 - learning_rate: 3.5481e-06
Epoch 53/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 1.0304 - learning_rate: 3.9811e-06
Epoch 54/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0158 - learning_rate: 4.4668e-06
Epoch 55/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 1.0039 - learning_rate: 5.0119e-06
Epoch 56/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 1.0127 - learning_rate: 5.6234e-06
Epoch 57/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.9992 - learning_rate: 6.3096e-06
Epoch 58/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.9882 - learning_rate: 7.0795e-06
Epoch 59/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.9902 - learning_rate: 7.9433e-06
Epoch 60/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.9839 - learning_rate: 8.9125e-06
Epoch 61/100
```

```
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.9709 - learning_rate: 1.0000e-05
Epoch 62/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.9464 - learning_rate: 1.1220e-05
Epoch 63/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.9408 - learning_rate: 1.2589e-05
Epoch 64/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.9237 - learning_rate: 1.4125e-05
Epoch 65/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.9007 - learning_rate: 1.5849e-05
Epoch 66/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.9043 - learning_rate: 1.7783e-05
Epoch 67/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.8718 - learning_rate: 1.9953e-05
Epoch 68/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.8349 - learning_rate: 2.2387e-05
Epoch 69/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.8053 - learning_rate: 2.5119e-05
Epoch 70/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.7787 - learning_rate: 2.8184e-05
Epoch 71/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.7432 - learning_rate: 3.1623e-05
Epoch 72/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.7056 - learning_rate: 3.5481e-05
Epoch 73/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.6511 - learning_rate: 3.9811e-05
Epoch 74/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.6035 - learning_rate: 4.4668e-05
Epoch 75/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.5657 - learning_rate: 5.0119e-05
Epoch 76/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.5150 - learning_rate: 5.6234e-05
Epoch 77/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.4717 - learning_rate: 6.3096e-05
Epoch 78/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4254 - learning_rate: 7.0795e-05
Epoch 79/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4001 - learning_rate: 7.9433e-05
Epoch 80/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.3654 - learning_rate: 8.9125e-05
Epoch 81/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.3415 - learning_rate: 1.0000e-04
Epoch 82/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.3244 - learning_rate: 1.1220e-04
Epoch 83/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.3043 - learning_rate: 1.2589e-04
Epoch 84/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.2898 - learning_rate: 1.4125e-04
Epoch 85/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.2785 - learning_rate: 1.5849e-04
Epoch 86/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.2744 - learning_rate: 1.7783e-04
Epoch 87/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.2557 - learning_rate: 1.9953e-04
Epoch 88/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.2479 - learning_rate: 2.2387e-04
Epoch 89/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.2384 - learning_rate: 2.5119e-04
Epoch 90/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.2238 - learning_rate: 2.8184e-04
Epoch 91/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.2172 - learning_rate: 3.1623e-04
Epoch 92/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.2081 - learning_rate: 3.5481e-04
Epoch 93/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.1982 - learning_rate: 3.9811e-04
Epoch 94/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.1848 - learning_rate: 4.4668e-04
Epoch 95/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.1725 - learning_rate: 5.0119e-04
Epoch 96/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.1585 - learning_rate: 5.6234e-04
Epoch 97/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.1497 - learning_rate: 6.3096e-04
Epoch 98/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.1313 - learning_rate: 7.0795e-04
Epoch 99/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.1191 - learning_rate: 7.9433e-04
Epoch 100/100
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.1082 - learning_rate: 8.9125e-04
```

In [81]:

```
plot_learning_rate(tuned_history)
```



In [82]:
```
# Compiling the Network

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=2e-4), loss='binary_crossentropy', metrics=['acc
# learning_rate=4e-4
```

In [83]:
```
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_8 (Dense)	(None, 256)	7,936
batch_normalization_2 (BatchNormalization)	(None, 256)	1,024
dropout_4 (Dropout)	(None, 256)	0
dense_9 (Dense)	(None, 256)	65,792
dropout_5 (Dropout)	(None, 256)	0
dense_10 (Dense)	(None, 128)	32,896
dense_11 (Dense)	(None, 1)	129

Total params: 107,777 (421.00 KB)

Trainable params: 107,265 (419.00 KB)

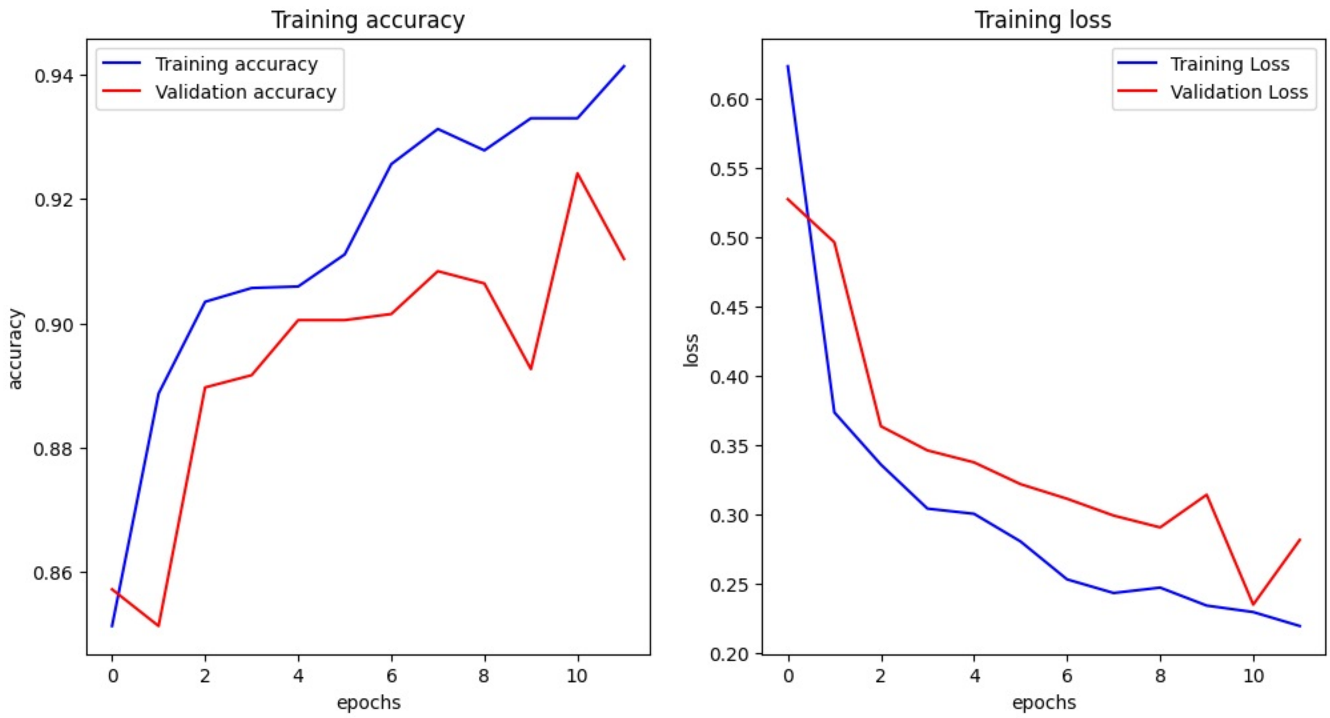
Non-trainable params: 512 (2.00 KB)

In [84]:
```
# Training the data on the network

history = model.fit(x=X_train, y=y_train, validation_split=0.2, batch_size=32, epochs=50, callbacks=[EarlyStopp
```

```
Epoch 1/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.7858 - loss: 0.9670 - val_accuracy: 0.8571 - val_loss: 0
.5272
Epoch 2/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8886 - loss: 0.4006 - val_accuracy: 0.8512 - val_loss: 0
.4961
Epoch 3/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8983 - loss: 0.3592 - val_accuracy: 0.8897 - val_loss: 0
.3633
Epoch 4/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9018 - loss: 0.3097 - val_accuracy: 0.8916 - val_loss: 0
.3459
Epoch 5/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9086 - loss: 0.2991 - val_accuracy: 0.9005 - val_loss: 0
.3372
Epoch 6/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9114 - loss: 0.2835 - val_accuracy: 0.9005 - val_loss: 0
.3215
Epoch 7/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9239 - loss: 0.2501 - val_accuracy: 0.9015 - val_loss: 0
.3110
Epoch 8/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9322 - loss: 0.2507 - val_accuracy: 0.9084 - val_loss: 0
.2988
Epoch 9/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9279 - loss: 0.2456 - val_accuracy: 0.9064 - val_loss: 0
.2903
Epoch 10/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9327 - loss: 0.2319 - val_accuracy: 0.8926 - val_loss: 0
.3139
Epoch 11/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9371 - loss: 0.2196 - val_accuracy: 0.9241 - val_loss: 0
.2346
Epoch 12/50
124/127 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9379 - loss: 0.2258
Reached 94% accuracy so cancelling training!
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9380 - loss: 0.2256 - val_accuracy: 0.9103 - val_loss: 0
.2813
```

In [85]:

```python
plot_loss_acc(history)
```



In [86]:

```python
y_pred = model.predict(X_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(-1, 1), y_test.reshape(-1, 1)), 1))
```

```
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
[[0 0]
 [0 0]
 [1 1]
 ...
 [0 0]
 [0 0]
 [0 0]]
```

In [87]:

```python
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
print(accuracy_score(y_test, y_pred))
```

```
[[735 298]
 [ 96 278]]
0.7199715707178393
```

In [88]:

```python
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.71      0.79      1033
           1       0.48      0.74      0.59       374

    accuracy                           0.72      1407
   macro avg       0.68      0.73      0.69      1407
weighted avg       0.78      0.72      0.73      1407
```