Customer Churn Prediction using ML Classification Algorithms

by: Vineet Srivastava

In [102]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [103]:

```
df = pd.read_csv('/content/data_regression.csv')
df.head(10)
```

Out[103]:

	year	customer_id	phone_no	gender	age	no_of_days_subscribed	multi_screen	mail_subs
0	2015	100198	409-8743	Female	36	62	no	
1	2015	100643	340-5930	Female	39	149	no	
2	2015	100756	372-3750	Female	65	126	no	
3	2015	101595	331-4902	Female	24	131	no	
4	2015	101653	351-8398	Female	40	191	no	
5	2015	101953	329-6603	NaN	31	65	no	
6	2015	103051	416-1845	NaN	54	59	no	
7	2015	103225	348-7193	Female	40	50	no	
8	2015	103408	413-4039	Male	61	205	no	
9	2015	103676	338-5207	Male	31	63	no	

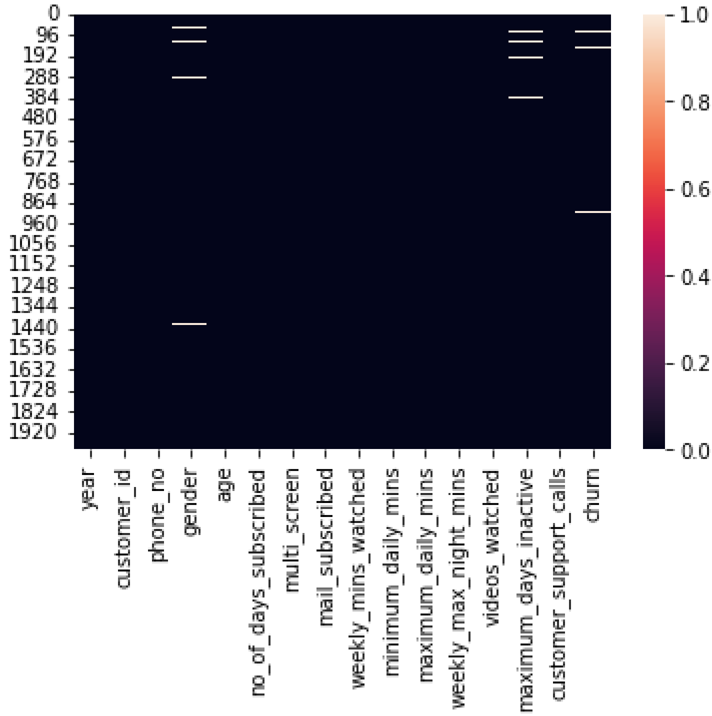
In [104]:

```
def data_inspection(df):
    print('### type of variables we are working with')
    print(df.dtypes)

    print('### total samples with missing values')
    print(df.isnull().any(axis=1).sum())

    print('### total missing values per feature/variable')
    print(df.isnull().sum())

    print('### heatmap of missing values')
    print(sns.heatmap(df.isnull()))

    print('### data shape')
    print(df.shape)
```

In [105]:

```
data_inspection(df)
```

```
### type of variables we are working with
year                        int64
customer_id                 int64
phone_no                   object
gender                     object
age                         int64
no_of_days_subscribed       int64
multi_screen               object
mail_subscribed            object
weekly_mins_watched       float64
minimum_daily_mins        float64
maximum_daily_mins        float64
weekly_max_night_mins       int64
videos_watched              int64
maximum_days_inactive     float64
customer_support_calls      int64
churn                     float64
dtype: object
### total samples with missing values
82
### total missing values per feature/variable
year                       0
customer_id                0
phone_no                   0
gender                    24
age                        0
no_of_days_subscribed      0
multi_screen               0
mail_subscribed            0
weekly_mins_watched        0
minimum_daily_mins         0
maximum_daily_mins         0
weekly_max_night_mins      0
videos_watched             0
maximum_days_inactive     28
customer_support_calls     0
churn                     35
dtype: int64
### heatmap of missing values
AxesSubplot(0.125,0.125;0.62x0.755)
### data shape
(2000, 16)
```



In [106]:

```
def percent_missing(df):
    percent_nan = 100 *(df.isnull().sum()/(len(df)))
    percent_nan = percent_nan[percent_nan >0]
    return percent_nan
```

In [107]:

```
percent_nan = percent_missing(df)
percent_nan
```

Out[107]:

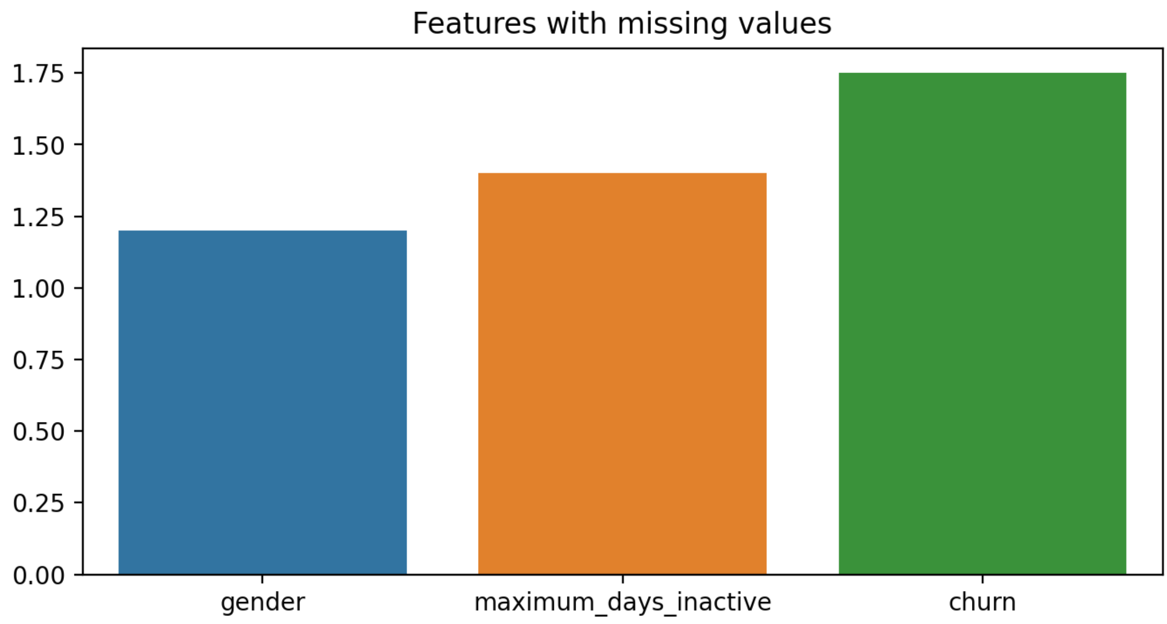
```
gender                   1.20
maximum_days_inactive    1.40
churn                    1.75
dtype: float64
```

In [108]:

```
plt.figure(figsize=(8,4),dpi=200)
sns.barplot(y=percent_nan,x=percent_nan.index)
plt.title('Features with missing values')
```

Out[108]:

```
Text(0.5, 1.0, 'Features with missing values')
```



There isn't much missing values so we can drop them

In [109]:

```
df = df.dropna(subset=['churn'])
```

In [110]:

```
percent_nan = percent_missing(df)
percent_nan
```

Out[110]:

```
gender                   1.221374
maximum_days_inactive    1.323155
dtype: float64
```

In [111]:

```
df['gender'] = df['gender'].fillna('Male')
```

```
<ipython-input-111-b0370f08b1ae>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  df['gender'] = df['gender'].fillna('Male')
```

In [112]:

```
percent_nan = percent_missing(df)
percent_nan
```

Out[112]:

```
maximum_days_inactive    1.323155
dtype: float64
```

In [113]:

```
df['maximum_days_inactive'] = df['maximum_days_inactive'].fillna(df['maximum_days_inactive'
```

```
<ipython-input-113-12b06ce651d8>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  df['maximum_days_inactive'] = df['maximum_days_inactive'].fillna(df['maxim
um_days_inactive'].median())
```

In [114]:

```
percent_nan = percent_missing(df)
percent_nan
```

Out[114]:

```
Series([], dtype: float64)
```

In [115]:

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

Out[115]:

```
0.0    1703
1.0     262
Name: churn, dtype: int64
```

In [116]:

```
100*(262/(262+1703))
```

Out[116]:

```
13.333333333333334
```

In [117]:

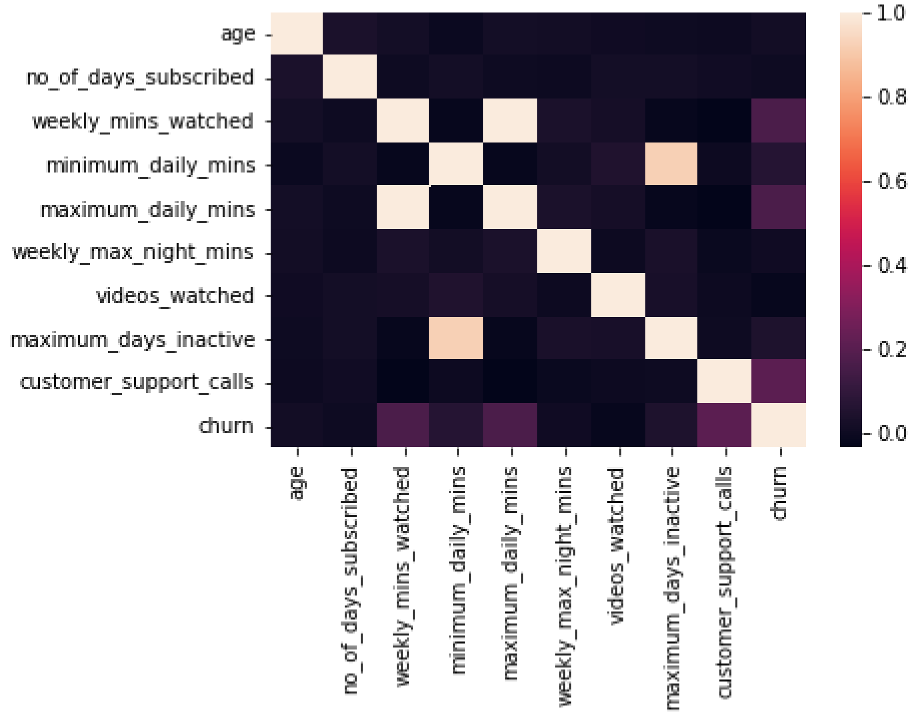
```
df = df.drop(['year','customer_id','phone_no'],axis=1)
```

In [118]:

```
sns.heatmap(df.corr())
```

Out[118]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1e74087f0>
```



In [119]:

```
df.corr()
```

Out[119]:

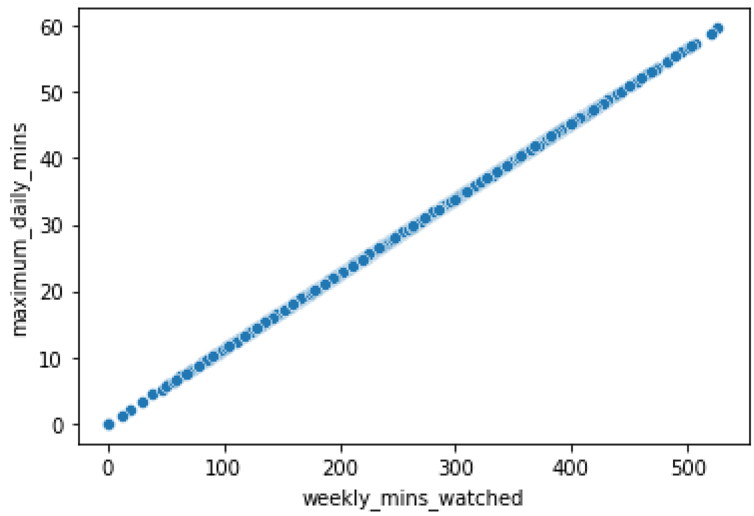
	age	no_of_days_subscribed	weekly_mins_watched	minimum_dail
age	1.000000	0.036144	0.017633	-0
no_of_days_subscribed	0.036144	1.000000	-0.000302	0
weekly_mins_watched	0.017633	-0.000302	1.000000	-0
minimum_daily_mins	-0.006965	0.015019	-0.021271	1
maximum_daily_mins	0.017644	-0.000307	1.000000	-0
weekly_max_night_mins	0.011828	-0.002595	0.037145	0
videos_watched	0.004724	0.018411	0.022442	0
maximum_days_inactive	-0.000168	0.018618	-0.017468	0
customer_support_calls	-0.004859	0.010115	-0.037698	-0
churn	0.011631	0.002528	0.165871	0

In [120]:

```
sns.scatterplot(x=df['weekly_mins_watched'],y=df['maximum_daily_mins']) # we can drop one o
```

Out[120]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1e7aabb80>
```



In [121]:

```
df = df.drop(['weekly_mins_watched'],axis=1)
```

In [122]:

```
df.head()
```

Out[122]:

	gender	age	no_of_days_subscribed	multi_screen	mail_subscribed	minimum_daily_mins	m
0	Female	36	62	no	no	12.2	
1	Female	39	149	no	no	7.7	
2	Female	65	126	no	no	11.9	
3	Female	24	131	no	yes	9.5	
4	Female	40	191	no	no	10.9	

Imbalanced dataset, need to balance it

Encoding Categorical variables

In [123]:

```
lst_string = list(df.select_dtypes(include='object'))
lst_string
```

Out[123]:

```
['gender', 'multi_screen', 'mail_subscribed']
```

In [124]:

```
df.head()
```

Out[124]:

	gender	age	no_of_days_subscribed	multi_screen	mail_subscribed	minimum_daily_mins	m
0	Female	36	62	no	no	12.2	
1	Female	39	149	no	no	7.7	
2	Female	65	126	no	no	11.9	
3	Female	24	131	no	yes	9.5	
4	Female	40	191	no	no	10.9	

In [125]:

```
def label_encoding(x):
    if x == 'Female':
        return 1
    elif x == 'Male':
        return 0
    elif x == 'no':
        return 0
    elif x == 'yes':
        return 1
    else:
        return -1
```

In [126]:

```
df['gender'] = df['gender'].apply(lambda x: label_encoding(x))
```

In [127]:

```
df['multi_screen'] = df['multi_screen'].apply(lambda x: label_encoding(x))
```

In [128]:

```
df['mail_subscribed'] = df['mail_subscribed'].apply(lambda x: label_encoding(x))
```

In [129]:

```
df.head(10)
```

Out[129]:

	gender	age	no_of_days_subscribed	multi_screen	mail_subscribed	minimum_daily_mins	n
0	1	36	62	0	0	12.2	
1	1	39	149	0	0	7.7	
2	1	65	126	0	0	11.9	
3	1	24	131	0	1	9.5	
4	1	40	191	0	0	10.9	
5	0	31	65	0	0	12.7	
6	0	54	59	0	0	10.2	
7	1	40	50	0	0	5.6	
8	0	61	205	0	1	7.8	
9	0	31	63	0	0	12.3	

In [130]:

```
sns.pairplot(df,hue='churn')
```

Out[130]:

```
<seaborn.axisgrid.PairGrid at 0x7fa1e7b867c0>
```

In [131]:

```
df.dtypes
```

Out[131]:

```
gender                      int64
age                         int64
no_of_days_subscribed       int64
multi_screen                int64
mail_subscribed             int64
minimum_daily_mins        float64
maximum_daily_mins        float64
weekly_max_night_mins       int64
videos_watched              int64
maximum_days_inactive     float64
customer_support_calls      int64
churn                     float64
dtype: object
```

Building Logistic Regression Model and handling class imbalance

In [132]:

```
import statsmodels.api as sm

X = df.drop('churn',axis=1)
y=df['churn'] # the target variable
logit_model=sm.Logit(y,X)
result=logit_model.fit() # fit the model
print(result.summary2()) # check for summary
```

```
Optimization terminated successfully.
         Current function value: 0.340411
         Iterations 7
                            Results: Logit
======================================================================
Model:                 Logit            Pseudo R-squared:  0.133
Dependent Variable:    churn            AIC:               1359.8148
Date:                  2022-12-04 09:29 BIC:               1421.2305
No. Observations:      1965             Log-Likelihood:    -668.91
Df Model:              10               LL-Null:           -771.61
Df Residuals:          1954             LLR p-value:       1.2077e-38
Converged:             1.0000           Scale:             1.0000
No. Iterations:        7.0000
----------------------------------------------------------------------
                        Coef.  Std.Err.    z    P>|z|   [0.025  0.975]
----------------------------------------------------------------------
gender                 -0.0200   0.1408 -0.1417 0.8873 -0.2959  0.2560
age                    -0.0216   0.0066 -3.2681 0.0011 -0.0346 -0.0087
no_of_days_subscribed  -0.0050   0.0018 -2.8789 0.0040 -0.0085 -0.0016
multi_screen            1.9152   0.1815 10.5491 0.0000  1.5593  2.2710
mail_subscribed        -0.8119   0.1785 -4.5495 0.0000 -1.1616 -0.4621
minimum_daily_mins      0.1735   0.0667  2.5990 0.0094  0.0426  0.3043
maximum_daily_mins      0.0367   0.0073  5.0425 0.0000  0.0224  0.0510
weekly_max_night_mins  -0.0167   0.0031 -5.3690 0.0000 -0.0228 -0.0106
videos_watched         -0.0971   0.0311 -3.1217 0.0018 -0.1581 -0.0362
maximum_days_inactive  -0.6846   0.2285 -2.9954 0.0027 -1.1325 -0.2366
customer_support_calls  0.4200   0.0493  8.5260 0.0000  0.3235  0.5166
======================================================================
```

some key observations here

1. r2 square is 13%, so not a good model ideally

2. gender is not statistically significant since P-value is greater than standard value of alpha(0.05)

Lets check the model from sklearn library

In [133]:

```
from sklearn.model_selection import train_test_split
X = df.drop('churn',axis=1)
y = df['churn']
```

In [134]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
```

In [135]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score,classification_report

logreg = LogisticRegression(random_state = 13)
logreg.fit(X_train, y_train) # fit the model

y_pred = logreg.predict(X_test) # make predictions on th test data
logit_roc_auc = roc_auc_score(y_test,y_pred)
print(classification_report(y_test, y_pred)) # check for classification report
print("The area under the curve is: %0.2f"%logit_roc_auc)  # check for  AUC
```

```
              precision    recall  f1-score   support

         0.0       0.88      0.99      0.93       509
         1.0       0.62      0.12      0.21        81

    accuracy                           0.87       590
   macro avg       0.75      0.56      0.57       590
weighted avg       0.84      0.87      0.83       590

The area under the curve is: 0.56

/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_logistic.py:81
4: 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 (https://scik
it-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-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

We can see from above report that even though accuracy is 87%, recall and precision is bad. Also the AUC is not that great too.

This is because our dataset is highly imbalanced as we discussed earlier, so first need to balance it and then build the model

In [136]:

```
logreg = LogisticRegression(random_state = 13,class_weight = 'balanced')
```

In [137]:

```
logreg.fit(X_train,y_train)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_logistic.py:81
4: 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 (https://scik
it-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-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[137]:

```
LogisticRegression(class_weight='balanced', random_state=13)
```

In [138]:

```
y_pred = logreg.predict(X_test) # predict on test data
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test)) # ROC AUC score
print(classification_report(y_test, y_pred))
print("The area under the curve is: %0.2f"%logit_roc_auc) # AUC curve
```

```
              precision    recall  f1-score   support

         0.0       0.95      0.72      0.82       509
         1.0       0.30      0.75      0.43        81

    accuracy                           0.73       590
   macro avg       0.62      0.74      0.62       590
weighted avg       0.86      0.73      0.77       590

The area under the curve is: 0.74
```

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Building Decision Tree model

In [139]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from imblearn.over_sampling import SMOTE
```

using smote to balance the dataset

In [140]:

```
sm = SMOTE()
X_train, y_train = sm.fit_resample(X_train, y_train)
```

In [141]:

```
dectree = DecisionTreeClassifier(random_state = 13,criterion = 'entropy')
dectree.fit(X_train, y_train)
```

Out[141]:

```
DecisionTreeClassifier(criterion='entropy', random_state=13)
```

In [142]:

```
y_pred = dectree.predict(X_test)
dectree_roc_auc = roc_auc_score(y_test, dectree.predict(X_test))
print(classification_report(y_test, y_pred))
print("The area under the curve is: %0.2f"%dectree_roc_auc)
```

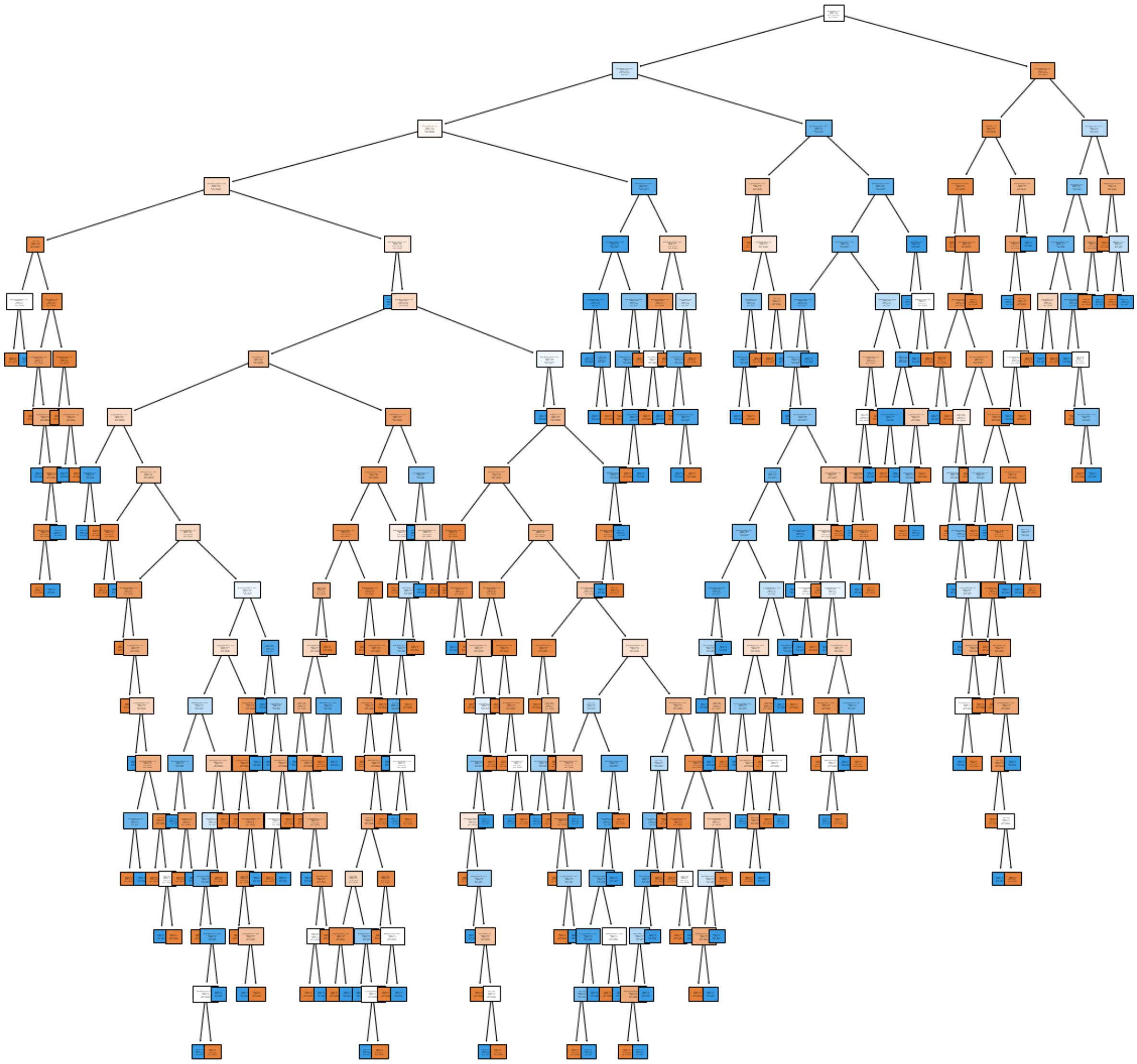
```
              precision    recall  f1-score   support

         0.0       0.92      0.84      0.88       509
         1.0       0.35      0.54      0.43        81

    accuracy                           0.80       590
   macro avg       0.63      0.69      0.65       590
weighted avg       0.84      0.80      0.82       590

The area under the curve is: 0.69
```

In [143]:

```
def plot_model(model,class_names,max_depth=None,figsize=(20,20),fontsize=1):
    plt.figure(figsize=figsize)
    tree.plot_tree(dectree
                   ,feature_names = dectree.feature_names_in_
                   ,fontsize=fontsize
                   ,max_depth = max_depth
                   ,class_names=class_names
                   ,filled = True);
```

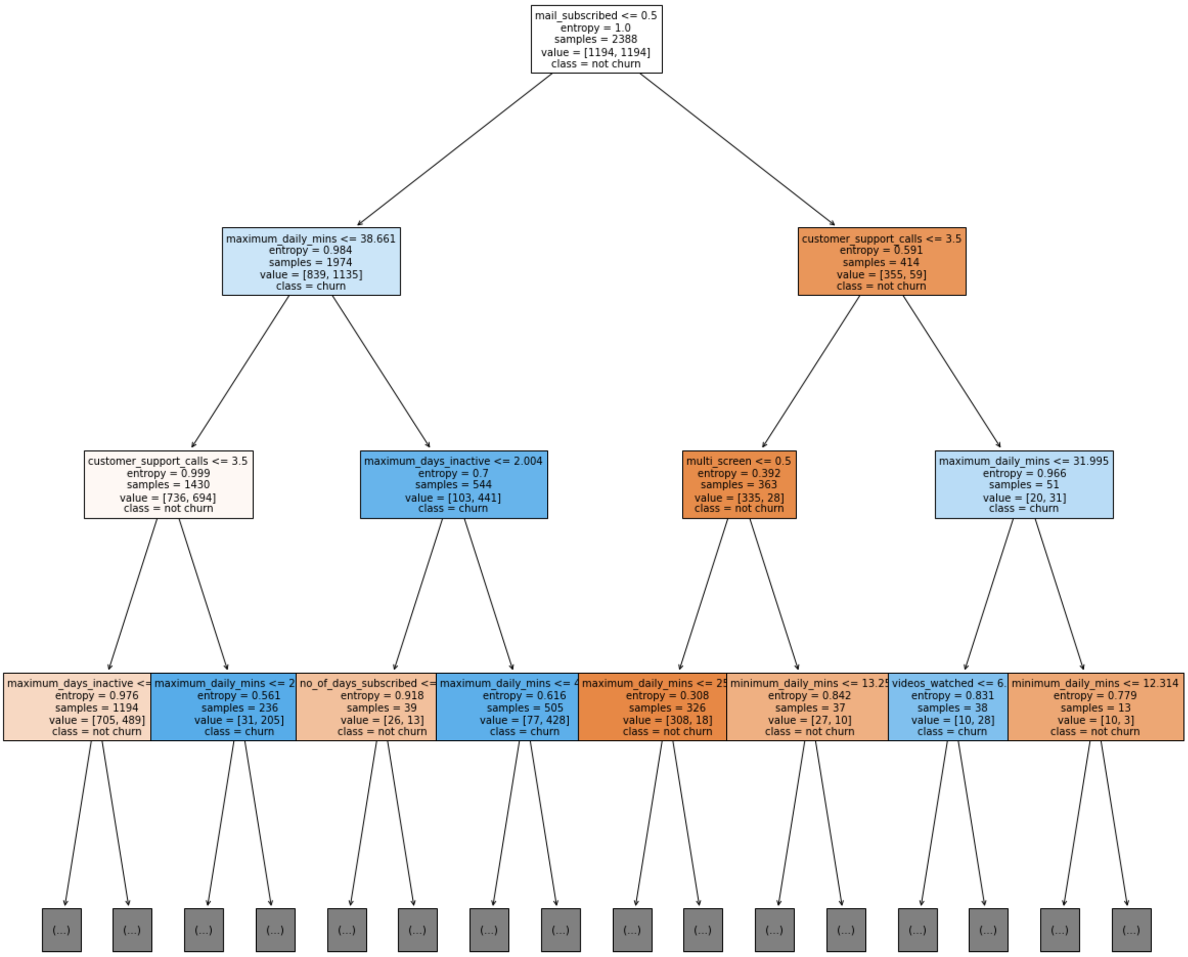
In [144]:

```
plot_model(dectree,['not churn','churn'])
```



In [145]:

```
plot_model(dectree,['not churn','churn'],max_depth = 3,figsize=(20,20),fontsize=10)
```

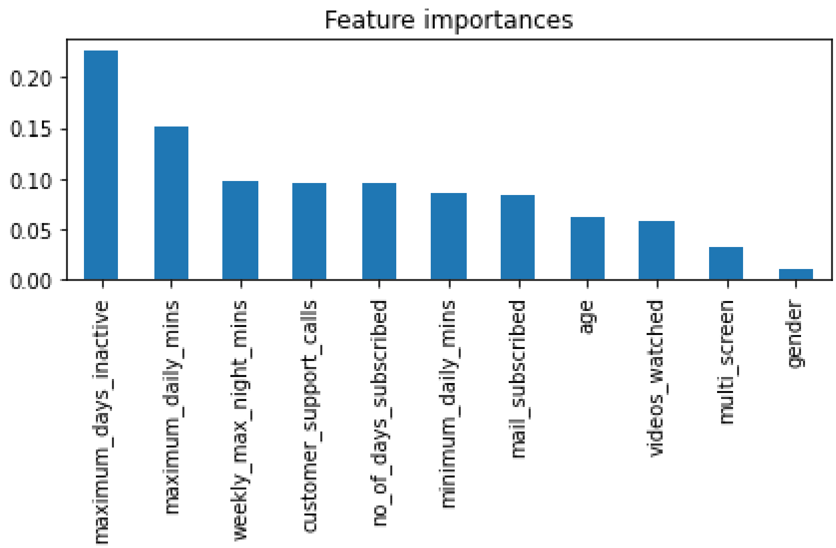


In [146]:

```
def plot_feature_importances(model):
  feature_importances = pd.Series(model.feature_importances_, index=model.feature_names_in_
  feature_importances = feature_importances.sort_values(axis=0, ascending=False)
  fig, ax = plt.subplots()
  feature_importances.plot.bar()
  ax.set_title("Feature importances")
  fig.tight_layout()
```

In [147]:

```
plot_feature_importances(dectree)
```



In [147]:

```

```

Building the model using Ensemble learning- Bagging (Random Forest) and Boosting

Random Forest- Bagging

In [148]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [148]:

```

```

Hypeparameter Tuning

In [149]:

```
n_estimators = [5,20,50,100] # number of trees in the random forest
max_features = ['auto', 'sqrt'] # number of features in consideration at every split
max_depth = [int(x) for x in np.linspace(10, 120, num = 12)] # maximum number of levels all
min_samples_split = [2, 6, 10] # minimum sample number to split a node
min_samples_leaf = [1, 3, 4] # minimum sample number that can be stored in a leaf node
bootstrap = [True, False] # method used to sample data points

random_grid = {'n_estimators': n_estimators,

'max_features': max_features,

'max_depth': max_depth,

'min_samples_split': min_samples_split,

'min_samples_leaf': min_samples_leaf,

'bootstrap': bootstrap}
```

In [150]:

```
randomforest = RandomForestClassifier()
```

In [151]:

```
from sklearn.model_selection import RandomizedSearchCV
rf_random = RandomizedSearchCV(estimator = randomforest,param_distributions = random_grid,
               n_iter = 100, cv = 5, verbose=2, random_state=35, n_jobs = -1)
```

In [152]:

```
rf_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

Out[152]:

```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 6
0,
                                                      70, 80, 90, 100, 110,
                                                      120],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 3, 4],
                                        'min_samples_split': [2, 6, 10],
                                        'n_estimators': [5, 20, 50, 100]},
                   random_state=35, verbose=2)
```

In [153]:

```
print ('Best Parameters: ', rf_random.best_params_, ' \n')
```

```
Best Parameters:  {'n_estimators': 50, 'min_samples_split': 6, 'min_samples_
leaf': 1, 'max_features': 'auto', 'max_depth': 110, 'bootstrap': False}
```

In [154]:

```
randomforest = RandomForestClassifier(n_estimators = 100, min_samples_split= 2, min_samples
                                      max_depth =  120, bootstrap =  True)

randomforest.fit(X_train, y_train)
```

Out[154]:

```
RandomForestClassifier(max_depth=120, max_features='sqrt')
```

In [155]:

```
y_pred = randomforest.predict(X_test)
randomforest_roc_auc = roc_auc_score(y_test, randomforest.predict(X_test))
print(classification_report(y_test, y_pred))
print("The area under the curve is: %0.2f"%randomforest_roc_auc)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.92      0.92       509
         1.0       0.52      0.53      0.52        81

    accuracy                           0.87       590
   macro avg       0.72      0.73      0.72       590
weighted avg       0.87      0.87      0.87       590

The area under the curve is: 0.73
```

In [155]:

In [155]:

AdaBoost- Boosting

In [156]:

```
from sklearn.ensemble import AdaBoostClassifier
```

In [157]:

```
adaboost = AdaBoostClassifier(n_estimators = 100)
adaboost.fit(X_train, y_train)
```

Out[157]:

```
AdaBoostClassifier(n_estimators=100)
```

In [158]:

```
y_pred = adaboost.predict(X_test)
adaboost_roc_auc = roc_auc_score(y_test, adaboost.predict(X_test))
print(classification_report(y_test, y_pred))
print("The area under the curve is: %0.2f"%adaboost_roc_auc)
```

```
              precision    recall  f1-score   support

         0.0       0.91      0.87      0.89       509
         1.0       0.37      0.49      0.42        81

    accuracy                           0.82       590
   macro avg       0.64      0.68      0.66       590
weighted avg       0.84      0.82      0.83       590

The area under the curve is: 0.68
```

In [158]:

```

```

Hyper-parameter Tuning

In [159]:

```
adaboost = AdaBoostClassifier(random_state = 96, base_estimator = RandomForestClassifier(ra
                              n_estimators = 100,learning_rate = 0.01)
```

In [160]:

```
adaboost.fit(X_train, y_train)
```

Out[160]:

```
AdaBoostClassifier(base_estimator=RandomForestClassifier(random_state=101),
                   learning_rate=0.01, n_estimators=100, random_state=96)
```

In [161]:

```
y_pred = adaboost.predict(X_test)
adaboost_roc_auc = roc_auc_score(y_test, adaboost.predict(X_test))
print(classification_report(y_test, y_pred))
print("The area under the curve is: %0.2f"%adaboost_roc_auc)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.93      0.93       509
         1.0       0.57      0.59      0.58        81

    accuracy                           0.88       590
   macro avg       0.75      0.76      0.76       590
weighted avg       0.88      0.88      0.88       590

The area under the curve is: 0.76
```

With hyper-paramter tuning overall accuracy and precision/recall improved

In [161]:

```
```

In [161]:

```
```

Gradient Boosting

In [162]:

```
from sklearn.ensemble import GradientBoostingClassifier
```

In [163]:

```
gradientboost = GradientBoostingClassifier()
gradientboost.fit(X_train, y_train)
```

Out[163]:

```
GradientBoostingClassifier()
```

In [198]:

```
gradientboost_roc_auc = roc_auc_score(y_test, gradientboost.predict(X_test))
print(classification_report(y_test, gradientboost.predict(X_test)))
print("The area under the curve is: %0.2f"%gradientboost_roc_auc)
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.91      0.92       509
         1.0       0.52      0.60      0.56        81

    accuracy                           0.87       590
   macro avg       0.73      0.76      0.74       590
weighted avg       0.88      0.87      0.87       590

The area under the curve is: 0.76
```

In [164]:

```

```

Evaluating all the model and performing Feature Importance

In [184]:

```
# define a fucntion for plotting the ROC curves
def roc_curve_eval(model):
  from sklearn.metrics import roc_auc_score
  from sklearn.metrics import roc_curve
  logreg_roc_auc = roc_auc_score(y_test, model.predict(X_test))
  fpr, tpr, thresholds = roc_curve(y_test, model.predict(X_test))
  #Setting the graph area
  plt.figure()
  plt.xlim([0.0, 1.0])
  plt.ylim([0.0, 1.05])

  #Plotting the worst line possiple
  plt.plot([0, 1], [0, 1],'b--')

  #Plotting the logistic regression we have built
  plt.plot(fpr, tpr, color='darkorange', label='Model (area = %0.2f)' % logreg_roc_auc)

  #Adding labels and etc
  plt.xlabel('False Positive Rate')
  plt.ylabel('True Positive Rate')
  plt.title('ROC Curve')
  plt.legend(loc="lower right")
  plt.savefig('Log_ROC')
  plt.show()
```

In [191]:

```
def accuracy_report(model):
  model_roc_auc = roc_auc_score(y_test, model.predict(X_test))
  print(classification_report(y_test, model.predict(X_test)))
  print("The area under the curve is: %0.2f"%model_roc_auc)
```

In [185]:

```
def plot_feature_importances(model):
  feature_importances = pd.Series(model.feature_importances_, index=model.feature_names_in_
  feature_importances = feature_importances.sort_values(axis=0, ascending=False)
  fig, ax = plt.subplots()
  feature_importances.plot.bar()
  ax.set_title("Feature importances")
  fig.tight_layout()
```

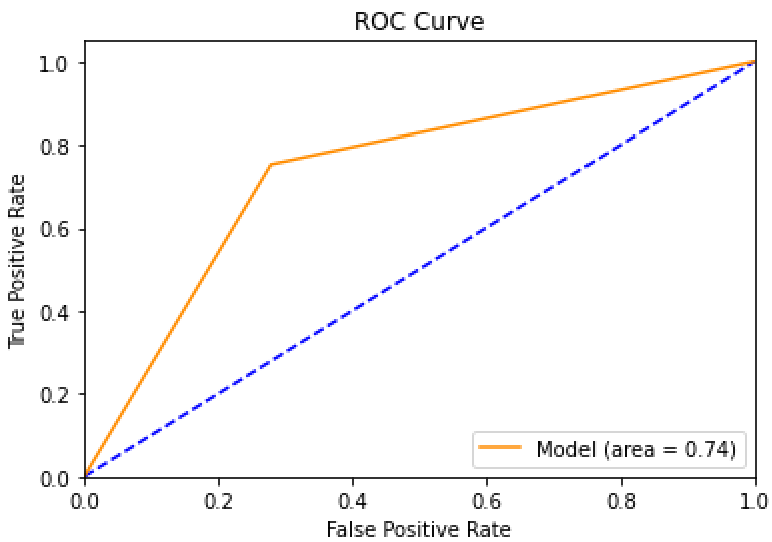
In [ ]:

```
```

In [199]:

```
# log regression
accuracy_report(logreg)
roc_curve_eval(logreg)
```

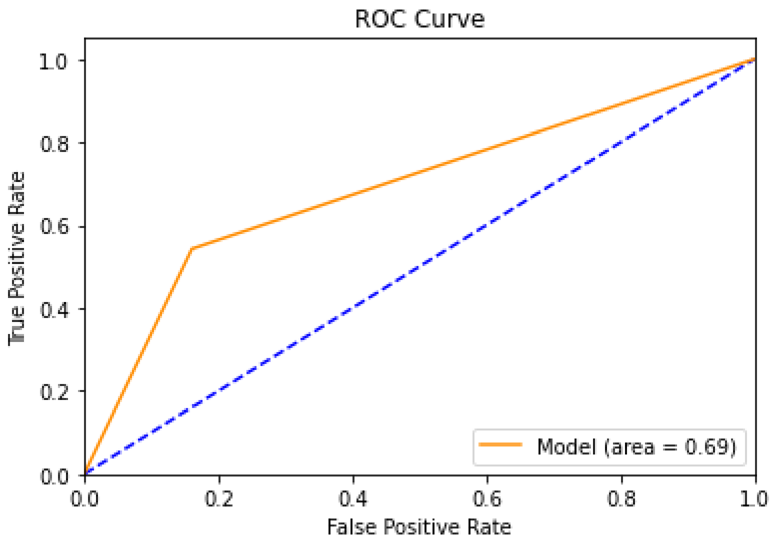
```
              precision    recall  f1-score   support

         0.0       0.95      0.72      0.82       509
         1.0       0.30      0.75      0.43        81

    accuracy                           0.73       590
   macro avg       0.62      0.74      0.62       590
weighted avg       0.86      0.73      0.77       590

The area under the curve is: 0.74
```

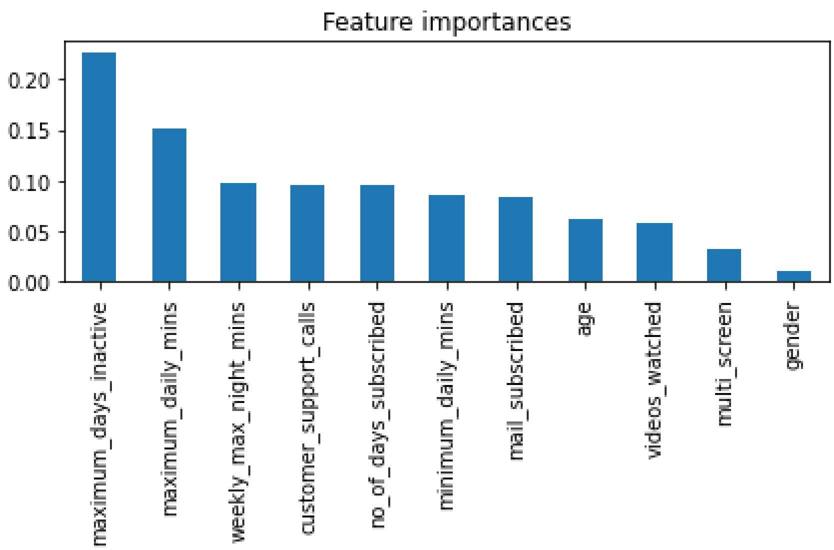


In [193]:

```
# decision tree
accuracy_report(dectree)
roc_curve_eval(dectree)
plot_feature_importances(dectree)
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.84      0.88       509
         1.0       0.35      0.54      0.43        81

    accuracy                           0.80       590
   macro avg       0.63      0.69      0.65       590
weighted avg       0.84      0.80      0.82       590

The area under the curve is: 0.69
```

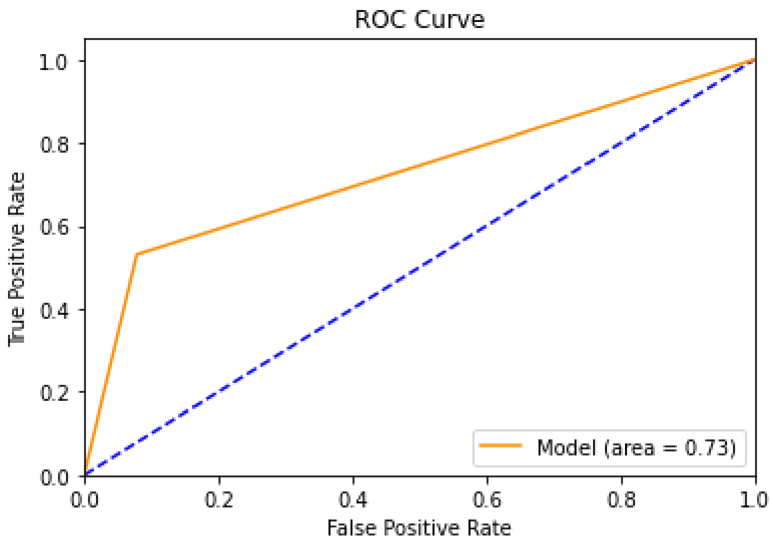


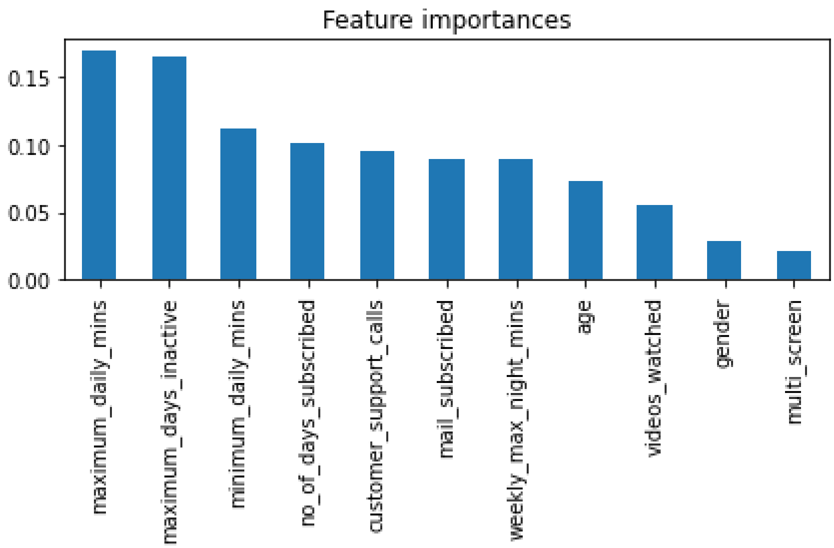


In [195]:

```
# Random Forest
accuracy_report(randomforest)
roc_curve_eval(randomforest)
plot_feature_importances(randomforest)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.92      0.92       509
         1.0       0.52      0.53      0.52        81

    accuracy                           0.87       590
   macro avg       0.72      0.73      0.72       590
weighted avg       0.87      0.87      0.87       590

The area under the curve is: 0.73
```

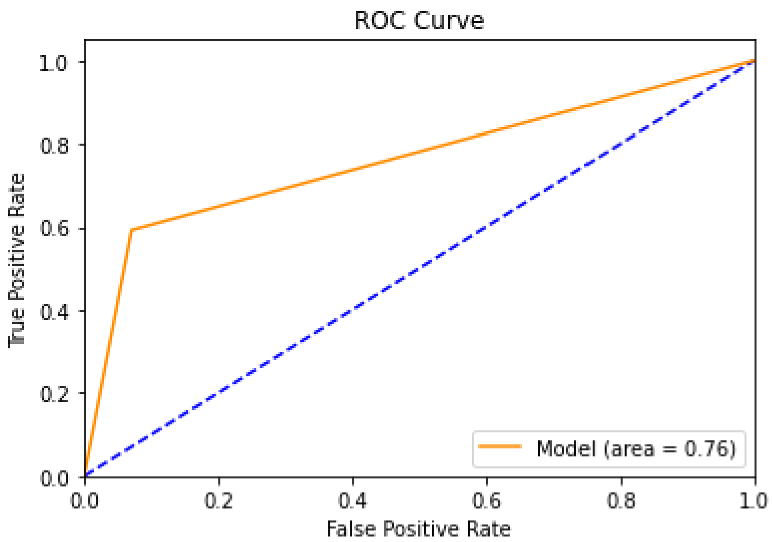


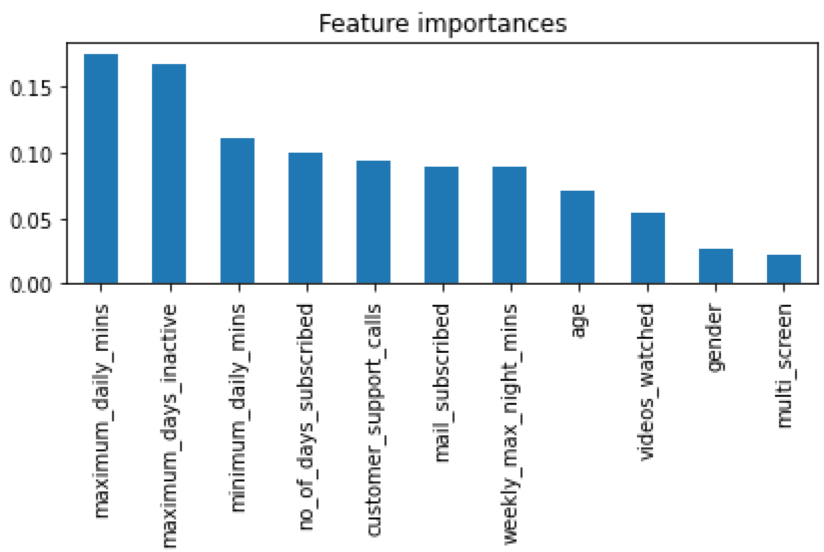


In [196]:

```
# Adaboost
accuracy_report(adaboost)
roc_curve_eval(adaboost)
plot_feature_importances(adaboost)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.93      0.93       509
         1.0       0.57      0.59      0.58        81

    accuracy                           0.88       590
   macro avg       0.75      0.76      0.76       590
weighted avg       0.88      0.88      0.88       590

The area under the curve is: 0.76
```

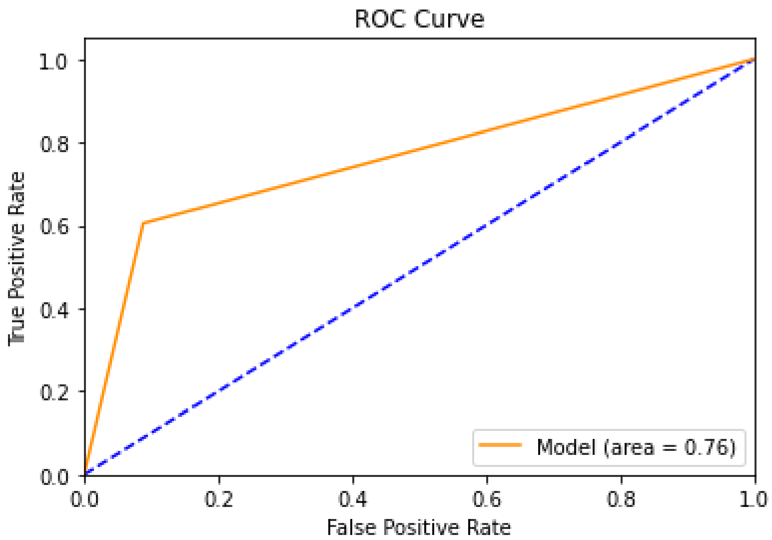


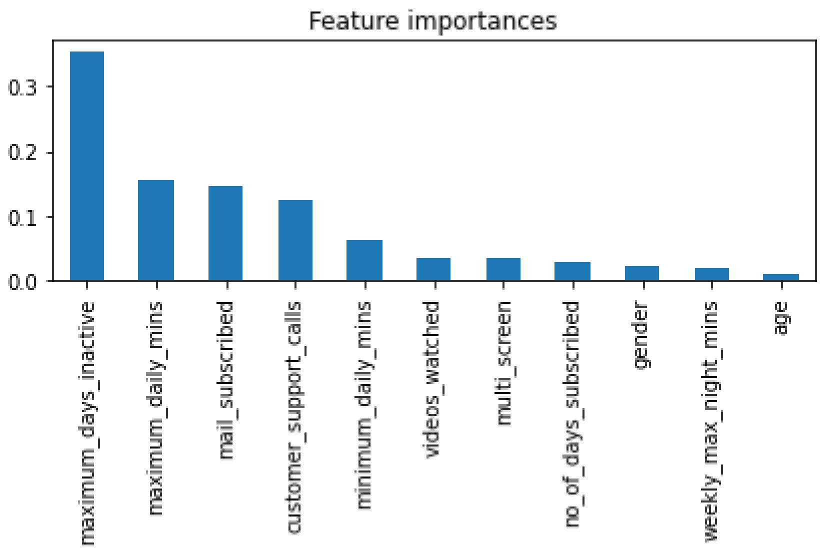


In [197]:

```
# Gradient Boost
accuracy_report(gradientboost)
roc_curve_eval(gradientboost)
plot_feature_importances(gradientboost)
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.91      0.92       509
         1.0       0.52      0.60      0.56        81

    accuracy                           0.87       590
   macro avg       0.73      0.76      0.74       590
weighted avg       0.88      0.87      0.87       590

The area under the curve is: 0.76
```





In [ ]: