Tree-based ML and Feature Selection

This week, your assignment is:

- use our prepared churn data from week 2
- break our data into features and targets, and train and test sets
- use sklearn to fit a decision tree to the training data
    - plot the decision tree
    - change the max_depth of the decision tree to improve the model if needed (or tune it with a hyperparameter search)
- plot the correlations between features and targets
- use sklearn to fit a random forest model to predict churn from our dataset
    - plot the feature importances from the random forest
- choose some of the less-important features to remove from the model using feature importances and correlations and fit the random forest model to the new data
    - examine the feature importances after removing less important features
- write a short analysis of the results of your work

__Optional__ **advanced tasks:**

- use H2O to fit a random forest to our original, unmodified data (missing values and all)
    - you can decide if you want to break the data into train and test sets or not, but remember it's best to evaluate performance on a test or validation dataset
    - plot the H2O random forest's feature importances
- tune the random forest hyperparameters for the sklearn and/or H2O models
- use forward and/or backward selection with feature importances from a random forest model
- use recursive feature selection
- compare the various feature selection methods you tried and write a short summary

Decision trees

In [1]:
```
#import pandas as pd
#from sklearn.tree import DecisionTreeClassifier, plot_tree
#from sklearn.model_selection import train_test_split
#import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv('../Week2/prepped_churn_data.csv', index_col='customerID')
df
```

Out[2]:

	tenure	PhoneService	Contract	PaymentMethod	MonthlyCharges	TotalCharg
customerID						
7590-VHVEG	1	0	0	0	29.85	29.
5575-GNVDE	34	1	1	1	56.95	1889.
3668-QPYBK	2	1	0	1	53.85	108.
7795-CFOCW	45	0	1	2	42.30	1840.
9237-HQITU	2	1	0	0	70.70	151.
...	...	...	...	...	...	
6840-RESVB	24	1	1	1	84.80	1990.
2234-XADUH	72	1	1	3	103.20	7362.
4801-JZAZL	11	0	0	0	29.60	346.
8361-LTMKD	4	1	0	1	74.40	306.
3186-AJIEK	66	1	2	2	105.65	6844.

7043 rows × 8 columns

In [3]:

```
features = df.drop('Churn', axis=1)
targets = df['Churn']

x_train, x_test, y_train, y_test = train_test_split(features, targets, stratify=tar
```

In [4]:

```
dt = DecisionTreeClassifier()
dt.fit(x_train, y_train)

print(dt.score(x_train, y_train))
print(dt.score(x_test, y_test))
```

```
0.993563044301401
0.7234525837592277
```

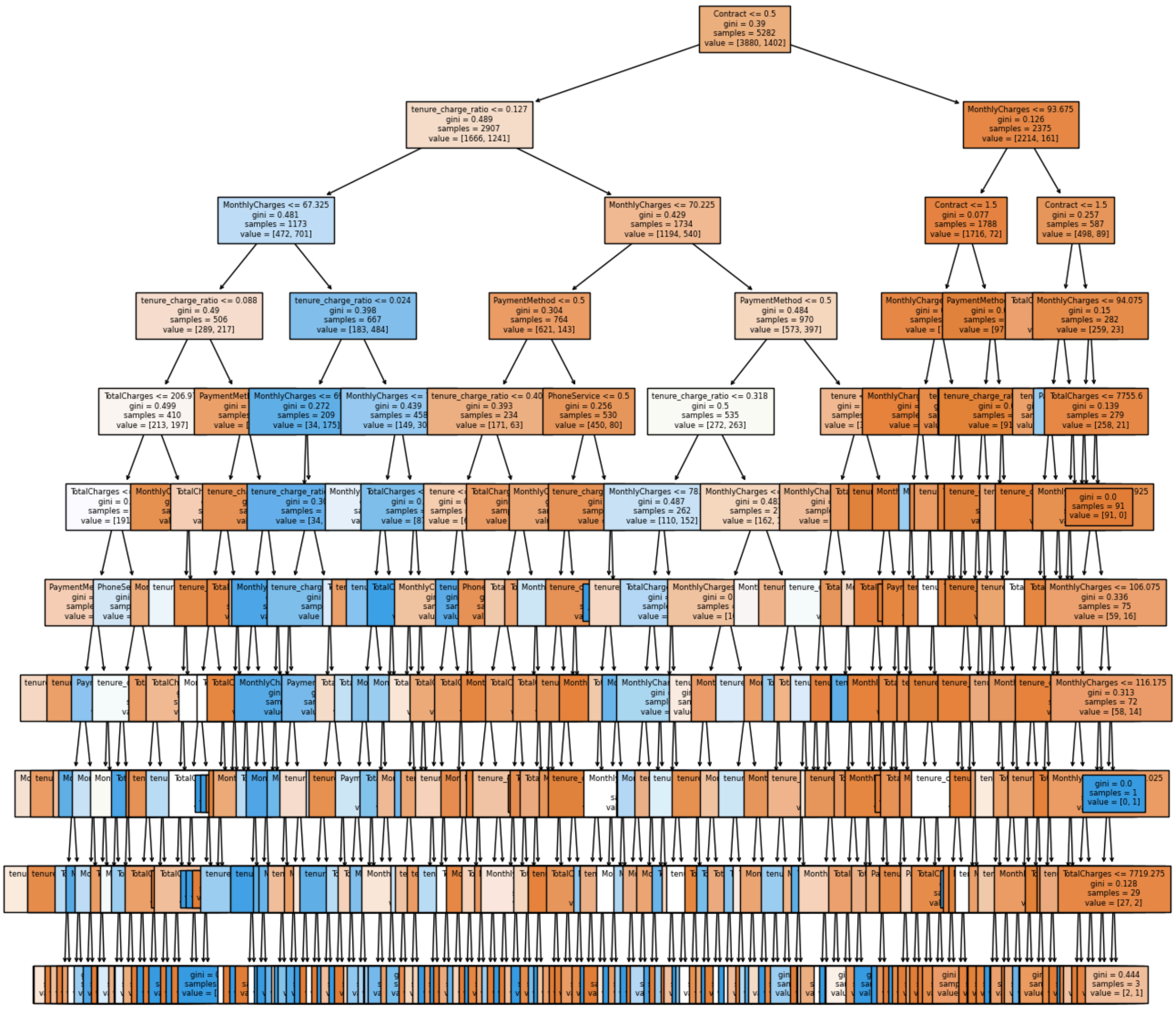
Accuracy on the train set is almost perfect at 99.4% The test score is much lower at 72.3%. - Classic sign of overfitting

Let's see how deep the tree is and plot:

In [5]:
```
dt.get_depth()
```

Out[5]: 32

In [31]:
```
f = plt.figure(figsize=(15, 15))
_ = plot_tree(dt, fontsize=6, feature_names=features.columns, filled=True)
```



Seeing the overwhelming number of samples in the leaf nodes is evidence of overfitting. We will use max_depth to restrict the number of levels.

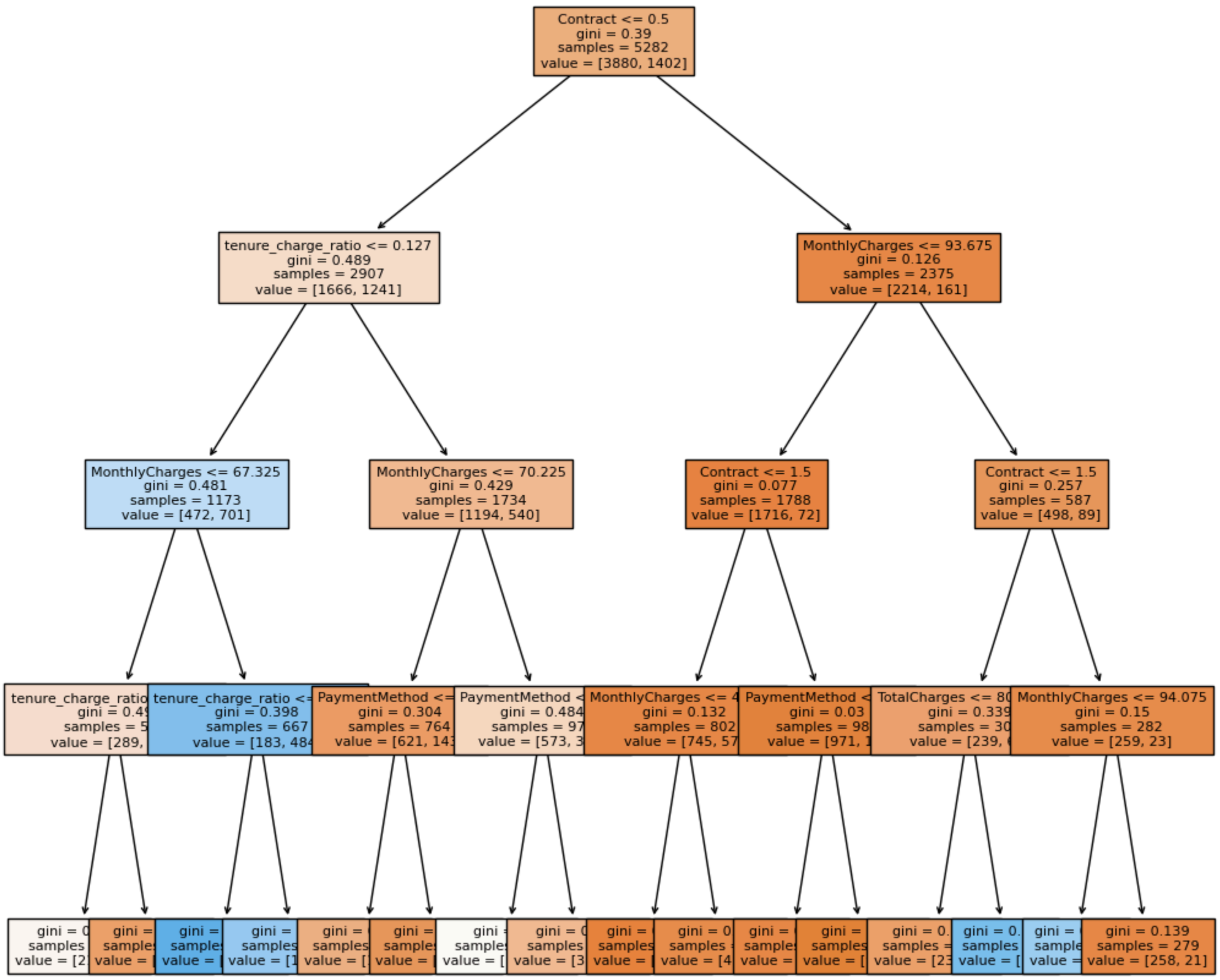
After trying various max_depth values, 20 looks to nearly equal the train/test scores and seems to eliminate the overfitting.

In [34]:
```
dt = DecisionTreeClassifier(max_depth=4)
dt.fit(x_train, y_train)

print(dt.score(x_train, y_train))
print(dt.score(x_test, y_test))
```

```
0.7921241953805377
0.7773992049971608
```

In [35]:
```
f = plt.figure(figsize=(12, 12))
_ = plot_tree(dt, fontsize=8, feature_names=features.columns, filled=True)
```



Random Forests

In [47]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(max_depth=5, random_state=42)
rfc.fit(x_train, y_train)

print(rfc.score(x_train, y_train))
print(rfc.score(x_test, y_test))
```

```
0.8057553956834532
0.7950028392958546
```

In [37]:
```
import math

math.sqrt(x_train.shape[1])
```

Out[37]: 2.6457513110645907

In [43]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(max_depth=5, max_features=10, random_state=42)
rfc.fit(x_train, y_train)

print(rfc.score(x_train, y_train))
print(rfc.score(x_test, y_test))
```

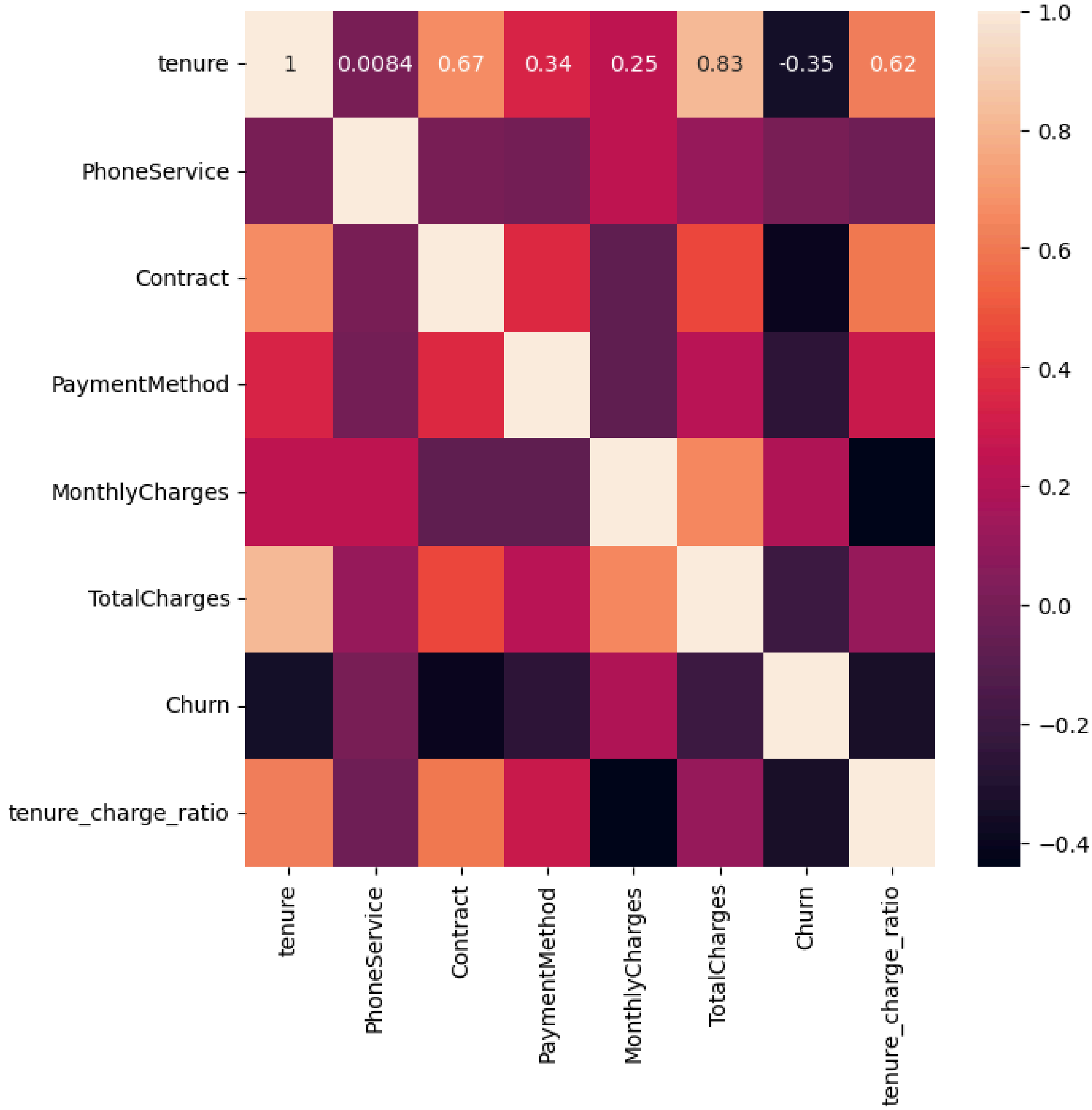
```
0.8091631957591822
0.7932992617830777
```

Feature Selection

In [48]:
```
import seaborn as sns
```

In [52]:
```
f = plt.figure(figsize=(7, 7))
sns.heatmap(df.corr(), annot=True)
```

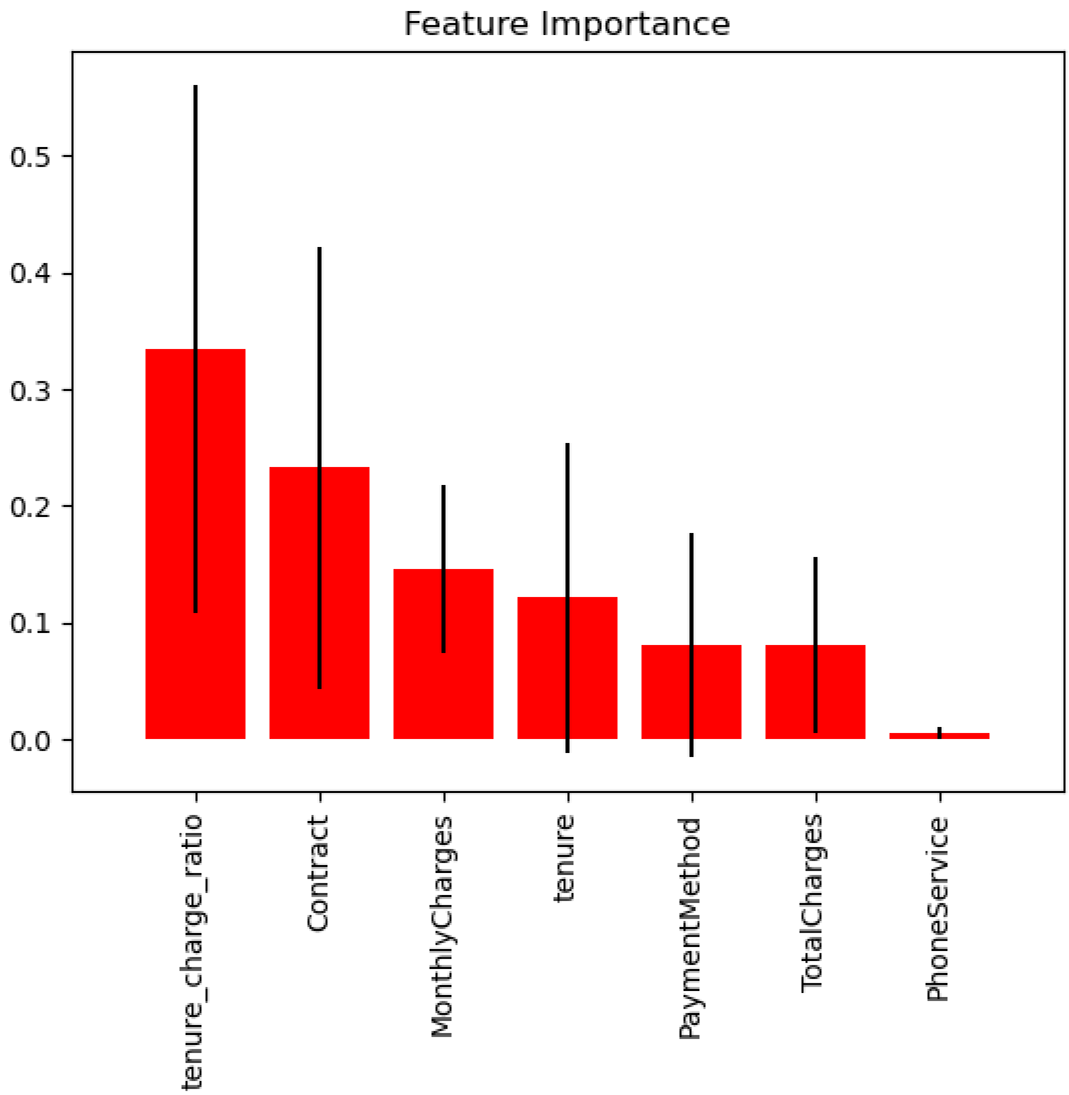
Out[52]: <Axes: >



In [56]:
```
from scikitplot.estimators import plot_feature_importances

plot_feature_importances(rfc, feature_names=features.columns, x_tick_rotation=90)
```

Out[56]:
```
<Axes: title={'center': 'Feature Importance'}>
```



In [63]:
```
new_features = features.drop(['PhoneService', 'TotalCharges', 'PaymentMethod','tenu

x_train, x_test, y_train, y_test = train_test_split(new_features, targets, stratify
```

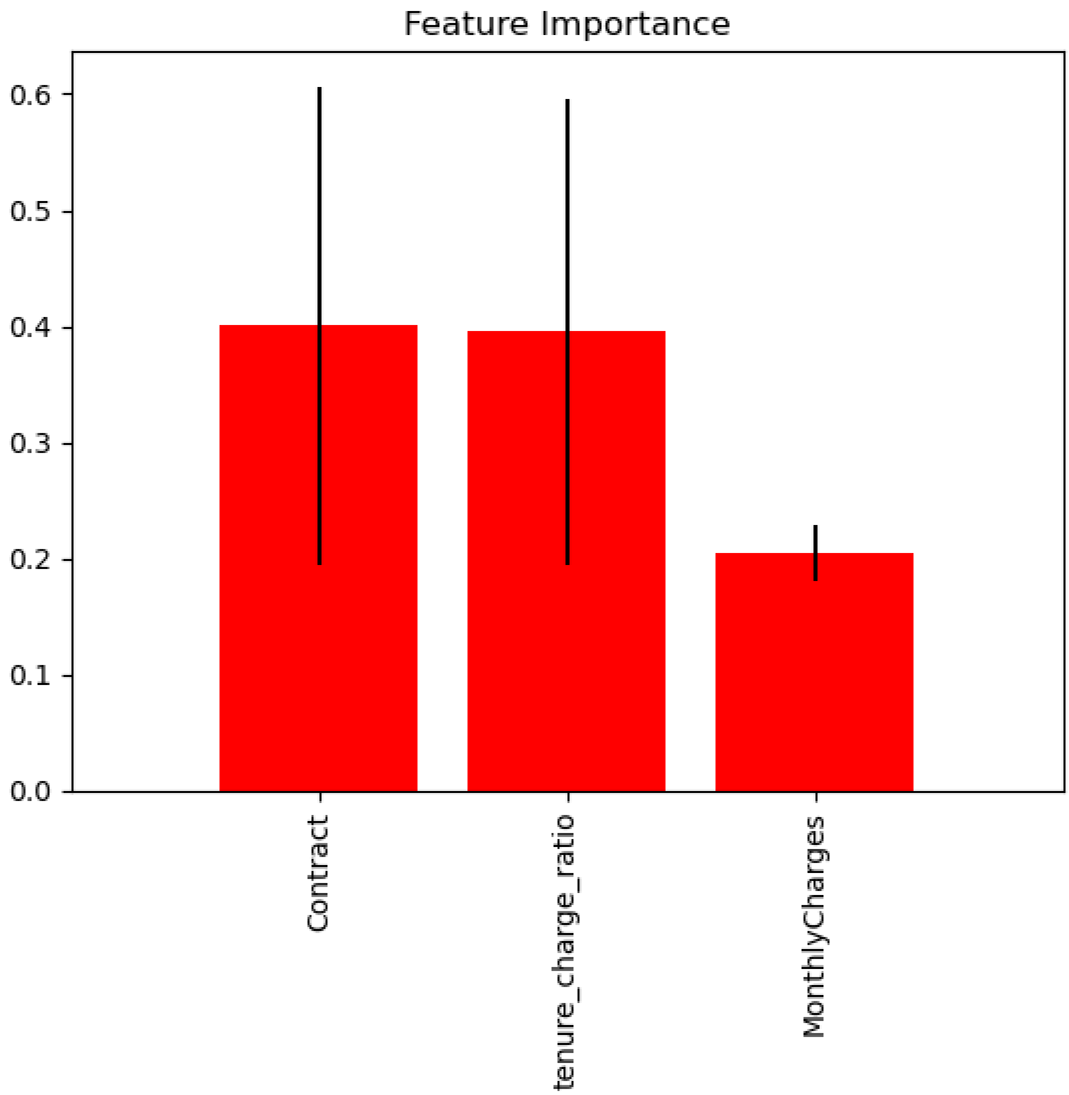
In [73]:
```
rfc = RandomForestClassifier(max_depth=4, max_features=8, random_state=42)
rfc.fit(x_train, y_train)

print(rfc.score(x_train, y_train))
print(rfc.score(x_test, y_test))
```

```
0.797235895494131
0.7864849517319704
```

In [70]:
```
plot_feature_importances(rfc, feature_names=new_features.columns, x_tick_rotation=9
```

Out[70]: `<Axes: title={'center': 'Feature Importance'}>`



Summary

Performance didn't change much, but our feature importances did. The contract measurement seems to be very important for predicting churn.