Week4_Assignment

February 11, 2024

[152]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier, export_text
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import seaborn as sns
```

0.1 Load and preprocess data

[153]:
```python
df = pd.read_csv("cleaned_churn_data.csv")

df.tail(15)
```

[153]:

	customerID	tenure	PhoneService	Contract	PaymentMethod \
7028	7029	68	1	3	Bank transfer (automatic)
7029	7030	6	0	0	Electronic check
7030	7031	2	1	0	Mailed check
7031	7032	55	1	1	Credit card (automatic)
7032	7033	1	1	0	Electronic check
7033	7034	38	1	0	Credit card (automatic)
7034	7035	67	1	0	Credit card (automatic)
7035	7036	19	1	0	Bank transfer (automatic)
7036	7037	12	0	1	Electronic check
7037	7038	72	1	3	Bank transfer (automatic)
7038	7039	24	1	1	Mailed check
7039	7040	72	1	1	Credit card (automatic)
7040	7041	11	0	0	Electronic check
7041	7042	4	1	0	Mailed check
7042	7043	66	1	3	Bank transfer (automatic)

	MonthlyCharges	TotalCharges	Churn	MonthlyCharges_to_tenure_Ratio
7028	64.10	4326.25	0	0.942647
7029	44.40	263.05	0	7.400000
7030	20.05	39.25	0	10.025000
7031	60.00	3316.10	0	1.090909
7032	75.75	75.75	1	75.750000

```
7033           69.50       2625.25      0                           1.828947
7034          102.95       6886.25      1                           1.536567
7035           78.70       1495.10      0                           4.142105
7036           60.65        743.30      0                           5.054167
7037           21.15       1419.40      0                           0.293750
7038           84.80       1990.50      0                           3.533333
7039          103.20       7362.90      0                           1.433333
7040           29.60        346.45      0                           2.690909
7041           74.40        306.60      1                          18.600000
7042          105.65       6844.50      0                           1.600758
```

[154]:

```python
# Drop customerID - not useful for modeling
df = df.drop('customerID', axis=1)
df
```

[154]:

```
      tenure  PhoneService  Contract              PaymentMethod  \
0          1             0         0           Electronic check
1         34             1         1               Mailed check
2          2             1         0               Mailed check
3         45             0         1  Bank transfer (automatic)
4          2             1         0           Electronic check
…        …             …        …                         …
7038      24             1         1               Mailed check
7039      72             1         1    Credit card (automatic)
7040      11             0         0           Electronic check
7041       4             1         0               Mailed check
7042      66             1         3  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  MonthlyCharges_to_tenure_Ratio
0              29.85         29.85      0                       29.850000
1              56.95       1889.50      0                        1.675000
2              53.85        108.15      1                       26.925000
3              42.30       1840.75      0                        0.940000
4              70.70        151.65      1                       35.350000
…                …            …    …                              …
7038           84.80       1990.50      0                        3.533333
7039          103.20       7362.90      0                        1.433333
7040           29.60        346.45      0                        2.690909
7041           74.40        306.60      1                       18.600000
7042          105.65       6844.50      0                        1.600758

[7043 rows x 8 columns]
```

[155]:

```python
payment_method_dummies = pd.get_dummies(df['PaymentMethod'])
df = pd.concat([df, payment_method_dummies], axis=1)
df.head()
```

[155]:
```
   tenure  PhoneService  Contract             PaymentMethod  MonthlyCharges  \
0       1             0         0          Electronic check           29.85
1      34             1         1              Mailed check           56.95
2       2             1         0              Mailed check           53.85
3      45             0         1  Bank transfer (automatic)           42.30
4       2             1         0          Electronic check           70.70

   TotalCharges  Churn  MonthlyCharges_to_tenure_Ratio  \
0         29.85      0                          29.850
1       1889.50      0                           1.675
2        108.15      1                          26.925
3       1840.75      0                           0.940
4        151.65      1                          35.350

   Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
0                      False                    False              True
1                      False                    False             False
2                      False                    False             False
3                       True                    False             False
4                      False                    False              True

   Mailed check
0         False
1          True
2          True
3         False
4         False
```

[156]:
```python
dummies = ['Electronic check', 'Mailed check', 'Bank transfer (automatic)',
 ↪'Credit card (automatic)']

for column in dummies:
    df[column] = pd.factorize(df[column])[0]

df.sample(5)
```

[156]:
```
      tenure  PhoneService  Contract              PaymentMethod  \
2088      36             1         1           Electronic check
153       62             1         3           Electronic check
6170       1             1         0    Credit card (automatic)
2178      53             1         3    Credit card (automatic)
619        7             1         0  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  MonthlyCharges_to_tenure_Ratio  \
2088           55.80       1941.50      0                        1.550000
153            86.10       5215.25      0                        1.388710
6170           19.40         19.40      0                       19.400000
```

```
2178          19.90       1110.05      0                        0.375472
619           78.55        522.95      0                       11.221429

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
2088                          0                        0                 0
153                           0                        0                 0
6170                          0                        1                 1
2178                          0                        1                 1
619                           1                        0                 1

      Mailed check
2088             0
153              0
6170             0
2178             0
619              0
```

[157]:

```python
df = df.drop('PaymentMethod', axis=1)
df
```

[157]:

```
      tenure  PhoneService  Contract  MonthlyCharges  TotalCharges  Churn  \
0          1             0         0           29.85         29.85      0
1         34             1         1           56.95       1889.50      0
2          2             1         0           53.85        108.15      1
3         45             0         1           42.30       1840.75      0
4          2             1         0           70.70        151.65      1
…         …             …         …               …           …      …
7038      24             1         1           84.80       1990.50      0
7039      72             1         1          103.20       7362.90      0
7040      11             0         0           29.60        346.45      0
7041       4             1         0           74.40        306.60      1
7042      66             1         3          105.65       6844.50      0

      MonthlyCharges_to_tenure_Ratio  Bank transfer (automatic)  \
0                          29.850000                          0
1                           1.675000                          0
2                          26.925000                          0
3                           0.940000                          1
4                          35.350000                          0
…                               …                        …
7038                        3.533333                          0
7039                        1.433333                          0
7040                        2.690909                          0
7041                       18.600000                          0
7042                        1.600758                          1

      Credit card (automatic)  Electronic check  Mailed check
```

```
0                            0                  0              0
1                            0                  1              1
2                            0                  1              1
3                            0                  1              0
4                            0                  0              0
…                        …                …            …
7038                         0                  1              1
7039                         1                  1              0
7040                         0                  0              0
7041                         0                  1              1
7042                         0                  1              0

[7043 rows x 11 columns]
```

[158]:
```
df.isna().sum()
```

[158]:
```
tenure                            0
PhoneService                      0
Contract                          0
MonthlyCharges                    0
TotalCharges                      0
Churn                             0
MonthlyCharges_to_tenure_Ratio    0
Bank transfer (automatic)         0
Credit card (automatic)           0
Electronic check                  0
Mailed check                      0
dtype: int64
```

0.2 Remove outliers

[159]:
```
numerical_columns = df.select_dtypes(include=[np.number]).columns

# Function to remove outliers based on IQR
def remove_outliers_iqr(data_frame, columns):
    for column in columns:
        Q1 = data_frame[column].quantile(0.25)
        Q3 = data_frame[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        data_frame = data_frame[(data_frame[column] >= lower_bound) &
 ↪(data_frame[column] <= upper_bound)]
    return data_frame

df_clean = remove_outliers_iqr(df, numerical_columns)
df_clean
```

[159]:
```
      tenure  PhoneService  Contract  MonthlyCharges  TotalCharges  Churn  \
1         34             1         1           56.95       1889.50      0
5          8             1         0           99.65        820.50      1
8         28             1         0          104.80       3046.05      1
10        13             1         0           49.95        587.45      0
14        25             1         0          105.50       2686.05      0
…        …             …       …              …             …     …
7023      63             1         0          103.50       6479.40      0
7027      13             1         0           73.35        931.55      0
7030       2             1         0           20.05         39.25      0
7038      24             1         1           84.80       1990.50      0
7041       4             1         0           74.40        306.60      1

      MonthlyCharges_to_tenure_Ratio  Bank transfer (automatic)  \
1                           1.675000                          0
5                          12.456250                          0
8                           3.742857                          0
10                          3.842308                          0
14                          4.220000                          0
…                                …                         …
7023                        1.642857                          0
7027                        5.642308                          0
7030                       10.025000                          0
7038                        3.533333                          0
7041                       18.600000                          0

      Credit card (automatic)  Electronic check  Mailed check
1                           0                 1             1
5                           0                 0             0
8                           0                 0             0
10                          0                 1             1
14                          0                 0             0
…                        …                …            …
7023                        0                 0             0
7027                        0                 1             1
7030                        0                 1             1
7038                        0                 1             1
7041                        0                 1             1

[2523 rows x 11 columns]
```

0.3 Split data into features and targets

[160]:
```python
X = df.drop('Churn', axis=1)
y = df['Churn']
```

0.4 Split data into training and test sets

[161]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.5 Fix infinity values error in the dataset

[162]:
```
print("Infinity values in X_train:", np.any(np.isinf(X_train)))
print("NaN values in X_train:", np.any(np.isnan(X_train)))
```

```
Infinity values in X_train: True
NaN values in X_train: False
```

0.6 Handle infinity values

[163]:
```
columns_with_infinity = X_train.columns[np.isinf(X_train).any()]

print("Columns with Infinity values:", columns_with_infinity)

# Replace infinity values
X_train[columns_with_infinity] = X_train[columns_with_infinity].replace([np.
↪inf, -np.inf], np.nan)
```

```
Columns with Infinity values: Index(['MonthlyCharges_to_tenure_Ratio'],
dtype='object')
```

0.7 Align the data to avoid mismatch

[164]:
```
print("Shape of X_train:", X_train.shape)
print("Shape of y_train:", y_train.shape)

print("Duplicate index values in X_train:", X_train.index.duplicated().any())
print("Duplicate index values in y_train:", y_train.index.duplicated().any())

# Reindex y_train to match X_train
y_train = y_train.reindex(X_train.index)
```

```
Shape of X_train: (5634, 10)
Shape of y_train: (5634,)
Duplicate index values in X_train: False
Duplicate index values in y_train: False
```

[165]:
```
print("Shape of X_train:", X_train.shape)
print("Shape of y_train:", y_train.shape)
```

```
Shape of X_train: (5634, 10)
Shape of y_train: (5634,)
```

0.8 Fit and plot DT

[166]:
```python
dt_model = DecisionTreeClassifier(max_depth=3)
dt_model.fit(X_train, y_train)
tree_rules = export_text(dt_model, feature_names=list(X.columns))
print(tree_rules)
```

```
|--- Contract <= 0.50
|   |--- MonthlyCharges_to_tenure_Ratio <= 7.84
|   |   |--- MonthlyCharges <= 69.97
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges >  69.97
|   |   |   |--- class: 0
|   |--- MonthlyCharges_to_tenure_Ratio >  7.84
|   |   |--- MonthlyCharges <= 67.30
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges >  67.30
|   |   |   |--- class: 1
|--- Contract >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- Contract <= 2.00
|   |   |   |--- class: 0
|   |   |--- Contract >  2.00
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- Contract <= 2.00
|   |   |   |--- class: 0
|   |   |--- Contract >  2.00
|   |   |   |--- class: 0
```

First Decision Node (Contract $<=$ 0.50)

If the contract duration is short (month-to-month contracts)

The model looks at the ratio of MonthlyCharges to tenure. If this ratio is low, and MonthlyCharges is low, predict class 0 (indicating no churn).

If this ratio is high, and MonthlyCharges is high, predict class 0 (indicating no churn).

If this ratio is high, and MonthlyCharges is relatively moderate, predict class 1 (indicating potential churn).

Second Decision Node (Contract $>$ 0.50)

If the contract duration is longer (one or two-year contracts)

The model looks at the MonthlyCharges. If MonthlyCharges is low, predict class 0 (no churn).

If MonthlyCharges is high, the model further considers the contract duration.

If the contract duration is short (less than or equal to 2.00), predict class 0 (no churn).

If the contract duration is long (greater than 2.00), predict class 0 (no churn).

0.9 Interpretation

Short-term or month-to-month contracts with high monthly charges and a moderate ratio of monthly charges to tenure are associated with a higher likelihood of churn.

Longer-term contracts with low or high monthly charges are less likely to result in churn, regardless of the contract duration.

These interpretations provide insights into the factors that the model considers important for predicting customer churn, and they align with the business understanding of wanting to identify potential churners.

0.10 Hyperparameter tuning for DT

[167]:
```
param_grid = {'max_depth': [3, 5, 7, 10]}
dt_model = DecisionTreeClassifier()
grid_search = GridSearchCV(dt_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

best_max_depth = grid_search.best_params_['max_depth']

print(best_max_depth)
```

```
3
```

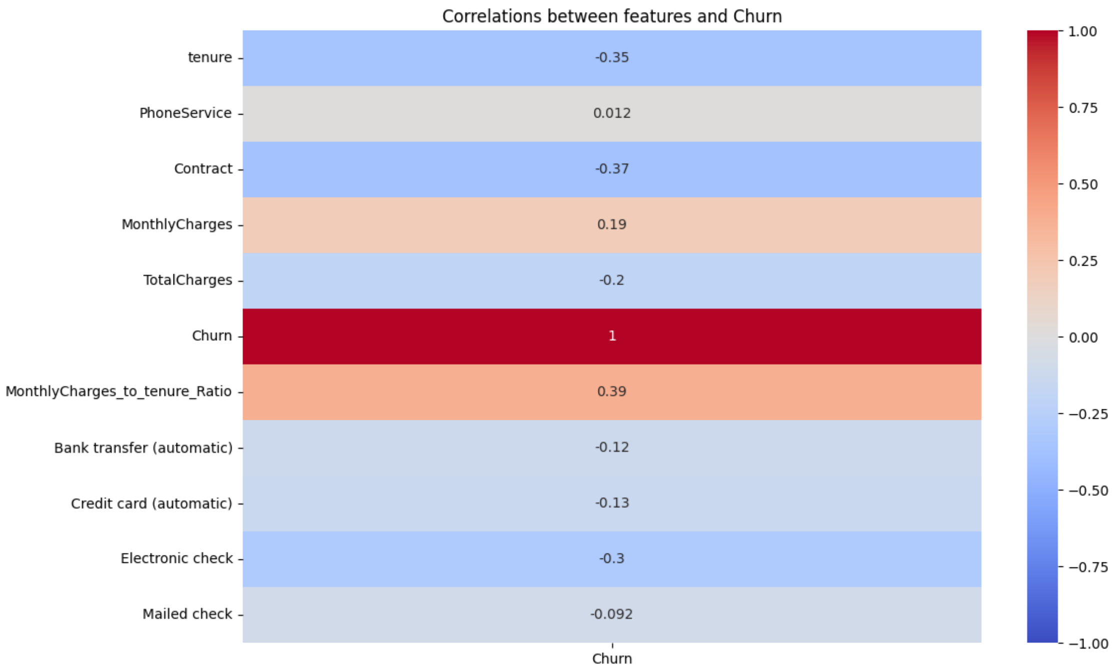
[168]:
```
dt_model_tuned = DecisionTreeClassifier(max_depth=best_max_depth)
dt_model_tuned.fit(X_train, y_train)
tree_rules_tuned = export_text(dt_model_tuned, feature_names=list(X.columns))
print(tree_rules_tuned)
```

```
|--- Contract <= 0.50
|   |--- MonthlyCharges_to_tenure_Ratio <= 7.84
|   |   |--- MonthlyCharges <= 69.97
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges >  69.97
|   |   |   |--- class: 0
|   |--- MonthlyCharges_to_tenure_Ratio >  7.84
|   |   |--- MonthlyCharges <= 67.30
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges >  67.30
|   |   |   |--- class: 1
|--- Contract >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- Contract <= 2.00
|   |   |   |--- class: 0
|   |   |--- Contract >  2.00
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- Contract <= 2.00
|   |   |   |--- class: 0
```

```
|   |   |--- Contract >  2.00
|   |   |   |--- class: 0
```

0.11 Correlations between features and targets

[169]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr()[['Churn']], annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title("Correlations between features and Churn")
plt.show()
```



0.12 Handle Nan and infinity values in X__train

[170]:
```
nan_values_in_X_train = X_train.isna().any().any()
print("NaN values in X_train:", nan_values_in_X_train)

# Check for Infinite values in X_train
infinite_values_in_X_train = np.isfinite(X_train).all().all()
print("Infinity values in X_train:", not infinite_values_in_X_train)

# Check for Constant features in X_train
constant_features_in_X_train = X_train.columns[X_train.nunique() == 1].tolist()
print("Constant features in X_train:", constant_features_in_X_train)
```

```
NaN values in X_train: True
Infinity values in X_train: True
```

```
Constant features in X_train: []
```

0.13 Fill nan values with mean

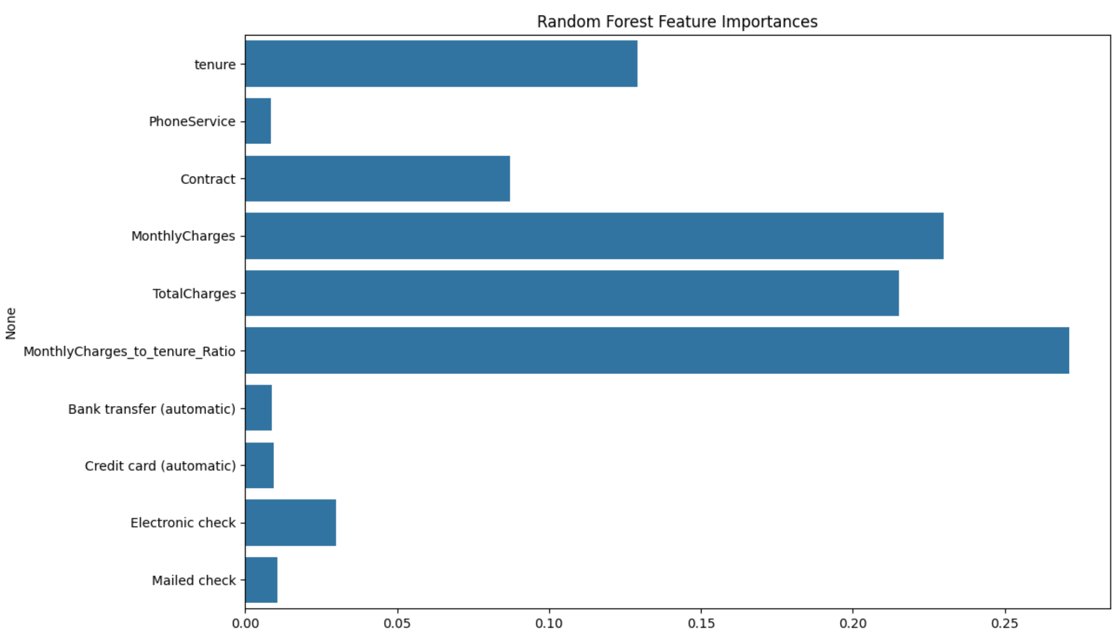
[171]:
```python
X_train_filled = X_train.fillna(X_train.mean())

# Replace infinity values with a large finite value
X_train_filled.replace([np.inf, -np.inf], np.finfo(np.float64).max, 
 ↪inplace=True)
```

0.14 Fit and plot model

[173]:
```python
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_filled, y_train)
```

[173]:
```
RandomForestClassifier(random_state=42)
```

[174]:
```python
plt.figure(figsize=(12, 8))
sns.barplot(x=rf_model.feature_importances_, y=X.columns)
plt.title("Random Forest Feature Importances")
plt.show()
```



0.15 Remove less imortant features

[175]:
```
less_important_features = ['PhoneService', 'Bank transfer (automatic)', 'Credit␣
↪card (automatic)', 'Mailed check']

X_train_filtered = X_train_filled.drop(less_important_features, axis=1)
X_test_filtered = X_test.drop(less_important_features, axis=1)
X_train_filtered.shape
```

[175]:
```
(5634, 6)
```

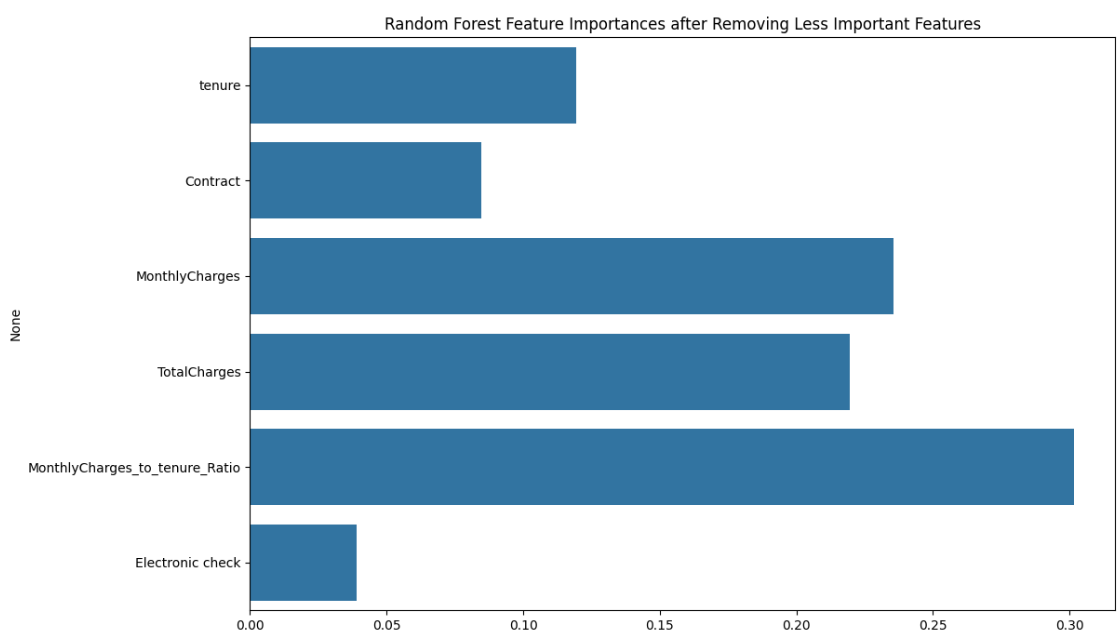
0.16 Fit to new data

[176]:
```
rf_model_filtered = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model_filtered.fit(X_train_filtered, y_train)
```

[176]:
```
RandomForestClassifier(random_state=42)
```

0.17 Plot feature imporatnces

[177]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=rf_model_filtered.feature_importances_, y=X_train_filtered.
↪columns)
plt.title("Random Forest Feature Importances after Removing Less Important␣
↪Features")
plt.show()
```



0.18 Summary

We perform a comprehensive analysis on customer churn data, focusing on building, tuning, and evaluating machine learning models. Initial data preprocessing involves loading, dummy encoding, and factorization of categorical features. We then ensure data integrity by handling Infinity and NaN values.

We then construct an initial decision tree model, conduct hyperparameter tuning using GridSearchCV, and visualize the decision tree rules. Additionally, we plot correlations between features and the target variable (Churn). Random Forest modeling is introduced, featuring an initial model with visualized feature importances. We then identify and remove less-important features, leading to a new Random Forest model. The overall goal is to enhance the predictive capabilities of these models for customer churn prediction in a telecommunications company.