University of Messina

Bachelor of Data Analysis

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Machine Learning

(Project report)

Supervisor:
Prof. Giacomo Fiumara

Student:
Sahil Nakrani

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Introduction

In the modern business landscape, retaining customers is just as important as acquiring new ones. Customer churn, which refers to the loss of clients or customers, is a critical metric for companies, especially in highly competitive markets. Predicting customer churn can help organizations take pre-emptive actions to retain customers, thereby enhancing profitability and growth. This project aims to predict customer churn using various machine learning models. The process includes data preprocessing, exploratory data analysis (EDA), feature engineering, model training, evaluation, and tuning to achieve the best possible predictive performance.

Understanding the Dataset

The dataset consists of 3749 entries with 17 columns. (But here we are not considering 2 columns which are ‘Unnamed: 0’ and ‘CustomerId’. Because which are just indexes for the entries.)

In this dataset, there is two columns ‘Unnamed: 0’ and ‘CustomerID’ which are only showing the index. So, I have removed it to not have unnecessary feature.

```
# removing the index column from the dataset.
data = data.drop('Unnamed: 0', axis=1)
data = data.drop('CustomerID', axis=1)
```

Basic Information and Statistical Details

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3749 entries, 0 to 3748
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Age               3562 non-null   float64
 1   Gender            3749 non-null   object 
 2   Tenure            3749 non-null   int64  
 3   Service_Internet  3028 non-null   object 
 4   Service_Phone     3749 non-null   object 
 5   Service_TV        3749 non-null   object 
 6   Contract          3749 non-null   object 
 7   PaymentMethod     3562 non-null   object 
 8   MonthlyCharges    3749 non-null   float64
 9   TotalCharges      3749 non-null   float64
 10  StreamingMovies   3749 non-null   object 
 11  StreamingMusic    3749 non-null   object 
 12  OnlineSecurity    3749 non-null   object 
 13  TechSupport       3749 non-null   object 
 14  Churn             3749 non-null   object 
dtypes: float64(3), int64(1), object(11)
memory usage: 439.5+ KB
```

	Age	Tenure	MonthlyCharges	TotalCharges
count	3562.000000	3749.000000	3749.000000	3749.000000
mean	43.655531	36.264070	75.844318	2718.968266
std	14.914474	20.505528	73.062971	3211.879149
min	18.000000	1.000000	20.000000	13.190000
25%	31.000000	19.000000	44.570000	1076.240000
50%	44.000000	36.000000	69.590000	2132.260000
75%	56.000000	54.000000	95.540000	3619.710000
max	69.000000	71.000000	1179.300000	79951.800000

Data Preprocessing

Handling the missing values

We utilize both the functions “isnull()” to inspect null values.

```
# Check for missing values
missing_values = data.isnull().sum()

# Display columns with missing values
missing_values = missing_values[missing_values > 0]
missing_values
```

```
Age                187
Service_Internet   721
PaymentMethod      187
dtype: int64
```

Here, feature ‘Age’ is numerical feature and [‘Service_Internet’, ‘PaymentMethod’] are categorical features.

- Replacing the numerical missing values with the median of the column.

```
imputer = SimpleImputer(missing_values=np.nan, strategy='median')
data['Age'] = imputer.fit_transform(data['Age'].values.reshape(-1, 1))
```

- Replacing the categorical missing values with the random instance of the column.

```
for column in ['Service_Internet', 'PaymentMethod']:
    data[column] = data[column].fillna(random.choice(data[column].dropna().unique()))
```

Here, we can also replace categorical feature’s missing values with mode (most frequent instance) but we have replaced with random instance. Just because already mode is having majority of distribution and as per me, it is not good to put again the mode to let the model to rely on single instance (category).

Label Encoding for the categorical features

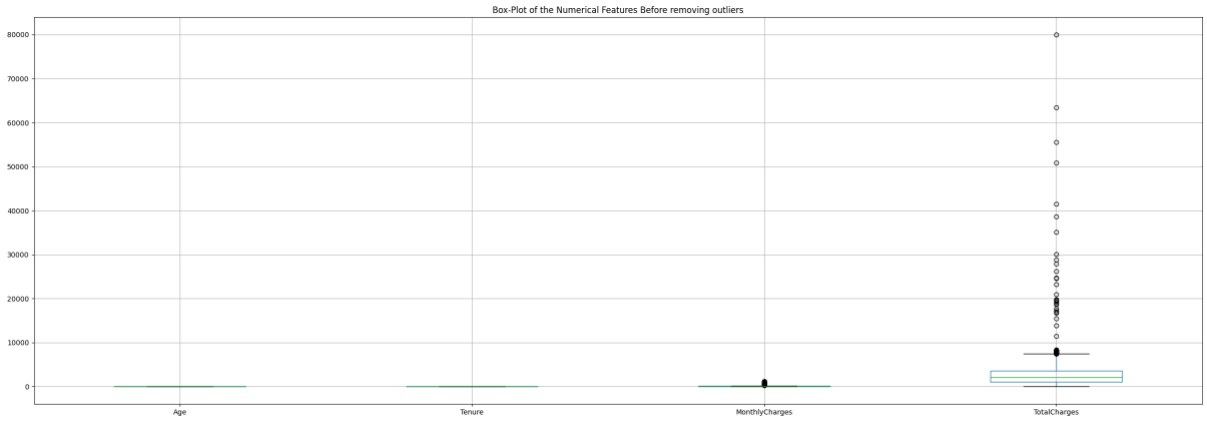
For the Exploratory Data Analysis (EDA) and for the model training part. For example terraforming the values of categorical value ‘yes’ and ‘no’ to 1 and 0.

First, I have listed all the categorical features. I’m using ‘**LabelEncoder()’** function to encode the categories of the features.

```
cat_features = ['Gender', 'Service_Internet', 'Service_Phone', 'Service_TV', 'Contract', 'PaymentMethod',
'StreamingMovies', 'StreamingMusic', 'OnlineSecurity', 'TechSupport']

# Label encoding for binary categorical feature
label_encoder = LabelEncoder()
for feature in cat_features:
    data[feature] = label_encoder.fit_transform(data[feature])
```

Handling the Outliers

Outliers are datapoints that deviate significantly from the rest of the dataset and can have a substantial impact on analysis.



In the above box-plot, you can see there are outliers in two right sided features which are ‘MonthlyCharges’ and ‘TotalCharges’. And we are going to handle it with the technique called inter quartile range.

So, first I have made the function to handle the outliers and then I will apply it on all the numerical features and I will save the index of the outlier.

```python
def iqr_outliers(dataset,feature_name, multiplier=2):

    Q1 = dataset[feature_name].quantile(0.25)
    Q3 = dataset[feature_name].quantile(0.75)

    IQR = Q3 - Q1

    lwr_bound = Q1 - multiplier * IQR
    upp_bound = Q3 + multiplier * IQR

    ls = dataset.index[np.logical_or(dataset[feature_name]<lwr_bound,
                                     dataset[feature_name]>upp_bound)]
    return ls #return the indexes

outliers_detected={}
for i in numerical_features:
    outliers = iqr_outliers(data,i)
    outliers_detected[i] = outliers

    print('Variable',i)
    print(outliers)
    print(data[i].iloc[outliers])
    print('\n')
```

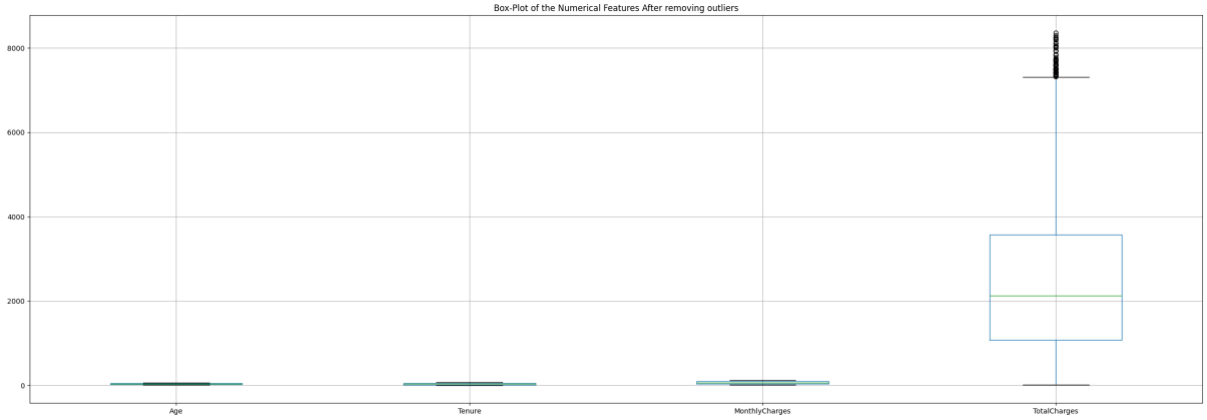
For example :

```
Variable MonthlyCharges
Index([  34,  106,  217,  253,  379,  590,  639,  667,  733,  787,  791,  938,
        944, 1043, 1151, 1258, 1261, 1343, 1619, 1904, 1952, 1982, 2356, 2495,
       2497, 2509, 2590, 2601, 2736, 2851, 2977, 3085, 3137, 3210, 3246, 3459,
       3514],
```

Then, I have just replaced that detected outliers with the median of the column. We can also remove the outliers, but since our dataset is small so it is better to replace it with middle value not to remove.

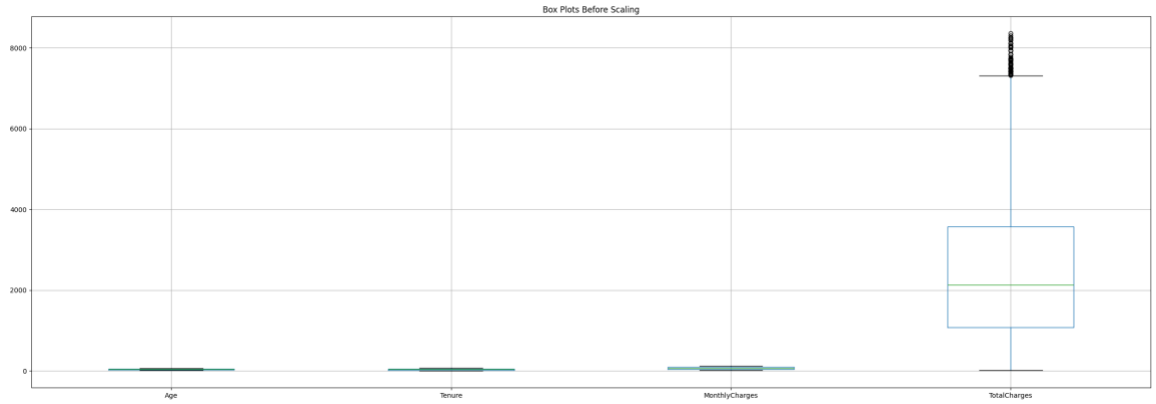
```python
for i in numerical_features:
    data[i] = data[i].replace(data[i].iloc[outliers_detected[i]].values,data[i].median())
```

Let’s see now the box-plot.



Scaling the Feature

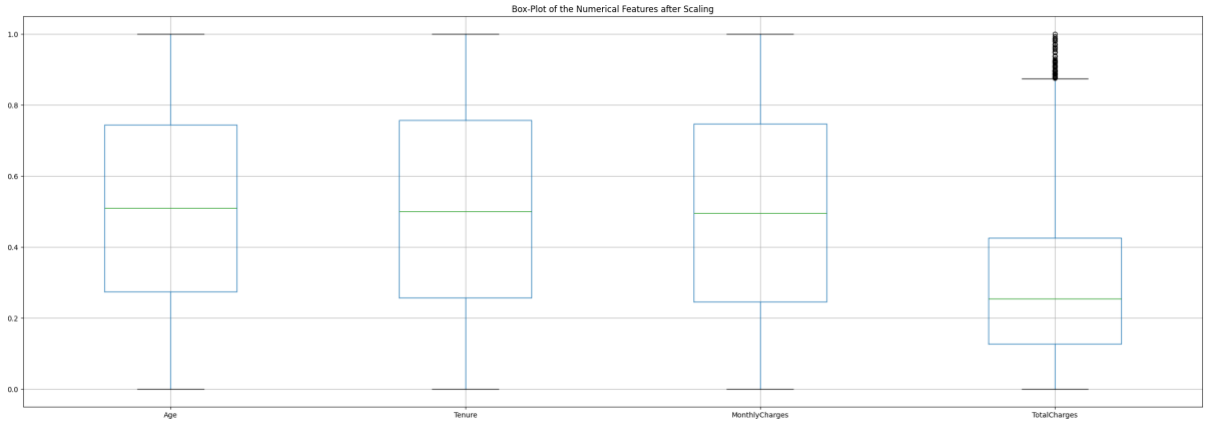
Before scaling the data, features are not in one range. They are in different range which is not good for training phase.



here, I'm using a MinMaxScaler() to scale the data not a Standard Scaler. Because we have some features which is showing time period and standard scaler is converting the range between -1 and 1. Negative values are not usual for the time period. That's why here I have used MinMaxScaler to have range between 0 and 1.

```
scaler = MinMaxScaler()
data[numerical_features] = scaler.fit_transform(data[numerical_features])
```

Here is the box-plot after scaling the numerical features.



EDA (Exploratory Data Analysis)

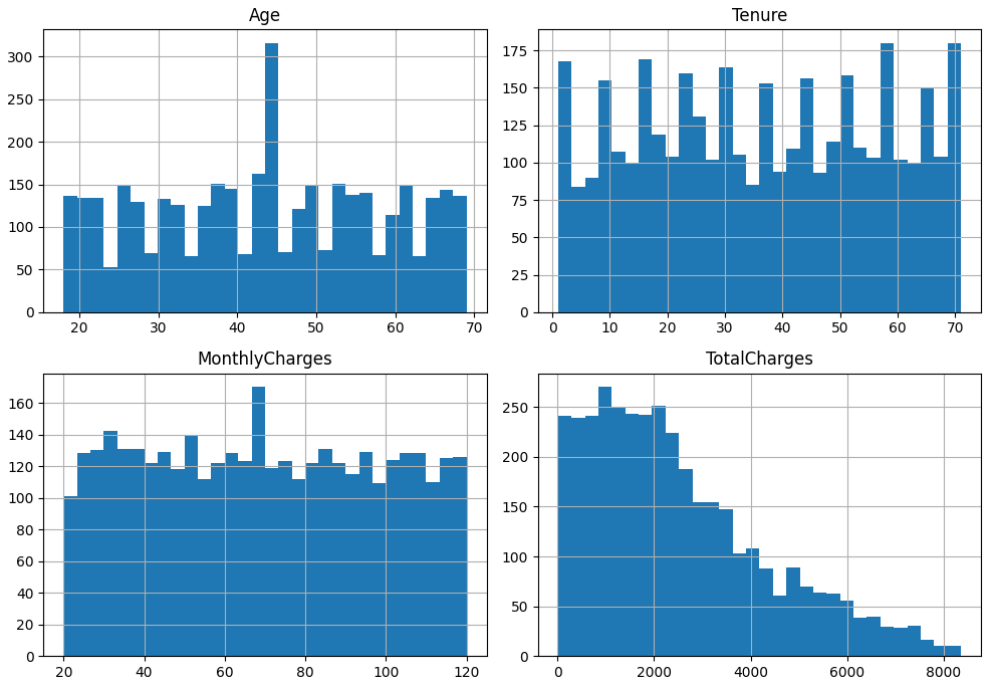
Exploratory Data Analysis (EDA) is a crucial step in understanding the dataset and uncovering underlying patterns that inform feature engineering and model building. This section provides a detailed analysis based on the graphs and plots generated during the EDA process.

Overview of the Dataset

The dataset consists of 3749 entries with 17 columns, excluding 'Unnamed: 0' and 'CustomerID', which are irrelevant for analysis.

Distribution of Numerical Features

First, we are going to make a distribution graph for the numerical features using histogram.



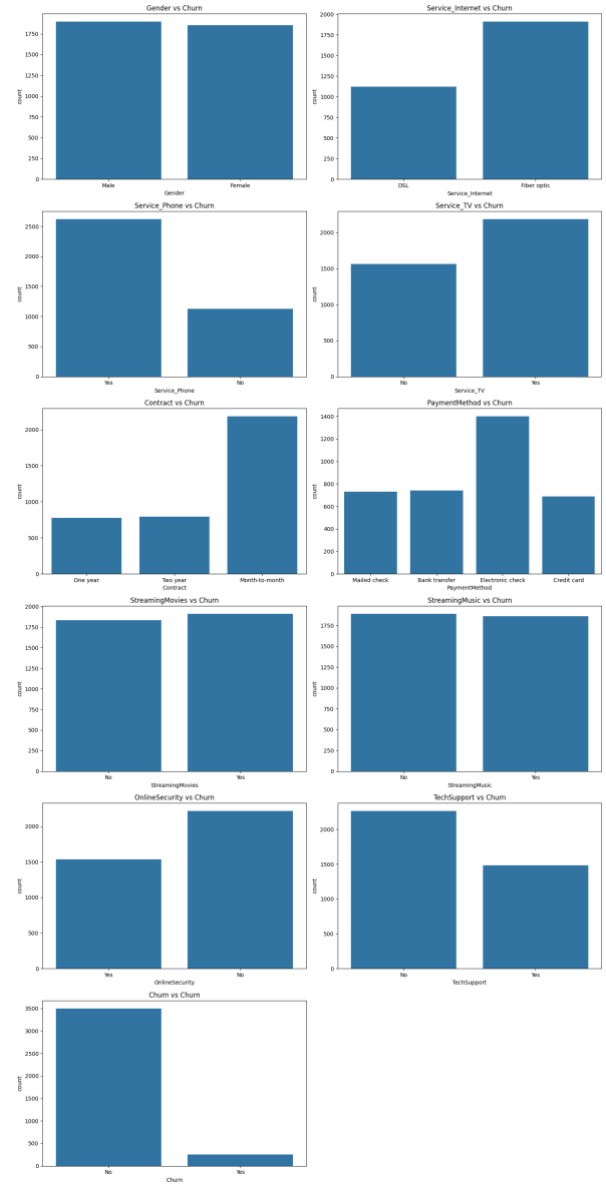
By this histogram, we can see the distribution, frequencies, and also skewness in the distribution.

For example, the histogram for 'TotalCharges' reveals a left-skewed distribution, indicating that most customers have total charges less than 3000. This skewness suggests that a large portion of the customer base incurs relatively lower total charges.

Analysis of Categorical Features

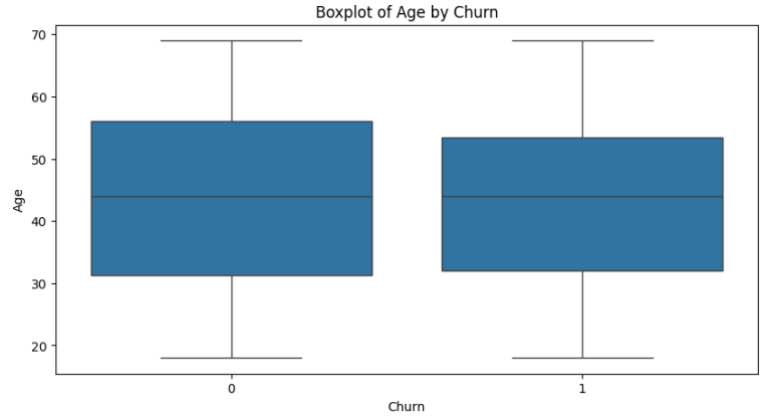
Categorical features were analyzed using bar plots to visualize the frequency of each category. The bar plot indicates that a significant number of customers involved in specific category.

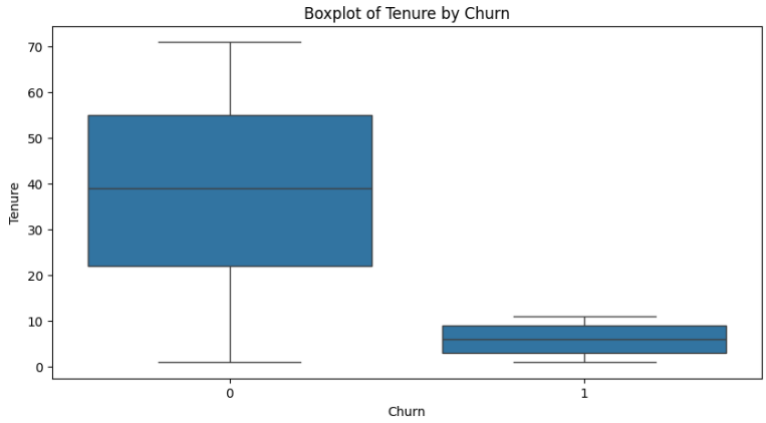
```
n_features = len(cat_features)
n_cols = 2
n_rows = (n_features + 1) // n_cols

fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, n_rows * 5))
axes = axes.flatten()

for i, feature in enumerate(cat_features):
    sns.countplot(x=feature, data=data2, ax=axes[i])
    axes[i].set_title(f'{feature} vs Churn')

# Remove any empty subplots
for j in range(i+1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```

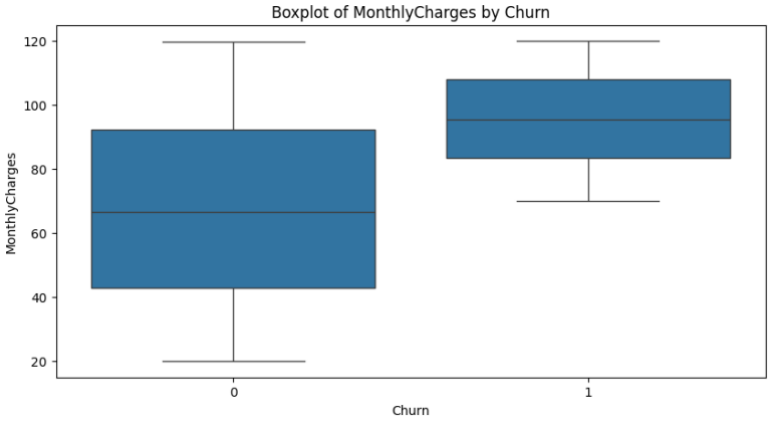


Relationship Between Features and Target Variable

Now here is the relation between a numerical features and the target feature which is Churn. This relation is visualized with the box-plot.



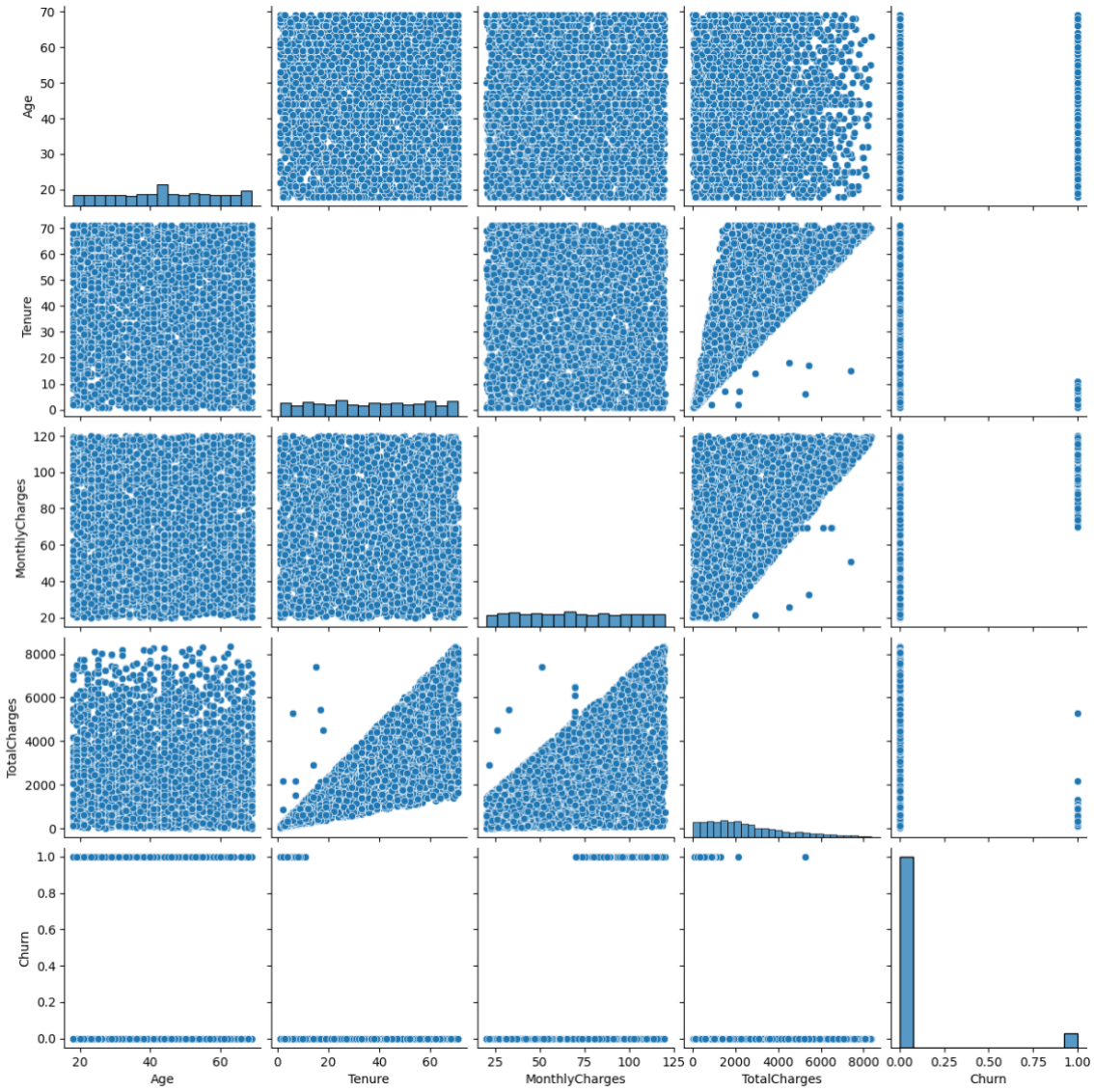




Here, we can see some relationship and trends between the feature and target. For example, the box plot illustrates that customers with higher monthly charges are more likely to churn. This trend highlights 'MonthlyCharges' as a significant predictor of churn.

Pairwise Scatter Plot

Also I have visualized the relation with the help of pairwise scatter plot. Where we can identify the relational trends, actual trends in the data, and also distribution and outliers. Here, I have mentioned the pairwise scatter plot below.



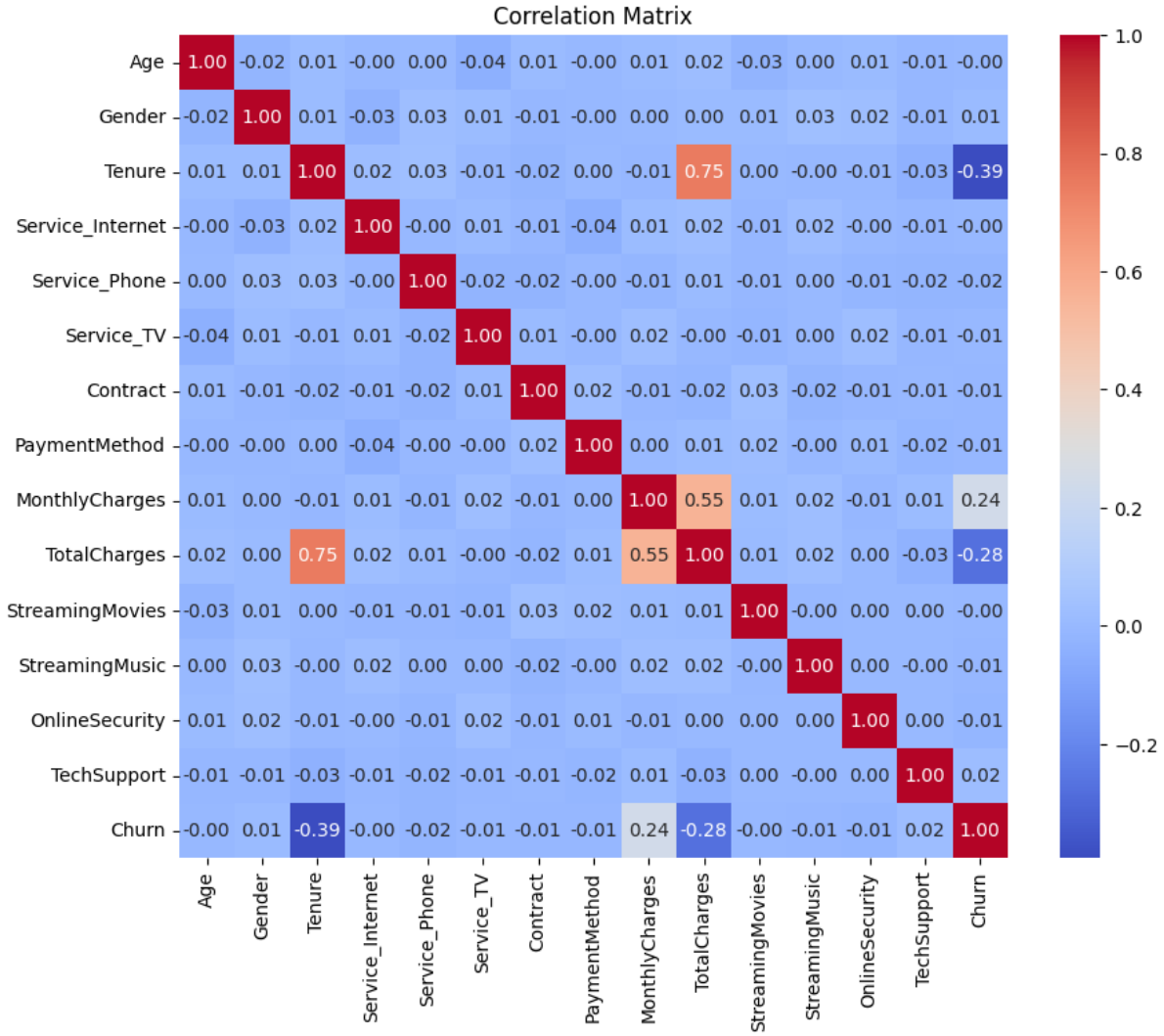
Then, let's create a heatmap of the correlation matrix. This is very important step of EDA because, by correlation matrix, we can identify the relation between the feature and other features and asl between the feature and target feature.

The scatter plot between 'MonthlyCharges' and 'TotalCharges' and also between 'TotalCharges' and 'Tenure' shows a positive linear relationship, confirming the correlation analysis. This plot also helps in visualizing the distribution of data points and identifying potential outliers.

Correlation Analysis

The heatmap of the correlation matrix visualizes the relationships between features. For example, 'MonthlyCharges' and 'TotalCharges' show a strong positive correlation, indicating that customers with higher monthly charges tend to accumulate higher total charges over time. This heatmap also helps in identifying multicollinearity.

By correlation matrix, we can also look the percentage of dependencies of the features on other features. Because, correlation coefficient ranges between -1 and 1. Where 1 mean strongly positive correlation and -1 means strongly negative correlation.



Feature Engineering

I have already scaled the features, and also have put the labels for the categorical features.

Feature engineering involves creating new features from existing ones to improve model performance. This process is guided by domain knowledge and the insights gained from EDA.

Combine Existing Features :

- **MonthlyCharges_to_Tenure :** identifies high-cost users who might be at risk of churn.
- **TotalCharges_to_Tenure :** highlights customers who have spent a lot over their tenure and might be more sensitive to service issues.

Domain Knowledge :

- **TotalServices :** helps to identify customers having reliant on the company's services and might churn if dissatisfied.
- **isSeniorCitizen :** senior citizens might have different churn behaviour.

```python
# Function to engineer new features
def feature_engineering(data):

    data['MonthlyCharges_per_Tenure'] = data['MonthlyCharges'] / (data['Tenure'] + 1)

    data['TotalCharges_per_Tenure'] = data['TotalCharges'] / (data['Tenure'] + 1)

    # Total number of services
    data['TotalServices'] = (data['Service_Internet'] + data['Service_Phone'] + data['Service_TV'] +
                             data['StreamingMovies'] + data['StreamingMusic'] + data['OnlineSecurity'] + data
                             ['TechSupport'])

    # Flag for senior citizen status
    data['IsSeniorCitizen'] = (data['Age'] >= 65).astype(int)

    return data

# Apply feature engineering
data = feature_engineering(data)
```

Modelling and Evaluation

Frist we are going to split the data into target variables and other features.

```
X = data.drop('Churn', axis=1)
y = data['Churn']
```

I have tried to train model now, but it is overfitting. May be because we have very less data and three features with high missing values. So, that's why I have used feature selection technique to select most important features.

```
def select_features(X, y):
    model = RandomForestClassifier(random_state=42)
    rfe = RFE(model, n_features_to_select=10)
    X_final = rfe.fit_transform(X, y)
    final_features = X.columns[rfe.get_support()]
    print(final_features)
    return final_features
```

So, we are selecting 10 most important features from our dataset to train the model on. The next step involves training various machine learning models to predict customer churn. The dataset was split into training (70%) and testing (30%) sets using the train_test_split() function with random_state=42 to ensure reproducibility.

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
selected_features = select_features(X_train, y_train)
X_test = X_test[selected_features]
X_train = X_train[selected_features]
```

Model Selection

We tested four models for this task:

- Random Forest Classifier
- Logistic Regression Classifier
- Gradient Boost Classifier

- Decision Tree Classifier

But first, I'm making a common function to train all the models by that function. Which is mentioned below.

```python
def evaluate_model(model, param_grid, X, y):
    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

    # GridSearchCV for hyperparameter tuning
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5, scoring='accuracy')
    grid_search.fit(X_train, y_train)

    # Training the model with the best parameters
    best_model = grid_search.best_estimator_

    # Predictions
    predictions = best_model.predict(X_test)

    # Best parameters
    best_parameters = grid_search.best_params_
    print("Best Parameters:", best_parameters)

    print("Classification Report:")
    print(classification_report(y_test, predictions))

    # Evaluation
    conf_matrix = confusion_matrix(y_test, predictions)

    # Visualization of Confusion Matrix
    plt.figure(figsize=(6, 4))
    sns.heatmap(pd.DataFrame(conf_matrix), annot=True, cmap="YlGnBu", fmt='g')
    plt.title('Confusion matrix')
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.show()

    return best_model
```

Here, I'm also using a GridSearchCV() function to split the dataset in several part and train on each split to get best model and best parameters which will suitable to improve the accuracy of the model.

And by this function as you can see, I'm printing best parameters, classification report, confusion matrix, and returning the best model.

Evaluation Metrics

```python
def feature_importance(model):
    # Feature importances from Best Random Forest
    importances = model.feature_importances_
    feature_names = X.columns
    feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance': importances})
    print(feature_importance_df.sort_values(by='importance', ascending=False))
```

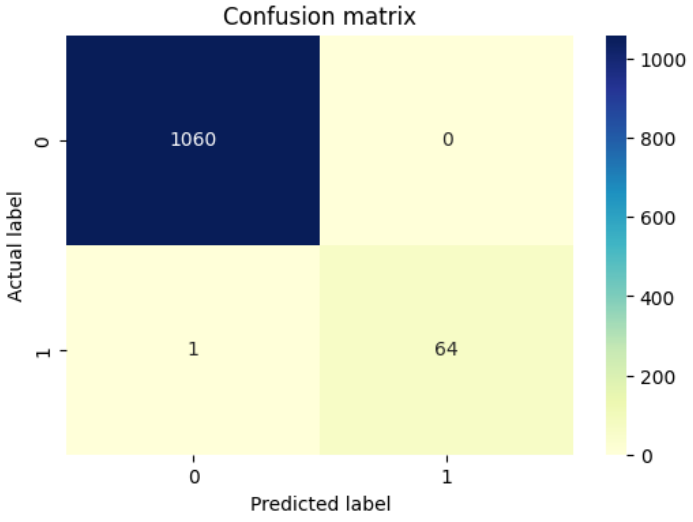
By the upper function, we can see the importance of the features for that specific model to train the model. And by below mentioned function, by checking the accuracy of the train and test, it is overfitting or not.

```python
# Check overfitting
def check_overfitting(model, X_train, y_train, X_test, y_test):
    train_accuracy = model.score(X_train, y_train)
    test_accuracy = model.score(X_test, y_test)
    print(f"Training Accuracy: {train_accuracy:.4f}")
    print(f"Testing Accuracy: {test_accuracy:.4f}")
```

And here is the example that how I'm training the model with some range of parameters, and with the help of functions which I made before. This is the example of the random forest classifier and below this I have mentioned result of this model. Like this I have trained other models and got the results which you can see in the code file.

```python
# Example usage for Random Forest
rf_param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
rf = evaluate_model(RandomForestClassifier(random_state=42), rf_param_grid, X, y)
check_overfitting(rf, X_train, y_train, X_test, y_test)
feature_importance(rf)
```

```
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1060
           1       1.00      0.98      0.99        65

    accuracy                           1.00      1125
   macro avg       1.00      0.99      1.00      1125
weighted avg       1.00      1.00      1.00      1125
```

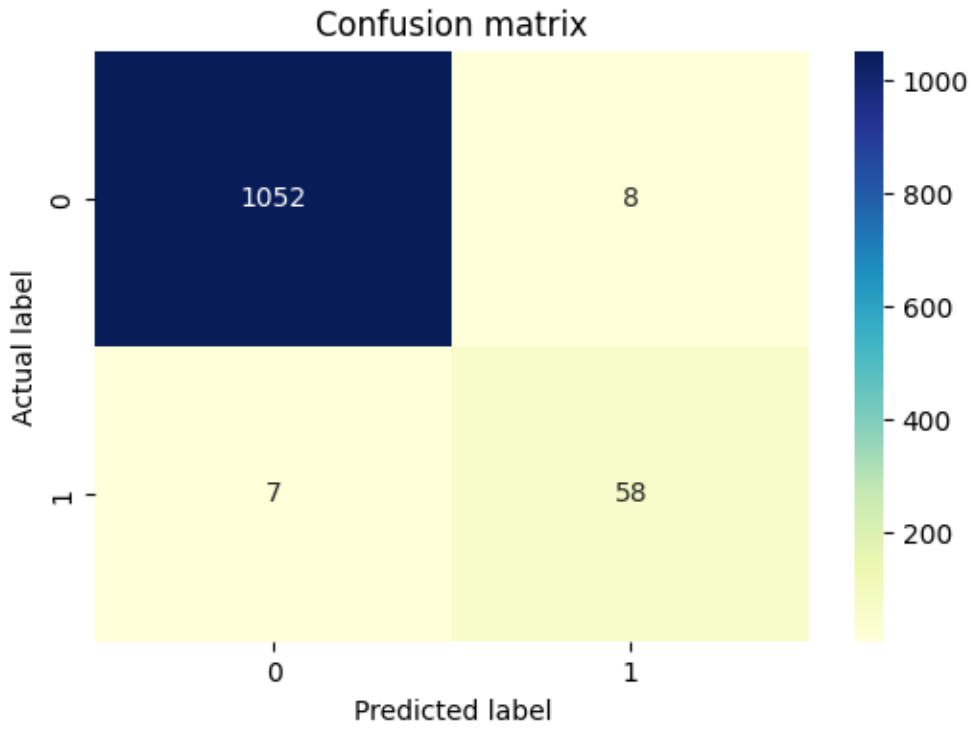



```
Training Accuracy: 1.0000
Testing Accuracy: 0.9991
```

	feature	importance
14	MonthlyCharges_per_Tenure	0.268580
2	Tenure	0.257185
8	MonthlyCharges	0.184816
9	TotalCharges	0.138522
15	TotalCharges_per_Tenure	0.132573
0	Age	0.004617
16	TotalServices	0.002740
7	PaymentMethod	0.002008
6	Contract	0.001818
5	Service_TV	0.001092
12	OnlineSecurity	0.001070
4	Service_Phone	0.000990
10	StreamingMovies	0.000866
1	Gender	0.000838
11	StreamingMusic	0.000727
13	TechSupport	0.000713
3	Service_Internet	0.000515
17	IsSeniorCitizen	0.000330

But in the Logistic Regression, I have noticed that it is giving reliable result.

```
Best Parameters: {'C': 100, 'penalty': 'l1', 'solver': 'liblinear'}
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1060
           1       0.88      0.89      0.89        65

    accuracy                           0.99      1125
   macro avg       0.94      0.94      0.94      1125
weighted avg       0.99      0.99      0.99      1125
```




```
Training Accuracy: 0.9882
Testing Accuracy: 0.9867
```

Discussion

The project revealed several key insights into predicting customer churn:

- **Data Quality:** Handling missing values and outliers is crucial for improving model performance. The chosen methods for imputation and outlier treatment maintained data integrity and variability.

- **Feature Engineering:** Creating new features based on domain knowledge significantly enhanced the models' ability to capture important patterns in the data.

- **Model Performance:** While all models showed some degree of overfitting, cross-validation and hyperparameter tuning helped mitigate this issue but here we are seeing overfitting after using those techniques so, it might be because of the dataset quality. The Random Forest model, in particular, demonstrated a balanced trade-off between bias and variance, making it a top performer.

- **Business Insights:** The findings provide valuable insights into customer behaviour. For instance, features like 'MonthlyCharges_to_Tenure' and 'TotalServices' highlight high-risk customer segments, enabling targeted interventions to reduce churn.

And in this project, I have tried to use many techniques to avoid and fix the overfitting problem. But, it was not fixable. So, as per my consideration and experience, there is no value of model if it is very perfect until you have good data. So, it is also very important to have a good related data structure of our dataset.

Conclusion

In this project, we undertook a comprehensive approach to predict customer churn using various machine learning models. Starting with data preprocessing and EDA, we gained an in-depth understanding of the dataset's characteristics and patterns. Feature engineering allowed us to create additional features that improved model performance.

We implemented and evaluated multiple machine learning models, addressing overfitting through feature selection, cross-validation, and hyperparameter tuning. The Random Forest model emerged as a robust predictor of customer churn, offering a balanced performance.

These findings offer strategic insights into customer behaviour, enabling organizations to implement targeted interventions to reduce churn and enhance customer retention.

Future work could involve expanding the dataset, exploring more advanced machine learning techniques, and incorporating additional features to further improve prediction accuracy.