

```
In [ ]: NAME: MANE SHIVRAJ PANDURANG
        COURSE: CL I
        CLASS: BE AI&DS
```

```
In [ ]: # Data Cleaning and Preparation
        # Problem Statement: Analyzing Customer Churn in a Telecommunications Company
        # Dataset: "Telecom_Customer_Churn.csv"
        # Description: The dataset contains information about customers of a telecommunicat
        # services). The dataset includes various attributes of the customers, such as their
        # account information. The goal is to perform data cleaning and preparation to gain
        # Tasks to Perform:
        # 1. Import the "Telecom_Customer_Churn.csv" dataset.
        # 2. Explore the dataset to understand its structure and content.
        # 3. Handle missing values in the dataset, deciding on an appropriate strategy.
        # 4. Remove any duplicate records from the dataset.
        # 5. Check for inconsistent data, such as inconsistent formatting or spelling varia
        # 6. Convert columns to the correct data types as needed.
        # 7. Identify and handle outliers in the data.
        # 8. Perform feature engineering, creating new features that may be relevant to pre
        # 9. Normalize or scale the data if necessary.
        # 10. Split the dataset into training and testing sets for further analysis.
        # 11. Export the cleaned dataset for future analysis or modeling.
```

```
In [39]: import pandas as pd
        import numpy as np
        from scipy import stats
        from sklearn.preprocessing import MinMaxScaler, StandardScaler
        from sklearn.model_selection import train_test_split
```

```
In [6]: # 1. Import the "Telecom_Customer_Churn.csv" dataset.
        df = pd.read_csv("D:\DMV\dataset's\Telecom_customer_churn.csv")
```

```
In [30]: #2. Explore the dataset to understand its structure and content.
        print('OUTPUT=')
        print(df.head())
        # Get a summary of the dataset
        print(df.info())

        # Check for missing values
        print(df.isnull().sum())
```

OUTPUT=

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	0	Yes	No	1	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	
4	9237-HQITU	Female	0	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	Yes	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	Yes	
4	No	Fiber Optic	No	...	No	

	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	\
0	No	No	No	NaT	Yes	
1	No	No	No	NaT	No	
2	No	No	No	NaT	Yes	
3	Yes	No	No	NaT	No	
4	No	No	No	NaT	Yes	

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Electronic check	29.85	29.85	No
1	Mailed check	56.95	1889.50	No
2	Mailed check	53.85	108.15	Yes
3	Bank transfer (automatic)	42.30	1840.75	No
4	Electronic check	70.70	151.65	Yes

[5 rows x 21 columns]

&lt;class 'pandas.core.frame.DataFrame'&gt;

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	SeniorCitizen	7043 non-null	int64
3	Partner	7043 non-null	object
4	Dependents	7043 non-null	object
5	tenure	7043 non-null	int64
6	PhoneService	7043 non-null	object
7	MultipleLines	7043 non-null	object
8	InternetService	7043 non-null	object
9	OnlineSecurity	7043 non-null	object
10	OnlineBackup	7043 non-null	object
11	DeviceProtection	7043 non-null	object
12	TechSupport	7043 non-null	object
13	StreamingTV	7043 non-null	object
14	StreamingMovies	7043 non-null	object
15	Contract	0 non-null	datetime64[ns]
16	PaperlessBilling	7043 non-null	object
17	PaymentMethod	7043 non-null	object
18	MonthlyCharges	7043 non-null	float64
19	TotalCharges	7043 non-null	float64
20	Churn	7043 non-null	category

```

dtypes: category(1), datetime64[ns](1), float64(2), int64(2), object(15)
memory usage: 1.1+ MB
None
customerID          0
gender              0
SeniorCitizen      0
Partner            0
Dependents         0
tenure             0
PhoneService       0
MultipleLines      0
InternetService    0
OnlineSecurity     0
OnlineBackup       0
DeviceProtection   0
TechSupport        0
StreamingTV        0
StreamingMovies    0
Contract           7043
PaperlessBilling   0
PaymentMethod      0
MonthlyCharges     0
TotalCharges       0
Churn              0
dtype: int64

```

In [29]: *#3. Handle missing values in the dataset, deciding on an appropriate strategy.*

```

print('OUTPUT=')
# Check for missing values
print("Missing values before handling:")
print(df.isnull().sum())

# Fill missing values with the mean for numerical columns only
numeric_cols = df.select_dtypes(include=['number']).columns
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].mean())

# Fill missing values with the mode for categorical columns
for column in df.select_dtypes(include=['object']).columns:
    df[column].fillna(df[column].mode()[0], inplace=True)

# Verify the changes
print("Missing values after handling:")
print(df.isnull().sum())

```

```

OUTPUT=
Missing values before handling:
customerID      0
gender          0
SeniorCitizen   0
Partner         0
Dependents      0
tenure          0
PhoneService    0
MultipleLines   0
InternetService 0
OnlineSecurity  0
OnlineBackup    0
DeviceProtection 0
TechSupport     0
StreamingTV     0
StreamingMovies 0
Contract        7043
PaperlessBilling 0
PaymentMethod   0
MonthlyCharges  0
TotalCharges    11
Churn           0
dtype: int64
Missing values after handling:
customerID      0
gender          0
SeniorCitizen   0
Partner         0
Dependents      0
tenure          0
PhoneService    0
MultipleLines   0
InternetService 0
OnlineSecurity  0
OnlineBackup    0
DeviceProtection 0
TechSupport     0
StreamingTV     0
StreamingMovies 0
Contract        7043
PaperlessBilling 0
PaymentMethod   0
MonthlyCharges  0
TotalCharges    0
Churn           0
dtype: int64

```

```

In [28]: # 4. Remove any duplicate records from the dataset.
# Check for duplicate rows
print('OUTPUT=')
duplicate_rows = df.duplicated()
print(f"Number of duplicate rows: {duplicate_rows.sum()}")

# Remove duplicate rows
df.drop_duplicates(inplace=True)

```

```
# Verify that duplicates have been removed
duplicate_rows = df.duplicated()
print(f"Number of duplicate rows after removal: {duplicate_rows.sum()}")
```

OUTPUT=

Number of duplicate rows: 0

Number of duplicate rows after removal: 0

In [27]: #5. Check for inconsistent data, such as inconsistent formatting or spelling variations

```
print('OUTPUT=')
df['gender'] = df['gender'].str.strip().str.lower().replace({'male': 'Male', 'female': 'Female'})

# Standardize 'InternetService' column
df['InternetService'] = df['InternetService'].str.strip().str.lower().replace({'dsl': 'DSL', 'fiber': 'Fiber Optic'})

# Convert 'TotalCharges' to numeric, handling errors
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# Standardize 'Contract' column if it contains dates
df['Contract'] = pd.to_datetime(df['Contract'], errors='coerce')

# Verify the changes
print(df.head())
```

OUTPUT=

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	0	Yes	No	1	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	
4	9237-HQITU	Female	0	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	Yes	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	Yes	
4	No	Fiber Optic	No	...	No	

	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	\
0	No	No	No	NaT	Yes	
1	No	No	No	NaT	No	
2	No	No	No	NaT	Yes	
3	Yes	No	No	NaT	No	
4	No	No	No	NaT	Yes	

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Electronic check	29.85	29.85	No
1	Mailed check	56.95	1889.50	No
2	Mailed check	53.85	108.15	Yes
3	Bank transfer (automatic)	42.30	1840.75	No
4	Electronic check	70.70	151.65	Yes

[5 rows x 21 columns]

```
In [26]: # 6. Convert columns to the correct data types as needed.
print('OUTPUT=')
print("Data types before conversion:")
print(df.dtypes)

# Convert 'TotalCharges' to numeric, handling errors
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# Convert 'Churn' to a categorical type
df['Churn'] = df['Churn'].astype('category')

# If there are any date columns, convert them to datetime
# Example: df['Contract'] = pd.to_datetime(df['Contract'], errors='coerce')

# Display updated data types
print("Data types after conversion:")
print(df.dtypes)
```

```

OUTPUT=
Data types before conversion:
customerID          object
gender              object
SeniorCitizen       int64
Partner             object
Dependents          object
tenure              int64
PhoneService        object
MultipleLines       object
InternetService     object
OnlineSecurity      object
OnlineBackup        object
DeviceProtection    object
TechSupport         object
StreamingTV         object
StreamingMovies     object
Contract            datetime64[ns]
PaperlessBilling    object
PaymentMethod       object
MonthlyCharges      float64
TotalCharges        float64
Churn               category
dtype: object
Data types after conversion:
customerID          object
gender              object
SeniorCitizen       int64
Partner             object
Dependents          object
tenure              int64
PhoneService        object
MultipleLines       object
InternetService     object
OnlineSecurity      object
OnlineBackup        object
DeviceProtection    object
TechSupport         object
StreamingTV         object
StreamingMovies     object
Contract            datetime64[ns]
PaperlessBilling    object
PaymentMethod       object
MonthlyCharges      float64
TotalCharges        float64
Churn               category
dtype: object

```

```

In [25]: # 7. Identify and handle outliers in the data.

# Select only numeric columns
print('OUTPUT=')
numeric_cols = df.select_dtypes(include=[np.number])

# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = numeric_cols.quantile(0.25)

```

```

Q3 = numeric_cols.quantile(0.75)
IQR = Q3 - Q1

# Identify outliers
outliers = ((numeric_cols < (Q1 - 1.5 * IQR)) | (numeric_cols > (Q3 + 1.5 * IQR))).
print(f"Number of outliers: {outliers.sum()}")

# Handle outliers by removing them
df_cleaned = df[~outliers]
print(f"Number of rows after removing outliers: {df_cleaned.shape[0]}")

# Handle outliers by capping them
df_capped = df.copy()
for col in numeric_cols.columns:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_capped[col] = np.where(df[col] < lower_bound, lower_bound, df[col])
    df_capped[col] = np.where(df[col] > upper_bound, upper_bound, df_capped[col])

# Verify the changes
print(df_cleaned.describe())
print(df_capped.describe())

```

#### OUTPUT

Number of outliers: 1142

Number of rows after removing outliers: 5901

	SeniorCitizen	tenure	Contract	MonthlyCharges	TotalCharges
count	5901.0	5901.000000	0	5901.000000	5890.000000
mean	0.0	32.192171	NaT	61.847441	2181.089550
min	0.0	0.000000	NaT	18.250000	18.800000
25%	0.0	9.000000	NaT	25.600000	365.575000
50%	0.0	28.000000	NaT	65.800000	1295.775000
75%	0.0	55.000000	NaT	86.700000	3566.362500
max	0.0	72.000000	NaT	118.750000	8684.800000
std	0.0	24.628639	NaN	30.316041	2233.217848

  

	SeniorCitizen	tenure	Contract	MonthlyCharges	TotalCharges
count	7043.0	7043.000000	0	7043.000000	7032.000000
mean	0.0	32.371149	NaT	64.761692	2283.300441
min	0.0	0.000000	NaT	18.250000	18.800000
25%	0.0	9.000000	NaT	35.500000	401.450000
50%	0.0	29.000000	NaT	70.350000	1397.475000
75%	0.0	55.000000	NaT	89.850000	3794.737500
max	0.0	72.000000	NaT	118.750000	8684.800000
std	0.0	24.559481	NaN	30.090047	2266.771362

```

In [31]: # 8. Perform feature engineering, creating new features that may be relevant to pre
print('OUTPUT=')
df['TotalServices'] = df[['PhoneService', 'InternetService', 'OnlineSecurity', 'Onl

# Create 'AvgMonthlyCharges' feature
df['AvgMonthlyCharges'] = df['TotalCharges'] / df['tenure']

# Convert 'SeniorCitizen' to categorical

```



```
df['SeniorCitizen'] = df['SeniorCitizen'].map({1: 'Yes', 0: 'No'})

# Create 'TenureGroup' feature
def tenure_group(tenure):
    if tenure <= 12:
        return '0-1 year'
    elif tenure <= 24:
        return '1-2 years'
    elif tenure <= 48:
        return '2-4 years'
    elif tenure <= 60:
        return '4-5 years'
    else:
        return '5+ years'

df['TenureGroup'] = df['tenure'].apply(tenure_group)

# Verify the new features
print(df.head())
```

OUTPUT=

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	1	No	
1	5575-GNVDE	Male	No	No	No	34	Yes	
2	3668-QPYBK	Male	No	No	No	2	Yes	
3	7795-CFOCW	Male	No	No	No	45	No	
4	9237-HQITU	Female	No	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service		DSL	No	...	No
1	No		DSL	Yes	...	No
2	No		DSL	Yes	...	No
3	No phone service		DSL	Yes	...	No
4	No	Fiber Optic		No	...	No

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	29.85	
1	NaT	No	Mailed check	56.95	
2	NaT	Yes	Mailed check	53.85	
3	NaT	No	Bank transfer (automatic)	42.30	
4	NaT	Yes	Electronic check	70.70	

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	29.85	No	NoDSLNoYesNoNoNoNo	29.850000	
1	1889.50	No	YesDSLYesNoYesNoNoNo	55.573529	
2	108.15	Yes	YesDSLYesYesNoNoNoNo	54.075000	
3	1840.75	No	NoDSLYesNoYesYesNoNo	40.905556	
4	151.65	Yes	YesFiber OpticNoNoNoNoNo	75.825000	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

```
In [38]: # 9. Normalize or scale the data if necessary.
print('OUTPUT=')
# Replace infinite values with NaN
df.replace([np.inf, -np.inf], np.nan, inplace=True)

# Fill NaN values in numeric columns with the mean of the column
numeric_cols = df.select_dtypes(include=[np.number])
df[numeric_cols.columns] = numeric_cols.fillna(numeric_cols.mean())

# Min-Max Scaling
min_max_scaler = MinMaxScaler()
df_min_max_scaled = df.copy()
df_min_max_scaled[numeric_cols.columns] = min_max_scaler.fit_transform(numeric_cols)

# Z-Score Scaling
standard_scaler = StandardScaler()
df_standard_scaled = df.copy()
df_standard_scaled[numeric_cols.columns] = standard_scaler.fit_transform(numeric_co
```

```
# Verify the changes
print("Min-Max Scaled Data:")
print(df_min_max_scaled.head())

print("\nZ-Score Scaled Data:")
print(df_standard_scaled.head())
```

OUTPUT=

Min-Max Scaled Data:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	0.013889	No	
1	5575-GNVDE	Male	No	No	No	0.472222	Yes	
2	3668-QPYBK	Male	No	No	No	0.027778	Yes	
3	7795-CFOCW	Male	No	No	No	0.625000	No	
4	9237-HQITU	Female	No	No	No	0.027778	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	0.115423	
1	NaT	No	Mailed check	0.385075	
2	NaT	Yes	Mailed check	0.354229	
3	NaT	No	Bank transfer (automatic)	0.239303	
4	NaT	Yes	Electronic check	0.521891	

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	0.001275	No	NoDSLNoYesNoNoNoNo	0.149361	
1	0.215867	No	YesDSLYesNoYesNoNoNo	0.388372	
2	0.010310	Yes	YesDSLYesYesNoNoNoNo	0.374448	
3	0.210241	No	NoDSLYesNoYesYesNoNo	0.252084	
4	0.015330	Yes	YesFiber OpticNoNoNoNoNo	0.576539	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

Z-Score Scaled Data:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	-1.277445	No	
1	5575-GNVDE	Male	No	No	No	0.066327	Yes	
2	3668-QPYBK	Male	No	No	No	-1.236724	Yes	
3	7795-CFOCW	Male	No	No	No	0.514251	No	
4	9237-HQITU	Female	No	No	No	-1.236724	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	-1.160323	

1	NaT	No	Mailed check	-0.259629
2	NaT	Yes	Mailed check	-0.362660
3	NaT	No	Bank transfer (automatic)	-0.746535
4	NaT	Yes	Electronic check	0.197365

  

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	-0.994971	No	NoDSLNoYesNoNoNoNo	-1.158794	
1	-0.173876	No	YesDSLYesNoYesNoNoNo	-0.305897	
2	-0.960399	Yes	YesDSLYesYesNoNoNoNo	-0.355582	
3	-0.195400	No	NoDSLYesNoYesYesNoNo	-0.792233	
4	-0.941193	Yes	YesFiber OpticNoNoNoNoNo	0.365568	

  

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

```
In [41]: # 10. Split the dataset into training and testing sets for further analysis.
print('OUTPUT=')
# Define features and target variable
X = df.drop('Churn', axis=1) # Features
y = df['Churn'] # Target variable

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Verify the split
print(f"Training set size: {X_train.shape[0]}")
print(f"Testing set size: {X_test.shape[0]}")
```

OUTPUT=

Training set size: 5634

Testing set size: 1409

```
In [47]: # 11. Export the cleaned dataset for future analysis or modeling.
print('OUTPUT=')
print("Dataset loaded successfully.")
print(df.head())

# Remove duplicates
df.drop_duplicates(inplace=True)
print("Duplicates removed.")
print(df.head())

# Replace infinite values with NaN
df.replace([np.inf, -np.inf], np.nan, inplace=True)
print("Infinite values replaced with NaN.")

# Fill NaN values in numeric columns with the mean of the column
numeric_cols = df.select_dtypes(include=[np.number])
df[numeric_cols.columns] = numeric_cols.fillna(numeric_cols.mean())
print("NaN values filled with column mean.")
```

```
print(df.head())

# Min-Max Scaling
min_max_scaler = MinMaxScaler()
df_min_max_scaled = df.copy()
df_min_max_scaled[numeric_cols.columns] = min_max_scaler.fit_transform(numeric_cols)
print("Min-Max Scaling applied.")
print(df_min_max_scaled.head())

# Z-Score Scaling
standard_scaler = StandardScaler()
df_standard_scaled = df.copy()
df_standard_scaled[numeric_cols.columns] = standard_scaler.fit_transform(numeric_cols)
print("Z-Score Scaling applied.")
print(df_standard_scaled.head())

# Define features and target variable
X = df.drop('Churn', axis=1) # Features
y = df['Churn'] # Target variable

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print("Dataset split into training and testing sets.")
print(f"Training set size: {X_train.shape[0]}")
print(f"Testing set size: {X_test.shape[0]}")

# Export the cleaned dataset
df.to_csv('Telecom_Customer_Churn_Cleaned.csv', index=False)
print("Cleaned dataset exported successfully.")
```

OUTPUT=

Dataset loaded successfully.

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	1	No	
1	5575-GNVDE	Male	No	No	No	34	Yes	
2	3668-QPYBK	Male	No	No	No	2	Yes	
3	7795-CFOCW	Male	No	No	No	45	No	
4	9237-HQITU	Female	No	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	29.85	
1	NaT	No	Mailed check	56.95	
2	NaT	Yes	Mailed check	53.85	
3	NaT	No	Bank transfer (automatic)	42.30	
4	NaT	Yes	Electronic check	70.70	

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	29.85	No	NoDSLNoYesNoNoNoNo	29.850000	
1	1889.50	No	YesDSLYesNoYesNoNoNo	55.573529	
2	108.15	Yes	YesDSLYesYesNoNoNoNo	54.075000	
3	1840.75	No	NoDSLYesNoYesYesNoNo	40.905556	
4	151.65	Yes	YesFiber OpticNoNoNoNoNo	75.825000	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

Duplicates removed.

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	1	No	
1	5575-GNVDE	Male	No	No	No	34	Yes	
2	3668-QPYBK	Male	No	No	No	2	Yes	
3	7795-CFOCW	Male	No	No	No	45	No	
4	9237-HQITU	Female	No	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	29.85	
1	NaT	No	Mailed check	56.95	

2	NaT	Yes	Mailed check	53.85
3	NaT	No	Bank transfer (automatic)	42.30
4	NaT	Yes	Electronic check	70.70

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	29.85	No	NoDSLNoYesNoNoNoNo	29.850000	
1	1889.50	No	YesDSLYesNoYesNoNoNo	55.573529	
2	108.15	Yes	YesDSLYesYesNoNoNoNo	54.075000	
3	1840.75	No	NoDSLYesNoYesYesNoNo	40.905556	
4	151.65	Yes	YesFiber OpticNoNoNoNoNoNo	75.825000	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

Infinite values replaced with NaN.

NaN values filled with column mean.

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	1	No	
1	5575-GNVDE	Male	No	No	No	34	Yes	
2	3668-QPYBK	Male	No	No	No	2	Yes	
3	7795-CFOCW	Male	No	No	No	45	No	
4	9237-HQITU	Female	No	No	No	2	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	29.85	
1	NaT	No	Mailed check	56.95	
2	NaT	Yes	Mailed check	53.85	
3	NaT	No	Bank transfer (automatic)	42.30	
4	NaT	Yes	Electronic check	70.70	

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	29.85	No	NoDSLNoYesNoNoNoNo	29.850000	
1	1889.50	No	YesDSLYesNoYesNoNoNo	55.573529	
2	108.15	Yes	YesDSLYesYesNoNoNoNo	54.075000	
3	1840.75	No	NoDSLYesNoYesYesNoNo	40.905556	
4	151.65	Yes	YesFiber OpticNoNoNoNoNoNo	75.825000	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year



[5 rows x 24 columns]

Min-Max Scaling applied.

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	0.013889	No	
1	5575-GNVDE	Male	No	No	No	0.472222	Yes	
2	3668-QPYBK	Male	No	No	No	0.027778	Yes	
3	7795-CFOCW	Male	No	No	No	0.625000	No	
4	9237-HQITU	Female	No	No	No	0.027778	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	0.115423	
1	NaT	No	Mailed check	0.385075	
2	NaT	Yes	Mailed check	0.354229	
3	NaT	No	Bank transfer (automatic)	0.239303	
4	NaT	Yes	Electronic check	0.521891	

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	0.001275	No	NoDSLNoYesNoNoNoNo	0.149361	
1	0.215867	No	YesDSLYesNoYesNoNoNo	0.388372	
2	0.010310	Yes	YesDSLYesYesNoNoNoNo	0.374448	
3	0.210241	No	NoDSLYesNoYesYesNoNo	0.252084	
4	0.015330	Yes	YesFiber OpticNoNoNoNoNo	0.576539	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

Z-Score Scaling applied.

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	7590-VHVEG	Female	No	Yes	No	-1.277445	No	
1	5575-GNVDE	Male	No	No	No	0.066327	Yes	
2	3668-QPYBK	Male	No	No	No	-1.236724	Yes	
3	7795-CFOCW	Male	No	No	No	0.514251	No	
4	9237-HQITU	Female	No	No	No	-1.236724	Yes	

	MultipleLines	InternetService	OnlineSecurity	...	StreamingMovies	\
0	No phone service	DSL	No	...	No	
1	No	DSL	Yes	...	No	
2	No	DSL	Yes	...	No	
3	No phone service	DSL	Yes	...	No	
4	No	Fiber Optic	No	...	No	

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
0	NaT	Yes	Electronic check	-1.160323	
1	NaT	No	Mailed check	-0.259629	

2	NaT	Yes	Mailed check	-0.362660
3	NaT	No	Bank transfer (automatic)	-0.746535
4	NaT	Yes	Electronic check	0.197365

	TotalCharges	Churn	TotalServices	AvgMonthlyCharges	\
0	-0.994971	No	NoDSLNoYesNoNoNoNo	-1.158794	
1	-0.173876	No	YesDSLYesNoYesNoNoNo	-0.305897	
2	-0.960399	Yes	YesDSLYesYesNoNoNoNo	-0.355582	
3	-0.195400	No	NoDSLYesNoYesYesNoNo	-0.792233	
4	-0.941193	Yes	YesFiber OpticNoNoNoNoNo	0.365568	

	TenureGroup
0	0-1 year
1	2-4 years
2	0-1 year
3	2-4 years
4	0-1 year

[5 rows x 24 columns]

Dataset split into training and testing sets.

Training set size: 5634

Testing set size: 1409

Cleaned dataset exported successfully.