**Task 4**: Churn Prediction Model Description: Choose suitable machine learning algorithms (e.g., logistic regression, decision trees) for churn prediction. Split data into training and testing sets, train and evaluate multiple models using metrics like accuracy, precision, recall, and F1-score. Perform feature selection and hyperparameter tuning for optimal performance.

Skills: Machine learning algorithms

Model training and evaluation,

Feature selection, hyperparameter tuning

Understanding of classification metrics.

```
In [142...
          import pandas as pd
           import numpy as np
           from sklearn.model_selection import train_test_split, GridSearchCV
           from sklearn.preprocessing import StandardScaler, LabelEncoder
           from sklearn.impute import SimpleImputer
           from sklearn.ensemble import RandomForestClassifier
           from sklearn.linear model import LogisticRegression
           from sklearn.tree import DecisionTreeClassifier
           from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
In [143...
          df=pd.read csv('C://Users//ALWAYSRAMESH//Downloads//Telco Customer Churn Dataset
In [144...
          df.head()
Out[144...
              customerID
                         gender SeniorCitizen Partner Dependents tenure PhoneService Multipl
                   7590-
                                                                                              No
           0
                          Female
                                             0
                                                    Yes
                                                                No
                                                                          1
                                                                                      No
                  VHVEG
                   5575-
                            Male
                                             0
                                                    No
                                                                No
                                                                         34
                                                                                      Yes
                  GNVDE
                   3668-
           2
                                             0
                                                                          2
                            Male
                                                    No
                                                                No
                                                                                      Yes
                  QPYBK
                   7795-
                                                                                              No
           3
                                             0
                                                    No
                                                                No
                                                                        45
                                                                                      No
                            Male
                  CFOCW
                   9237-
                          Female
                                             0
                                                    No
                                                                No
                                                                          2
                                                                                      Yes
           4
                   HOITU
          5 rows × 21 columns
```

```
In [145...
          # Replace missing values with mode (categorical) or mean (numerical)
          imputer = SimpleImputer(strategy='most_frequent')
          df.fillna(df.mode().iloc[0], inplace=True)
In [146...
          label enc = LabelEncoder()
          # Apply Label Encoding to categorical columns
          for col in df.select_dtypes(include=['object']).columns:
              df[col] = label enc.fit transform(df[col])
          # Define Features and Target
In [147...
          X = df.drop(columns=['Churn']) # Assuming 'Churn' is the target column
          y = df['Churn']
In [148...
          # Train-Test Split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
          # Standardization
In [149...
          scaler = StandardScaler()
          X_train = scaler.fit_transform(X_train)
          X_test = scaler.transform(X_test)
          # Define models
In [150...
          models = {
              "Logistic Regression": LogisticRegression(),
              "Decision Tree": DecisionTreeClassifier(),
              "Random Forest": RandomForestClassifier()
In [151...
          # Train & Evaluate Models
          for name, model in models.items():
              model.fit(X train, y train)
              y_pred = model.predict(X_test)
          # Evaluate Model
In [152...
          print(f"\n{name} Performance:")
          print("Accuracy:", accuracy_score(y_test, y_pred))
          print("Precision:", precision_score(y_test, y_pred))
          print("Recall:", recall_score(y_test, y_pred))
          print("F1 Score:", f1_score(y_test, y_pred))
          print(classification_report(y_test, y_pred))
```

```
Random Forest Performance:
         Accuracy: 0.7927608232789212
         Precision: 0.6423611111111112
         Recall: 0.4946524064171123
         F1 Score: 0.5589123867069486
                      precision recall f1-score support
                           0.83
                   0
                                     0.90
                                               0.86
                                                         1035
                   1
                           0.64
                                     0.49
                                               0.56
                                                         374
                                               0.79
                                                         1409
            accuracy
                          0.74
                                     0.70
                                               0.71
                                                         1409
           macro avg
         weighted avg
                           0.78
                                     0.79
                                               0.78
                                                         1409
In [153...
          # Hyperparameter Grid
          param_grid = {
              'n_estimators': [50, 100, 200],
              'max_depth': [5, 10, None],
              'min_samples_split': [2, 5, 10]
          # Grid Search CV
In [154...
          grid_search = GridSearchCV(RandomForestClassifier(), param_grid, cv=5, scoring='acc
          grid_search.fit(X_train, y_train)
Out[154...
                         GridSearchCV
           ▶ best_estimator_: RandomForestClassifier
                   RandomForestClassifier
In [155...
         # Best Parameters
          print("\nBest Parameters for Random Forest:", grid_search.best_params_)
         Best Parameters for Random Forest: {'max_depth': None, 'min_samples_split': 10, 'n_e
         stimators': 200}
In [156... # Best Model Performance
          best model = grid search.best estimator
          y_pred_best = best_model.predict(X_test)
In [157...
          print("\nOptimized Model Performance:")
          print("Accuracy:", accuracy_score(y_test, y_pred_best))
          print("Precision:", precision_score(y_test, y_pred_best))
          print("Recall:", recall_score(y_test, y_pred_best))
          print("F1 Score:", f1_score(y_test, y_pred_best))
         Optimized Model Performance:
         Accuracy: 0.7970191625266146
         Precision: 0.6571428571428571
         Recall: 0.4919786096256685
         F1 Score: 0.5626911314984709
```

In [ ]: