CS6220: Data Mining Techniques

Fall 2024: Final Project

Aloe Vera Team

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Notebook and Data Setup

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import model_selection, neural_network
import seaborn as sns
import random
import time
```

In [ ]:
```
path = "https://drive.google.com/uc?id=1emwgCjecANSlXqHuVEaTph02ob9M6_Wm"
```

In [ ]:
```
oridf = pd.read_csv(path)
```

In [ ]:
```
display(oridf.shape)
display(oridf.head())
display(oridf.tail(1))
```

```
(30204, 25)
```

	MyUnknownColumn	X1	X2	X3	X4	X5	X6	X7
0	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2
1	1	20000	female	university	1	24	2	2
2	2	120000	female	university	2	26	-1	2
3	3	90000	female	university	2	34	0	0
4	4	50000	female	university	1	37	0	0

5 rows × 25 columns

	MyUnknownColumn	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X
30203	30000	50000	male	university	1	46	0	0	0	0	...	365

1 rows × 25 columns

In [ ]:
```python
# Drop the redundant column header
oridf.columns = oridf.loc[0]
oridf = oridf.drop(index=0)
oridf = oridf.set_index("ID")
display(oridf.head())
```

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PA
ID										
1	20000	female	university	1	24	2	2	-1	-1	
2	120000	female	university	2	26	-1	2	0	0	
3	90000	female	university	2	34	0	0	0	0	
4	50000	female	university	1	37	0	0	0	0	
5	50000	male	university	1	57	-1	0	-1	0	

5 rows × 24 columns

In [ ]:
```python
#Troubleshoting a bad row
oridf[oridf["LIMIT_BAL"]== "X1"]
```

Out[ ]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4
ID									
NaN	X1	X2	X3	X4	X5	X6	X7	X8	X9

1 rows × 24 columns

In [ ]:
```python
#Troubleshoting another bad row
oridf[oridf["LIMIT_BAL"]== "LIMIT_BAL"]
```

Out[ ]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PA
ID										
ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PA

1 rows × 24 columns

In [ ]:
```
oridf = oridf.drop(index = "ID")
oridf = oridf.drop(index = np.nan)
```

In [ ]:
```
oridf
```

Out[ ]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY
ID									
1	20000	female	university	1	24	2	2	-1	
2	120000	female	university	2	26	-1	2	0	
3	90000	female	university	2	34	0	0	0	
4	50000	female	university	1	37	0	0	0	
5	50000	male	university	1	57	-1	0	-1	
...	...	...	...	...	...	...	...	...	
29996	220000	male	high school	1	39	0	0	0	
29997	150000	male	high school	2	43	-1	-1	-1	
29998	30000	male	university	2	37	4	3	2	
29999	80000	male	high school	1	41	1	-1	0	
30000	50000	male	university	1	46	0	0	0	

30201 rows × 24 columns

Clean the data

In [ ]:
```
# Check for Missing Values
oridf.isna().sum()
```

Out[ ]:

	0
0	
LIMIT_BAL	0
SEX	0
EDUCATION	0
MARRIAGE	0
AGE	0
PAY_0	0
PAY_2	0
PAY_3	0
PAY_4	0
PAY_5	0
PAY_6	0
BILL_AMT1	0
BILL_AMT2	0
BILL_AMT3	0
BILL_AMT4	0
BILL_AMT5	0
BILL_AMT6	0
PAY_AMT1	0
PAY_AMT2	0
PAY_AMT3	0
PAY_AMT4	0
PAY_AMT5	0
PAY_AMT6	0
default payment next month	0

dtype: int64

In [ ]:
```
# Check for duplicate Values:
oridf.duplicated().sum()
```

Out[ ]: 236

In [ ]:
```
# Check for duplicate rows:
oridf[oridf.duplicated(keep=False)].drop_duplicates().shape
```

Out[ ]: (235, 24)

In [ ]:
```
# Remove duplicate rows:
oridf = oridf.drop_duplicates()
```

In [ ]:
```
oridf
```

Out[ ]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY
ID									
1	20000	female	university	1	24	2	2	-1	
2	120000	female	university	2	26	-1	2	0	
3	90000	female	university	2	34	0	0	0	
4	50000	female	university	1	37	0	0	0	
5	50000	male	university	1	57	-1	0	-1	
...	...	...	...	...	...	...	...	...	
29996	220000	male	high school	1	39	0	0	0	
29997	150000	male	high school	2	43	-1	-1	-1	
29998	30000	male	university	2	37	4	3	2	
29999	80000	male	high school	1	41	1	-1	0	
30000	50000	male	university	1	46	0	0	0	

29965 rows × 24 columns

Checking the dtypes

In [ ]:
```
oridf.dtypes
```

Out[ ]:

	0
0	
LIMIT_BAL	object
SEX	object
EDUCATION	object
MARRIAGE	object
AGE	object
PAY_0	object
PAY_2	object
PAY_3	object
PAY_4	object
PAY_5	object
PAY_6	object
BILL_AMT1	object
BILL_AMT2	object
BILL_AMT3	object
BILL_AMT4	object
BILL_AMT5	object
BILL_AMT6	object
PAY_AMT1	object
PAY_AMT2	object
PAY_AMT3	object
PAY_AMT4	object
PAY_AMT5	object
PAY_AMT6	object
default payment next month	object

dtype: object

dividing the dataframe into a string version and a numeric version

In [ ]:
```
# Drop non-numeric columns
```

```
numericdf = oridf.drop(columns=["SEX", "EDUCATION", "default payment next mo
```

In [ ]:
```
numericdf
```

Out[ ]:

ID	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	B
1	20000	1	24	2	2	-1	-1	-2	-2	
2	120000	2	26	-1	2	0	0	0	2	
3	90000	2	34	0	0	0	0	0	0	
4	50000	1	37	0	0	0	0	0	0	
5	50000	1	57	-1	0	-1	0	0	0	
...	...	...	...	...	...	...	...	...	...	
29996	220000	1	39	0	0	0	0	0	0	
29997	150000	2	43	-1	-1	-1	-1	0	0	
29998	30000	2	37	4	3	2	-1	0	0	
29999	80000	1	41	1	-1	0	0	0	-1	
30000	50000	1	46	0	0	0	0	0	0	

29965 rows × 21 columns

In [ ]:
```
numericdf = numericdf.astype(int)
```

In [ ]:
```
# Extract string columns
stringdf = oridf[["SEX", "EDUCATION", "default payment next month"]]
```

In [ ]:
```
stringdf.head()
```

Out[ ]:

ID	SEX	EDUCATION	default payment next month
1	female	university	default
2	female	university	default
3	female	university	not default
4	female	university	not default
5	male	university	not default

In [ ]:
```
numericdf.dtypes
```

Out[ ]:

	0
0	
LIMIT_BAL	int64
MARRIAGE	int64
AGE	int64
PAY_0	int64
PAY_2	int64
PAY_3	int64
PAY_4	int64
PAY_5	int64
PAY_6	int64
BILL_AMT1	int64
BILL_AMT2	int64
BILL_AMT3	int64
BILL_AMT4	int64
BILL_AMT5	int64
BILL_AMT6	int64
PAY_AMT1	int64
PAY_AMT2	int64
PAY_AMT3	int64
PAY_AMT4	int64
PAY_AMT5	int64
PAY_AMT6	int64

dtype: object

In [ ]:
```
tempdf = pd.concat([stringdf, numericdf], axis="columns")
```

In [ ]:
```
# this df has a duplicate in it
tempdf
```

Out[ ]:

ID	SEX	EDUCATION	default payment next month	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	P
1	female	university	default	20000	1	24	2	2	
2	female	university	default	120000	2	26	-1	2	
3	female	university	not default	90000	2	34	0	0	
4	female	university	not default	50000	1	37	0	0	
5	male	university	not default	50000	1	57	-1	0	
...	...	...	...	...	...	...	...	...	
29996	male	high school	not default	220000	1	39	0	0	
29997	male	high school	not default	150000	2	43	-1	-1	
29998	male	university	default	30000	2	37	4	3	
29999	male	high school	default	80000	1	41	1	-1	
30000	male	university	default	50000	1	46	0	0	

29965 rows × 24 columns

In [ ]:

```
tempdf.dtypes
```

Out[ ]:

	0
0	
SEX	object
EDUCATION	object
default payment next month	object
LIMIT_BAL	int64
MARRIAGE	int64
AGE	int64
PAY_0	int64
PAY_2	int64
PAY_3	int64
PAY_4	int64
PAY_5	int64
PAY_6	int64
BILL_AMT1	int64
BILL_AMT2	int64
BILL_AMT3	int64
BILL_AMT4	int64
BILL_AMT5	int64
BILL_AMT6	int64
PAY_AMT1	int64
PAY_AMT2	int64
PAY_AMT3	int64
PAY_AMT4	int64
PAY_AMT5	int64
PAY_AMT6	int64

dtype: object

In [ ]:
```
cleaned_df = tempdf.copy()
# savepoint 1 - AS using for savepoint 1
```

Savepoint for decision tree - so other code doesn't break

In [ ]:
```
savepoint1 = cleaned_df.copy()
```

In [ ]:
```
# Convert object columns to categorical type for efficiency and clarity
tempdf["SEX"] = tempdf["SEX"].astype("category")
tempdf["EDUCATION"] = tempdf["EDUCATION"].astype("category")
tempdf["default payment next month"] = tempdf["default payment next month"].
```

In [ ]:
```
tempdf.dtypes
```

Out[ ]:

	0
0	
SEX	category
EDUCATION	category
default payment next month	category
LIMIT_BAL	int64
MARRIAGE	int64
AGE	int64
PAY_0	int64
PAY_2	int64
PAY_3	int64
PAY_4	int64
PAY_5	int64
PAY_6	int64
BILL_AMT1	int64
BILL_AMT2	int64
BILL_AMT3	int64
BILL_AMT4	int64
BILL_AMT5	int64
BILL_AMT6	int64
PAY_AMT1	int64
PAY_AMT2	int64
PAY_AMT3	int64
PAY_AMT4	int64
PAY_AMT5	int64
PAY_AMT6	int64

dtype: object

In [ ]:
```
print(tempdf["SEX"].unique())
print("\n")
print(tempdf["EDUCATION"].unique())
print("\n")
print(tempdf["default payment next month"].unique())
```

```
['female', 'male']
Categories (2, object): ['female', 'male']


['university', 'graduate school', 'high school', 'other']
Categories (4, object): ['graduate school', 'high school', 'other', 'univers
ity']


['default', 'not default']
Categories (2, object): ['default', 'not default']
```

In [ ]:
```
# Convert 'default payment next month' to binary values: 1 for 'default' and
tempdf["default payment next month"] = tempdf["default payment next month"].

# Verify the conversion
print(tempdf["default payment next month"].unique())
```

```
[1, 0]
Categories (2, int64): [1, 0]
```

In [ ]:
```
tempdf["default payment next month"].value_counts()
```

Out[ ]:

	count
default payment next month	
0	23335
1	6630

dtype: int64

In [ ]:
```
cleandf = tempdf.copy()
```

SAVEPOINT 1

This is one of the cleaned versions

In [ ]:
```
savepoint1
```

Out[ ]:

ID	SEX	EDUCATION	default payment next month	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	P
1	female	university	default	20000	1	24	2	2	
2	female	university	default	120000	2	26	-1	2	
3	female	university	not default	90000	2	34	0	0	
4	female	university	not default	50000	1	37	0	0	
5	male	university	not default	50000	1	57	-1	0	
...	...	...	...	...	...	...	...	...	
29996	male	high school	not default	220000	1	39	0	0	
29997	male	high school	not default	150000	2	43	-1	-1	
29998	male	university	default	30000	2	37	4	3	
29999	male	high school	default	80000	1	41	1	-1	
30000	male	university	default	50000	1	46	0	0	

29965 rows × 24 columns

Data Analysis

In [ ]:

```
sex = cleaned_df["SEX"].value_counts()
sex
```

Out[ ]:

SEX	count
female	18091
male	11874

dtype: int64

In [ ]:

```
education = cleaned_df["EDUCATION"].value_counts()
education
```

Out[ ]:

EDUCATION	count
university	14019
graduate school	10563
high school	4915
other	468

dtype: int64

In [ ]:
```
marriage = cleaned_df["MARRIAGE"].value_counts()
marriage
```

Out[ ]:

MARRIAGE	count
2	15945
1	13643
3	323
0	54

dtype: int64

In [ ]:
```
def get_color(df):
    lst = []
    string = "123456789ABCDEF"
    for i in range(len(df)):
        temp = random.choices(string, k = 6)
        temp = "".join(temp)
        temp = "#" + temp
        lst.append(temp)
    # print(temp)
    return lst
```

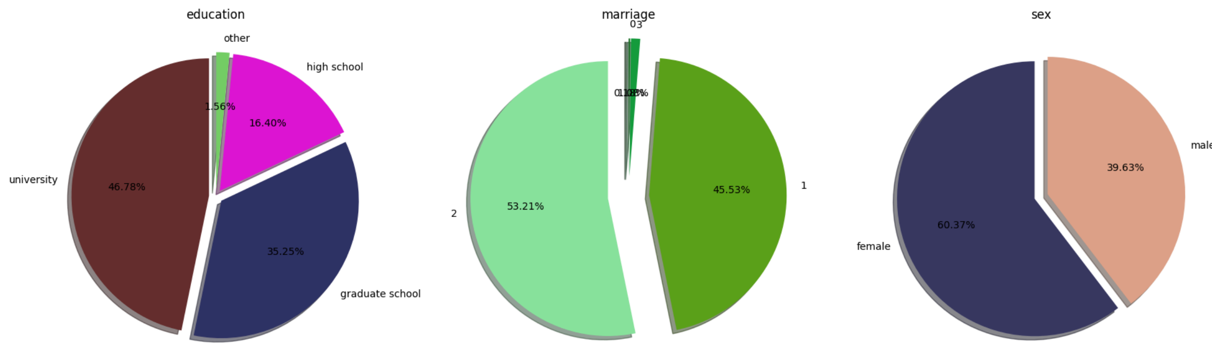
In [ ]:
```
get_color(education)
```

Out[ ]:
```
['#C6F91F', '#428C92', '#BA9383', '#831C76']
```

In [ ]:
```
fig,axs = plt.subplots(1,3, figsize = (21,7))
education.plot(kind='pie', ax=axs[0], label = "", title="education",
               explode = [0.05,0.05,0.05,0.05], shadow = True,
               startangle = 90, autopct = "%.2f%%", colors=get_color(educati

# marriage.plot(kind='pie', ax=axs[1])
marriage.plot(kind='pie', ax=axs[1], label = "", title="marriage",
               explode = [0.15,0.15,0.15,0.15], shadow = True,
```

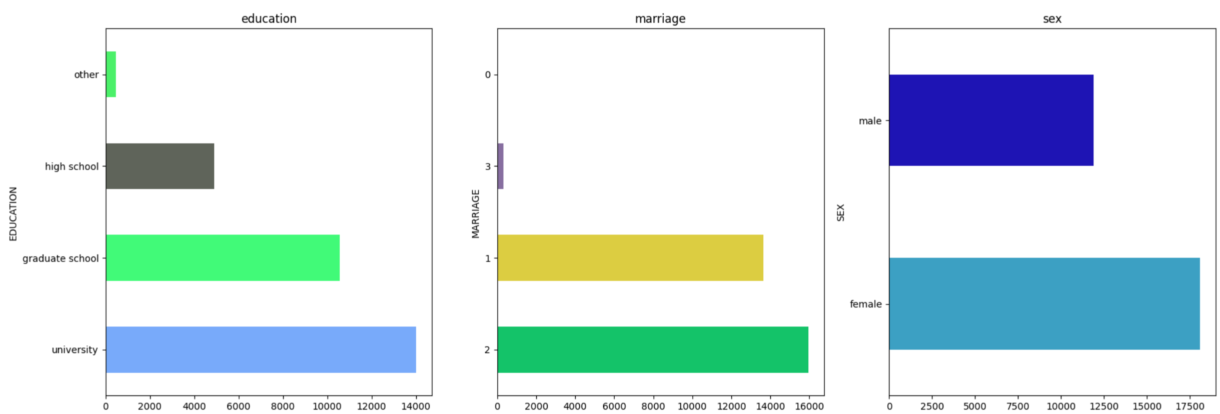
```
                 startangle = 90, autopct = "%.2f%%", colors=get_color(marriag

# sex.plot(kind='pie', ax=axs[2])
sex.plot(kind='pie', ax=axs[2], label = "", title="sex",
                 explode = [0.05,0.05], shadow = True,
                 startangle = 90, autopct = "%.2f%%", colors=get_color(sex))
```

Out[ ]: <Axes: title={'center': 'sex'}>



In [ ]:
```
fig,axs = plt.subplots(1,3, figsize = (21,7))
education.plot(kind='barh', ax=axs[0], label = "", title="education", color=
marriage.plot(kind='barh', ax=axs[1], label = "", title="marriage", color=ge
sex.plot(kind='barh', ax=axs[2], label = "", title="sex", color=get_color(se
```

Out[ ]: <Axes: title={'center': 'sex'}, ylabel='SEX'>



Model building

In [ ]:
```
# Import libraries
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

from imblearn.over_sampling import SMOTE
```

In [ ]:
```
# ---- Data Preparation ----

# 1. Create a copy of the dataset for processing
cleandf = tempdf.copy()

# 2. Separate features (X) and target (y)
X = cleandf.drop(columns=["default payment next month"])
y = cleandf["default payment next month"]

# 3. Perform One-hot encoding on categorical variables ('SEX' and 'EDUCATION
#    This converts categorical variables into binary columns
X = pd.get_dummies(X, columns=["SEX", "EDUCATION"], drop_first=True)

# 4. Scale numeric features using StandardScaler
#    Scaling ensures all features are on a similar scale, necessary for mode
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 5. Split the data into training and testing sets (70% train, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0


# 6. Apply SMOTE to the training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

Cross Validation

In [ ]:
```
class CrossValidation:
    @staticmethod
    def run_cross_validation(model_class, X, y, splits, model_params=None):
        '''
        Perform cross-validation on the given model and dataset.

        Parameters:
        - model_class: The class or callable to instantiate a new model (e.g
        - X: Feature set (DataFrame, Series, or array-like).
        - y: Target labels (Series or array-like).
        - splits: Number of folds for K-Fold cross-validation.
        - model_params: Dictionary of parameters to initialize the model (op

        Returns:
        - Lists of accuracy, precision, recall, and F1 scores for each fold.
        '''
        # Initialize KFold with shuffling
        kf = KFold(n_splits=splits, shuffle=True, random_state=42)

        # Initialize lists to store results
        accuracy_scores = []
        precision_scores = []
        recall_scores = []
        f1_scores = []
        confusion_matrices = []
```

```
        # Perform cross-validation
        for train_index, test_index in kf.split(X):
            # Use .iloc if X and y are pandas objects; otherwise, index dire
            if isinstance(X, pd.DataFrame) or isinstance(X, pd.Series):
                X_train, X_test = X.iloc[train_index], X.iloc[test_index]
            else:
                X_train, X_test = X[train_index], X[test_index]

            # Always use .iloc for y when it's a pandas Series
            if isinstance(y, pd.Series):
                y_train, y_test = y.iloc[train_index], y.iloc[test_index]
            else:
                y_train, y_test = y[train_index], y[test_index]


            # Create a new instance of the model for this fold
            model = model_class(**(model_params if model_params else {}))

            # Train the model
            model.fit(X_train, y_train)

            # Predict and evaluate
            y_pred = model.predict(X_test)

            # Compute metrics
            accuracy_scores.append(accuracy_score(y_test, y_pred))
            precision_scores.append(precision_score(y_test, y_pred))
            recall_scores.append(recall_score(y_test, y_pred))
            f1_scores.append(f1_score(y_test, y_pred))
            confusion_matrices.append(confusion_matrix(y_test, y_pred))

        return accuracy_scores, precision_scores, recall_scores, f1_scores,


    @staticmethod
    def calculate_scores(accuracy_scores, precision_scores, recall_scores, f
        '''
        Calculate and display average and standard deviation of scores.
        '''
        # Calculate averages and standard deviations
        avg_accuracy = np.mean(accuracy_scores)
        std_accuracy = np.std(accuracy_scores)

        avg_precision = np.mean(precision_scores)
        std_precision = np.std(precision_scores)

        avg_recall = np.mean(recall_scores)
        std_recall = np.std(recall_scores)

        avg_f1 = np.mean(f1_scores)
        std_f1 = np.std(f1_scores)

        # print(f"Accuracy -> Avg: {avg_accuracy:.4f}, Std Dev: {std_accurac
        # print(f"Precision -> Avg: {avg_precision:.4f}, Std Dev: {std_preci
        # print(f"Recall -> Avg: {avg_recall:.4f}, Std Dev: {std_recall:.4f}
        # print(f"F1 -> Avg: {avg_f1:.4f}, Std Dev: {std_f1:.4f}")
```

```
        return avg_accuracy, avg_precision, avg_recall, avg_f1
```

Logistic Regression

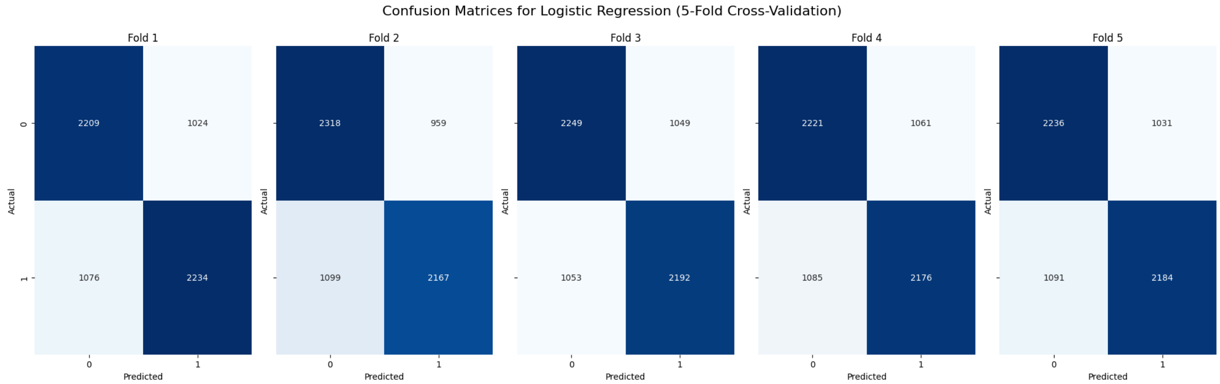
eror in below cell :ValueError: pos_label=1 is not a valid label. It should be one of ['default', 'not default']

In [ ]:
```
# Parameters for Logistic Regression
log_reg_params = {'class_weight': 'balanced', 'random_state': 42}

# Instantiate the CrossValidation class and run cross-validation
cv = CrossValidation()

# Run 5-fold cross-validation
log_reg_accuracy_scores, log_reg_precision_scores, log_reg_recall_scores, lo
    model_class=LogisticRegression,  # Pass the model class
    X=X_train_resampled,                        # Use the preprocessed traini
    y=y_train_resampled,                        # Use the corresponding trair
    splits=5,                         # Number of folds
    model_params=log_reg_params       # Parameters for Logistic Regression
)

# Calculate and display the average scores
log_reg_avg_accuracy, log_reg_avg_precision, log_reg_avg_recall, log_reg_avg
    log_reg_accuracy_scores, log_reg_precision_scores, log_reg_recall_scores
)

# Print a summary of the results
print("Cross-Validation Results for Logistic Regression:")
print(f"Average Accuracy:  {log_reg_avg_accuracy:.4f}")
print(f"Average Precision: {log_reg_avg_precision:.4f}")
print(f"Average Recall:    {log_reg_avg_recall:.4f}")
print(f"Average F1-Score:  {log_reg_avg_f1:.4f}")
```

```
Cross-Validation Results for Logistic Regression:
Average Accuracy:  0.6782
Average Precision: 0.6814
Average Recall:    0.6696
Average F1-Score:  0.6754
```

In [ ]:
```
# Create subplots
fig, axes = plt.subplots(1, len(log_reg_confusion_matrices), figsize=(20, 6)

# Plot each confusion matrix
for i, ax in enumerate(axes):
    sns.heatmap(log_reg_confusion_matrices[i], annot=True, fmt="d", cmap="Bl
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
```

```
plt.suptitle("Confusion Matrices for Logistic Regression (5-Fold Cross-Valic
plt.show()
```



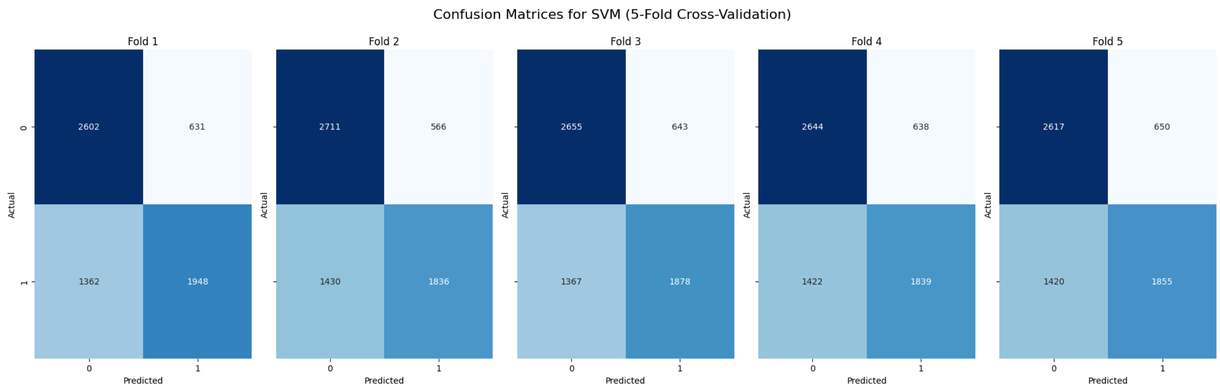
Support Vector Machine (SVM)

In [ ]:
```
# Parameters for SVM
svm_params = {'kernel': 'linear', 'class_weight': 'balanced', 'random_state'


# Instantiate the CrossValidation class and run cross-validation
cv = CrossValidation()

# Run 5-fold cross-validation
svm_accuracy_scores, svm_precision_scores, svm_recall_scores, svm_f1_scores,
    model_class=SVC,            # Pass the SVM class
    X=X_train_resampled,                  # Use the preprocessed training da
    y=y_train_resampled,                  # Use the corresponding training l
    splits=5,                   # Number of folds
    model_params=svm_params     # Parameters for SVM
)

# Calculate and display the average scores
svm_avg_accuracy, svm_avg_precision, svm_avg_recall, svm_avg_f1 = cv.calcula
    svm_accuracy_scores, svm_precision_scores, svm_recall_scores, svm_f1_scc
)

# Print a summary of the results
print("Cross-Validation Results for SVM:")
print(f"Average Accuracy:  {svm_avg_accuracy:.4f}")
print(f"Average Precision: {svm_avg_precision:.4f}")
print(f"Average Recall:    {svm_avg_recall:.4f}")
print(f"Average F1-Score:  {svm_avg_f1:.4f}")
```

```
Cross-Validation Results for SVM:
Average Accuracy:  0.6904
Average Precision: 0.7495
Average Recall:    0.5720
Average F1-Score:  0.6487
```

In [ ]:
```
# Create subplots for SVM confusion matrices
fig, axes = plt.subplots(1, len(svm_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for SVM
```

```
for i, ax in enumerate(axes):
    sns.heatmap(svm_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for SVM (5-Fold Cross-Validation)", y=1.05,
plt.show()
```



Artificial Neural Network (ANN)

Single Layer: (100,)

In [ ]:

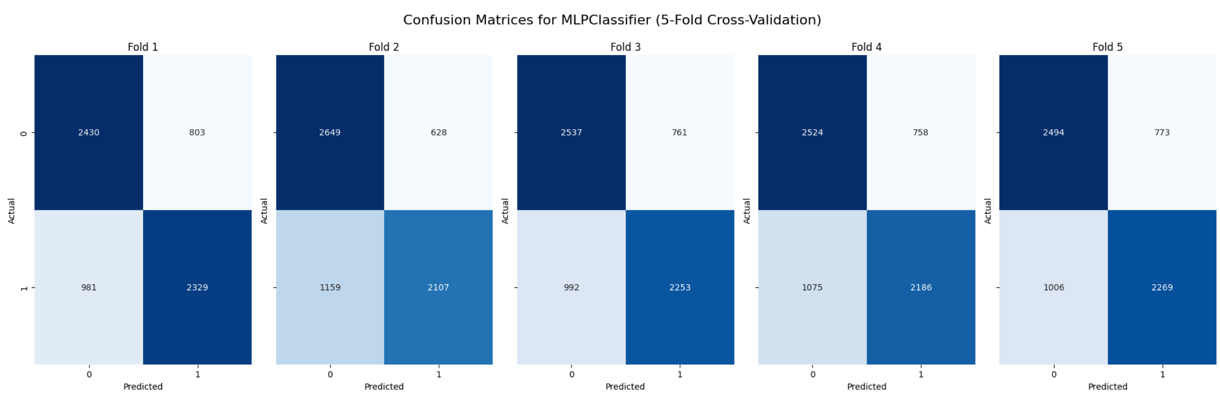
```
from sklearn.neural_network import MLPClassifier

# ---- Cross-Validation for MLPClassifier ----

# Parameters for MLPClassifier
mlp_params = {
    'hidden_layer_sizes': (100,),  # Single hidden layer with 100 neurons
    'activation': 'relu',          # Activation function
    'solver': 'adam',              # Optimizer
    'random_state': 42,            # For reproducibility
    'max_iter': 200,               # Maximum number of iterations
    'early_stopping': True,        # Enable early stopping
    'n_iter_no_change': 10         # Stop if no improvement in 10 epochs
}

# Instantiate the CrossValidation class and run cross-validation
cv = CrossValidation()

# Run 5-fold cross-validation
mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scores,
    model_class=MLPClassifier,   # Pass the MLPClassifier class
    X=X_train_resampled,                    # Use the preprocessed training d
    y=y_train_resampled,                    # Use the corresponding training
    splits=5,                    # Number of folds
    model_params=mlp_params      # Parameters for MLPClassifier
)
```

```
# Calculate and display the average scores
mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, mlp_avg_f1 = cv.calcula
    mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_sco
)

# Print a summary of the results
print("\nCross-Validation Results for MLPClassifier:")
print(f"Average Accuracy:  {mlp_avg_accuracy:.4f}")
print(f"Average Precision: {mlp_avg_precision:.4f}")
print(f"Average Recall:    {mlp_avg_recall:.4f}")
print(f"Average F1-Score:  {mlp_avg_f1:.4f}")
```

```
Cross-Validation Results for MLPClassifier:
Average Accuracy:  0.7268
Average Precision: 0.7500
Average Recall:    0.6812
Average F1-Score:  0.7136
```

In [ ]:

```
################################################## Abdelrahman
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(mlp_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(mlp_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for MLPClassifier (5-Fold Cross-Validation)
plt.show()
```



Two Layer: (100, 100)

In [ ]:

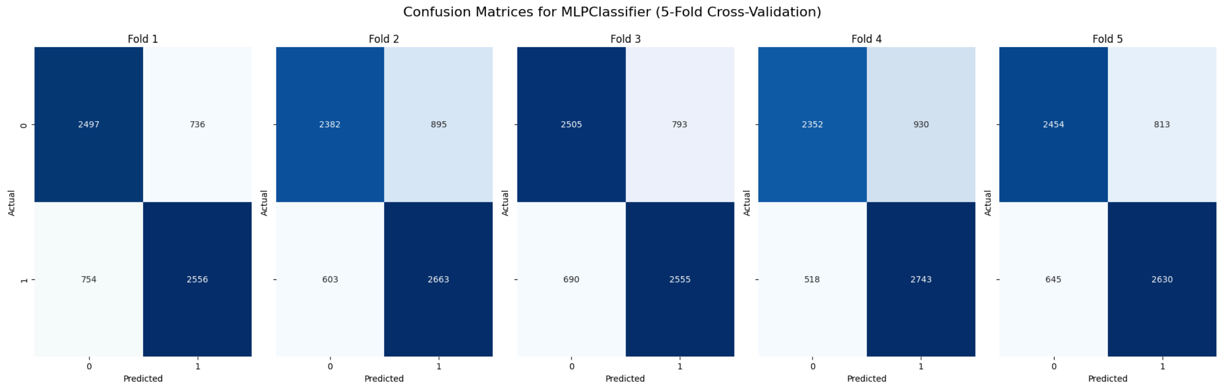
```
# ---- Cross-Validation for MLPClassifier ----

# Parameters for MLPClassifier
mlp_params = {
    'hidden_layer_sizes': (100,100),  # 2 layers, 100 neurons
    'activation': 'relu',           # Activation function
    'solver': 'adam',               # Optimizer
    'random_state': 42,             # For reproducibility
```

```
    'max_iter': 200,              # Maximum number of iterations
    'early_stopping': True,       # Enable early stopping
    'n_iter_no_change': 10        # Stop if no improvement in 10 epochs
}

# Run 5-fold cross-validation
mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scores,
    model_class=MLPClassifier,   # Pass the MLPClassifier class
    X=X_train_resampled,                    # Use the preprocessed training c
    y=y_train_resampled,                    # Use the corresponding training
    splits=5,                    # Number of folds
    model_params=mlp_params      # Parameters for MLPClassifier
)

# Calculate and display the average scores
mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, mlp_avg_f1 = cv.calcula
    mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scc
)

# Print a summary of the results
print("\nCross-Validation Results for MLPClassifier:")
print(f"Average Accuracy:  {mlp_avg_accuracy:.4f}")
print(f"Average Precision: {mlp_avg_precision:.4f}")
print(f"Average Recall:    {mlp_avg_recall:.4f}")
print(f"Average F1-Score:  {mlp_avg_f1:.4f}")
```

```
Cross-Validation Results for MLPClassifier:
Average Accuracy:  0.7745
Average Precision: 0.7597
Average Recall:    0.8038
Average F1-Score:  0.7808
```

In [ ]:

```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(mlp_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(mlp_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for MLPClassifier (5-Fold Cross-Validation)
plt.show()
```

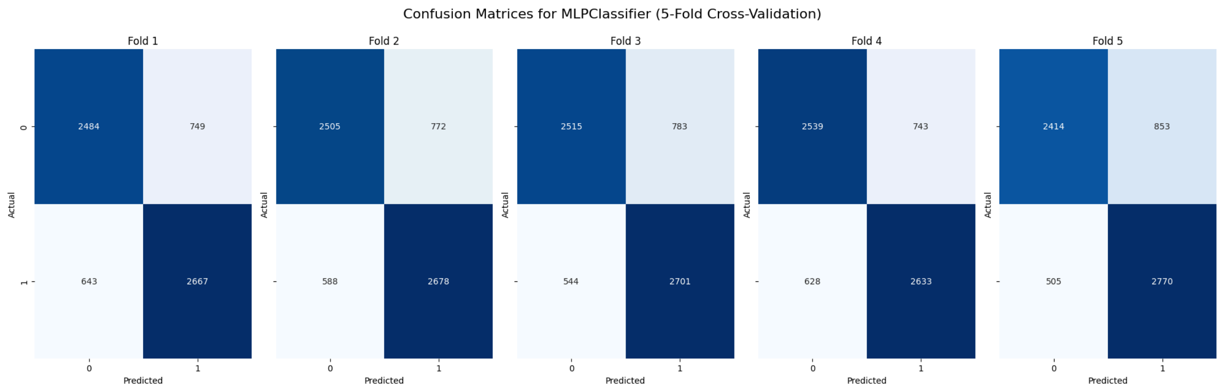


Three Layer: (100, 100, 100)

In [ ]:
```
# ---- Cross-Validation for MLPClassifier ----

# Parameters for MLPClassifier
mlp_params = {
    'hidden_layer_sizes': (100,100,100),  # Three hidden layers with 100 neu
    'activation': 'relu',          # Activation function
    'solver': 'adam',              # Optimizer
    'random_state': 42,            # For reproducibility
    'max_iter': 200,               # Maximum number of iterations
    'early_stopping': True,        # Enable early stopping
    'n_iter_no_change': 10         # Stop if no improvement in 10 epochs
}

# Run 5-fold cross-validation
mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scores,
    model_class=MLPClassifier,   # Pass the MLPClassifier class
    X=X_train_resampled,                    # Use the preprocessed training d
    y=y_train_resampled,                    # Use the corresponding training
    splits=5,                    # Number of folds
    model_params=mlp_params      # Parameters for MLPClassifier
)

# Calculate and display the average scores
mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, mlp_avg_f1 = cv.calcula
    mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_sco
)

# Print a summary of the results
print("\nCross-Validation Results for MLPClassifier:")
print(f"Average Accuracy:  {mlp_avg_accuracy:.4f}")
print(f"Average Precision: {mlp_avg_precision:.4f}")
print(f"Average Recall:    {mlp_avg_recall:.4f}")
print(f"Average F1-Score:  {mlp_avg_f1:.4f}")
```

```
Cross-Validation Results for MLPClassifier:
Average Accuracy:  0.7919
Average Precision: 0.7753
Average Recall:    0.8223
Average F1-Score:  0.7980
```

In [ ]:
```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(mlp_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(mlp_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for MLPClassifier (5-Fold Cross-Validation)
plt.show()
```



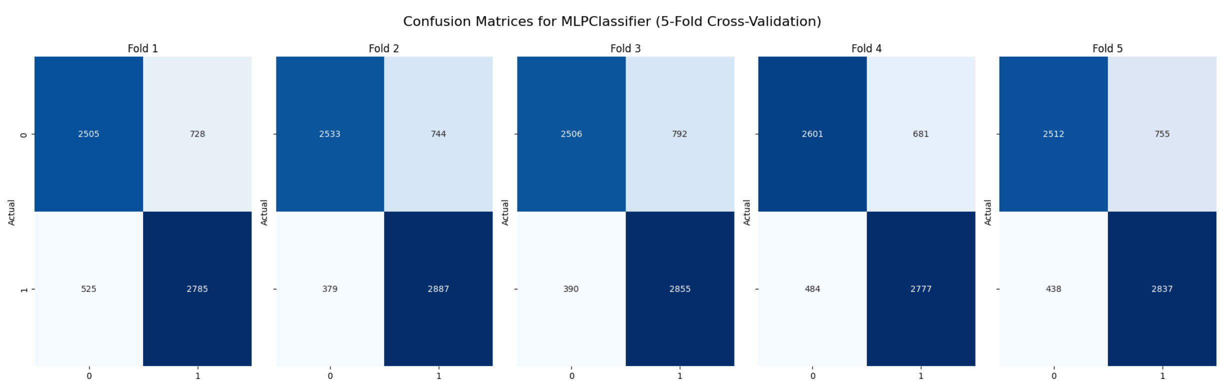
Three Layer: (200, 200, 200)

In [ ]:
```
# ---- Cross-Validation for MLPClassifier ----

# Parameters for MLPClassifier
mlp_params = {
    'hidden_layer_sizes': (200,200,200),  # Three hidden layer with 200 neur
    'activation': 'relu',          # Activation function
    'solver': 'adam',              # Optimizer
    'random_state': 42,            # For reproducibility
    'max_iter': 200,               # Maximum number of iterations
    'early_stopping': True,        # Enable early stopping
    'n_iter_no_change': 10         # Stop if no improvement in 10 epochs
}

# Run 5-fold cross-validation
mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scores,
    model_class=MLPClassifier,   # Pass the MLPClassifier class
    X=X_train_resampled,                   # Use the preprocessed training d
    y=y_train_resampled,                   # Use the corresponding training
    splits=5,                    # Number of folds
    model_params=mlp_params      # Parameters for MLPClassifier
)

# Calculate and display the average scores
mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, mlp_avg_f1 = cv.calcula
    mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scc
)
```

```
winning_scores_mlp = [mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, m

# Print a summary of the results
print("\nCross-Validation Results for MLPClassifier:")
print(f"Average Accuracy:  {mlp_avg_accuracy:.4f}")
print(f"Average Precision: {mlp_avg_precision:.4f}")
print(f"Average Recall:    {mlp_avg_recall:.4f}")
print(f"Average F1-Score:  {mlp_avg_f1:.4f}")
```

```
Cross-Validation Results for MLPClassifier:
Average Accuracy:  0.8192
Average Precision: 0.7927
Average Recall:    0.8646
Average F1-Score:  0.8270
```

In [ ]:
```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(mlp_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(mlp_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for MLPClassifier (5-Fold Cross-Validation)
plt.show()
```



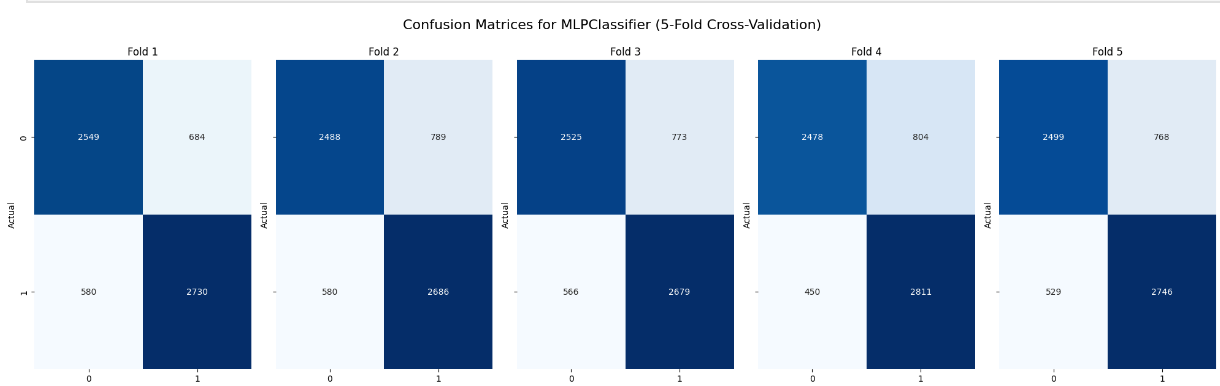
Four Layer: (100,100,100,100)

In [ ]:
```
# ---- Cross-Validation for MLPClassifier ----

# Parameters for MLPClassifier
mlp_params = {
    'hidden_layer_sizes': (100,100,100,100),  # Four hidden layer with 100 r
    'activation': 'relu',         # Activation function
    'solver': 'adam',             # Optimizer
    'random_state': 42,           # For reproducibility
    'max_iter': 200,              # Maximum number of iterations
    'early_stopping': True,       # Enable early stopping
    'n_iter_no_change': 10        # Stop if no improvement in 10 epochs
```

```
}

# Run 5-fold cross-validation
mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scores,
    model_class=MLPClassifier,   # Pass the MLPClassifier class
    X=X_train_resampled,                    # Use the preprocessed training d
    y=y_train_resampled,                    # Use the corresponding training
    splits=5,                    # Number of folds
    model_params=mlp_params      # Parameters for MLPClassifier
)

# Calculate and display the average scores
mlp_avg_accuracy, mlp_avg_precision, mlp_avg_recall, mlp_avg_f1 = cv.calcula
    mlp_accuracy_scores, mlp_precision_scores, mlp_recall_scores, mlp_f1_scc
)

# Print a summary of the results
print("\nCross-Validation Results for MLPClassifier:")
print(f"Average Accuracy:  {mlp_avg_accuracy:.4f}")
print(f"Average Precision: {mlp_avg_precision:.4f}")
print(f"Average Recall:    {mlp_avg_recall:.4f}")
print(f"Average F1-Score:  {mlp_avg_f1:.4f}")
```

```
Cross-Validation Results for MLPClassifier:
Average Accuracy:  0.8006
Average Precision: 0.7815
Average Recall:    0.8346
Average F1-Score:  0.8071
```

In [ ]:
```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(mlp_confusion_matrices), figsize=(20, 6), sh

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(mlp_confusion_matrices[i], annot=True, fmt="d", cmap="Blues"
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for MLPClassifier (5-Fold Cross-Validation)
plt.show()
```



Random Forest

In [ ]:
```
# Initializing the RF model with balanced class weights

rf = RandomForestClassifier(
    n_estimators = 500,
    max_depth = None,
    min_samples_split = 2,
    min_samples_leaf = 1,
    #max_features = 'sqrt',
    class_weight = 'balanced_subsample',
    random_state = 42
)

# Training the model
rf.fit(X_train, y_train)
```

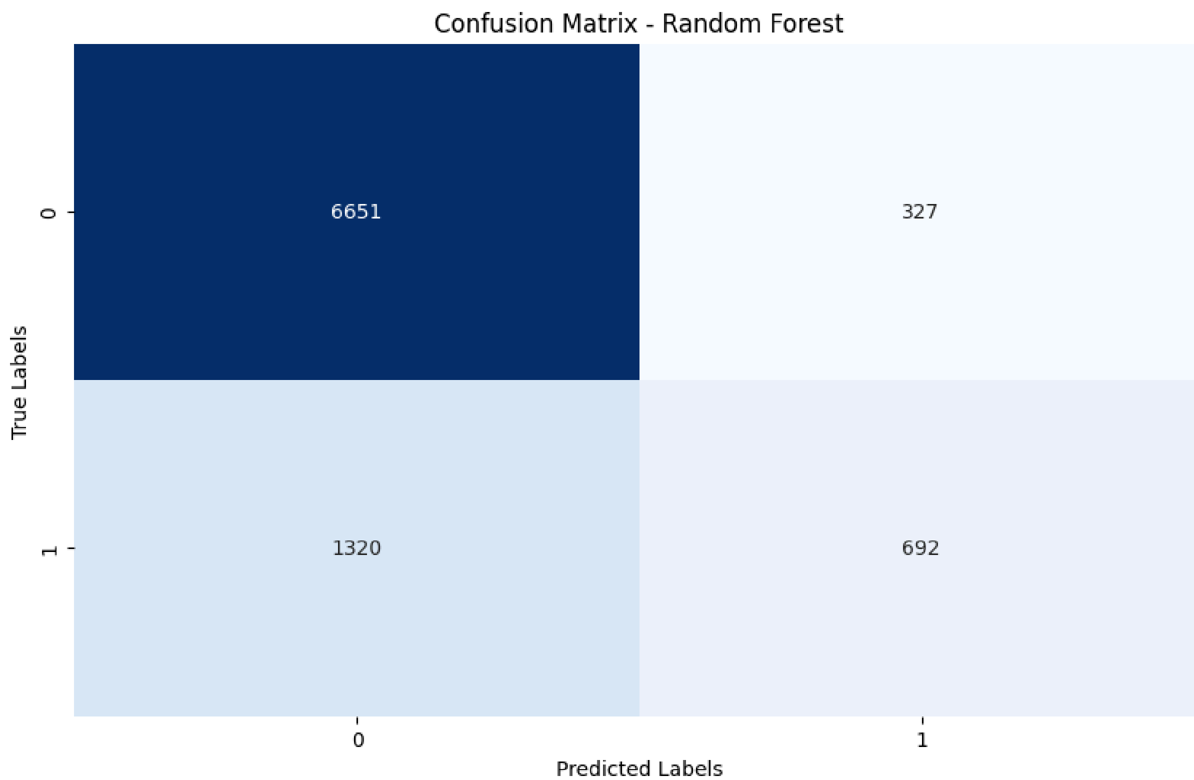
Out[ ]:
```
RandomForestClassifier

RandomForestClassifier(class_weight='balanced_subsample', n_estimat
ors=500,
                       random_state=42)
```

In [ ]:
```
# Making predictions
rf_pred = rf.predict(X_test)

rf_params = {
    'n_estimators': 500,
    'max_depth': None,
    'min_samples_split': 2,
    'min_samples_leaf': 1,
    #'max_features': 'sqrt',
    'class_weight': 'balanced_subsample',
    'random_state': 42
}

rf_accuracy_scores, rf_precision_scores, rf_recall_scores, rf_f1_scores, rf_
    model_class=RandomForestClassifier,
    X=X_train_resampled,
    y=y_train_resampled,
    splits=5,
    model_params=rf_params
)

rf_avg_accuracy, rf_avg_precision, rf_avg_recall, rf_avg_f1 = cv.calculate_s
    rf_accuracy_scores, rf_precision_scores, rf_recall_scores, rf_f1_scores
)

rf_conf_matrix = confusion_matrix(y_test, rf_pred)

print("Random Forest:\n")
print(f"Avg Accuracy: {rf_avg_accuracy:.4f}")
```

```
print(f"Avg Precision: {rf_avg_precision:.4f}")
print(f"Avg Recall: {rf_avg_recall:.4f}")
print(f"Avg F1-Score: {rf_avg_f1:.4f}")
```

```
Random Forest:

Avg Accuracy: 0.8593
Avg Precision: 0.8742
Avg Recall: 0.8394
Avg F1-Score: 0.8564
```

In [ ]:
```
# Confusion Matrix - visualization

plt.figure(figsize=(10, 6))
sns.heatmap(rf_conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title("Confusion Matrix - Random Forest")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```

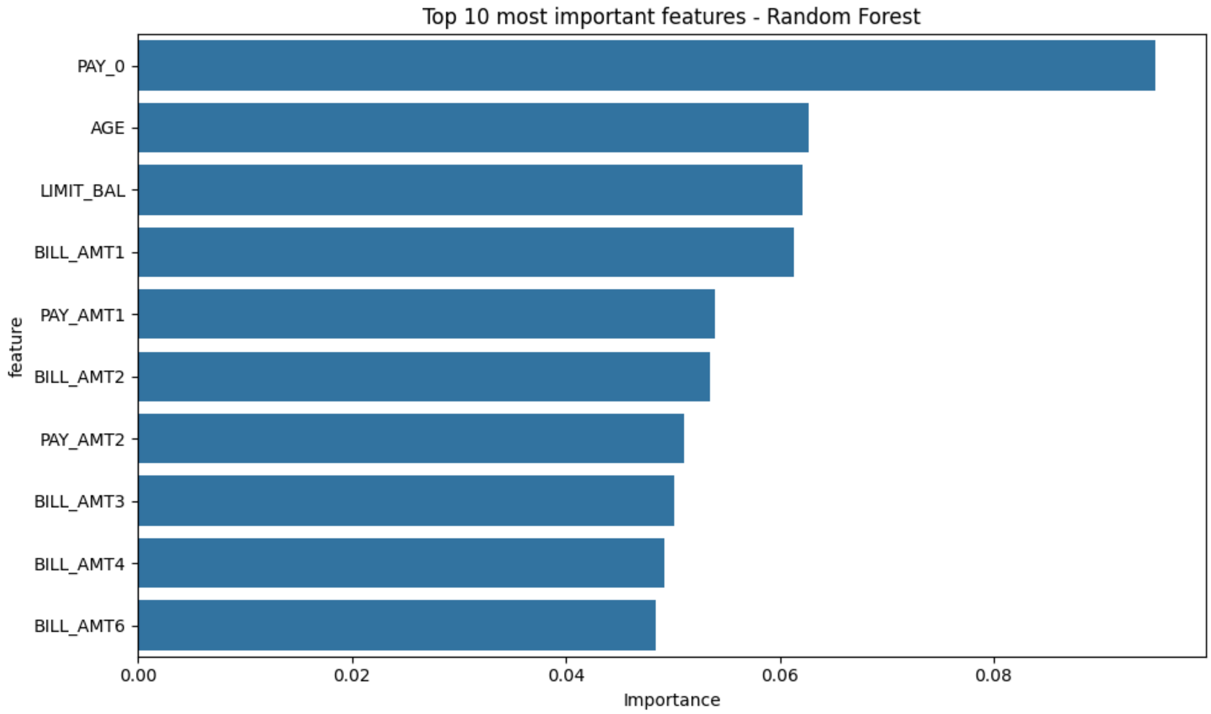


In [ ]:
```
# Getting feature importance

feature_importance = pd.DataFrame({'feature': X.columns, 'importance': rf.fe
```

In [ ]:
```
feature_importance = feature_importance.sort_values('importance', ascending=
```

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance.head(10))
plt.title("Top 10 most important features - Random Forest")
plt.xlabel("Importance")
```

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



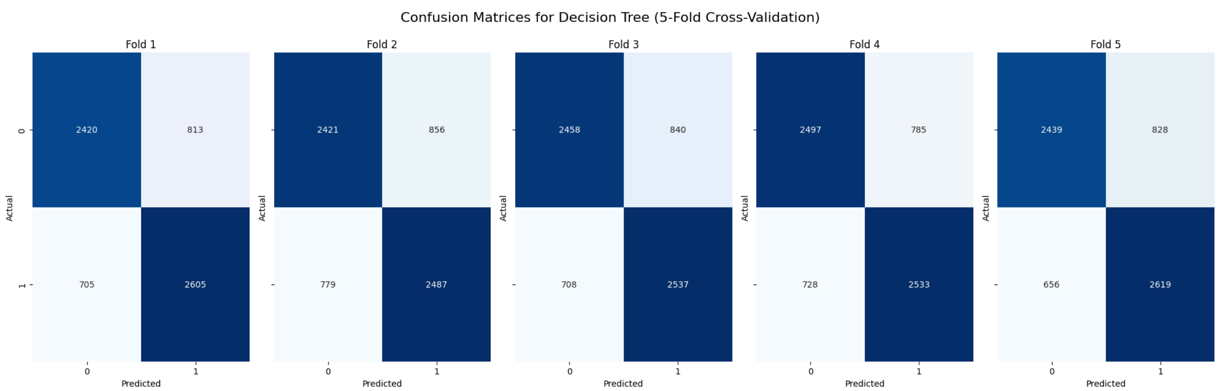
Decision Tree

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classificatio
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import tree
```

In [ ]:
```
###### Decision Tree with Cross Validation
dt_params = {}

dt_accuracy_scores, dt_precision_scores, dt_recall_scores, dt_f1_scores, dt_
    model_class=DecisionTreeClassifier,
    X=X_train_resampled,
    y=y_train_resampled,
    splits=5,
    model_params=dt_params
)

dt_avg_accuracy, dt_avg_precision, dt_avg_recall, dt_avg_f1 = cv.calculate_s
    dt_accuracy_scores, dt_precision_scores, dt_recall_scores, dt_f1_scores
)

print("Naive Tree:\n")
print(f"Avg Accuracy: {dt_avg_accuracy:.4f}")
print(f"Avg Precision: {dt_avg_precision:.4f}")
print(f"Avg Recall: {dt_avg_recall:.4f}")
print(f"Avg F1-Score: {dt_avg_f1:.4f}")
```

```
Naive Tree:

Avg Accuracy: 0.7647
Avg Precision: 0.7561
Avg Recall: 0.7814
Avg F1-Score: 0.7685
```

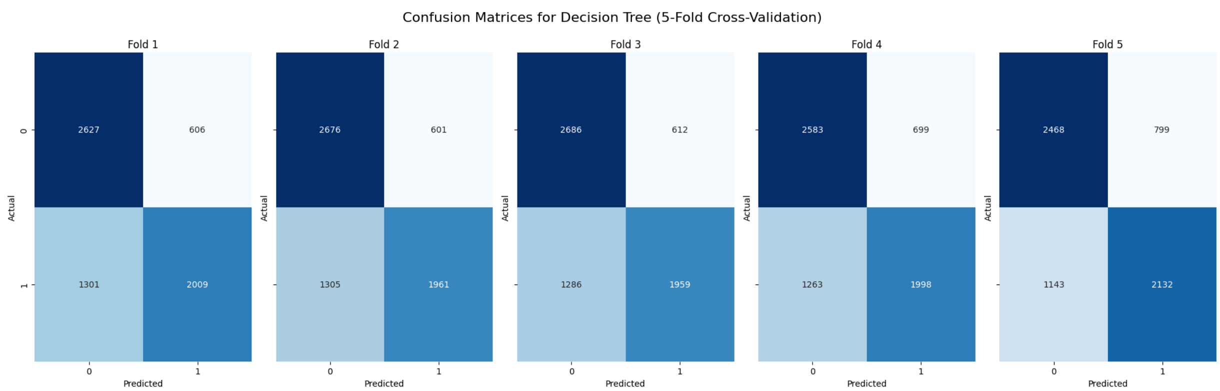
In [ ]:
```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(dt_confusion_matrices), figsize=(20, 6), sha

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(dt_confusion_matrices[i], annot=True, fmt="d", cmap="Blues",
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for Decision Tree (5-Fold Cross-Validation)
plt.show()
```



In [ ]:
```
##### Simple Tree
dt_params = {'max_depth': 3}

dt_accuracy_scores, dt_precision_scores, dt_recall_scores, dt_f1_scores, dt_
    model_class=DecisionTreeClassifier,
    X=X_train_resampled,
    y=y_train_resampled,
    splits=5,
    model_params=dt_params
)

dt_simple_avg_accuracy, dt_simple_avg_precision, dt_simple_avg_recall, dt_si
    dt_accuracy_scores, dt_precision_scores, dt_recall_scores, dt_f1_scores
)

print("Naive Tree:\n")
print(f"Avg Accuracy: {dt_simple_avg_accuracy:.4f}")
print(f"Avg Precision: {dt_simple_avg_precision:.4f}")
print(f"Avg Recall: {dt_simple_avg_recall:.4f}")
print(f"Avg F1-Score: {dt_simple_avg_f1:.4f}")
```

```
Naive Tree:

Avg Accuracy: 0.7061
Avg Precision: 0.7528
Avg Recall: 0.6150
Avg F1-Score: 0.6765
```

In [ ]:
```
# Create subplots for MLPClassifier confusion matrices
fig, axes = plt.subplots(1, len(dt_confusion_matrices), figsize=(20, 6), sha

# Plot each confusion matrix for MLPClassifier
for i, ax in enumerate(axes):
    sns.heatmap(dt_confusion_matrices[i], annot=True, fmt="d", cmap="Blues",
    ax.set_title(f"Fold {i + 1}")
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")

# Adjust layout
plt.tight_layout()
plt.suptitle("Confusion Matrices for Decision Tree (5-Fold Cross-Validation)
plt.show()
```



In [ ]:
```
cleaned_df = savepoint1.copy()
```

In [ ]:
```
cleaned_df.head(1)
```

Out[ ]:

	SEX	EDUCATION	default payment next month	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3
ID									
1	female	university	default	20000	1	24	2	2	-1

1 rows × 24 columns

In [ ]:
```
cleaned_df["default payment next month"].value_counts()
```

Out[ ]:

	count
default payment next month	
not default	23335
default	6630

dtype: int64

In [ ]:
```
cleaned_df["default payment next month"] = cleaned_df["default payment next
```

In [ ]:
```
cleaned_df.rename(columns = {"default payment next month":"target"}, inplace
```

In [ ]:
```
cleaned_df = cleaned_df.reset_index(drop = True)
```

In [ ]:
```
cleaned_df.head()
```

Out[ ]:

	SEX	EDUCATION	target	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	P
0	female	university	0	20000	1	24	2	2	-1	
1	female	university	0	120000	2	26	-1	2	0	
2	female	university	1	90000	2	34	0	0	0	
3	female	university	1	50000	1	37	0	0	0	
4	male	university	1	50000	1	57	-1	0	-1	

5 rows × 24 columns

In [ ]:
```
naiveX = cleaned_df.drop(columns = ["target", "SEX", "EDUCATION"])
naivey = cleaned_df["target"]
```

In [ ]:
```
nX_train,nX_test,ny_train,ny_test = train_test_split(naiveX, naivey, random_
```

In [ ]:
```
nX_train
```

Out[ ]:

	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	B
25971	230000	1	42	1	-2	-2	-2	-2	-2	
21621	50000	2	24	3	2	2	2	0	0	
16095	280000	1	42	2	0	0	0	0	0	
16297	100000	1	34	3	2	2	2	2	2	
28763	160000	1	31	-1	-1	0	0	-2	-2	
...	...	...	...	...	...	...	...	...	...	
3735	430000	2	31	-2	-2	-1	0	0	0	
14946	50000	1	44	0	0	0	0	0	0	
27518	20000	1	62	1	2	2	0	0	0	
26640	150000	2	25	0	0	0	0	0	0	
21202	200000	1	41	2	2	2	2	2	2	

22473 rows × 21 columns

In [ ]:

```
ny_train
```

Out[ ]:

	target
25971	1
21621	0
16095	0
16297	1
28763	1
...	...
3735	1
14946	1
27518	1
26640	1
21202	1

22473 rows × 1 columns

dtype: int64

In [ ]:

```
nX_test
```

Out[ ]:

	LIMIT_BAL	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	B
14274	70000	2	24	0	0	0	0	0	0	
21481	460000	2	28	0	0	0	0	-1	0	
29571	20000	1	38	0	0	0	0	0	0	
25629	20000	1	43	0	0	0	0	0	0	
28279	360000	1	36	-1	-1	-1	-1	-1	-1	
...	...	...	...	...	...	...	...	...	...	
25875	90000	2	32	0	0	0	0	0	0	
23146	90000	1	47	2	2	2	0	0	0	
23020	80000	2	32	0	0	0	0	0	0	
77	300000	1	45	-1	-1	-1	-1	-1	-1	
25633	230000	2	31	-1	-1	-1	-1	-1	-1	

7492 rows × 21 columns

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classificatior
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import tree
```

In [ ]:
```
naive_tree = DecisionTreeClassifier()
```

In [ ]:
```
naive_tree.fit(nX_train, ny_train)
```

Out[ ]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [ ]:
```
ny_predict = naive_tree.predict(nX_test)
```

In [ ]:
```
ny_predict
```

Out[ ]:
```
array([1, 0, 0, ..., 1, 1, 1])
```

In [ ]:
```
ny_test
```

Out[ ]:

	target
14274	1
21481	1
29571	1
25629	0
28279	1
...	...
25875	1
23146	0
23020	1
77	1
25633	1

7492 rows × 1 columns

dtype: int64

In [ ]:
```
naive_tree.score(nX_train, ny_train)
```

Out[ ]: 0.9984425755350865

In [ ]:
```
naive_tree.score(nX_test, ny_test)
```

Out[ ]: 0.7180993059263214

In [ ]:
```
precision_score(ny_test,ny_predict)
```

Out[ ]: 0.8257602236980077

In [ ]:
```
temp_df = pd.DataFrame({"true value":ny_test.values,"predicted value":ny_pre
temp_df["validation"] = temp_df["true value"] == temp_df["predicted value"]
temp_df
```

Out[ ]:

	true value	predicted value	validation
0	1	1	True
1	1	0	False
2	1	0	False
3	0	0	True
4	1	1	True
...	...	...	...
7487	1	1	True
7488	0	0	True
7489	1	1	True
7490	1	1	True
7491	1	1	True

7492 rows × 3 columns

In [ ]:
```
temp_df.value_counts("validation")
```

Out[ ]:

validation	count
True	5380
False	2112

dtype: int64

In [ ]:
```
print(classification_report(ny_test, ny_predict))
```

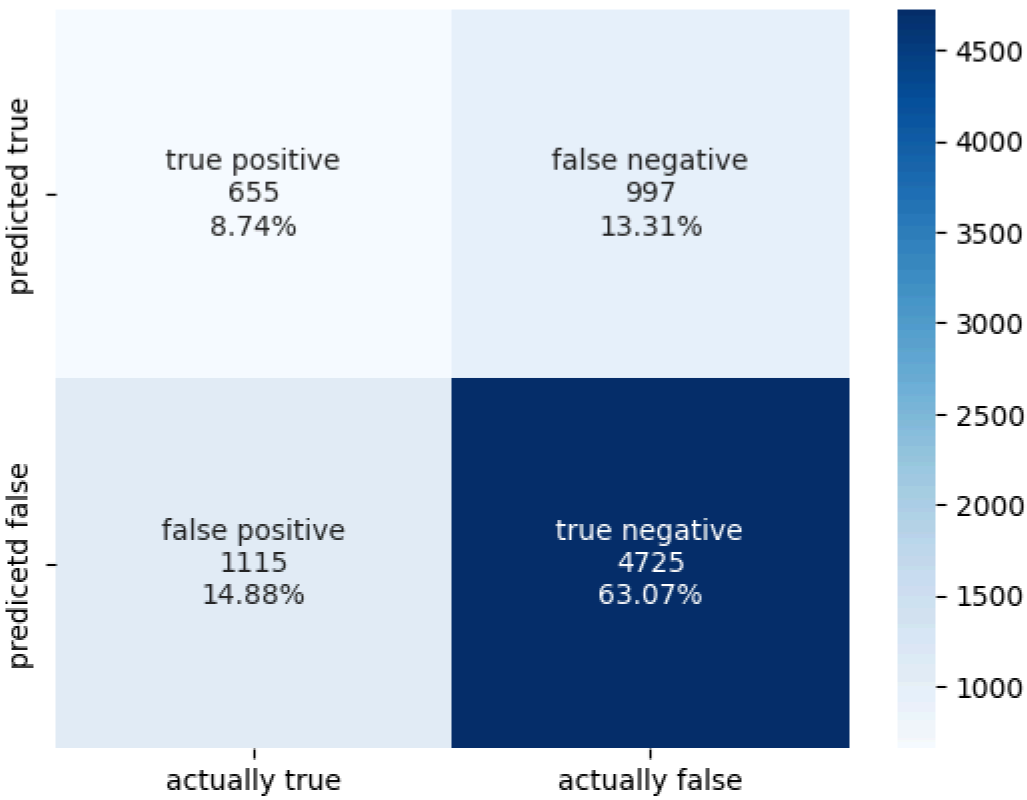
```
              precision    recall  f1-score   support

           0       0.37      0.40      0.38      1652
           1       0.83      0.81      0.82      5840

    accuracy                           0.72      7492
   macro avg       0.60      0.60      0.60      7492
weighted avg       0.73      0.72      0.72      7492
```

In [ ]:
```
matrix = confusion_matrix(ny_test, ny_predict)
matrix
```

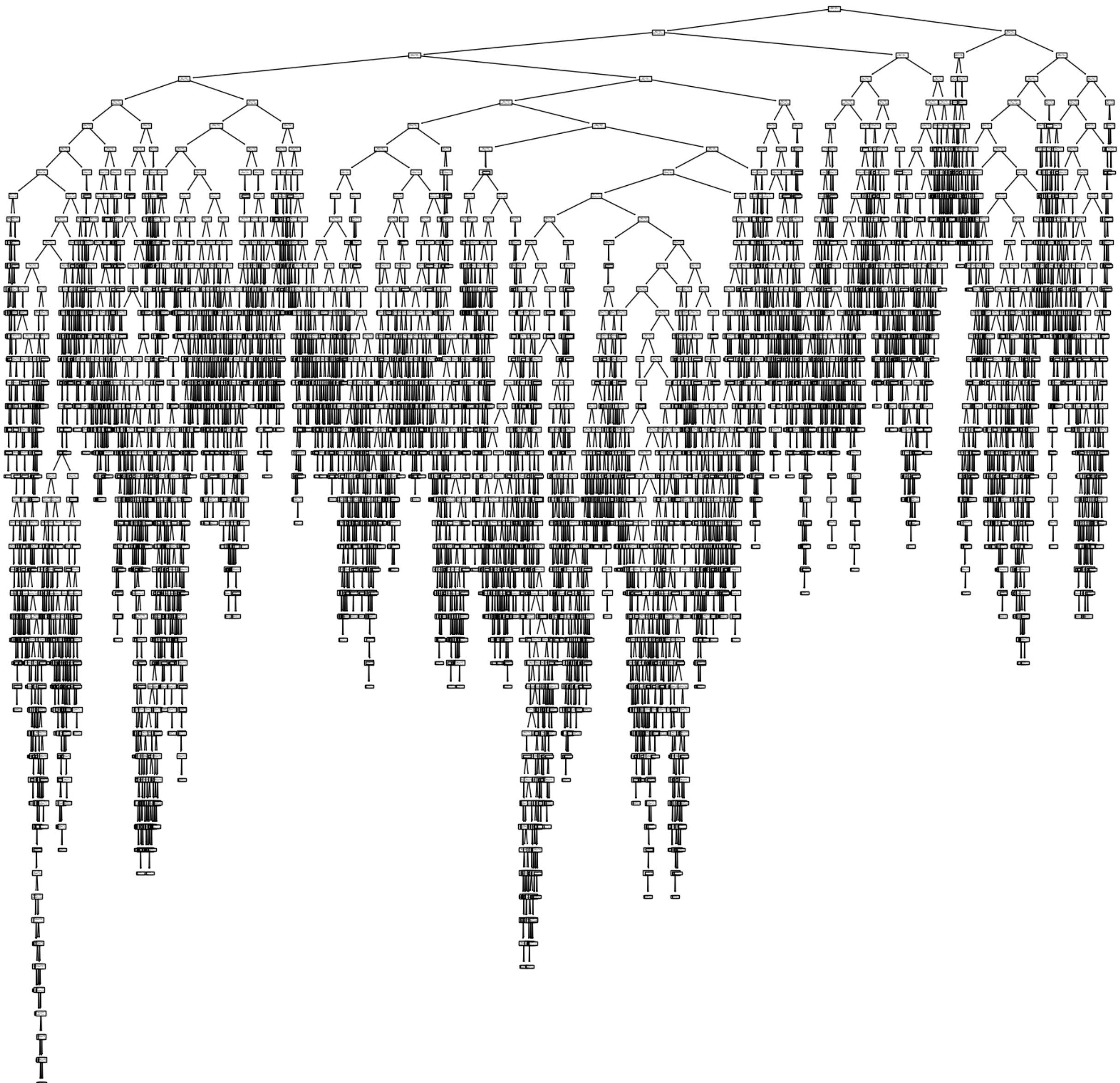
Out[ ]:
```
array([[ 655,  997],
       [1115, 4725]])
```

In [ ]:
```
group_name =  ["true positive", "false negative", "false positive", "true ne
group_counts = ["{0:0.0f}".format(value) for value in matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in matrix.flatten() /

labels = [f"{v1}\n{v2}\n{v3}" for v1,v2,v3 in zip(group_name, group_counts,
labels = np.array(labels).reshape(2,2)

sns.heatmap(matrix, annot=labels,
            fmt="", cmap = "Blues",
            xticklabels= ["actually true", "actually false"],
            yticklabels= ["predicted true", "predicetd false"])
```

Out[ ]: <Axes: >



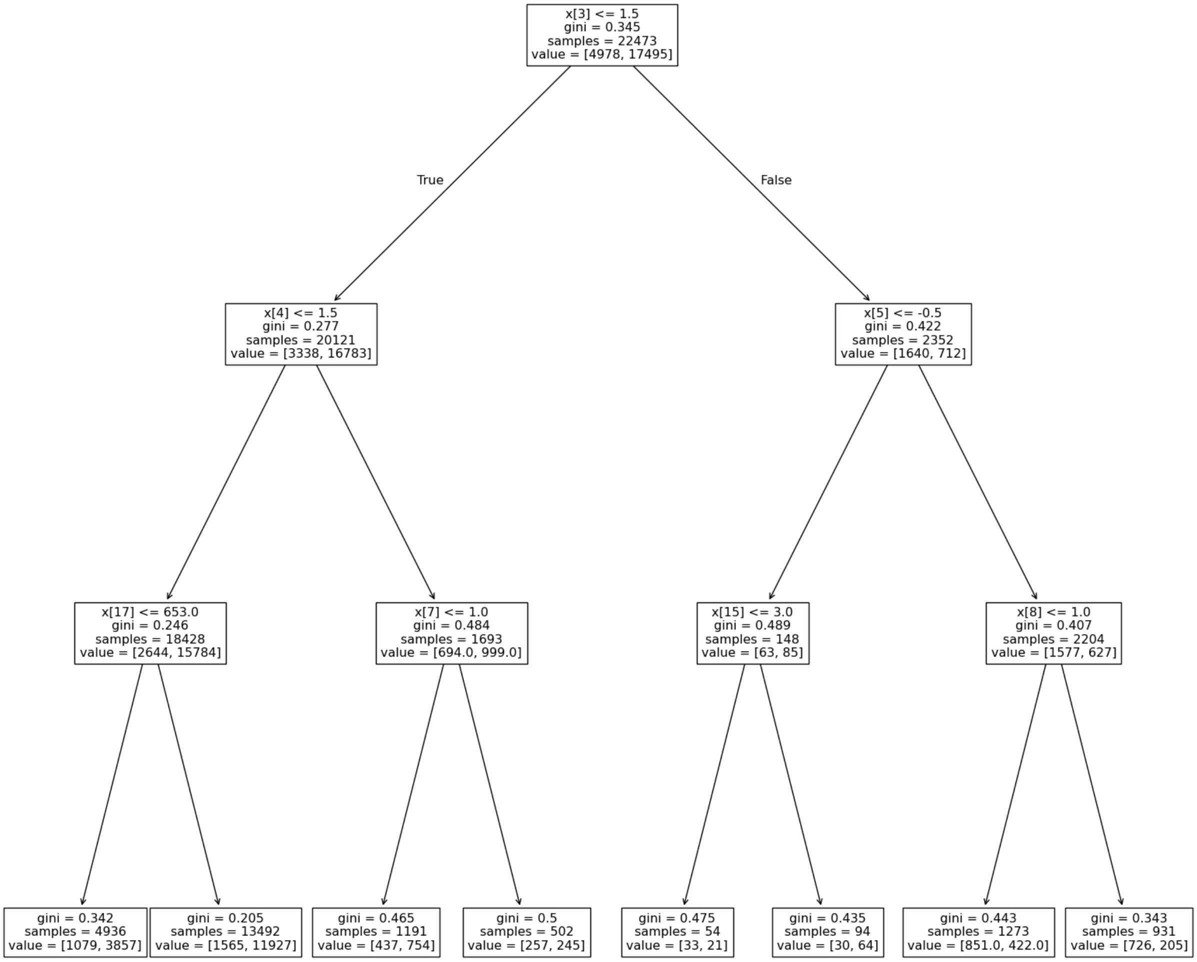
In [ ]:
```
plt.figure(figsize = (20,20))
tree.plot_tree(naive_tree)
plt.show()
```



In [ ]:
```
simple_tree = DecisionTreeClassifier(max_depth = 3)
simple_tree.fit(nX_train, ny_train)
```

Out[ ]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3)
```

In [ ]:
```
plt.figure(figsize = (20,20))
tree.plot_tree(simple_tree)
plt.show()
```



In [ ]:
```
cleaned_df.iloc[:,[3,4,17,7]]
```

Out[ ]:

	LIMIT_BAL	MARRIAGE	BILL_AMT6	PAY_2
0	20000	1	0	2
1	120000	2	3261	2
2	90000	2	15549	0
3	50000	1	29547	0
4	50000	1	19131	0
...	...	...	...	...
29960	220000	1	15980	0
29961	150000	2	0	-1
29962	30000	2	19357	3
29963	80000	1	48944	-1
29964	50000	1	15313	0

29965 rows × 4 columns

Compare Model Results

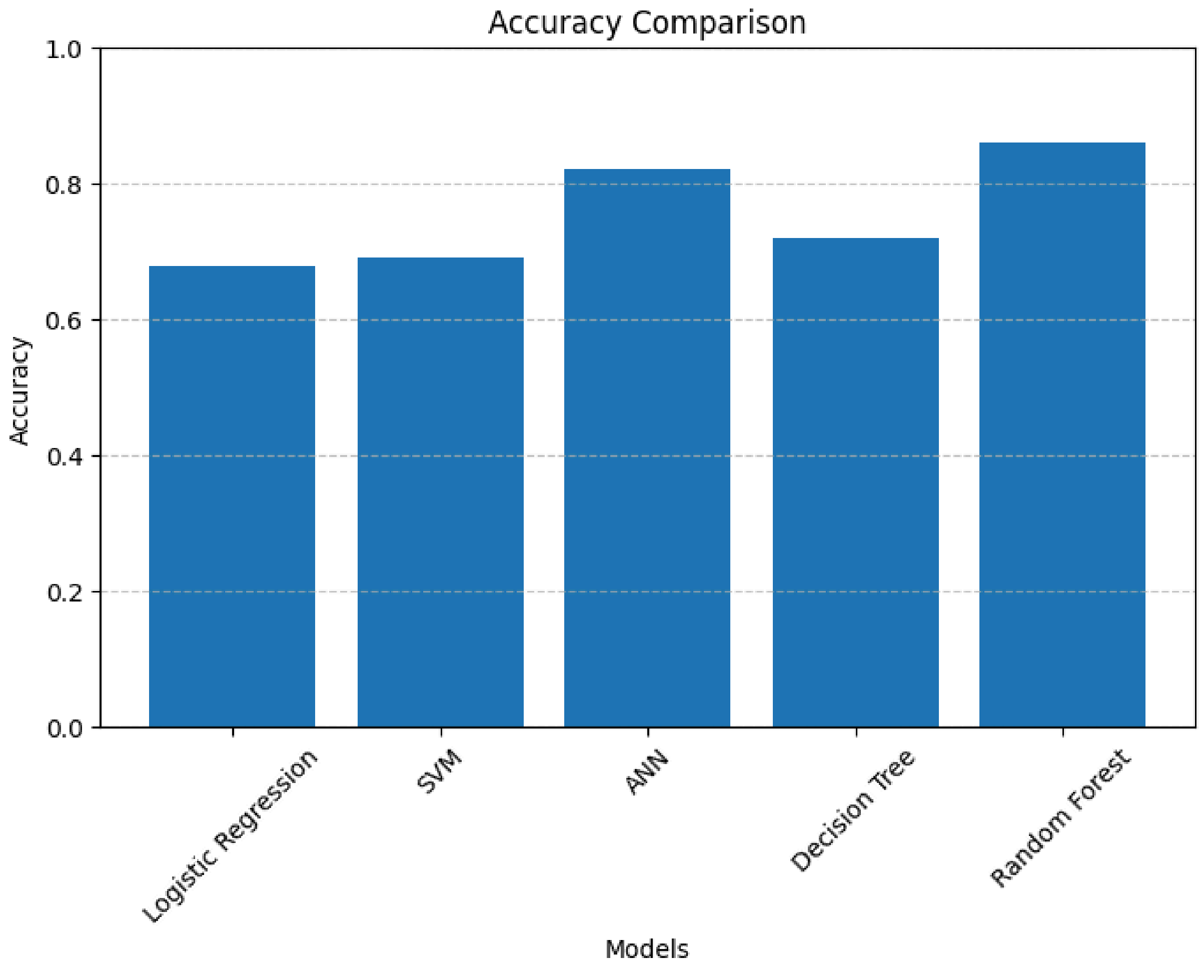
In [ ]:
```
# use best ANN model in comparison with others
mlp_avg_accuracy = winning_scores_mlp[0]
mlp_avg_precision = winning_scores_mlp[1]
mlp_avg_recall = winning_scores_mlp[2]
mlp_avg_f1 = winning_scores_mlp[3]
```

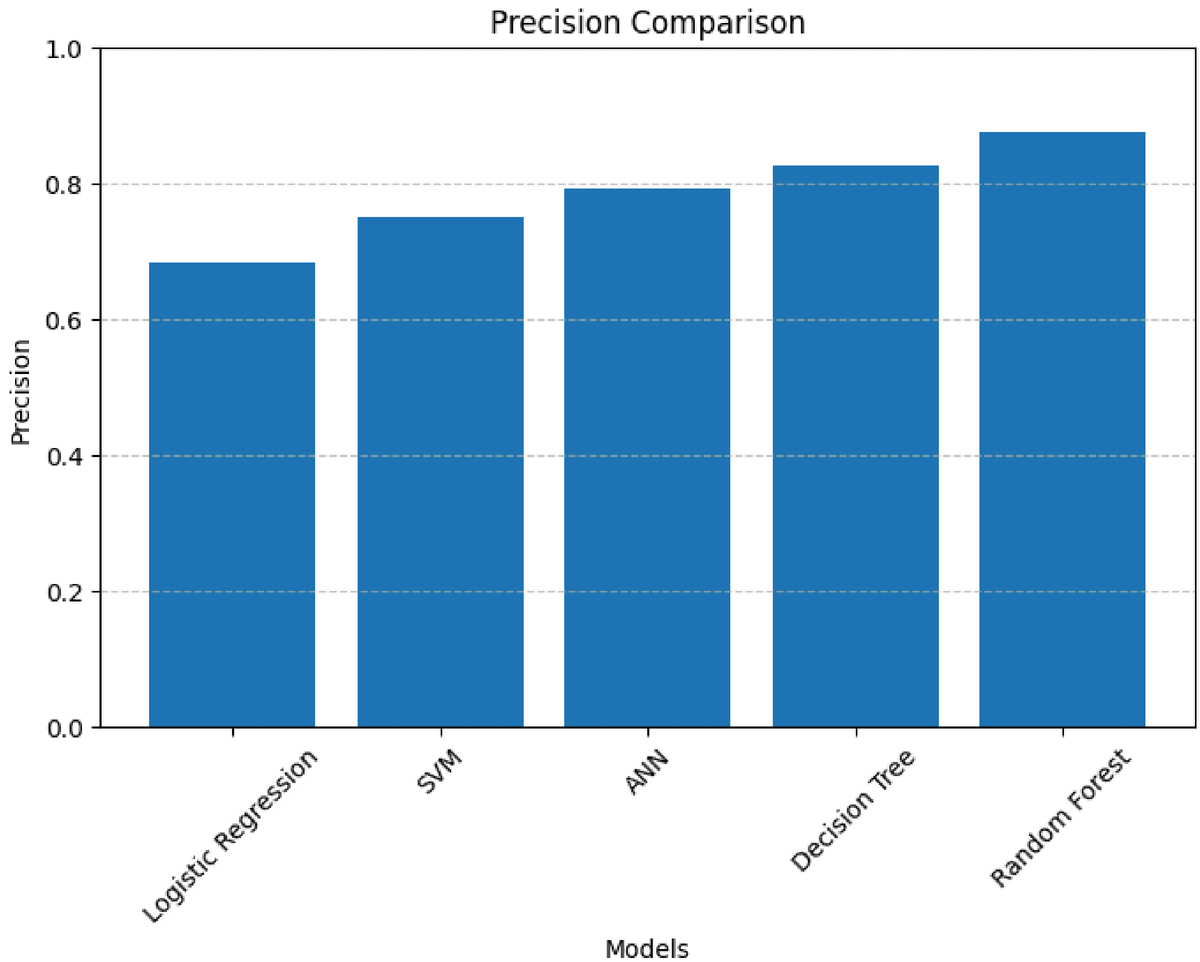
In [ ]:
```
# Decision Tree
dt_avg_accuracy = naive_tree.score(nX_test, ny_test)
dt_avg_precision = precision_score(ny_test, ny_predict)
dt_avg_recall = recall_score(ny_test, ny_predict)
dt_avg_f1 = f1_score(ny_test, ny_predict)
```

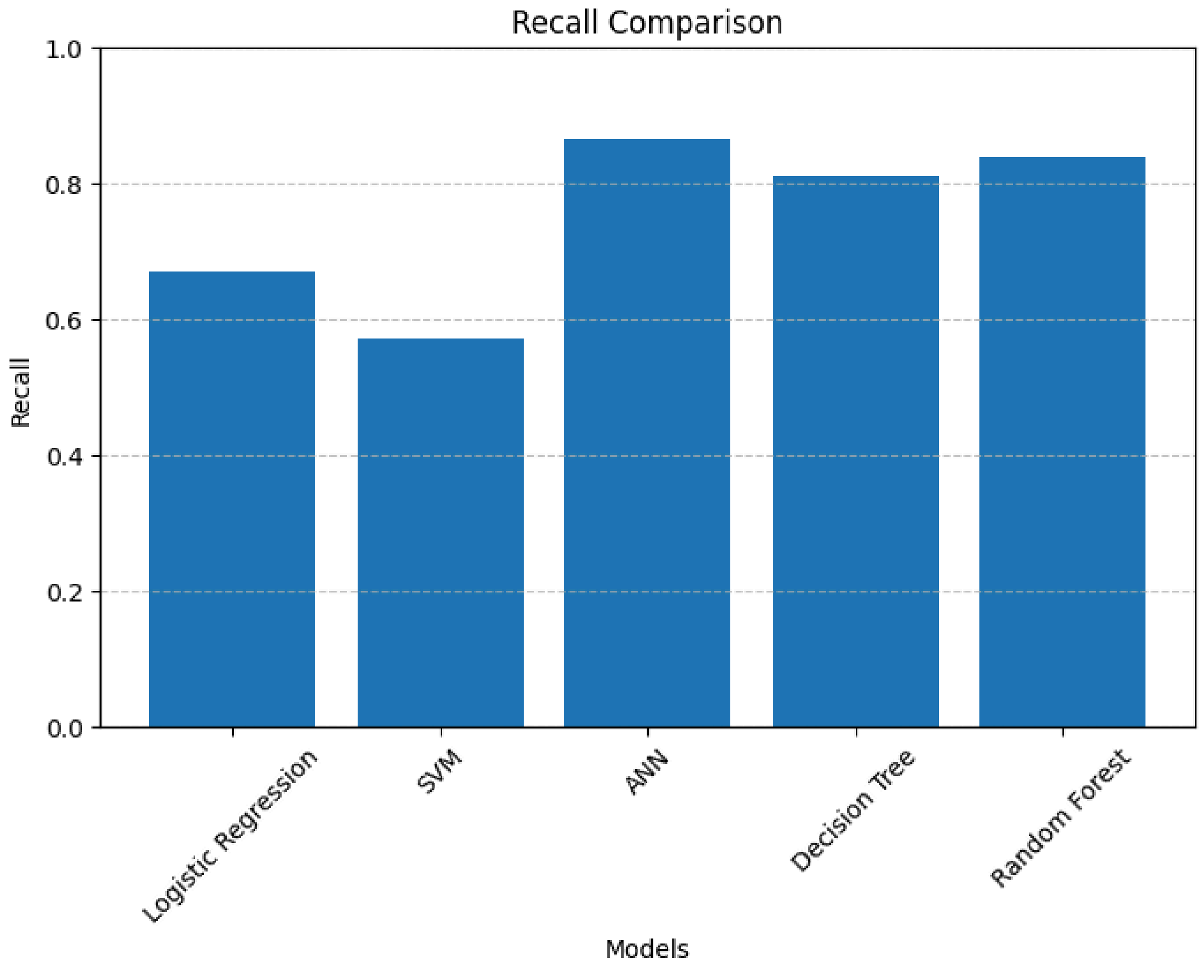
In [ ]:
```
# build dictionaries for comparing results across models
accuracy_results = {'Logistic Regression': log_reg_avg_accuracy,
                    'SVM': svm_avg_accuracy,
                    'ANN': mlp_avg_accuracy,
                    'Decision Tree': dt_avg_accuracy,
                    'Random Forest': rf_avg_accuracy}

precision_results = {'Logistic Regression': log_reg_avg_precision,
                    'SVM': svm_avg_precision,
                    'ANN': mlp_avg_precision,
                    'Decision Tree': dt_avg_precision,
                    'Random Forest': rf_avg_precision}

recall_results = {'Logistic Regression': log_reg_avg_recall,
                    'SVM': svm_avg_recall,
```

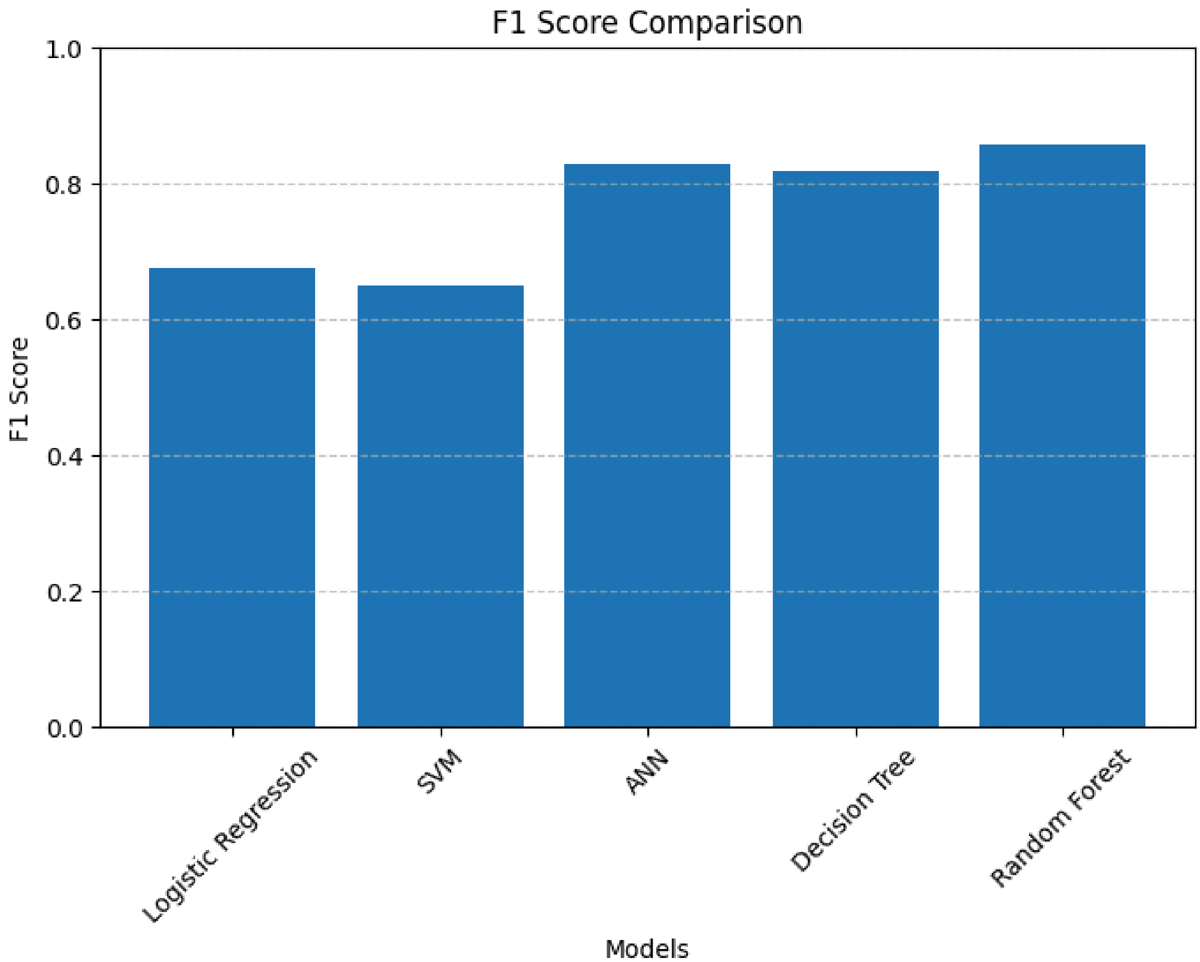
```
                    'ANN': mlp_avg_recall,
                    'Decision Tree': dt_avg_recall,
                    'Random Forest': rf_avg_recall}

f1_results = {'Logistic Regression': log_reg_avg_f1,
                    'SVM': svm_avg_f1,
                    'ANN': mlp_avg_f1,
                    'Decision Tree': dt_avg_f1,
                    'Random Forest': rf_avg_f1}
```

In [ ]:
```
# Function to create bar charts for each metric
def plot_metrics(metrics_dict, metric_name):
    models = list(metrics_dict.keys())
    scores = list(metrics_dict.values())

    plt.figure(figsize=(8, 5))
    plt.bar(models, scores)
    plt.title(f'{metric_name} Comparison')
    plt.xlabel('Models')
    plt.ylabel(metric_name)
    plt.ylim(0, 1)  # Assuming scores are between 0 and 1
    plt.xticks(rotation=45)
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.show()

# Plot each metric
plot_metrics(accuracy_results, 'Accuracy')
plot_metrics(precision_results, 'Precision')
plot_metrics(recall_results, 'Recall')
plot_metrics(f1_results, 'F1 Score')
```


Accuracy Comparison
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Logistic Regression
SVM
ANN
Decision Tree
Random Forest
Models


Precision Comparison
1.0
0.8
0.6
0.4
0.2
0.0
Precision
Logistic Regression
SVM
ANN
Decision Tree
Random Forest
Models


Recall Comparison
1.0
0.8
0.6
0.4
0.2
0.0
Recall
Logistic Regression
SVM
ANN
Decision Tree
Random Forest
Models


F1 Score Comparison
1.0
0.8
0.6
0.4
0.2
0.0
F1 Score
Logistic Regression
SVM
ANN
Decision Tree
Random Forest
Models