Problem Framing & Big Picture

1. Problem and objective in business terms and how the solution will be used.

In this project, we aim to address a critical challenge within the Portuguese school system by developing a machine learning model to predict students' final grades (G3) without the input of their first (G1) and second (G2) term grades. This approach focuses on early identification of students who may require additional support and interventions to improve their academic performance. The model will serve as a proactive tool for the school's advising team. The implementation of this predictive model promises to improve student retention rates, boost the school system's reputation through enhanced academic outcomes, and lead to better overall student success.

2. Problem Framing

This project is best framed as a supervised learning problem that operates in an offline environment. Supervised learning is a type of machine learning where the model is trained on a labeled dataset, which means that each example in the training set is accompanied by the correct output. In the context of predicting student performance, the model learns from historical data that includes both the features (such as demographic and academic attributes) and the target variable (the final grade, G3). This approach allows the model to learn the relationships between the features and the target, enabling it to make predictions for new, unseen data. On the other hand, unsupervised learning involves working with datasets without labeled outcomes, focusing on identifying patterns or structures within the data.

3. Machine Learning Approach (Classification)

For this project, we will focus on a classification task as the specific machine learning approach to predict whether a student passes or fails based on their final G3 grade. Classification involves categorizing data into predefined groups or classes. In our context, this means determining if a student's performance will result in a pass or fail outcome, simplifying the target into a binary choice that directly aligns with the need for intervention. This approach is chosen over regression, which predicts a continuous quantity (the exact final grade), because it more directly addresses the business problem of identifying students who require additional support. By classifying students into "pass" or "fail" categories, the school can efficiently allocate resources and support to those most in need, thereby preventing failures and improving overall student success rates. This method simplifies the decision-making process for interventions and is particularly effective in educational settings where the primary concern is ensuring students achieve a minimum level of proficiency.

4. Metrics for measuring model performance

To measure the performance of our classification model, we will primarily use accuracy, precision, recall, and the F1 score as our metrics. Accuracy indicates the proportion of total predictions our model gets right, combining both pass and fail predictions. However, accuracy alone might not give a complete picture, especially if our data is imbalanced (e.g., more pass cases than fail). Precision measures the proportion of positive identifications (students predicted to fail) that were actually correct, which is crucial for ensuring that interventions are not mistakenly targeted. Recall, or sensitivity, assesses the proportion of actual fails that were correctly identified, highlighting the model's ability to catch all at-risk students. The F1 score harmonizes precision and recall into a single metric, balancing the trade-off between the two and providing a comprehensive measure of the model's performance in cases where an equal importance is placed on both precision and recall.

Get the data

1. Import data

```
import pandas as pd

# Load the dataset
data = '/content/student-mat.csv'
df = pd.read_csv(data)
```

2. The size and type of data

```
#Size of the dataset
print("Dataset size (rows, columns):", df.shape)

# Data types of each column
print("Data types of each column:\n", df.dtypes)
```

```
Dataset size (rows, columns): (395, 35)
Data types of each column:
 school          object
sex             object
age            float64
address         object
famsize         object
Pstatus         object
Medu             int64
Fedu             int64
Mjob            object
```

```
Fjob           object
reason         object
guardian       object
traveltime      int64
studytime       int64
failures        int64
schoolsup      object
famsup         object
paid           object
activities     object
nursery        object
higher         object
internet       object
romantic       object
famrel          int64
freetime        int64
goout           int64
Dalc            int64
Walc            int64
health          int64
absences_G1   float64
absences_G2   float64
absences_G3   float64
G1              int64
G2              int64
G3              int64
dtype: object
```

3. Available features and description

- school: The student's school (GP - Gabriel Pereira or MS - Mousinho da Silveira).
- sex: The student's sex (F - female or M - male).
- age: The student's age (numeric: from 15 to 22).
- address: The student's home address type (U - urban or R - rural).
- famsize: Family size (LE3 - less or equal to 3 or GT3 - greater than 3).
- Pstatus: Parent's cohabitation status (T - living together or A - apart).
- Medu: Mother's education (0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education, 4 – higher education).
- Fedu: Father's education (0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education, 4 – higher education).
- Mjob: Mother's job (teacher, health care related, civil services (e.g., administrative or police), at_home, or other).
- Fjob: Father's job (teacher, health care related, civil services (e.g., administrative or police), at_home, or other).
- reason: Reason to choose this school (close to home, school reputation, course preference, or other).

- guardian: Student's guardian (mother, father, or other).
- traveltime: Home to school travel time (1 - <15 min, 2 - 15 to 30 min, 3 - 30 min. to 1 hour, 4 - >1 hour).
- studytime: Weekly study time (1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours).
- failures: Number of past class failures (n if 1<=n<3, else 4).
- schoolsup: Extra educational support (yes or no).
- famsup: Family educational support (yes or no).
- paid: Extra paid classes within the course subject (Math or Portuguese) (yes or no).
- activities: Extra-curricular activities (yes or no).
- nursery: Attended nursery school (yes or no).
- higher: Wants to take higher education (yes or no).
- internet: Internet access at home (yes or no).
- romantic: In a romantic relationship (yes or no).
- famrel: Quality of family relationships (from 1 - very bad to 5 - excellent).
- freetime: Free time after school (from 1 - very low to 5 - very high).
- goout: Going out with friends (from 1 - very low to 5 - very high).
- rDalc: Workday alcohol consumption (from 1 - very low to 5 - very high).
- rWalc: Weekend alcohol consumption (from 1 - very low to 5 - very high).
- health: Current health status (from 1 - very bad to 5 - very good).
- absences_G1, absences_G2, absences_G3: Number of school absences for G1,G2, and G3 terms (numeric).
- G1, G2, G3: First term, second term, and final grade (numeric: from 0 to 20).

4. Target Variable

The target variable is G3, which will be used to determine whether a student passes or fails

5. Training and test data

```
from sklearn.model_selection import train_test_split

# Transform 'G3' into a binary variable for classification ('Pass' column: 1 for pas
df['Pass'] = (df['G3'] >= 10).astype(int)

# Define the features (X) and the target variable (y)
X = df.drop(['G3', 'Pass'], axis=1)
y = df['Pass']  # Target variable

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

Explore the data

1. Training set attributes and their characteristics

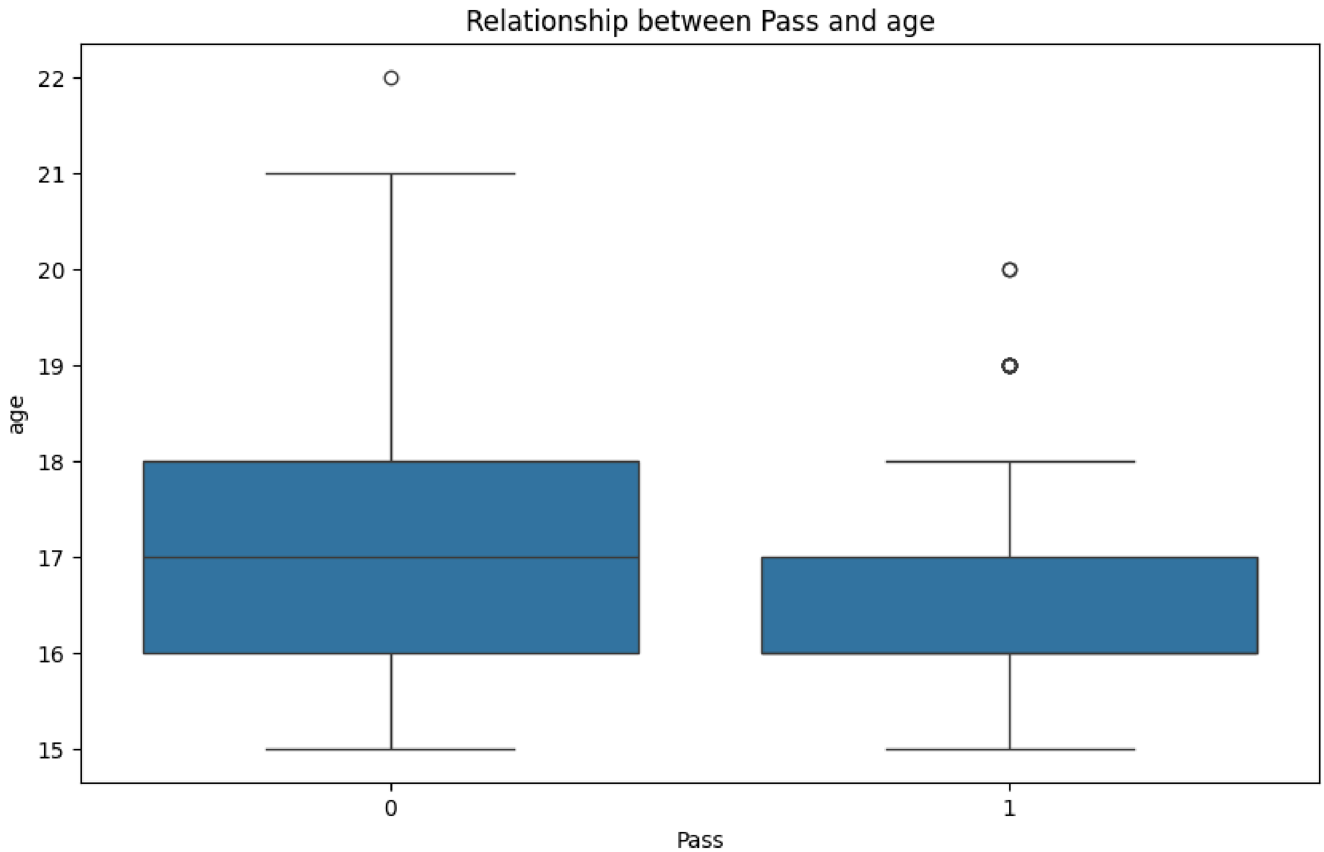
```
# Descriptive statistics for numerical features
print("Descriptive Statistics for Numerical Features:")
print(X_train.describe())

# Descriptive statistics for categorical features
print("\nDescriptive Statistics for Categorical Features:")
print(X_train.describe(include=['object']))
```

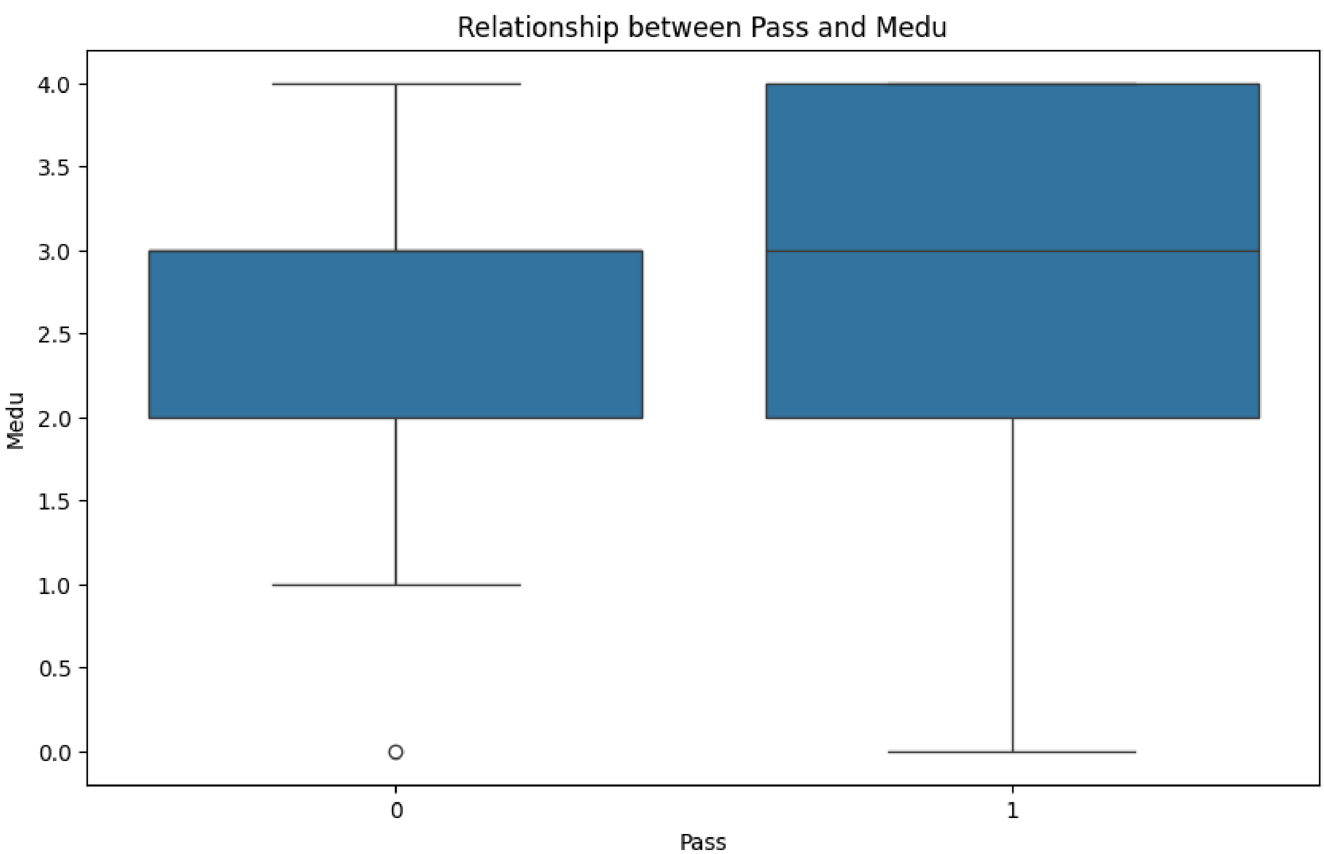
```
Descriptive Statistics for Numerical Features:
              age        Medu        Fedu  traveltime   studytime    failures  \
count  305.000000  316.000000  316.000000  316.000000  316.000000  316.000000   
mean    16.747541    2.734177    2.544304    1.430380    2.047468    0.335443   
std      1.274188    1.080375    1.078476    0.688842    0.836258    0.735588   
min     15.000000    0.000000    0.000000    1.000000    1.000000    0.000000   
25%     16.000000    2.000000    2.000000    1.000000    1.000000    0.000000   
50%     17.000000    3.000000    3.000000    1.000000    2.000000    0.000000   
75%     18.000000    4.000000    3.000000    2.000000    2.000000    0.000000   
max     22.000000    4.000000    4.000000    4.000000    4.000000    3.000000   

           famrel    freetime       goout        Dalc        Walc      health  \
count  316.000000  316.000000  316.000000  316.000000  316.000000  316.000000   
mean     3.943038    3.218354    3.161392    1.500000    2.344937    3.518987   
std      0.885464    1.020323    1.119480    0.903257    1.296395    1.410714   
min      1.000000    1.000000    1.000000    1.000000    1.000000    1.000000   
25%      4.000000    3.000000    2.000000    1.000000    1.000000    3.000000   
50%      4.000000    3.000000    3.000000    1.000000    2.000000    4.000000   
75%      5.000000    4.000000    4.000000    2.000000    3.000000    5.000000   
max      5.000000    5.000000    5.000000    5.000000    5.000000    5.000000   

       absences_G1  absences_G2  absences_G3          G1          G2  
count   305.000000   305.000000   305.000000  316.000000  316.000000  
mean      0.704918     0.704918     4.488525   10.933544   10.651899  
```

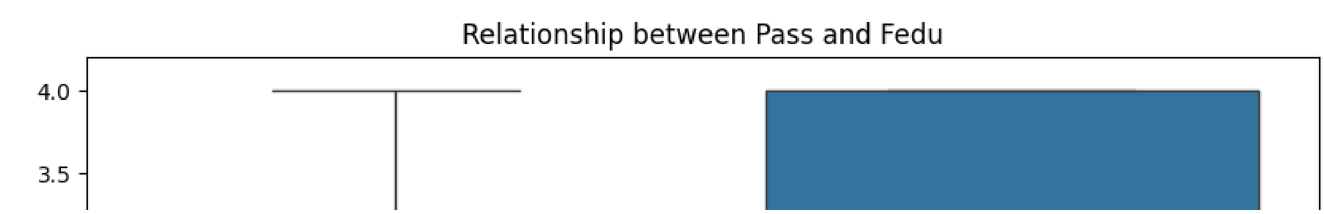
```
std       1.373435     1.373435     5.824238    3.216823    3.755930
min       0.000000     0.000000     0.000000    5.000000    0.000000
25%       0.000000     0.000000     0.000000    8.000000    9.000000
50%       0.000000     0.000000     4.000000   11.000000   11.000000
75%       1.000000     1.000000     6.000000   13.000000   13.000000
max      12.000000    12.000000    51.000000   19.000000   19.000000

Descriptive Statistics for Categorical Features:
       school  sex address famsize Pstatus   Mjob   Fjob  reason guardian  \
count     316  316     316     316     316    316    316     316      316
unique      2    2       2       2       2      5      5       4        3
top        GP    F       U     GT3       T  other  other  course   mother
freq      282  170     247     226     284    110    178     117      219

       schoolsup famsup paid activities nursery higher internet romantic
count        316    316  316        316     316    316      316      316
unique         2      2    2          2       2      2        2        2
top           no    yes   no         no     yes    yes      yes       no
freq         272    191  171        159     253    298      265      207
```

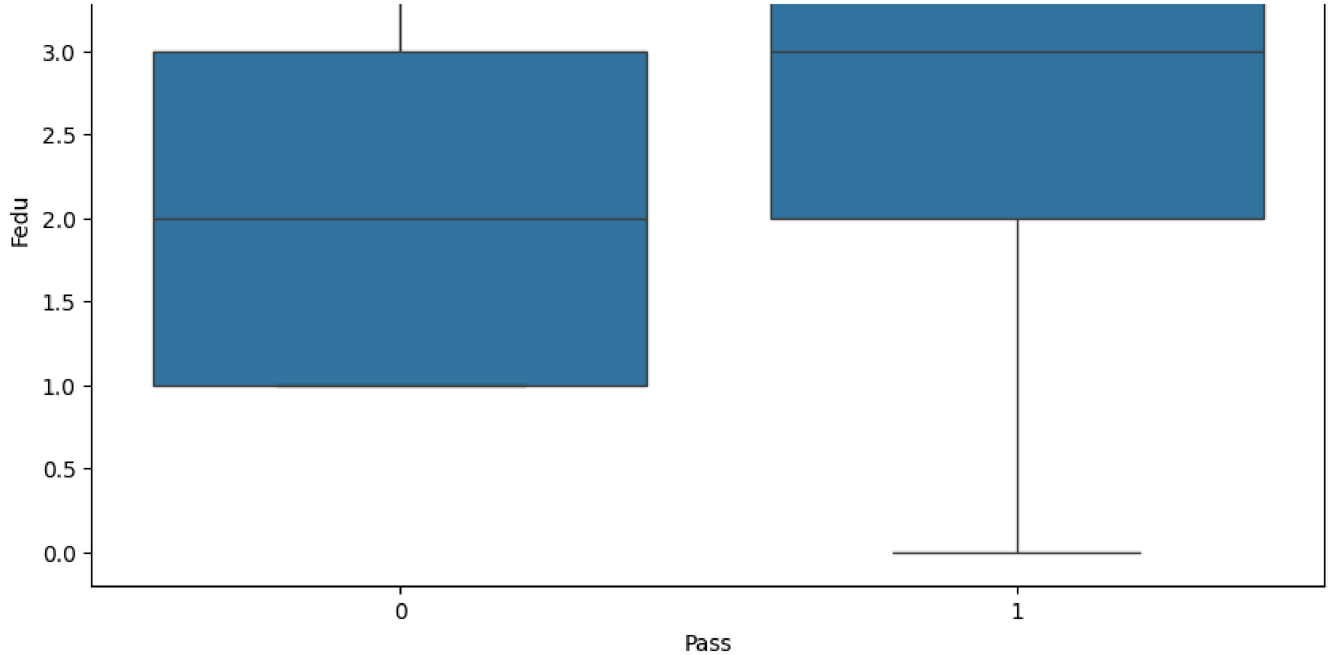
2. Visualizations using the training data

```
import matplotlib.pyplot as plt
import seaborn as sns

# Merging X_train with y_train for visualization
train_dataset = X_train.copy()
train_dataset['Pass'] = y_train

for column in ['age', 'Medu', 'Fedu', 'studytime']:
    if column in train_dataset.columns:
        plt.figure(figsize=(10,6))
        sns.boxplot(x='Pass', y=column, data=train_dataset)
        plt.title(f'Relationship between Pass and {column}')
        plt.show()
```

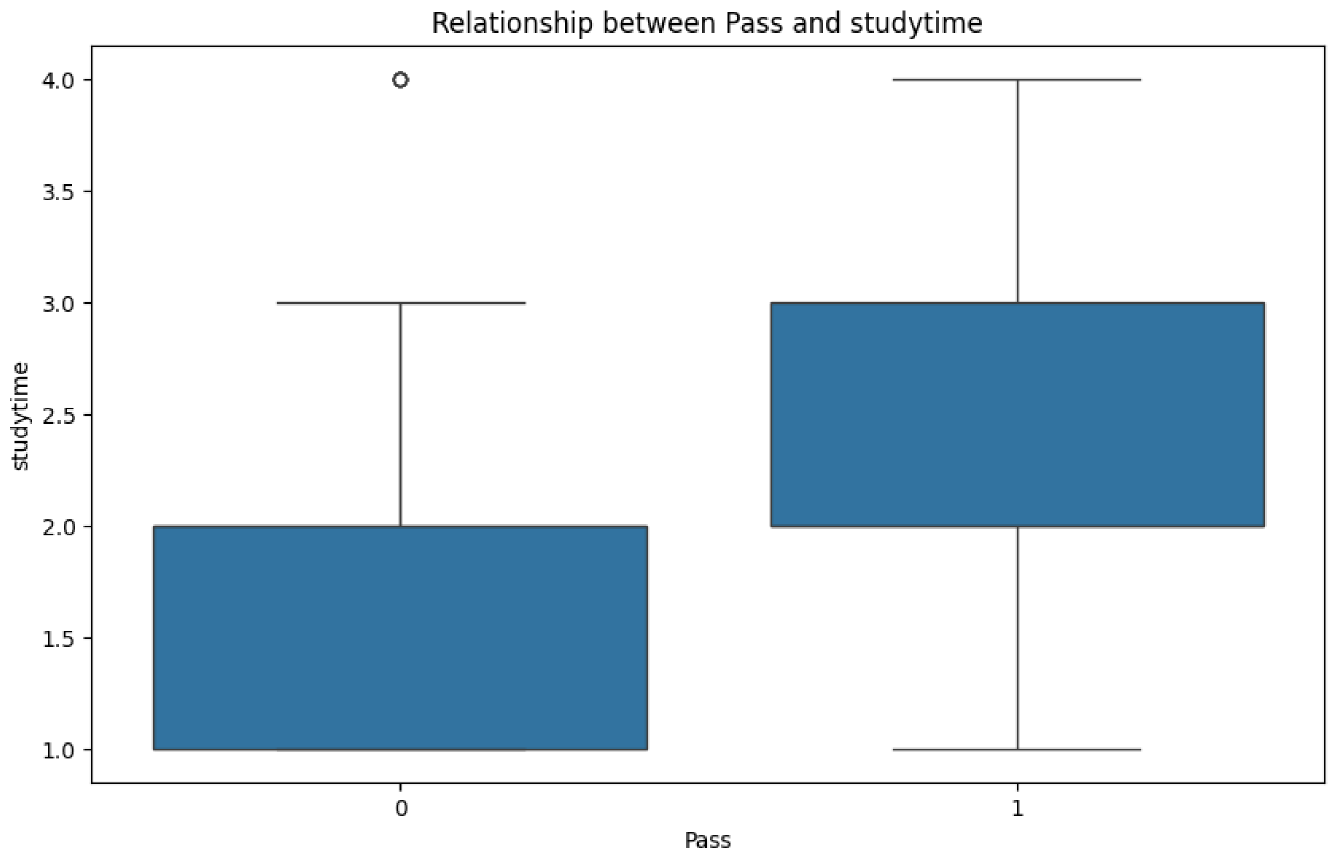

Relationship between Pass and age
age
Pass
22
21
20
19
18
17
16
15
0
1


Relationship between Pass and Medu
Medu
Pass
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1


Relationship between Pass and Fedu
4.0
3.5



3.0
2.5
2.0
1.5
1.0
0.5
0.0
Fedu
0
1
Pass



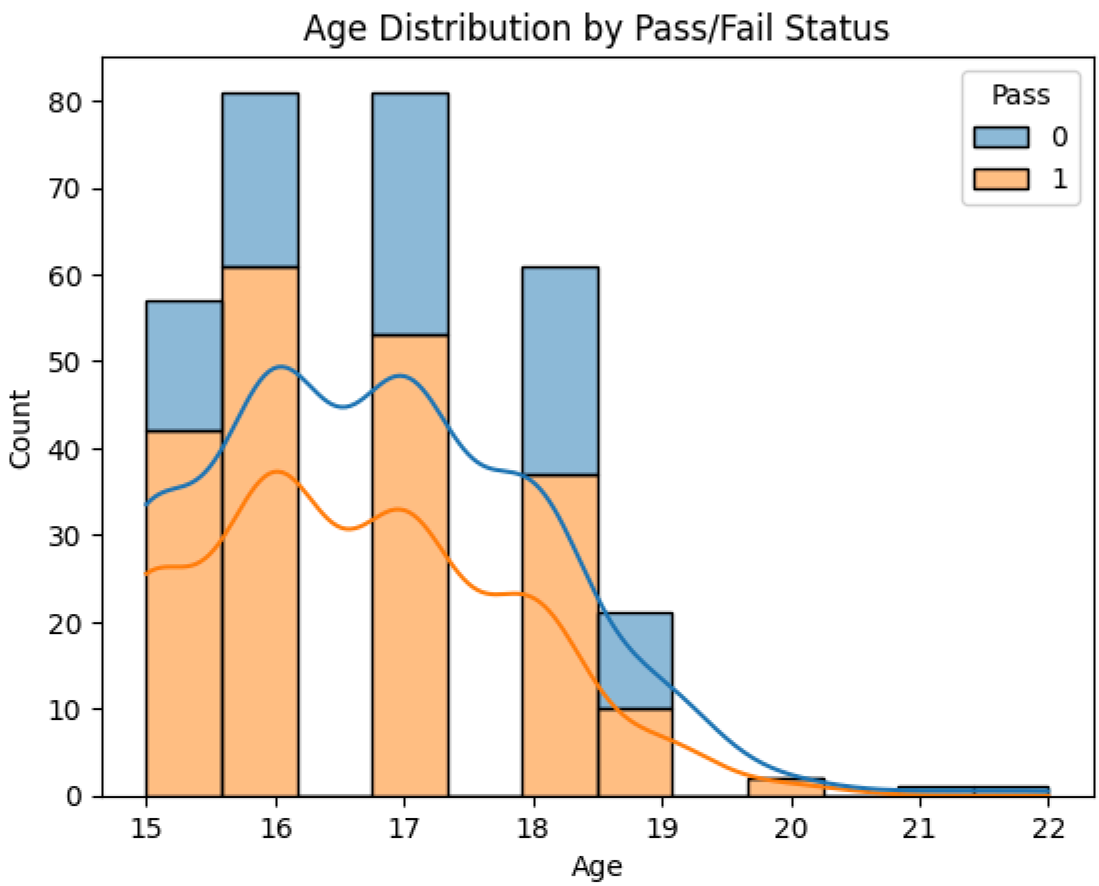
Relationship between Pass and studytime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
studytime
0
1
Pass

This histogram shows the distribution of students' ages, stacked by whether they passed or failed (Pass attribute). Overlaying a kernel density estimate (KDE) helps understand the age density.

Importance: Understanding age distribution relative to pass/fail status can reveal if certain age groups are more prone to failing.

Insights: Certain ages have higher failure rates, indicating that interventions could be age-targeted.

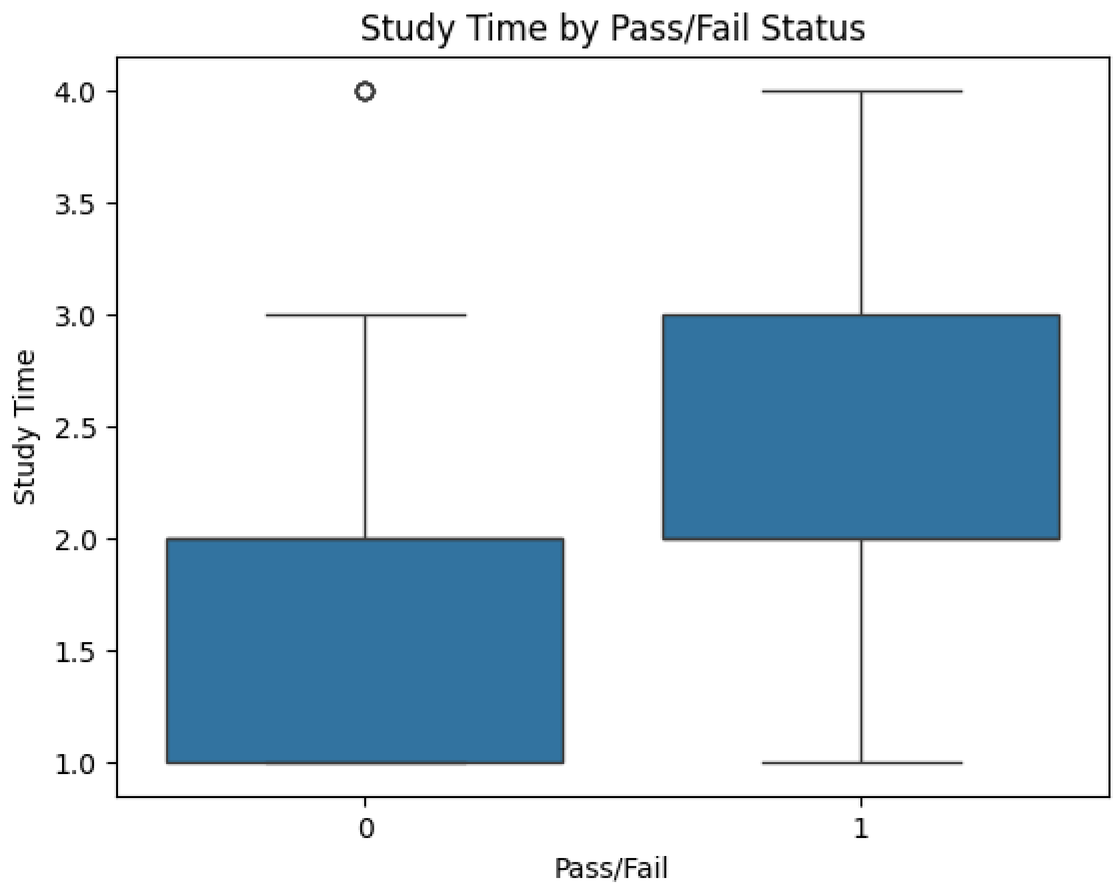
```
sns.histplot(data=train_dataset, x='age', hue='Pass', multiple='stack', kde=True)
plt.title('Age Distribution by Pass/Fail Status')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



Explanation: This boxplot compares the distribution of weekly study time between students who passed and those who failed.

Importance: It highlights the importance of study time as a factor in academic success.

```
sns.boxplot(data=train_dataset, x='Pass', y='studytime')
plt.title('Study Time by Pass/Fail Status')
plt.xlabel('Pass/Fail')
plt.ylabel('Study Time')
plt.show()
```

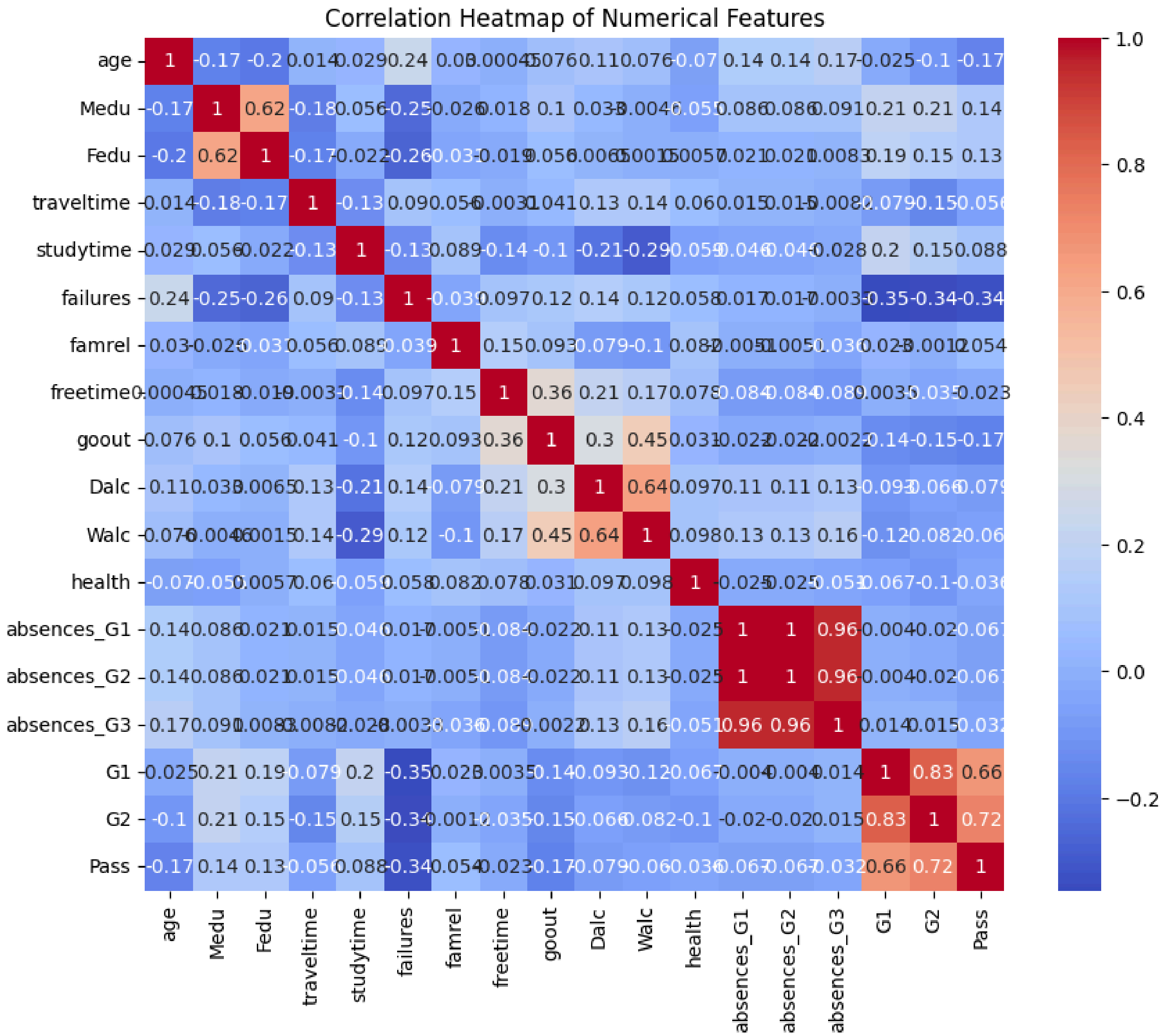


Explanation: This heatmap displays the correlation coefficients between numerical features, including the newly binary Pass variable.

Importance: Understanding how different numerical features correlate with each other and with the pass/fail status can uncover predictors of student performance.

Insights: Strong correlations (positive or negative) can guide feature selection for modeling. For instance, a high correlation between study time and passing could validate its predictive value.

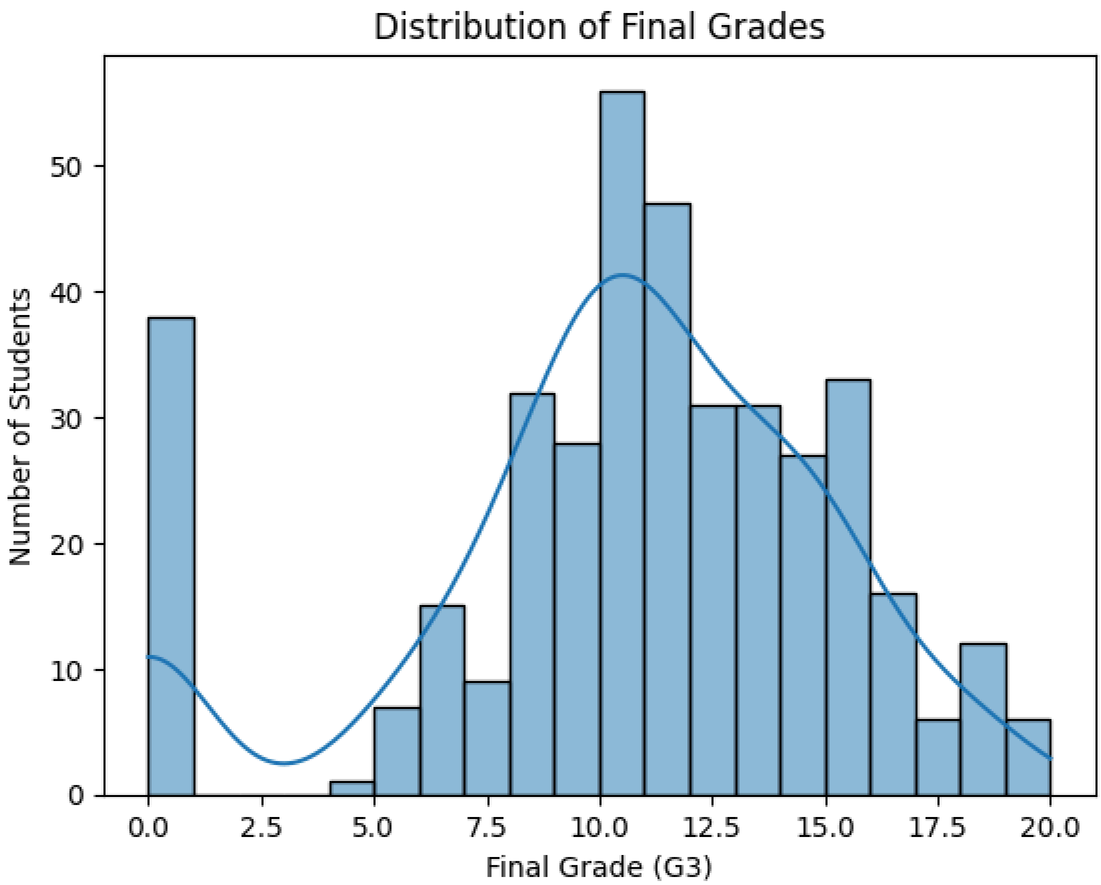
```
import numpy as np
plt.figure(figsize=(10, 8))
sns.heatmap(train_dataset.select_dtypes(include=[np.number]).corr(), annot=True, cma
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



Objective: Understand the distribution of final grades among students.

Insights: This visualization helps identify the general performance of students and how grades are distributed. For instance, if you see a left or right skew, it might indicate grading biases or the effectiveness of the teaching approach.

```
sns.histplot(data=df, x='G3', bins=20, kde=True)
plt.title('Distribution of Final Grades')
plt.xlabel('Final Grade (G3)')
plt.ylabel('Number of Students')
plt.show()
```



Prepare the data

1. Feature selection to narrow down the data.

```
from sklearn.base import BaseEstimator, TransformerMixin

class FeatureSelector(BaseEstimator, TransformerMixin):
    def __init__(self, feature_names):

        # list of feature names to keep.
        self.feature_names = feature_names

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        # new DataFrame with only the selected features
        return X[self.feature_names]

# Example
feature_names = ['studytime', 'failures', 'Medu', 'Fedu', 'Dalc', 'Walc', 'absences_
# Initialize the transformer with the names of features you've decided to keep
selector = FeatureSelector(feature_names=feature_names)

# Transform the training data
X_train_selected = selector.transform(X_train)
X_test_selected = selector.transform(X_test)
```

2. Data pipeline to handle the data preparation steps

```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

# Numerical features to scale
numerical_features = ['age', 'Medu', 'Fedu', 'studytime', 'failures', 'Dalc', 'Walc'

# Categorical features to encode
categorical_features = ['school', 'sex', 'address', 'famsize', 'Pstatus', 'Mjob', 'F

# Creating transformers
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine transformers into a ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Full pipeline: preprocessing + modeling
from sklearn.ensemble import RandomForestClassifier

pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('classifier', RandomForestClassifier(random_state=42))])
```

3. Drop the rows or columns with missing values inside the pipeline

```
from sklearn.impute import SimpleImputer

# Adjusting the numerical_transformer to fill in missing values for numerical featur
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='mean')),  # Filling missing values with the
    ('scaler', StandardScaler())
])

# Adjusting the categorical_transformer to fill in missing values for categorical fe
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),  # Filling missing values
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

from sklearn.ensemble import RandomForestClassifier

pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('classifier', RandomForestClassifier(random_state=42))])
```

4. Custom transformer for the pipeline

```
from sklearn.base import BaseEstimator, TransformerMixin
import numpy as np

class AbsenceTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, drop_G1_G2=True):
        self.drop_G1_G2 = drop_G1_G2

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        X = X.copy()
        X['total_absences'] = X['absences_G1'] + X['absences_G2'] + X['absences_G3']
        X.drop(['absences_G1', 'absences_G2', 'absences_G3'], axis=1, inplace=True)

        if self.drop_G1_G2:
            X.drop(['G1', 'G2'], axis=1, inplace=True)

        return X

# Incorporating the custom transformer into the preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features),
        ('absence_transform', AbsenceTransformer(drop_G1_G2=True), ['absences_G1', '
    ], remainder='passthrough')
```

5. Feature scaling on continuous numeric data in the pipeline

```
# feature scaling
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='mean')),  # Imputing missing values with the
    ('scaler', StandardScaler())  # Scaling the features
])
```

6. Ordinal encode features that are either binary or that are ordinal in nature; and/or one-hot encode nominal or categorical data in a pipeline

```
from sklearn.preprocessing import OrdinalEncoder

# Identify binary/ordinal features and nominal features
binary_ordinal_features = ['Pstatus']  # an example
nominal_features = ['school', 'sex', 'address', 'famsize', 'Mjob', 'Fjob', 'reason',

# Create transformers for binary/ordinal and nominal features
binary_ordinal_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('ordinal', OrdinalEncoder())
])

nominal_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Adjust the ColumnTransformer to include these transformations
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('binary_ordinal', binary_ordinal_transformer, binary_ordinal_features),
        ('nominal', nominal_transformer, nominal_features),
        ('absence_transform', AbsenceTransformer(drop_G1_G2=True), ['absences_G1', '
    ], remainder='passthrough')
```

7. Column Transformer to transform the numeric and categorical data

```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('binary_ordinal', binary_ordinal_transformer, binary_ordinal_features),
        ('nominal', nominal_transformer, nominal_features),

        # Ensure the custom absence_transform is properly integrated if needed
    ], remainder='passthrough')
```

8. Transform the training data using the above data preparation steps and pipelines and the output of the shape of your two transformed training sets

```
# Pipeline without dropping G1/G2
pipeline_with_G1_G2 = Pipeline(steps=[
    ('preprocessor', preprocessor),
])

# Adjusting the absence_transformer within the preprocessor for this scenario
preprocessor_with_G1_G2 = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('binary_ordinal', binary_ordinal_transformer, binary_ordinal_features),
        ('nominal', nominal_transformer, nominal_features),
        ('absence_transform', AbsenceTransformer(drop_G1_G2=False), ['absences_G1',
    ], remainder='passthrough')

# Pipeline with dropping G1/G2
pipeline_without_G1_G2 = Pipeline(steps=[
    ('preprocessor', preprocessor),
])

# Transforming the training data
X_train_transformed_with_G1_G2 = pipeline_with_G1_G2.fit_transform(X_train)
X_train_transformed_without_G1_G2 = pipeline_without_G1_G2.fit_transform(X_train)

# Output the shape of the two transformed training sets
print("Shape with G1/G2 columns:", X_train_transformed_with_G1_G2.shape)
print("Shape without G1/G2 columns:", X_train_transformed_without_G1_G2.shape)
```

```
Shape with G1/G2 columns: (316, 51)
Shape without G1/G2 columns: (316, 51)
```

Shortlisting Promising Models

1. Fit three promising models

```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
from sklearn.impute import SimpleImputer

# Transform 'G3' into a binary variable for classification ('Pass' column: 1 for pa
df['Pass'] = (df['G3'] >= 10).astype(int)

# Handling missing values for 'age' by imputing the median
df['age'] = df['age'].fillna(df['age'].median())

# Define the features (X) and the target variable (y)
X = df.drop(['G3', 'Pass'], axis=1)  # Excludes the 'G3' column and the newly creat
y = df['Pass']  # Target variable

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

# Identifying numerical and categorical features for preprocessing
numerical_features = X_train.select_dtypes(include=['int64', 'float64']).columns.tc
categorical_features = X_train.select_dtypes(include=['object']).columns.tolist()

# Creating preprocessing pipelines
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combining transformers into a ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Define the models to train
models = {
    "Random Forest": RandomForestClassifier(random_state=42),
    "Gradient Boosting": GradientBoostingClassifier(random_state=42),
    "SVM": SVC(random_state=42, probability=True),
    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=42)
```