



# Student Dropout Prediction Using Machine Learning

AI Model for Predicting Student Dropout Risk using Academic and Behavioral Insights.

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# Business Understanding

## SECTION 1: THE PROBLEM



Colleges struggle to identify students at risk of dropout



## SECTION 2: KEY CAUSES



Poor Academic Performance



Low Engagement



Financial Issues



## SECTION 3: IMPACT & NEED



Early prediction helps institutions provide timely intervention



## SECTION 4: PROJECT OBJECTIVE

**Objective:**

Predict dropout risk using Machine Learning models

- ! Many colleges struggle to identify students at risk of dropout.
- 🔍 Causes: poor academic performance, low engagement, financial issues.
- 💓 Early prediction helps institutes: Provide timely support, improve retention and student success.
- 🎯 Objective: Predict dropout risk using ML models.

# Dataset & Features

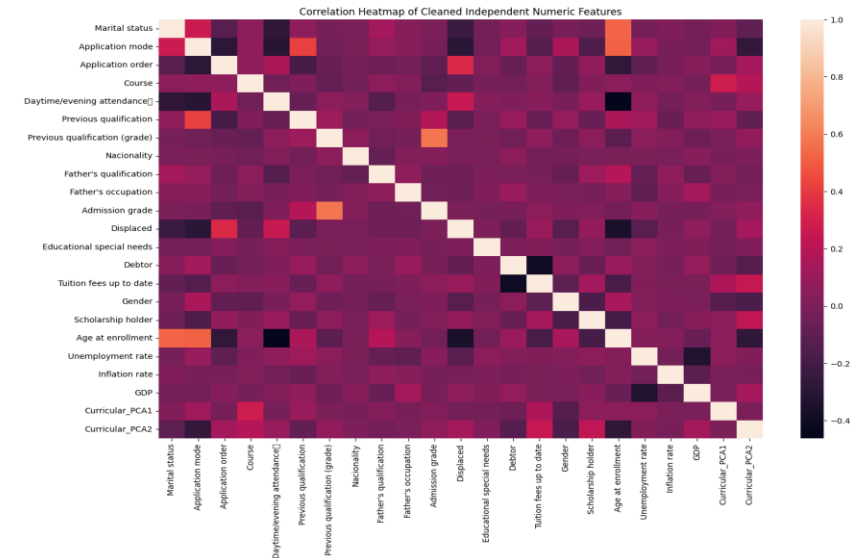
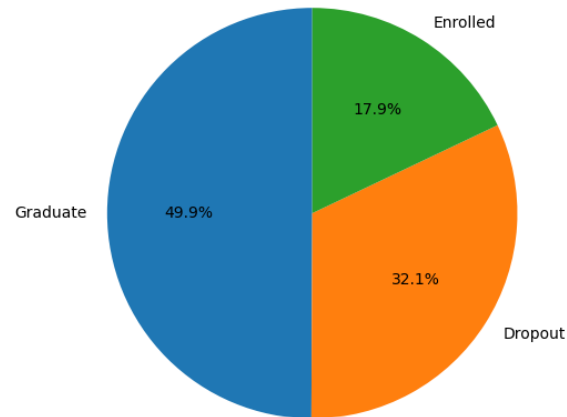
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Feature Category	Examples
Demographics	Age, Gender, Marital Status
Academic	Grades, credits, evaluations, approvals
Financial	Debtor, Scholarship, Fee up-to-date
Socio-economic	Unemployment, Inflation, GDP
Target	Transformed to binary: <b>Dropout</b> = 1, Enrolled/Graduate = 0

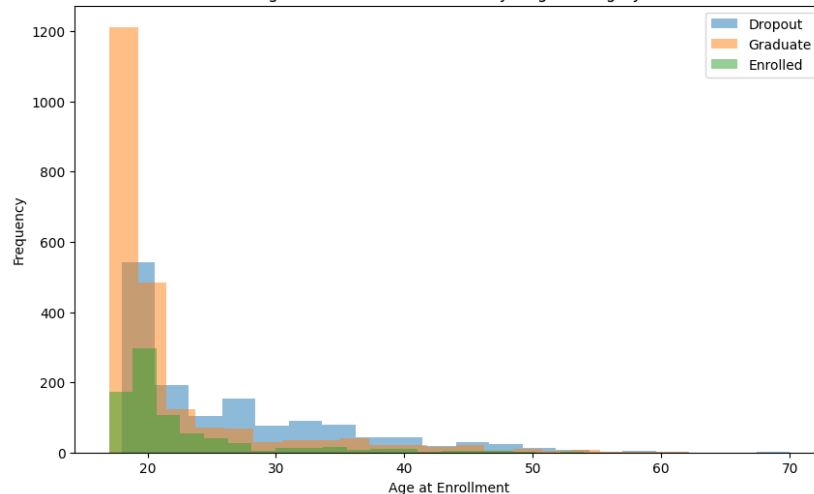
# Exploratory Data Analysis (EDA)

- Distribution of Target Column
- Age distribution across target categories
- Gender vs Target
- Course vs Target
- Marital status vs Target
- Correlation heatmap

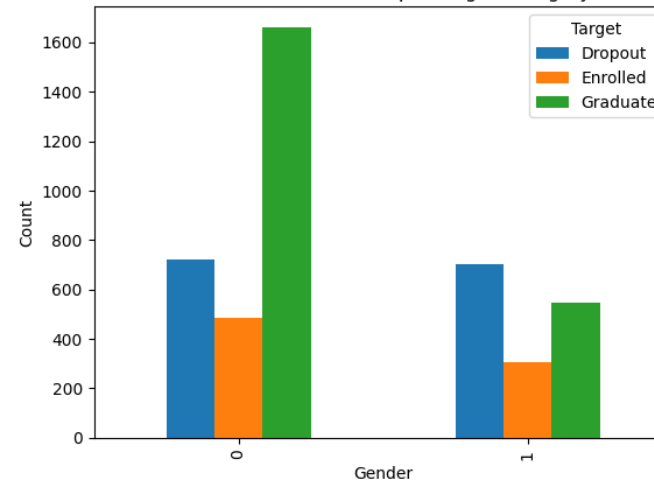
Distribution of Target Column



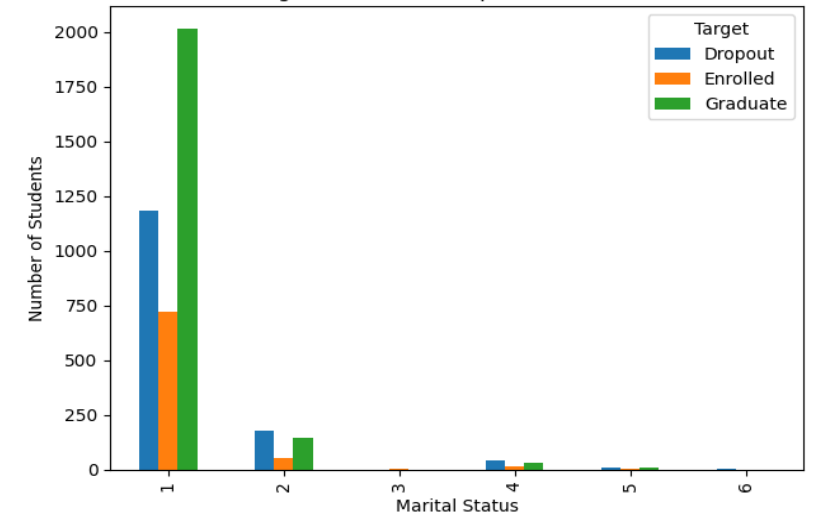
Age Distribution of Students by Target Category



Gender Distribution as per Target Category

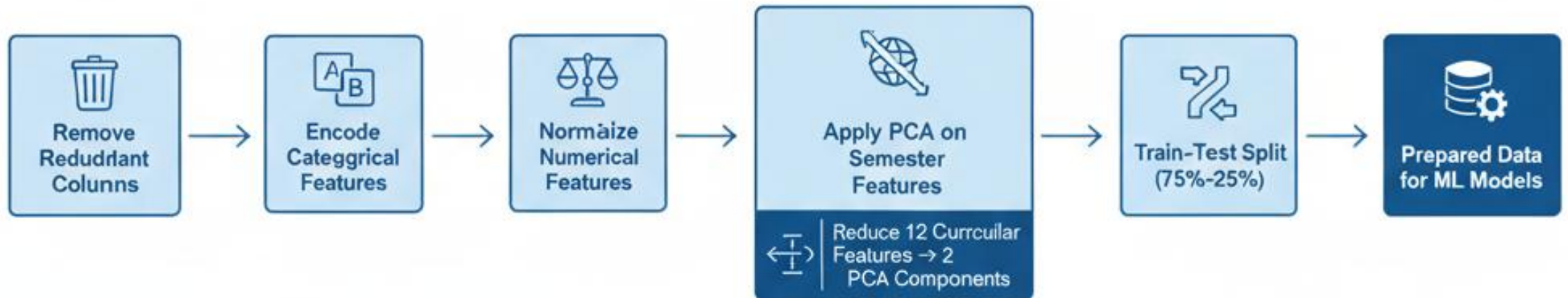


Target Distribution as per Marital Status



# Data Preparation

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PCA helped reduce dimoninsinity while keeping important information.

# KNN & Naive Bayes Models



## K-Nearest Neighbors (KNN)

- Distance-based algorithm
- Works well after normalization
- Accuracy: 0.82
- ROC-AUC: 85



## Naive Bayes Classifier

- Probabastic model
- Fast & simple
- Accuracy: 0.77
- ROC-AUC: 83

# Decision Tree & Random Forest

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## Decision Tree

- Easy to interpret
- Moderate performance
- Accuracy: 0.81
- Prone to overfitting



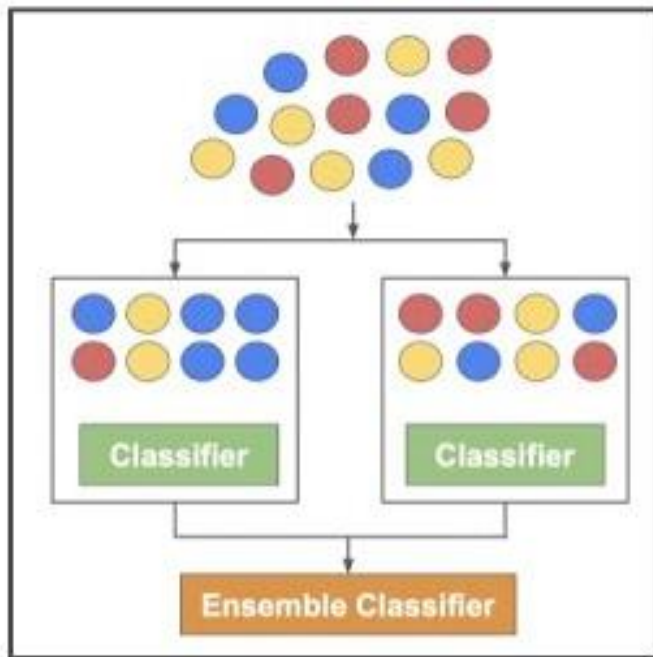
## Random Forest

- Ensemble of multiple decision trees
- Reduces overfitting
- Best standalone model
- Accuracy: 87, ROC-AUC: 0.92

Random Forest performed significantly better than a single Decision Tree.

# Bagging Ensemble

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## Key Metrics

- ✓ Reduces variance using multiple Decision Trees
- ✓ **Accuracy:** 0.8670
- ✓ **AUC:** 0.921
- ✓ Produces stable and robust predictions



# Boosting Techniques

## AdaBoost

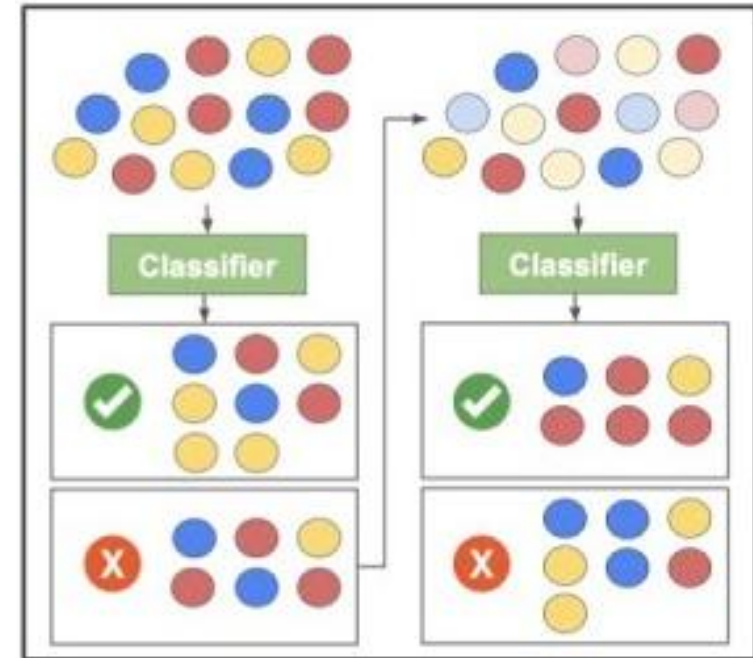
Accuracy: 0.872

AUC: 0.912

## Gradient Boosting

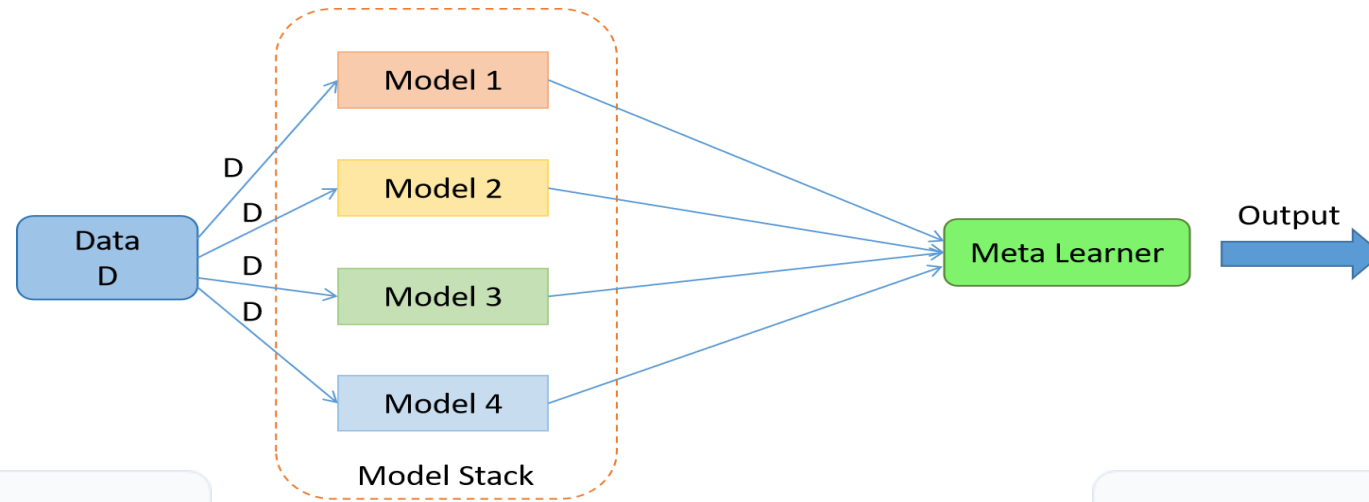
Accuracy: 0.874

AUC: 0.922



**Note:** Boosting improves classification by focusing on difficult samples.

# Stacking Ensemble (Final Model)



## Base Models

KNN, Naive Bayes, Decision Tree, and Random Forest.



## Meta-Model

Logistic Regression combines the predictions from base models.



## Final Result

**Best ROC-AUC: 0.928**  
Conclusion: Stacking model is the most reliable and recommended for deployment.

# Practical Outcome

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- The model can help institutions identify at-risk students for early academic and counseling interventions.
- **Stacking Ensemble** achieved the highest ROC-AUC (0.928) and excellent accuracy.

**Thank You !**