



# Key Message





Student dropouts significantly impact educational institutions both financially and reputationally.

A predictive model has been developed to identify at-risk students early.



The model enables timely interventions, potentially reducing dropout rates.

# Business Problem

#### **Problem Statement:**

 High dropout rates affect the institution's success metrics, including graduation rates, student satisfaction, and financial health.

#### Goal:

 To develop a predictive model that can identify students at risk of dropping out, allowing for early intervention.

# Data Overview

- Total Observation 4424, 34 variable
- After dropping highly correlated
   & irrelevant ones 4424
   observations and 22 variable.
- Dropped target variable 'Enrolled'

#### **Key Features: Academic Performance, Demographics and Personal Factors, Financial Situation, Course-Specific Factors.**

**Curricular units 2nd sem (approved):** A strong indicator of early academic success. Students struggling to pass courses early on might be at higher risk.

**Previous Qualification:** A student's prior academic background can influence their preparedness for higher education.

**Age:** Older students might face different challenges balancing academic life with other responsibilities.

**Marital status:** Family responsibilities could impact a student's ability to focus on studies.

**Gender:** There might be gender-specific factors influencing dropout rates.

**Tuition fees up to date:** Financial hardship is a major contributor to student dropout.

**Scholarship holder:** Financial support can help students stay enrolled.

**Course:** Certain courses might have inherently higher dropout rates due to difficulty or other factors.

#### Feature Engineering





Dropping Irrelevant Features: Removed several columns that were deemed irrelevant for predicting student dropout, such as 'Nationality' and 'Father's occupation',. This simplifies the model and potentially improves its performance by focusing on the most impactful features.

Encoding the Target Variable: Used **LabelEncoder** to convert the categorical 'Target' variable into numerical labels (0, 2). This is necessary for many machine learning algorithms that require numerical input.

# Modeling

- Techniques used:
  - Logistic regression
  - Decision trees
  - Random forest
  - Random Forest with Hyperparamter Tuning

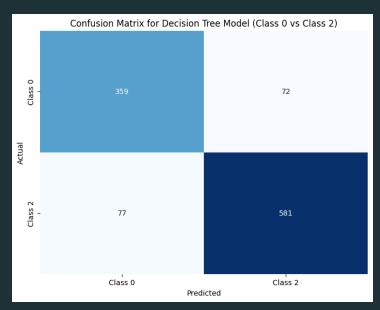


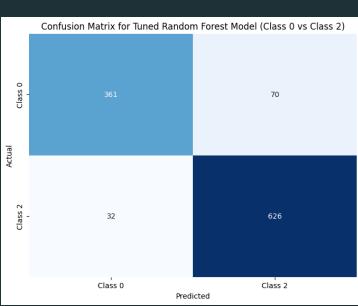
## **Model Performance:**

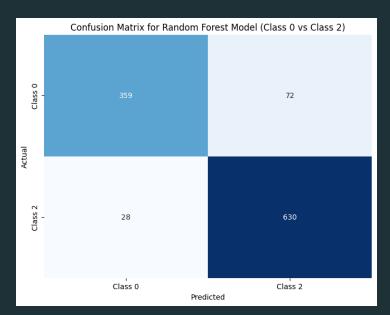
	Precision	Recall	F1-Score	Accuracy
Logistic Regression	Dropouts 89% Graduates 91%	Dropouts 86% Graduates 93%		90%
Decision Tree	Dropouts 82% Graduates 89%	Dropouts 83% Graduates 88%	Dropouts 83% Graduates 89%	86%
Random Forest	Dropouts 93%	Dropouts 83%		91%
Random Forest with Hyperparamter Tuning	Dropouts 92%	Dropouts 84% Graduates 95%	Dropouts 88%	91%

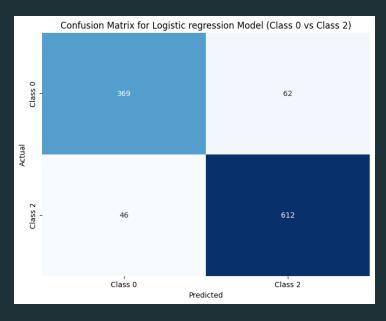
# Confusion Matrix Comparison

• This confusion matrix highlights how each model performs in classifying instances into Class 0 or Class 2, with the Logistic regression, Random Forest and Tuned Random Forest models generally performing better, especially in minimizing errors for Class 2.









#### Best Model Logistic Regression: For Better Readability

THE PRECISION FOR CLASS 0
(DROPOUTS) IS 0.89,
INDICATING THAT 89% OF
STUDENTS EXPECTED TO
DROP OUT DID SO. THE
PRECISION FOR CLASS 2
(GRADUATES) IS 0.91,
INDICATING THAT 91% OF THE
STUDENTS EXPECTED TO
GRADUATE ACTUALLY
GRADUATED.



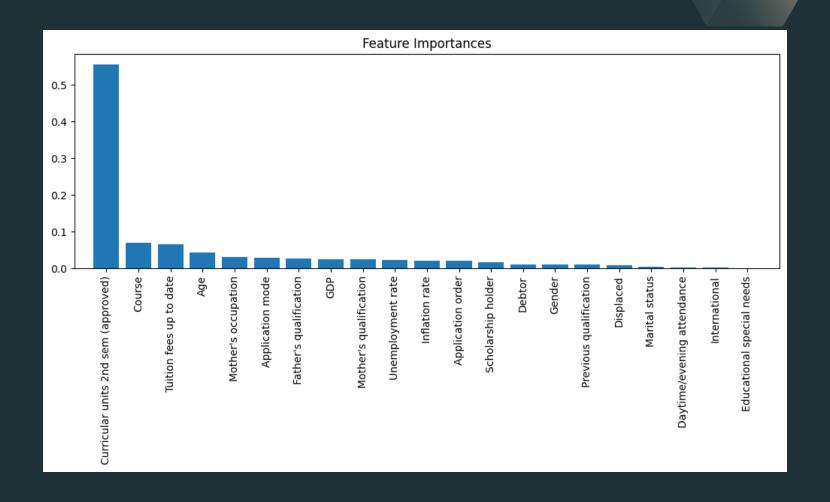
THE RECALL FOR CLASS 0
(DROPOUTS) IS 0.86,
INDICATING THAT THE MODEL
ACCURATELY DETECTED 86%
OF ALL REAL DROPOUT CASES.
FOR CLASS 2 (GRADS), THE
RECALL IS 0.93, INDICATING
THAT 93% OF ALL REAL
GRADUATES WERE CORRECTLY
IDENTIFIED. FOR CLASS 0, THE
F1-SCORE IS 0.87, SHOWING A
FAIR MIX OF PRECISION AND
RECALL FOR PREDICTING
DROPOUTS.



FOR CLASS 2, THE F1-SCORE IS 0.92, INDICATING AN EVEN GREATER BALANCE IN PREDICTING GRADS. 431 STUDENTS DROPPED OUT (CLASS 0), WHILE 658 GRADUATED (CLASS 2).

# Feature Importance

Curricular unit's 2nd semester
 (approved): This attribute
 represents the number of courses a
 student successfully finished during
 their second semester. A substantial
 positive link with dropout rates
 would indicate that students who
 do not pass enough courses early
 on are more likely to feel
 disheartened and leave. This
 emphasizes the value of early
 academic help.



# Actionable Insights



#### Recommendations:



Integrate predictive models into the institution's data systems to identify at-risk students early and accurately.



Collaborate with IT to ensure seamless integration into current systems.



Use insights from the predictive models to tailor support services such as academic advising, tutoring, and counseling.



Promote a culture of data-driven decision-making across the institution, ensuring that all staff understand the value and implications of predictive analytics.



Engage with external stakeholders, such as policymakers and educational consultants, to align predictive modeling efforts with broader educational goals.

# Business Impact



#### **Enhanced Institutional**

**Reputation:** Improved graduation rates boost the institution's rankings and reputation, making it more attractive to prospective students and faculty. Results in higher enrollment and competitive advantage in the educational market.



Increased Revenue from Higher Retention: Retaining more students results in sustained tuition revenue, reducing the need for constant

recruitment efforts.

Impacting in Financial stability and improved budget forecasting.



**Enhanced Student Experience:** By supporting at-risk students, the institution enhances overall student satisfaction, leading to a stronger alumni network. Resulting in Long-term alumni engagement and potential future contributions.



Risk Mitigation and Funding
Opportunities: Proactive management
of institutional risks & improved
retention rates ensure compliance with
accreditation standards and enhance
eligibility for grants and funding.





# Conclusion

This model is not just a solution for a business problem; it's a strategic approach to nurturing the next generation of leaders and innovators.

Today's students are tomorrow's assets. Ensuring their success is crucial not just for the institutions they attend, but for the society they will go on to shape.



By investing in predictive modeling for student success, we're investing in a brighter, more equitable future for all.



### References

• <a href="https://www.kaggle.com/datasets/n">https://www.kaggle.com/datasets/n</a>
<a href="aveenkumar20bps1137/predict-students-dropout-and-academic-success/data">https://www.kaggle.com/datasets/n</a>
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# Appendix

