ML Lab Assignment 4: Impact of Exam Type on Student Performance Prediction

25MCMI20, Sachin A

February 6, 2026

1   Introduction

This experiment extends the previous lab assignment by introducing a new feature called `Exam_Type` to analyze how exam classification affects student grading and machine learning model performance. The main objective was to understand whether adding information about exam type (Regular or Supplementary) as a feature improves the model's ability to predict student grades.

2   Dataset Description

The dataset is the same student marksheet used in the previous assignment, containing marks in four subjects for 250 students:

- **Name**: Student name

- **Maths**: Marks in Mathematics (out of 100)

- **Science**: Marks in Science (out of 100)

- **English**: Marks in English (out of 100)

- **History**: Marks in History (out of 100)

For this assignment, an additional feature was introduced:

- **Exam_Type**: Assigned such that exactly half of the students were labeled as "Regular" and the remaining half as "Supplementary", with the assignments randomly shuffled to avoid ordering bias.

3 Methodology

3.1 Step 1: Calculate Basic Metrics

First, the same metrics as in the previous lab were computed:

$$\text{Total Marks} = \text{Maths} + \text{Science} + \text{English} + \text{History} \tag{1}$$

$$\text{Percentage} = \frac{\text{Total Marks}}{400} \times 100 \tag{2}$$

Rank and percentile were calculated using the same formulas as in Lab 3.

3.2 Step 2: Generate Exam_Type Feature

The `Exam_Type` feature was generated such that exactly 125 students were assigned the Regular exam and 125 students were assigned the Supplementary exam. The labels were then randomly shuffled using NumPy to ensure a uniform distribution without positional bias. A fixed random seed was used to ensure reproducibility.

```
np.random.seed(42)
exam_types = ['Regular'] * 125 + ['Supplementary'] * 125
np.random.shuffle(exam_types)
df["Exam_Type"] = exam_types
```

3.3 Step 3: Assign Grades Based on Exam Type

Grades were assigned using different rules depending on the exam type.

3.3.1 Regular Exam Grading

For students with Regular exams, a full grading scale based on percentage was used:

Percentage Range	Grade
≥ 91	O
85–90	A+
75–84	A
65–74	B+
60–64	B
55–59	C
50–54	P
< 50	F

3.3.2 Supplementary Exam Grading

For students with Supplementary exams, a binary Pass/Fail grading scheme was used:

Total Marks	Grade
≥ 200 (50%)	Pass
< 200 (50%)	Fail

This design allows identical marks to map to different outcomes depending on the exam type.

4 Data Visualization

A bar chart was created to visualize the distribution of final grades:
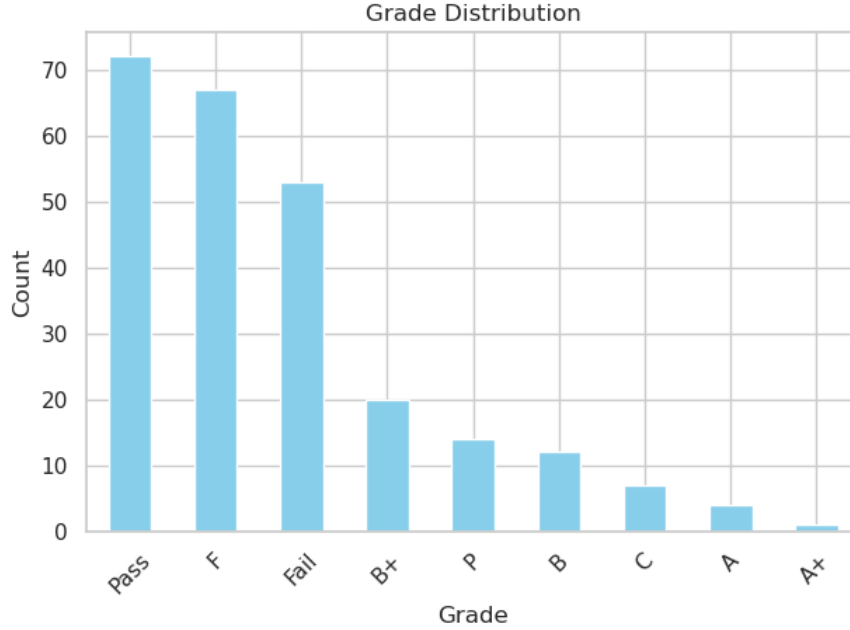
Figure 1: Distribution of final grades across all students, showing both Regular exam grades (O, A+, A, B+, B, C, P, F) and Supplementary exam outcomes (Pass, Fail).

5 Machine Learning Experiment

5.1 Research Question

The primary research question addressed in this experiment is: *Does including the Exam_Type feature improve the model's ability to predict student grades?*

5.2 Experimental Setup

Two Decision Tree classifiers were trained and compared:

1. **Model 1 (Baseline)**: Uses only subject marks as features.

   - Features: Maths, Science, English, History
   - Target: Final_Grade

2. **Model 2 (With Exam Type)**: Uses subject marks along with exam type information.

   - Features: Maths, Science, English, History, Exam_Type_Numeric
   - Target: Final_Grade

It is important to note that the goal of this experiment is not to replace the grading system, but to analyze how additional contextual information influences model behavior and prediction accuracy.

6 Evaluation Metrics

6.1 Accuracy

Accuracy measures the proportion of correct predictions:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \tag{3}$$

6.2 F1 Score

The weighted F1 score was used to balance precision and recall while accounting for class imbalance.

7 Results

7.1 Model Performance Comparison

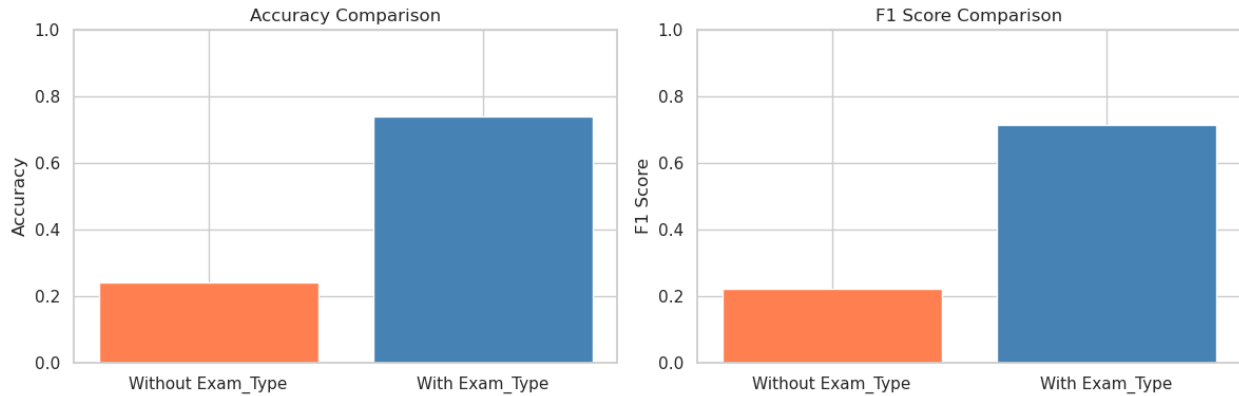The performance of both models was compared using accuracy and F1 score:

Figure 2: Comparison of accuracy and F1 score for models trained with and without the Exam_Type feature.

The observed results were:

- Model without Exam_Type: Accuracy = 0.24, F1 Score = 0.220866

- Model with Exam_Type: Accuracy = 0.74, F1 Score = 0.715618

- Improvement: 208.33%

8 Analysis

8.1 Why Does Exam_Type Help?

Including Exam_Type improves model performance for the following reasons:

1. **Additional context**: Exam type provides contextual information that explains why similar marks may result in different grades.

2. **Reduced ambiguity**: For Supplementary exams, the prediction task simplifies to a binary Pass/Fail decision.

9 Conclusion

This experiment demonstrated how the inclusion of the `Exam_Type` feature influences machine learning model behavior and prediction accuracy. The key observations are:

- Including Exam_Type improves predictive performance compared to using subject marks alone.

- The model learns approximate grading patterns for Regular and Supplementary exams, though it does not perfectly replicate the deterministic grading rules.

- Contextual features play an important role in improving model interpretability and performance.

Overall, the assignment highlights the importance of feature engineering and shows how contextual information can meaningfully influence machine learning predictions in educational data.