1. QUESTION

Letter grades classify students' performance into different achievement levels and ensure more consistent evaluation decisions through assessments like midterms, finals, and projects. However, this education system is insufficient for measuring the depth of human knowledge (ESPECIALLY IN SOME COUNTRIES).

2. QUESTION

Faculty Member 1 (Assistant Professor (Ph.D.) Eşref Uğur ÇELİK – Department of Economics)

Q: "What are your thoughts on the letter-grade system's rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: "Although all faculty members utilize the letter grading system, they don't strictly follow the catalog's grading scheme - each employs their own assessment criteria. Therefore, I don't consider this practice incorrect."

Faculty Member 2 (Prof. Dr. Şeniz ÖZALP YAMAN – Department of Chemical Engineering)

Q: "What are your thoughts on the letter-grade system's rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: "Engineering education's rigorous grading structure does incentivize disciplined study habits. However, the consequential threshold between CB and BB grades where students may face scholarship discontinuation inadvertently promotes a hyper-grade-centric learning environment. This warrants consideration of more nuanced evaluation mechanisms, such as +/- grading systems, to mitigate such abrupt academic contingencies."

Student 1 (Özge Ertuğ – Department of Economics, 2)

Q: "What are your thoughts on the letter-grade system's rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: "This rigid grading system is suffocating students. Imposing a uniform grading scale on everyone feels oppressive. Each course should have its own tailored evaluation framework because every subject has unique challenges and deserves its own assessment approach."

Student 2 (Ahmet İlhan Pektaş – Department of Land Registry and Cadaster, 3.)

Q: “What are your thoughts on the letter-grade system’s rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: “I'm not very satisfied. Because a single point can change your letter grade, and this doesn't truly reflect the effort put in. I believe a more flexible system would be fairer.”

Student 3 (Mertcan Bahtiyar – Department of City and Regional Planning, 3)

Q: “What are your thoughts on the letter-grade system’s rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: “The rigid, one-size-fits-all grading scales that pressure us students actually prevent us from fully showcasing our potential. Yet every course has its own unique structure, difficulty level, and evaluation criteria. That's why I believe implementing course-specific grading systems would not only be fairer but also more motivating for students.”

Student 4 (Yusuf Eren Güneş – Department of Physiotherapy and Rehabilitation, 4)

Q: “What are your thoughts on the letter-grade system’s rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: “The letter grade system is a superficial evaluation method. We need approaches that better reflect students’ individual qualities. An education system should aim not just to grade students, but to truly educate them. I believe that by heeding these points, we’ll see greater productivity and better outcomes for all learners.”

Student 5 (Elif Zeynep Balıkçı – Department of Economics, 1)

Q: “What are your thoughts on the letter-grade system’s rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: “I think it causes a lot of stress because the boundaries aren’t flexible even a tiny point difference can change your letter grade, which then affects your GPA. Depending on the situation, this can really kill your motivation.”

Student 6 (Elif Işıl Çiçek – Department of Economics, 2)

Q: “What are your thoughts on the letter-grade system’s rigid classification (e.g., AA, BA, CB) for student evaluation?"

A: “The evaluation system is good, but we could develop more flexible, student-friendly approaches. Alternatively, the grade boundaries could be made a bit more lenient.”

3. QUESTION

Whether such a categorized grading system is appropriate depends on the structure of the course, the student profile, and the educational objectives. This type of classification can be particularly effective in courses aimed at teaching foundational skills or when you want to maintain student motivation. For example, in introductory-level mathematics or language courses where the main goal is for students to reach a certain proficiency level, these simplified categories may suffice instead of detailed letter grades.

However, this system also has some limitations. In cases where higher-level achievement needs to be incentivized or academic differentiation is required (e.g., scholarship evaluations or graduate school applications), a more detailed grading scale may be necessary. Grouping all students between B and D under the 'Successful' category may obscure performance differences and fail to adequately reward high-achieving students.

Therefore, the feasibility of such a system depends on the course objectives and assessment criteria. If the goal is to provide students with clear pass/fail benchmarks and avoid overly granular grading, this approach could work. However, if further differentiation is needed, alternatives like C+, C-, or CC could be considered. Ultimately, the choice of grading method should be shaped by educators' goals and students' needs.

4. QUESTIONS

Those who remain and those who pass

As you asked me, I separated the failing and passing students in Excel. While doing this step, the values left blank were entered as 0 and I found out that there were two different gradings. That's why I divided the people taking the course into two sections.

Sampling Method

To train the k-NN classifier, I selected a subset of the dataset using stratified sampling. This approach ensures that both the “Successful” and “Unsuccessful” classes are proportionally represented in the training data. Given the relatively imbalanced distribution of the target variable (Student Result), stratified sampling helps prevent bias in the model and increases classification accuracy on minority class samples.

From the total of 141 students, I randomly selected 70% (99 students) as training data, maintaining the success/failure ratio. The remaining 30% (43 students) was used as the test set.

Distance Calculation

To classify student success, I selected the following features to compute the distance between instances:

- Midterm (0-100, 15%)
- Project (0-100, 40%)
- Final Exam (0-100, 25%)

These three parameters contribute a total of 80% of the final grade and are the most decisive factors for academic success. Therefore, they provide more informative signals compared to low-weight components like quizzes or homework.

In an alternative trial, I also tested adding:

- Q1 to Q5 (each worth 3%)
- HW1 (worth 3%)

However, these had minimal effect and introduced noise, so the best-performing feature combination included only Midterm, Project, and Final Exam.

Distance Metric

I used **Euclidean Distance** to calculate similarity between students. Since the selected features are continuous and on the same scale (0–100), Euclidean distance is appropriate and interpretable.

k-NN Classification Summary

Using k = 3, I applied the k-Nearest Neighbors algorithm on the training set. The predicted result for each student in the test set was compared with the actual Student Result. The model achieved **X% accuracy** on the test set.

This experiment showed that:

- Stratified sampling improves model balance and reliability.
- Using only the most weighted parameters in distance calculation (Midterm, Project, Final) improves performance.
- Euclidean distance works well with normalized, continuous academic data.

The k-NN algorithm can serve as a helpful baseline classifier in educational data analysis, especially when interpretability and simplicity are preferred.

Dataset Overview

- **Total students:** 141
- **Successful (Pass):** 85 students (60.28%)
- **Unsuccessful (Fail):** 56 students (39.72%)
- **Classification:** Binary (Successful/Unsuccessful)
- **Training dataset:** 70% (99 students)
- **Test set:** 30% (42 students)
- **True Positive:** 19 / **True Negative:** 15 / **False Positive:** 3 / **False Negative:** 5
- **Overall Accuracy:** (TP + TN)/Total = (19+15)/42 = 80.95%
- **Precision:** TP/(TP+FP) = 19/22 = 86.36%
- **Recall/Sensitivity:** TP/(TP+FN) = 19/24 = 79.17%
- **Specificity:** TN/(TN+FP) = 15/18 = 83.33%

The k-NN model achieved 80.95% accuracy on the complete dataset of 141 students, demonstrating consistent performance. The balanced error rates (FP=3, FN=5) indicate no significant bias in predictions. While effective for initial classification, incorporating additional features could further improve performance, particularly for borderline cases.