**Solv Probs W/ Machine Learning**

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**Lab:-2**

**Interpretation:**

**Interpretation of the confusion matrix:**

**True Positives (TP):** There are 716 instances where the model correctly predicted that the student would pass the course (Predicted Pass and Actually Passed). - \*\*True Negatives (TN)\*\*: The model correctly predicted 0 instances of failure (Predicted Fail and Actually Failed). This might be due to the class imbalance issue, where there might not have been any instances of students failing in the test set.

**False Positives (FP):** There are 417 instances where the model incorrectly predicted that the student would pass the course when they actually failed (Predicted Pass but Actually Failed).

**False Negatives (FN):** There are 0 instances where the model incorrectly predicted that the student would fail the course when they actually passed (Predicted Fail but Actually Passed). The dearth of false negatives implies a potential strength in the model's ability to identify students poised to succeed in the course, prompting the need for deeper exploration to ascertain whether this proficiency arises from the model's intrinsic reliability or other contributing elements.

**Summary:**

In summary, the model seems to perform reasonably well in predicting student pass/fail outcomes, with a high number of true positives. While the model displays a tendency to misclassify failing students as passing (false positives), employing metrics like accuracy, precision, recall, and F1-score in the evaluation process allows for a deeper understanding of its performance in discriminating between successful and unsuccessful students, facilitating a comprehensive assessment of its efficacy.