LAB 2
TASK A:CLASSIFICATION

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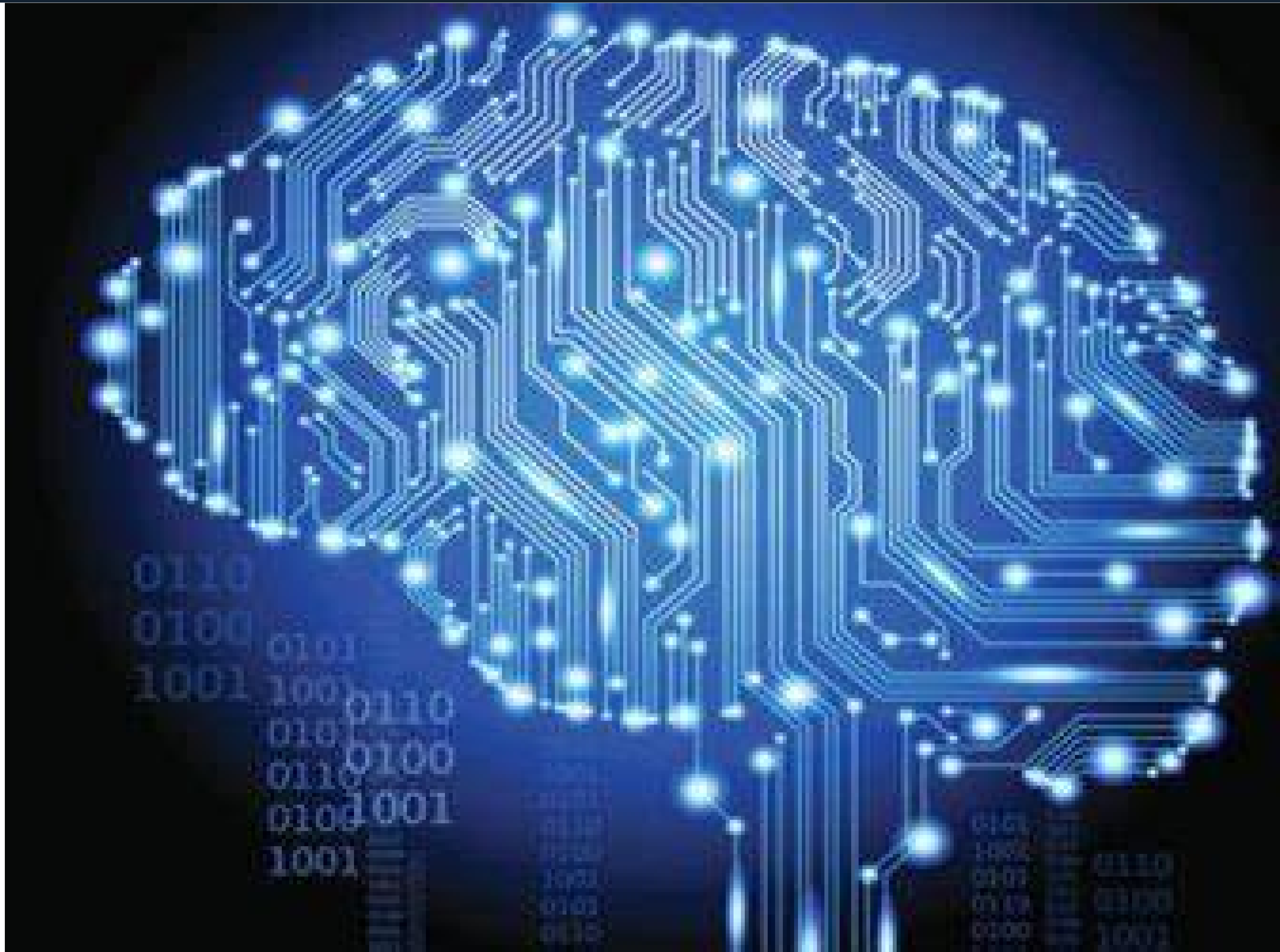
1 — INTRODUCTION

INRODUCTION

Classification algorithms are critical for deriving meaningful insights from complex biomedical data.

Performance evaluation is key to determining whether the model works and to comparing them.

This project focuses on evaluating various classification algorithms using metrics such as precision, recall, specificity, and accuracy.



2 — OBJECTIVES

OBJECTIVES

EVALUATE AND COMPARE
THE PERFORMANCE OF VARIOUS CLASSIFICATION METHODS.

ANALYZE DATASET CHARACTERISTICS
EXAMINE SAMPLES, CLASS DISTRIBUTION, AND BALANCE TO UNDERSTAND THEIR IMPACT ON PERFORMANCE.

SELECT THE BEST MODEL
CONDUCT A THOROUGH ANALYSIS OF METRICS TO SELECT THE MODEL WITH THE BEST OVERALL PERFORMANCE FOR PREDICTING OUTCOMES.

3 — METHODOLOGY AND RESULTS

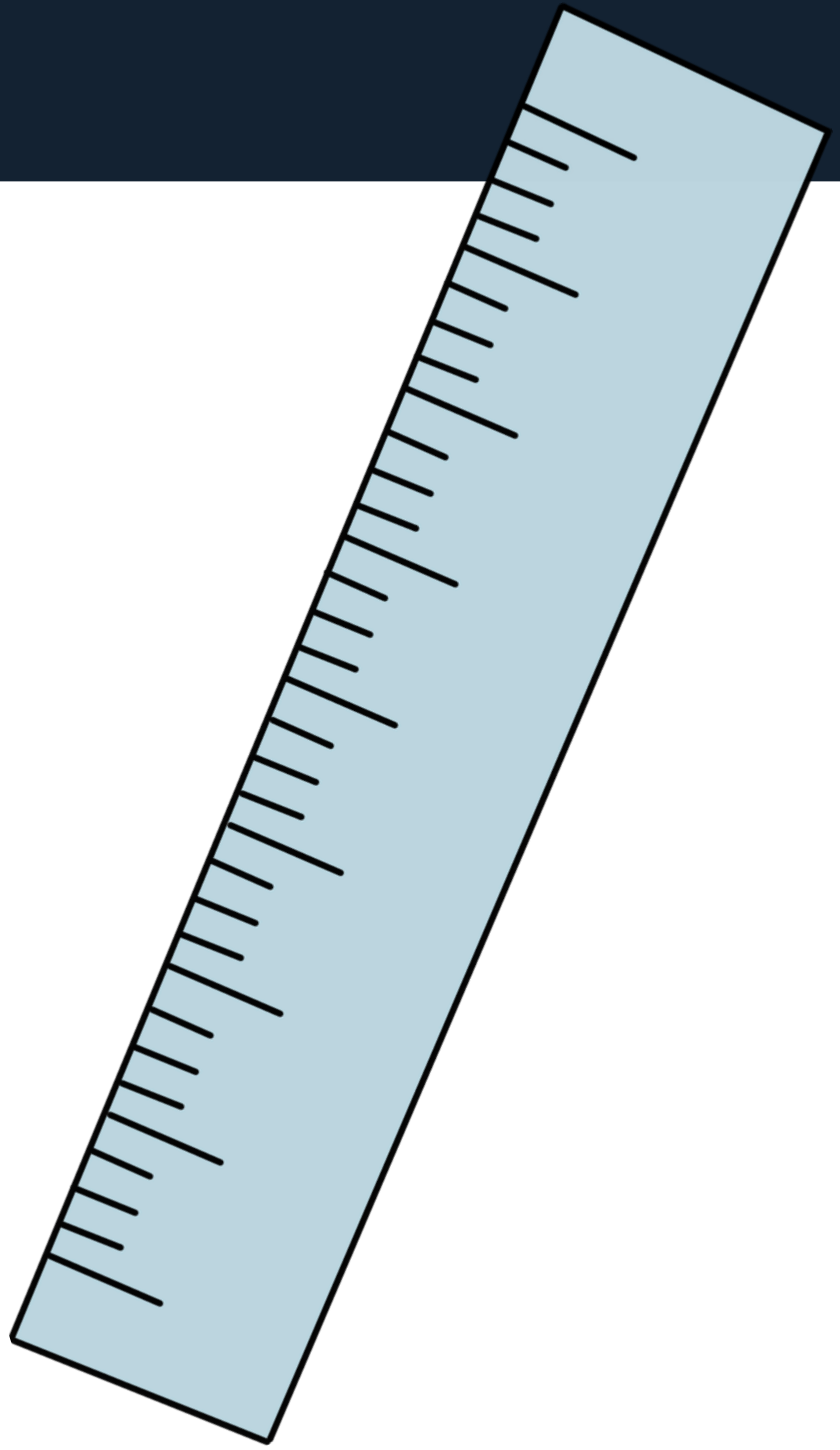
DATASET DESCRIPTION

- THERE ARE ONLY **TWO CLASSES** (POSITIVE AND NEGATIVE)
- METHOD A CLASSIFIES ALL TUPLES AS POSITIVE, RESULTING IN **100 TRUE POSITIVES**.
- METHOD E CLASSIFIES ALL INSTANCES AS NEGATIVE, CORRECTLY IDENTIFYING **900 TRUE NEGATIVES**.
- CLASS TRUE 100 TUPLES
- CLASS FALSE 900 TUPLES

UNBALANCED DATASET

METRICS USED FOR PERFORMANCE COMPARISON

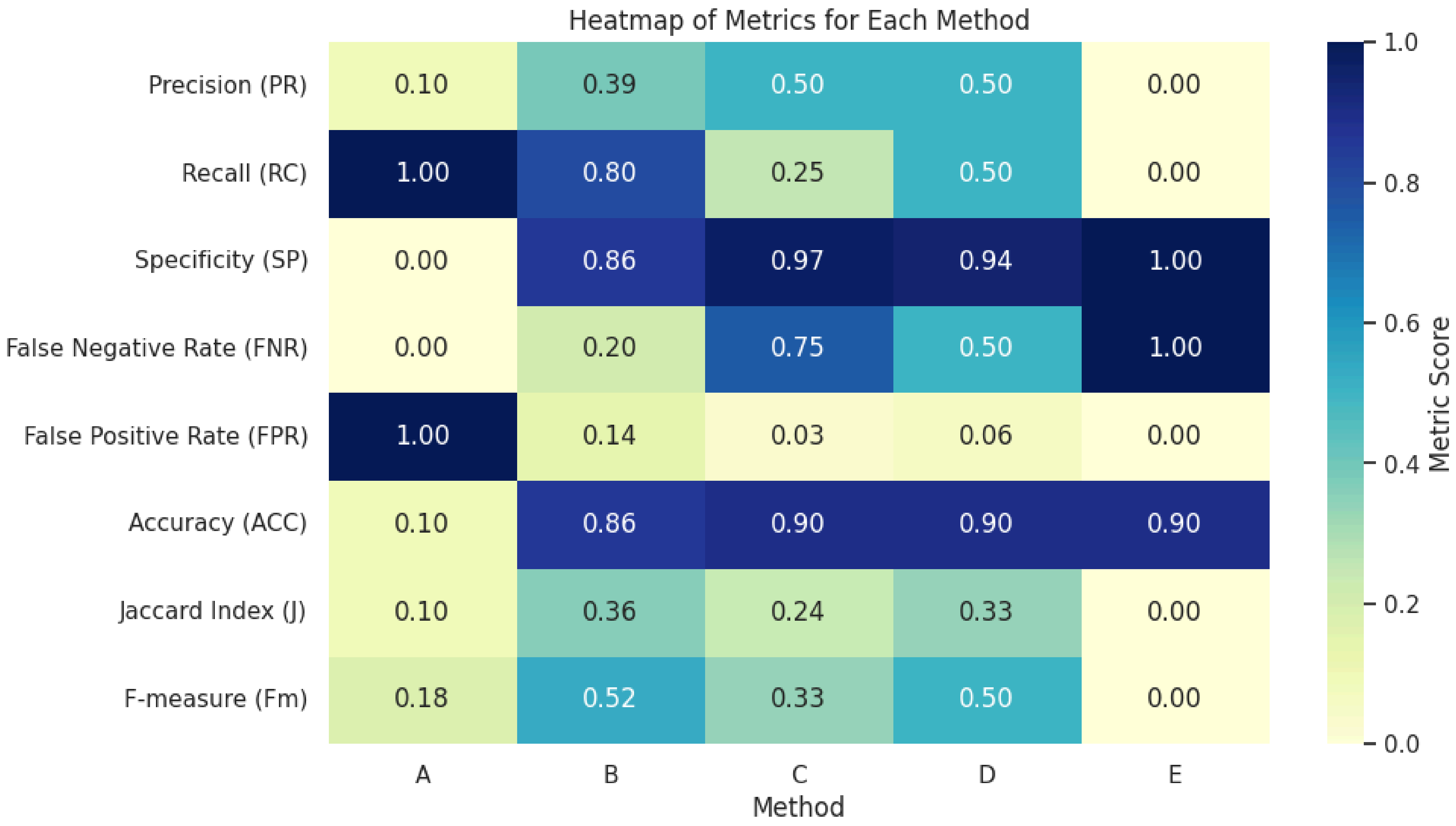
- **Precision (PR)**: Accuracy of positive predictions.
- **Recall (RC)**: Ability to identify relevant instances.
- **Specificity (SP)**: Identifying negative instances correctly.
- **False Negative Rate (FNR)**: Proportion of actual positives missed.
- **False Positive Rate (FPR)**: Proportion of actual negatives misclassified.
- **Accuracy (ACC)**: Overall correctness of predictions.
- **Jaccard Index (J)**: Similarity between predicted and actual positives.
- **F-measure (Fm)**: Balance between Precision and Recall.



COMPARATIVE PERFORMANCE OF METHODS ACROSS METRICS

The heatmap highlights each method's strengths and weaknesses by metric, enabling a quick comparison of performance across key values.

Color intensity makes it easy to identify the highest-performing methods in each metric.

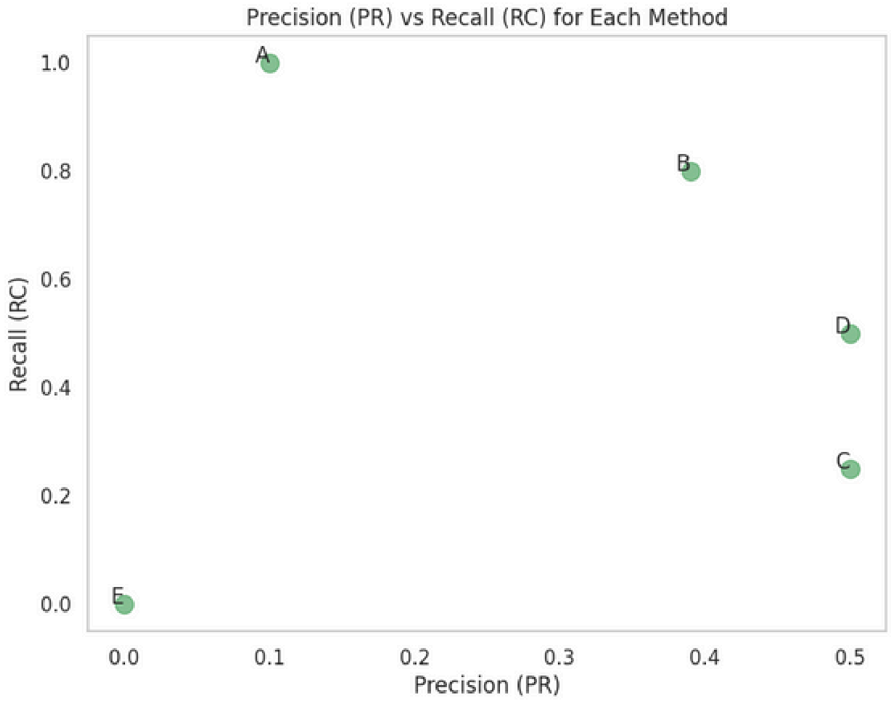


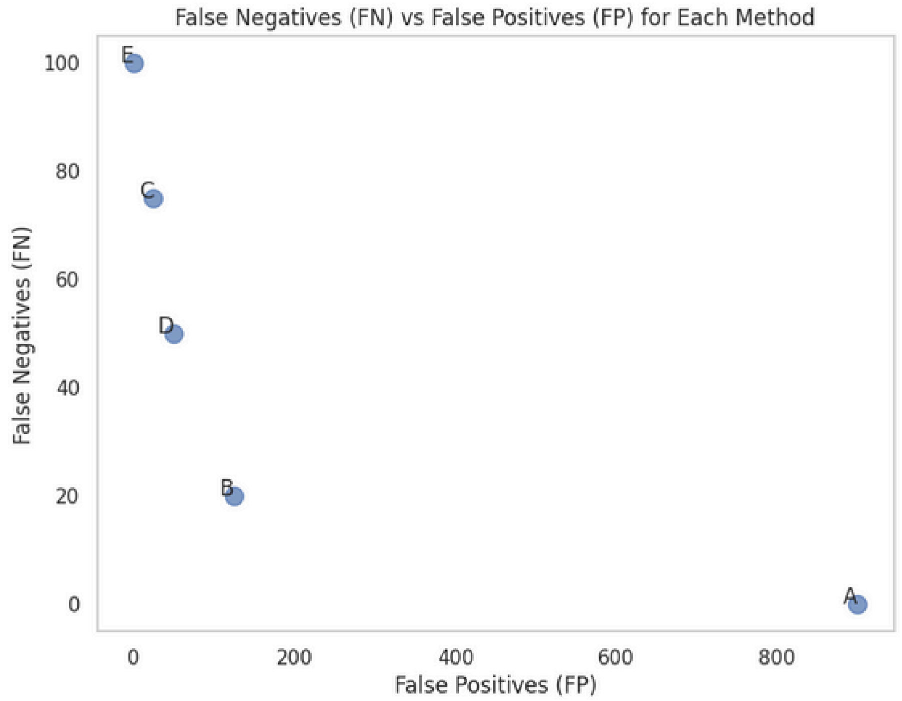
METRICS COMPARISON

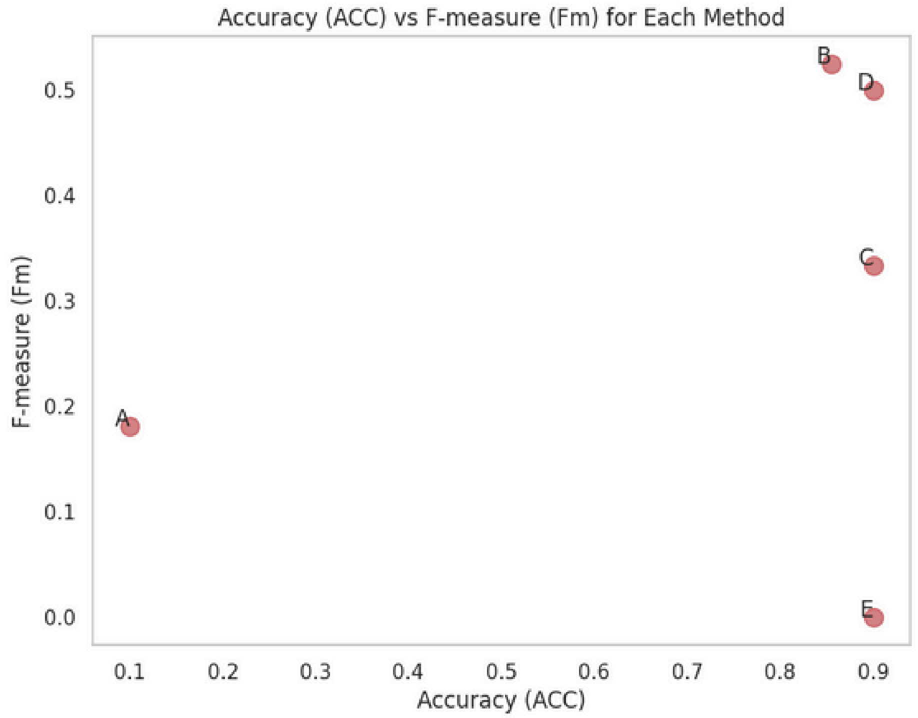
- **FN vs FP**: Method B balances false positives and false negatives best; Method A has high false positives, and Method E has high false negatives.

- **PR vs RC**: Method B achieves the best balance of recall and precision; Method A has high recall but low precision.

- **ACC vs Fm**: Method D has high accuracy and a strong F-measure, while Method B leads in F-measure but with slightly lower accuracy.







RADAR PLOT

- **Balance and Trade-offs:** The radar plot highlights the trade-offs in recall, precision, and specificity among methods, showing varied strengths across metrics.

- **Overall Balance:** Method B stands out as the most balanced performer, covering a broad area across most metrics.

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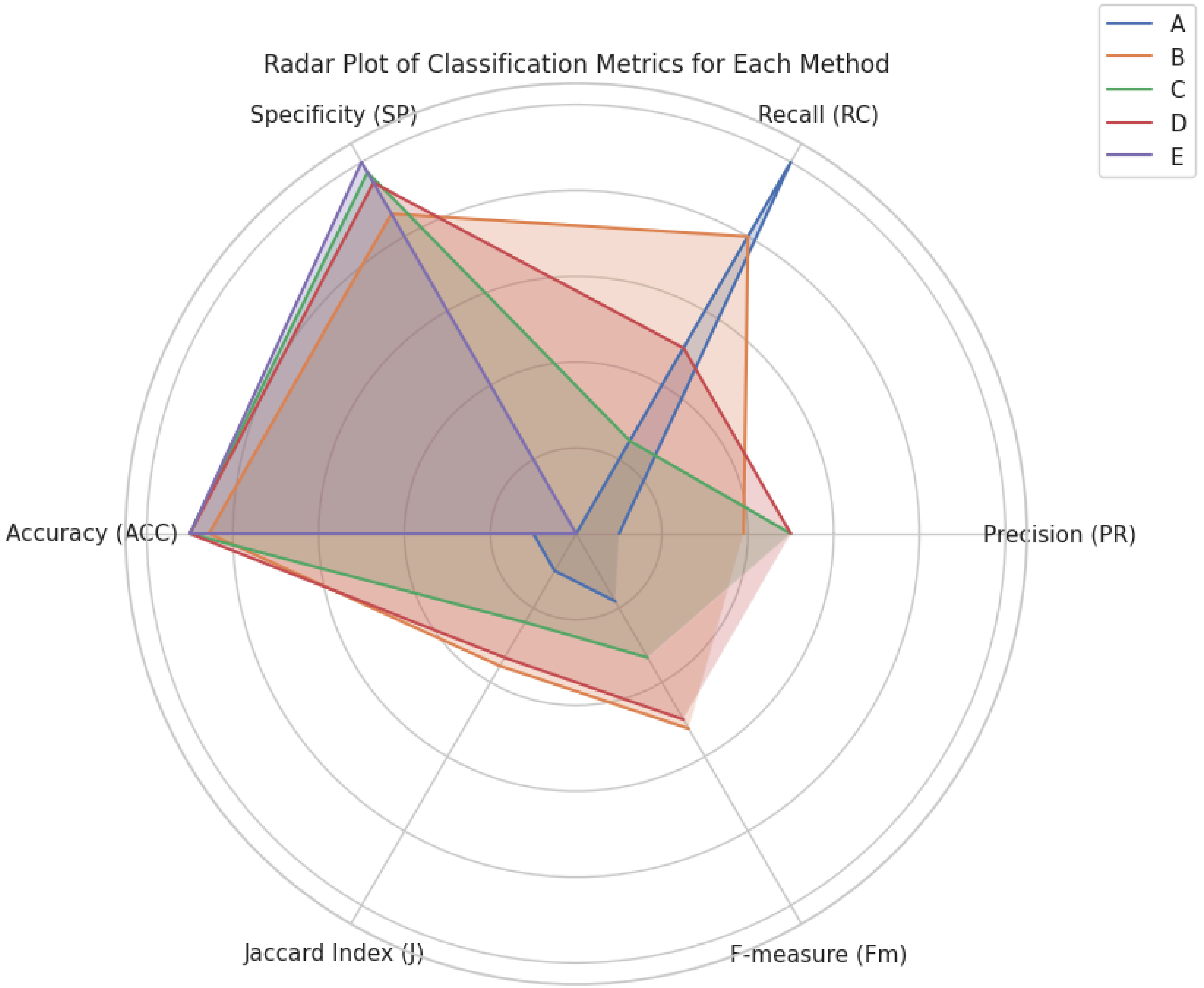
- **High-Accuracy Choices:** Method D offers the best balance for cases needing high accuracy and class balance, while Method E prioritizes specificity at the cost of other metrics.



3 — CONCLUSIONS

CONCLUSION

METHOD B:

THIS METHOD DEMONSTRATES THE BEST OVERALL BALANCE ACROSS PRECISION, RECALL, AND F-MEASURE, MAKING IT THE MOST ROBUST CHOICE FOR APPLICATIONS THAT REQUIRE BOTH ACCURATE POSITIVE IDENTIFICATION AND HIGH PRECISION.

METHODS A AND E:

THESE METHODS LACK ANY MEANINGFUL CLASSIFICATION CAPABILITY. METHOD A ONLY PREDICTS POSITIVES AND METHOD E ONLY NEGATIVES.

METHODS C AND D:

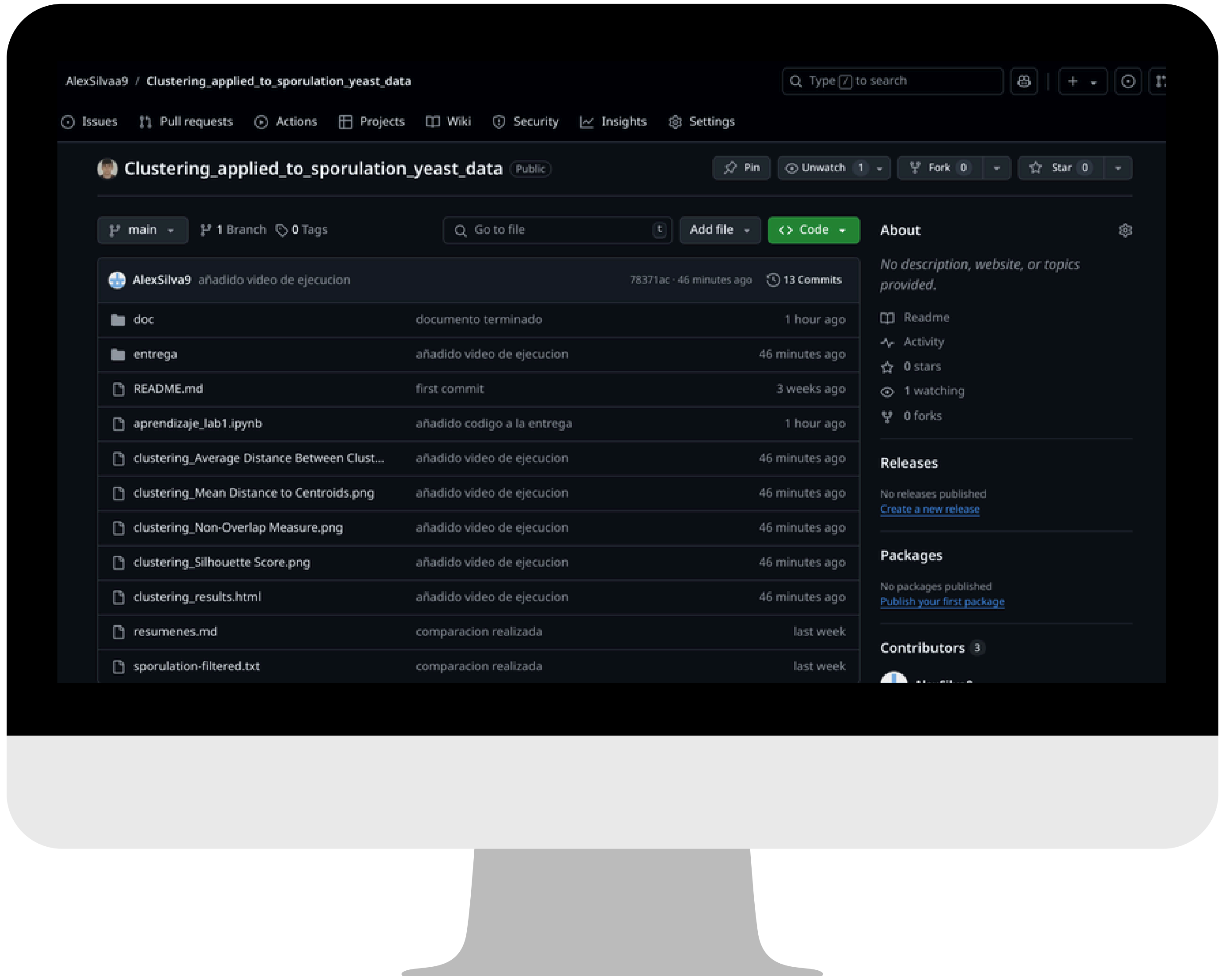
BOTH METHODS OFFER A MODERATE BALANCE BETWEEN PRECISION AND SPECIFICITY, BUT EACH IS LIMITED BY A HIGH FALSE NEGATIVE RATE. METHOD C SHOWS SOME IMPROVEMENT, BUT LACKS THE ROBUSTNESS OF METHOD B. METHOD D RANKS SECOND BEST, THOUGH ITS HIGHER FALSE NEGATIVE RATE REDUCES ITS OVERALL EFFECTIVENESS COMPARED TO METHOD B.

3 — REPOSITORY ACCESS

REPOSITORY ACCESS

- ALL ADDITIONAL INFORMATION, INCLUDING SOURCE CODE AND FULL DOCUMENTATION, IS AVAILABLE IN THE GITHUB REPOSITORY:

https://github.com/martacuevasr/Lab2_Computational_learning



THANK YOU