ML/DL in Disease Severity Detection

(Advancing Clinical Decision Support through Machine and Deep Learning Models)

Final Dessertation
For the Degree of
MSc Artificial Intelligence

Himanshu Bharti
(B00943643)
Presenter

Dr. Samuel Moore

(Supervisor)

School of Computing, Ulster University

BACKGROUND & MOTIVATION

- Cardiovascular diseases are the leading global cause of death.
- The severity of myocardial infarction (MI) strongly influences treatment urgency and patient outcomes [**1**].
- Traditional assessments are:
  - Subjective and prone to inter-observer variability
  - Not scalable in data-rich environments
- With the availability of Electronic Health Records (EHRs) and high-dimensional clinical data:
  - ML/DL models offer objective, scalable, and automated risk assessment [**2**]
- Existing research often predicts disease presence, not severity.

Motivation:

- Build robust and interpretable models to:
  - Enable early triage
  - Guide personalized treatment
  - Alleviate hospital burden
  - Integrate into clinical decision support systems [**3,4**]

OBJECTIVES

Aim: To develop and validate supervised ML/DL models for predicting myocardial infarction severity, enabling risk stratification and supporting clinical decisions.

Objectives:

- Develop multiple ML and DL models (RF, SVM, ANN, etc.)
- Perform comparative performance evaluation
- Stratify patients into low, moderate, and high-risk groups
- Validate model robustness using:
    - Y-randomization
    - Bootstrap statistical tests
    - Confusion matrices and learning curves

DATASET DESCRIPTION

•**Source:** UCI Machine Learning Repository

(https://archive.ics.uci.edu/dataset/579/myocardial+infarction+complications)

•**Instances:** 1,700 patients

•**Features:** 111 clinical and physiological variables [**5**]

•**Target:** Binary label

- 0: No complications
- 1: Complications post-MI
- Severity Stratification (Based on Random Forest Probability Scores):
    - **Low Risk:** Probability score < 0.30
    - **Moderate Risk:** 0.30 ≤ Probability score < 0.70
    - **High Risk:** Probability score ≥ 0.70

Workflow Overview

1.Data Acquisition: Retrieved from UCI Repository (MI Complications dataset)

2.Preprocessing: Imputation → Encoding → Scaling → SMOTE

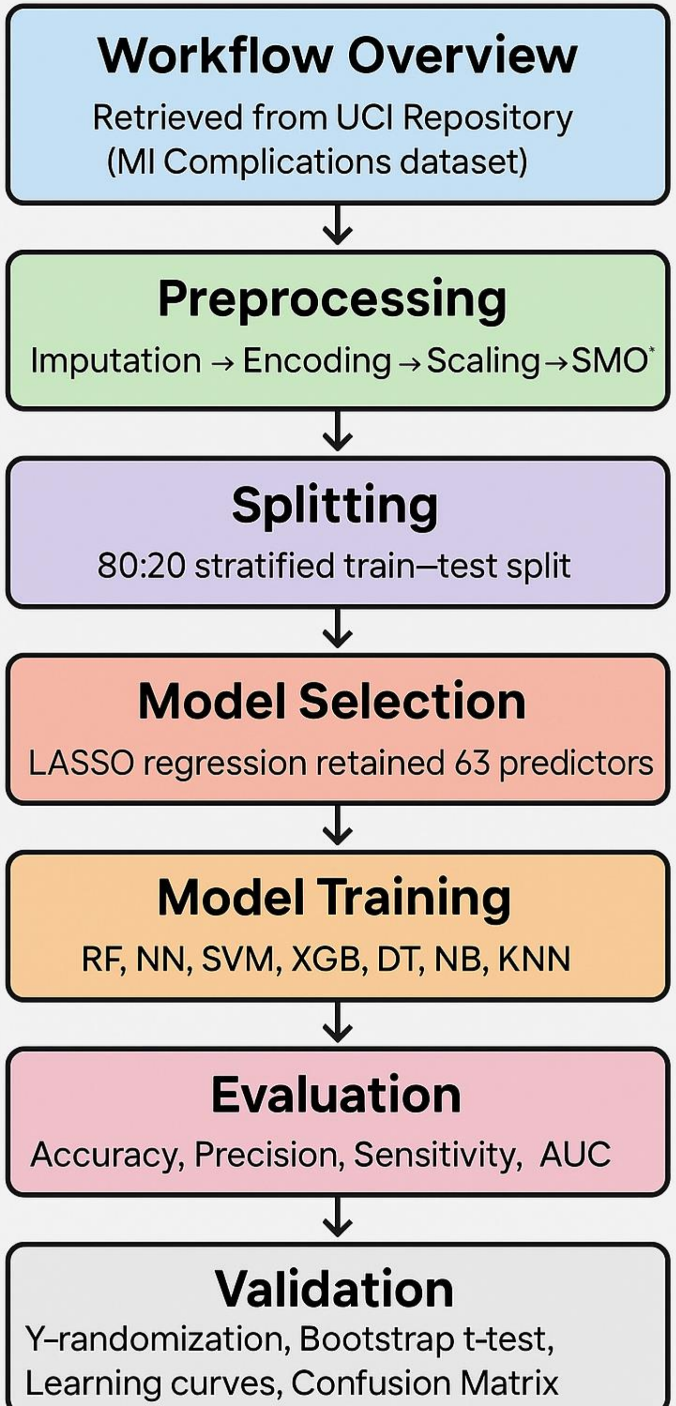
3.Splitting: 80:20 stratified train-test split

4.Feature Selection: LASSO regression retained 63 predictors

5.Model Training: RF, NN, SVM, XGB, DT, NB, KNN

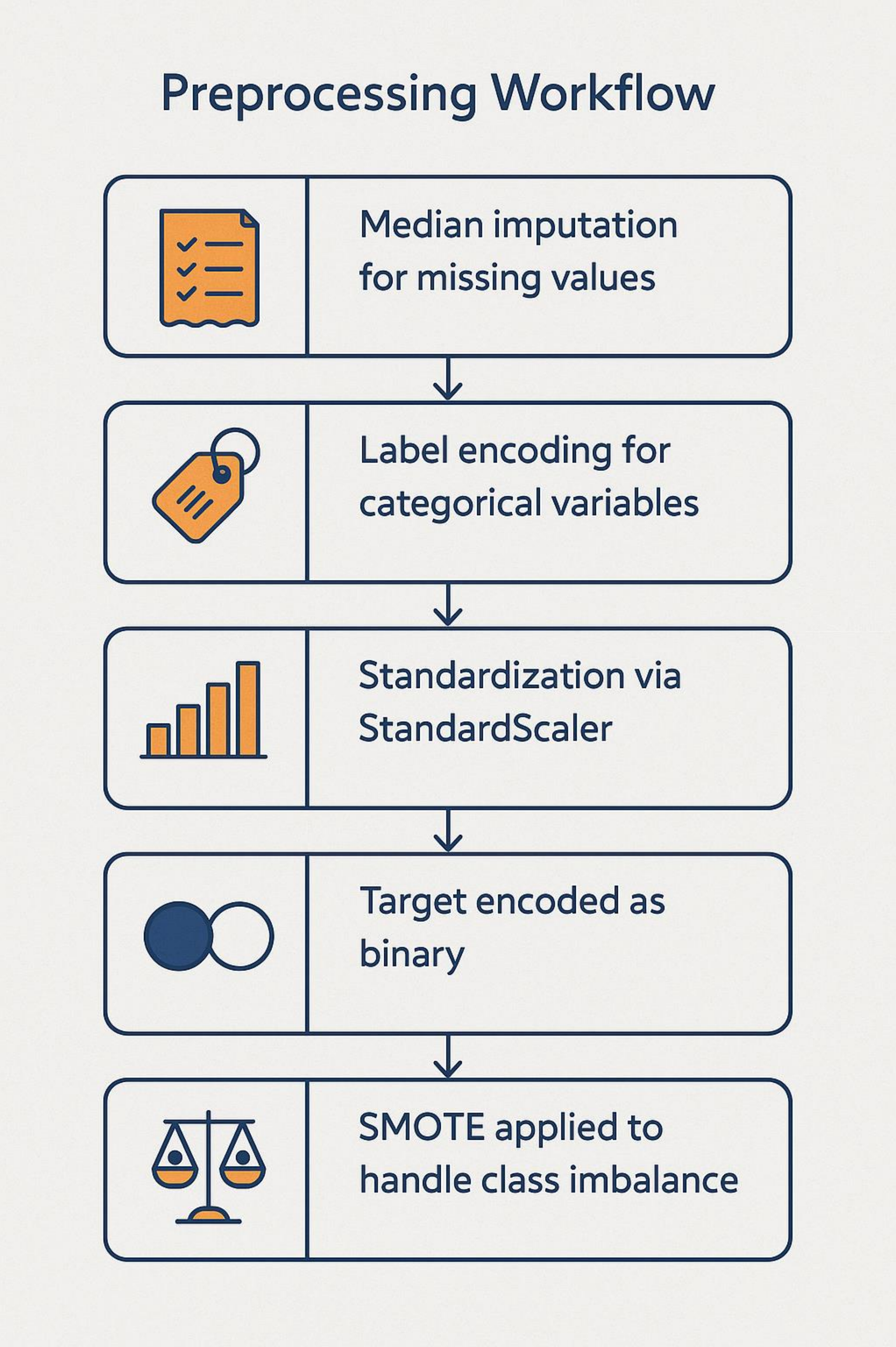
6.Evaluation: Accuracy, Precision, Sensitivity, Specificity, AUC

7.Validation: Y-randomization, Bootstrap t-test, Learning curves, Confusion Matrix



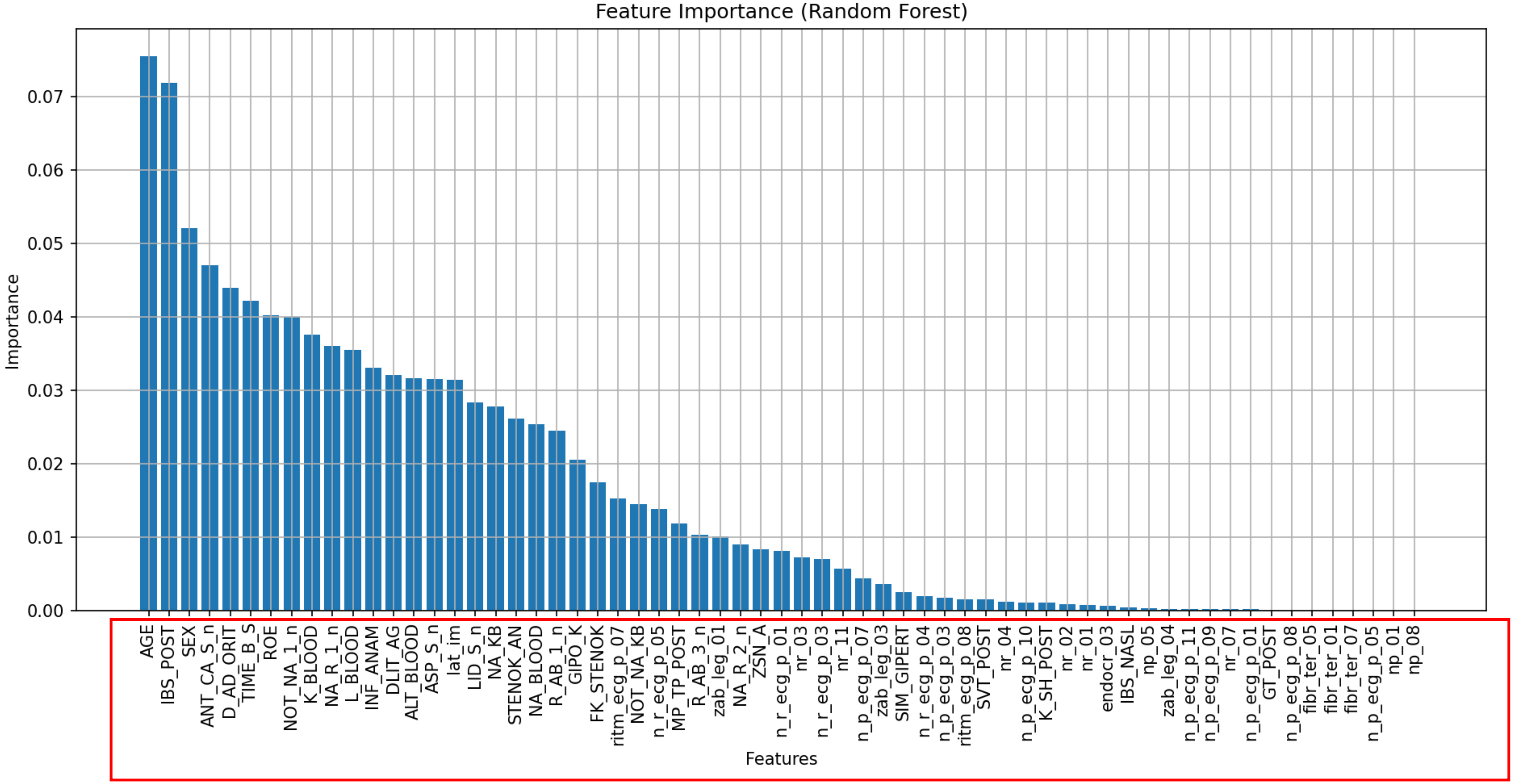
Preprocessing Workflow

- Median imputation for missing values
- Label encoding for categorical variables
- Standardization via StandardScaler
- Target encoded as binary
- SMOTE applied to handle class imbalance



FEATURES SELECTED

LASSO regression was employed for feature selection, resulting in 63 important features retained from the original dataset. These included clinical parameters



MODEL DEVELOPMENT

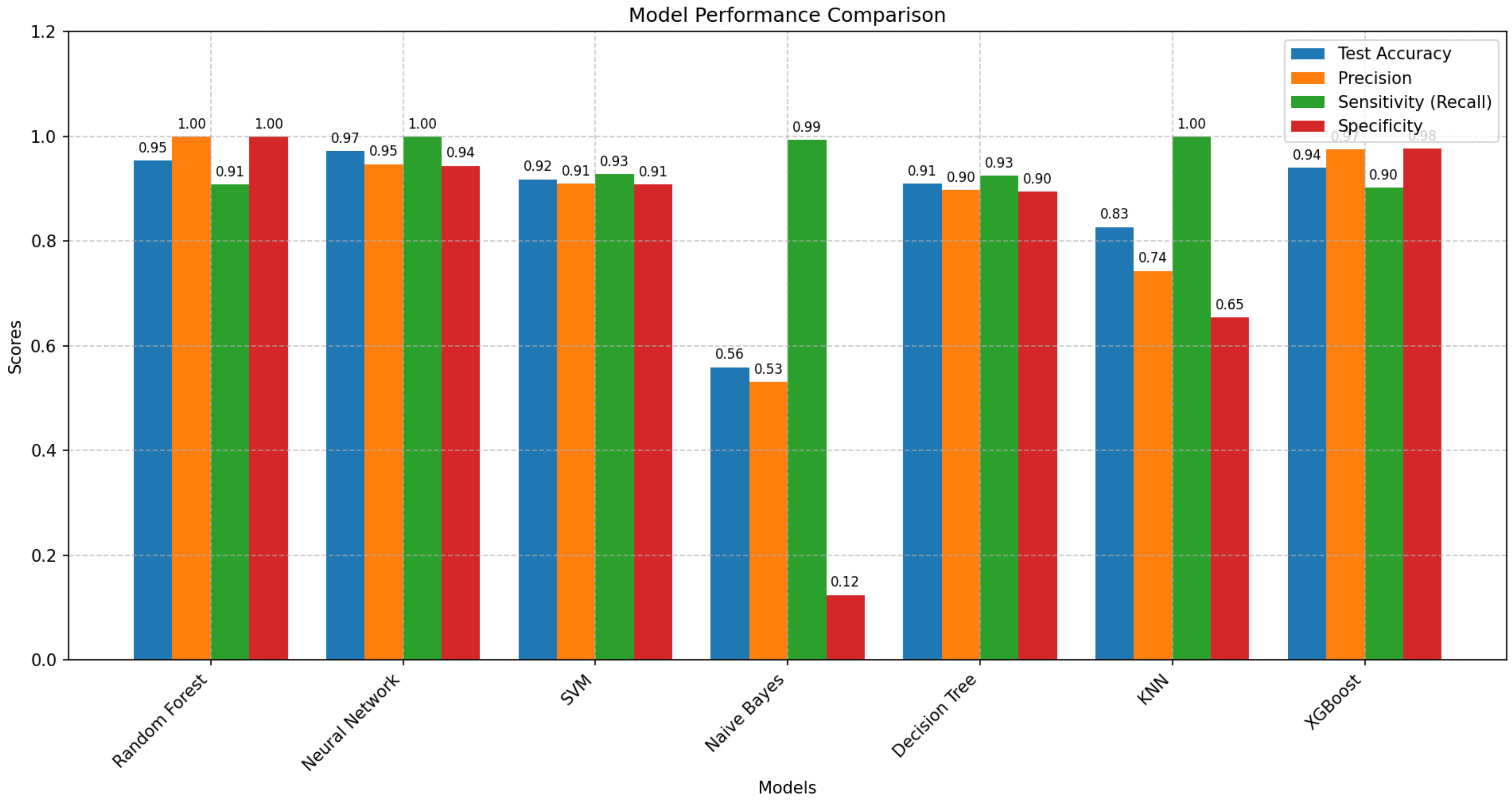
•Algorithms evaluated:

- Random Forest
- Neural Network
- Support Vector Machine
- XGBoost
- Decision Tree
- KNN
- Naive Bayes

•Probability-based severity classification:

- Low: < 0.3
- Moderate: 0.3 - 0.7
- High: > 0.7

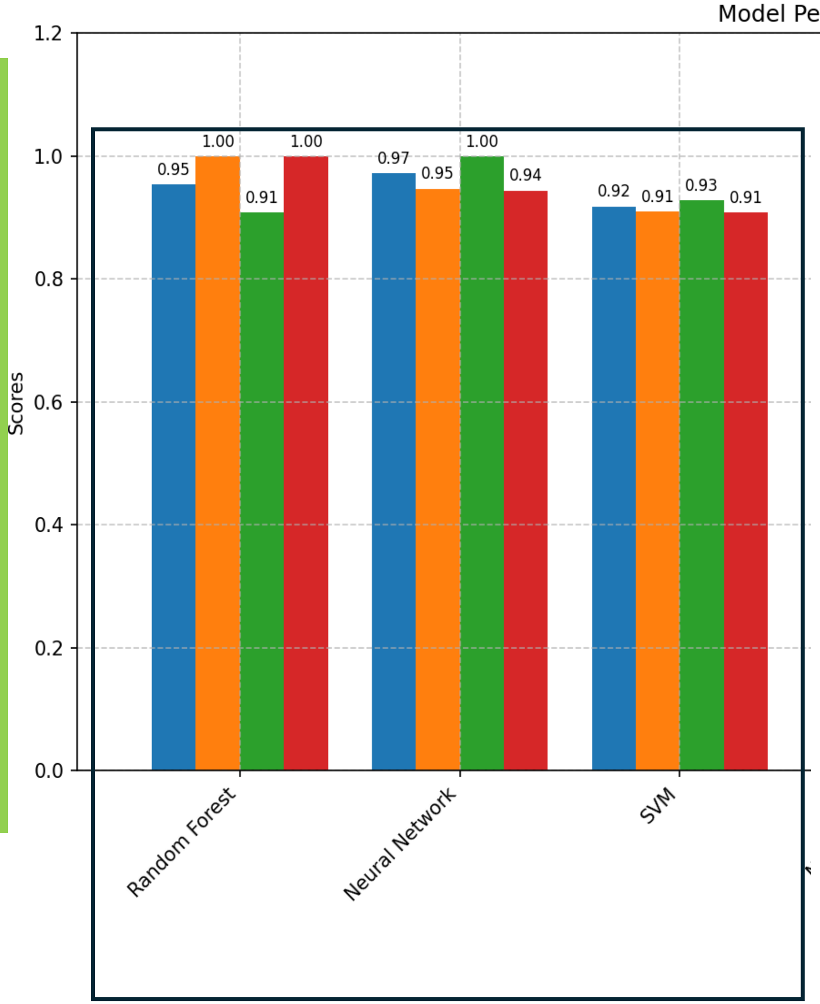
Performance Metrics

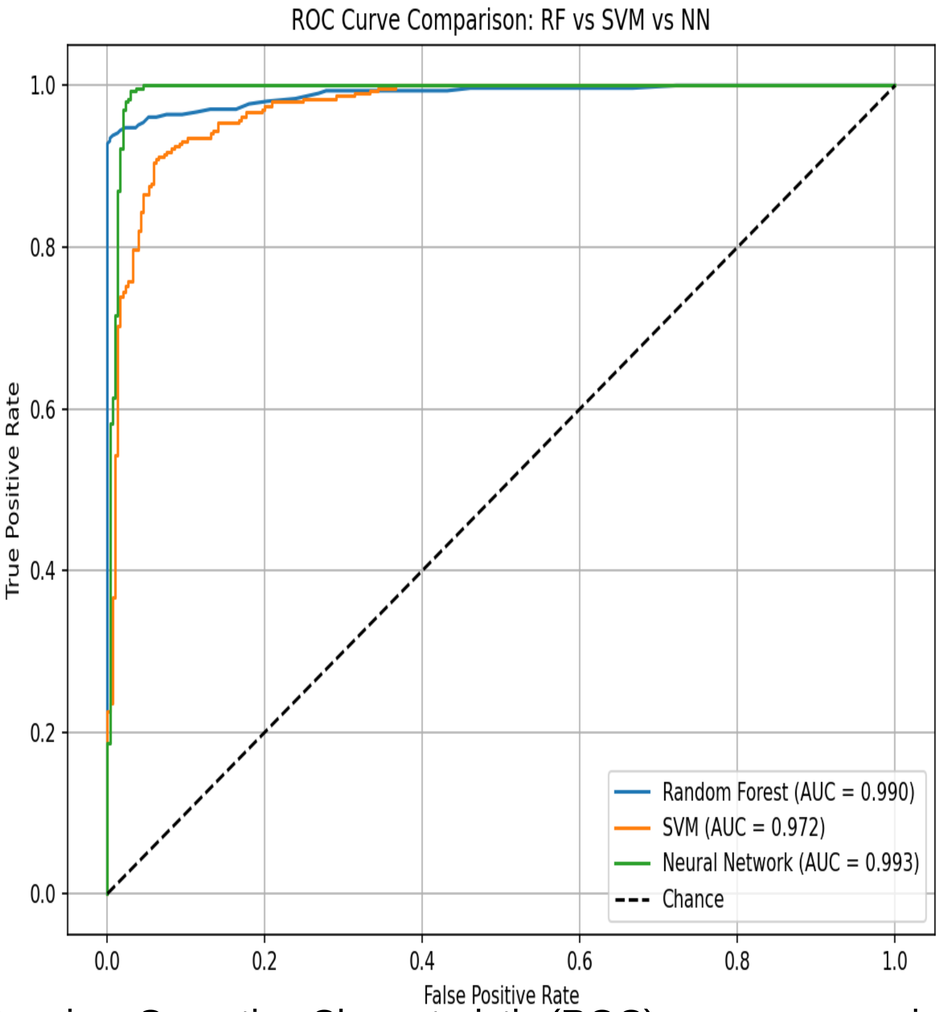


Performance comparison of Random Forest, Neural Network, SVM, Naive Bayes, Decision Tree, KNN, and XGBoost models

BEST MODELS

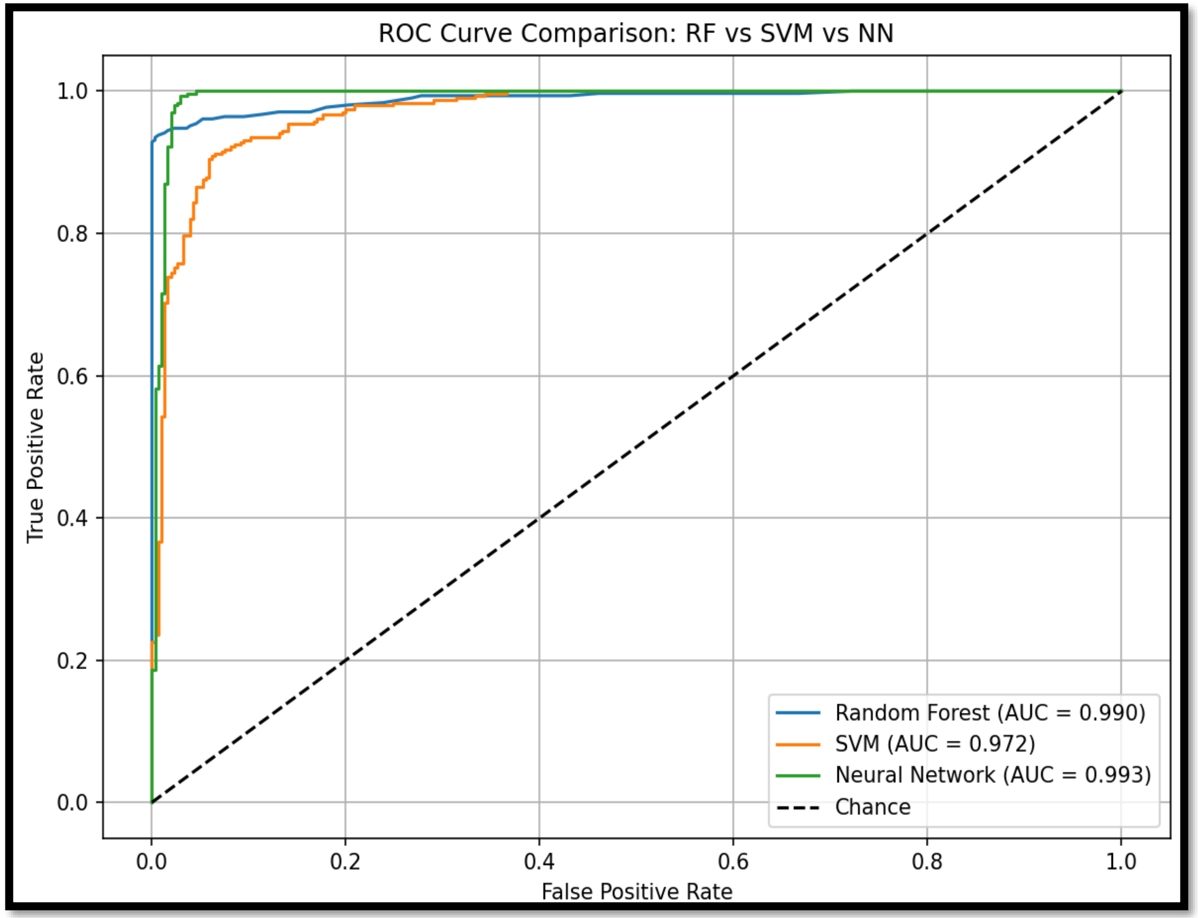
- **Random Forest:**
  - Accuracy: 95.4%
  - AUC: 0.990
  - Precision: 100%, Specificity: 100%, Sensitivity: 90.8%
- **Neural Network:**
  - Accuracy: 95.9%, AUC: ~0.98
- **SVM:**
  - Accuracy: 91.8%, AUC: 0.972



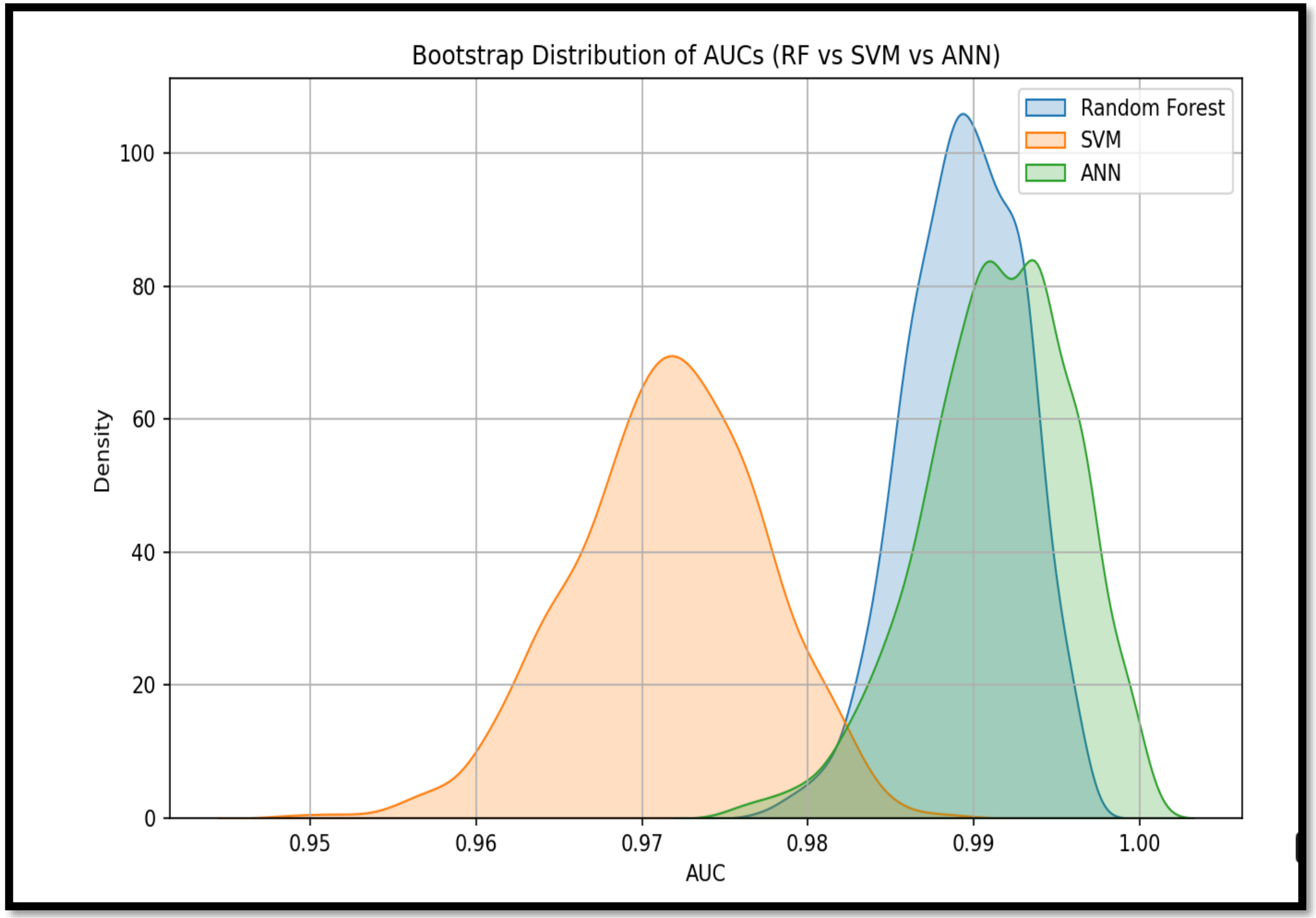


Receiver Operating Characteristic (ROC) curves comparing the performance of the Random Forest, Support Vector Machine (SVM), Artificial Neural Network models

ROC/ AUCS CURVES



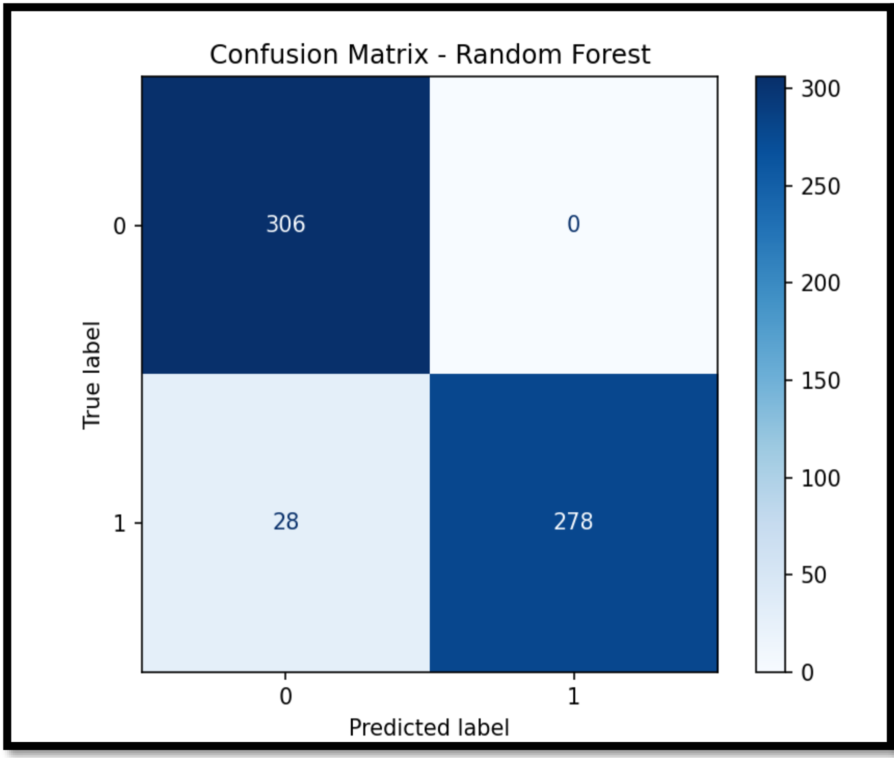
Receiver Operating Characteristic (ROC) curves comparing the performance of the Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN) models on the heart disease dataset.



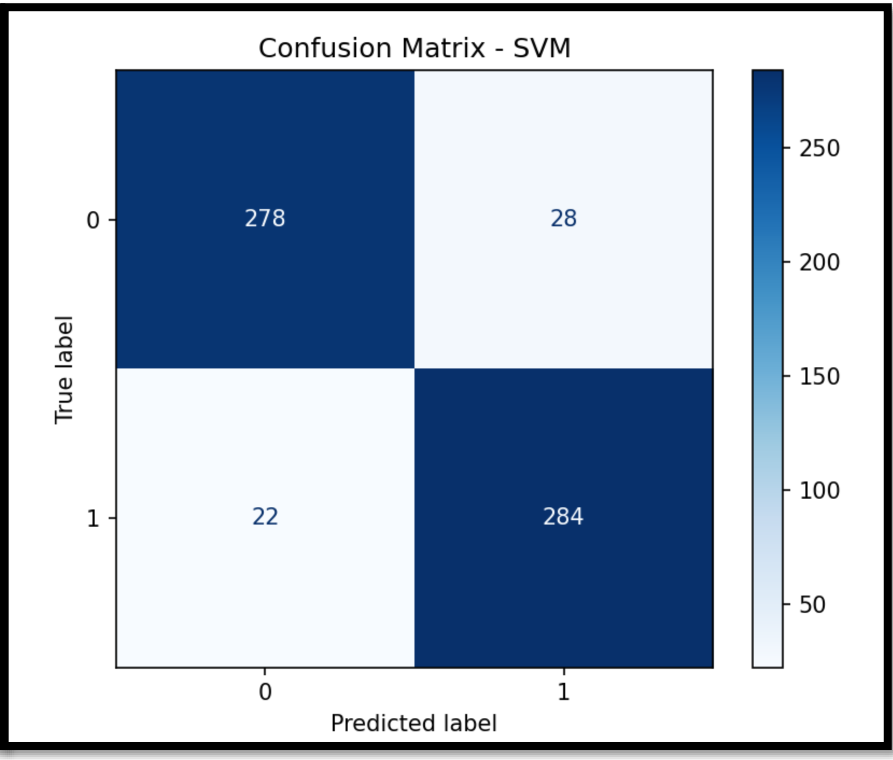
Bootstrap distribution of AUC scores for Random Forest, SVM and ANN models based on 1,000 resamplings of the test dataset.

COMPLEX MATRICS

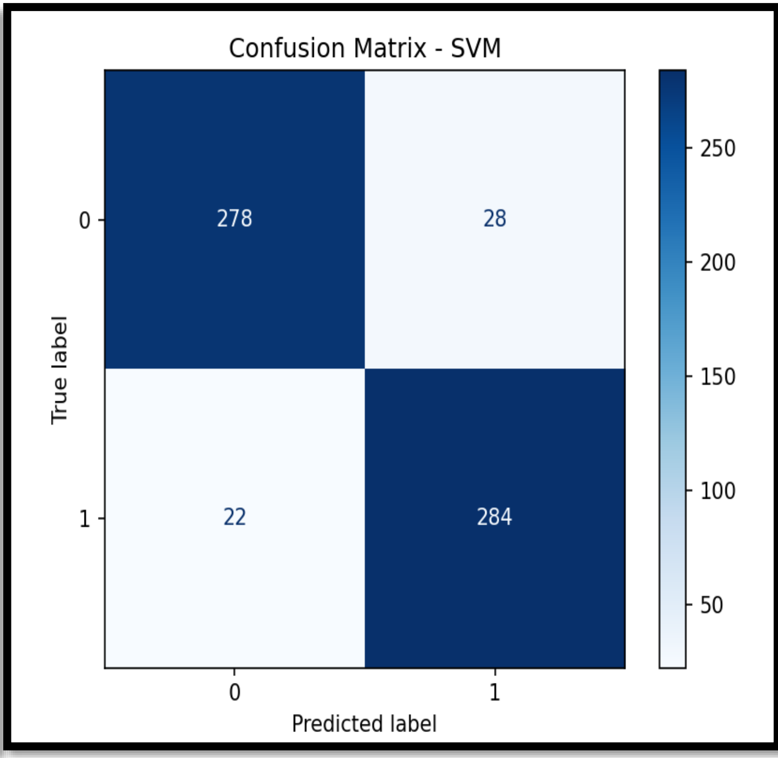
(A)



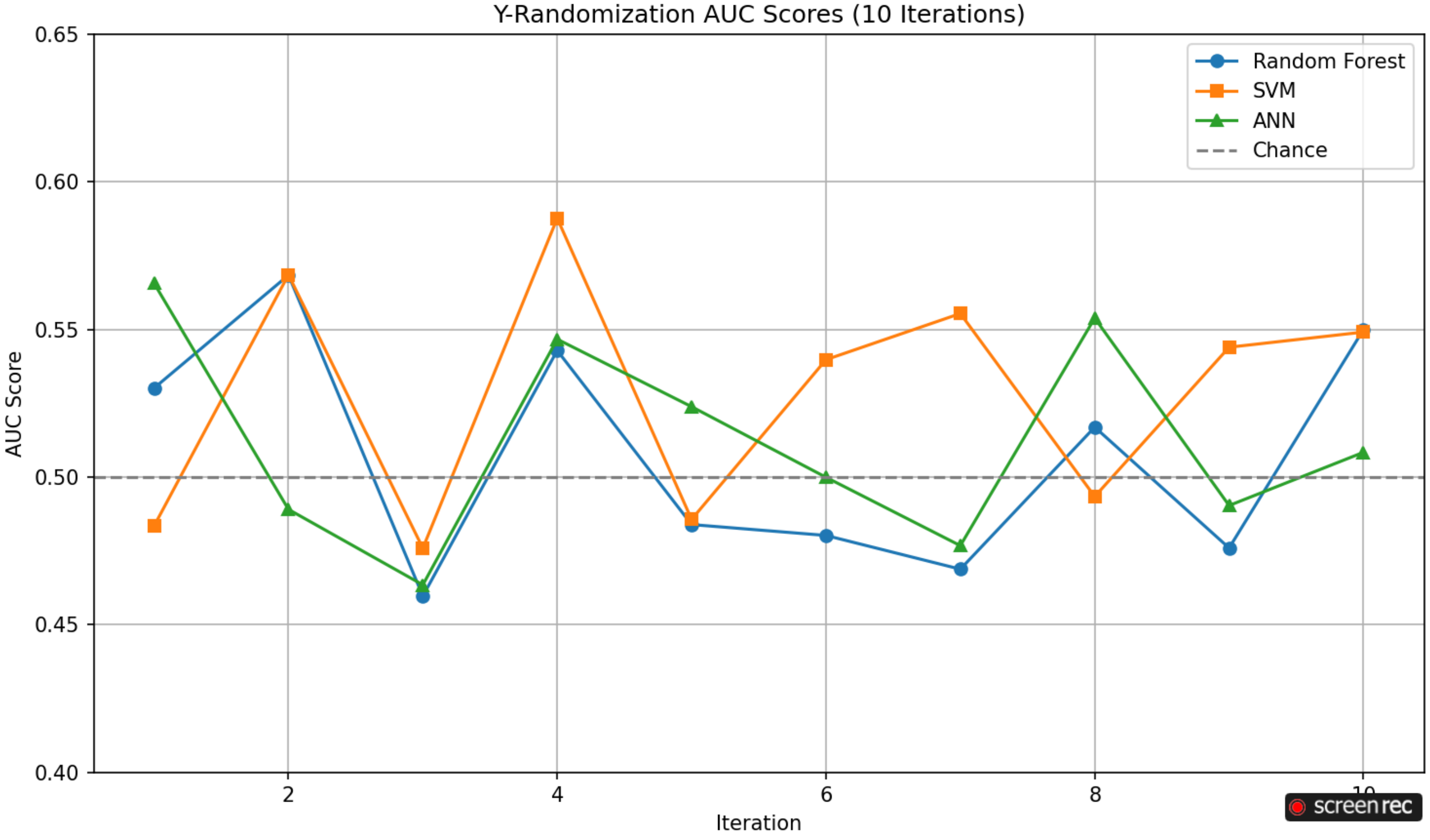
(B)



(C)



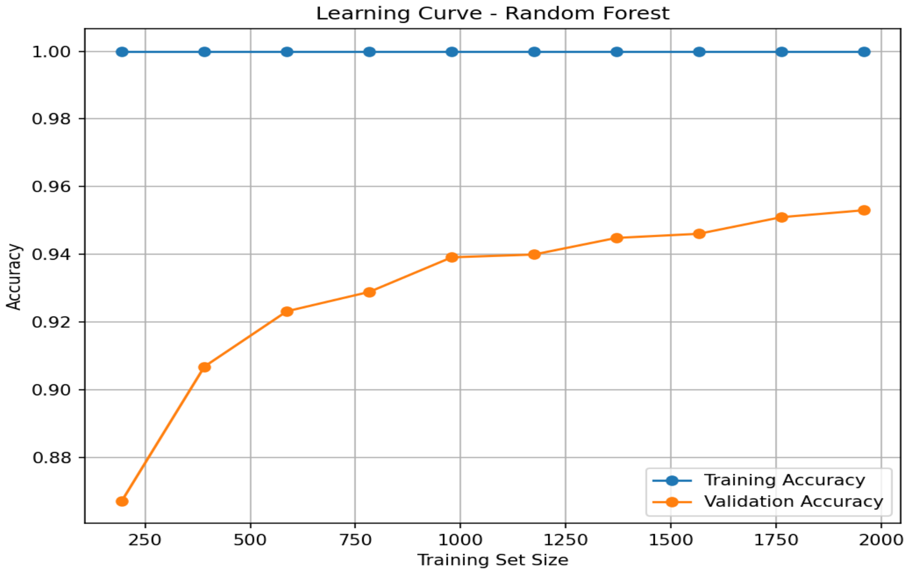
Y-RANDOMIZATION



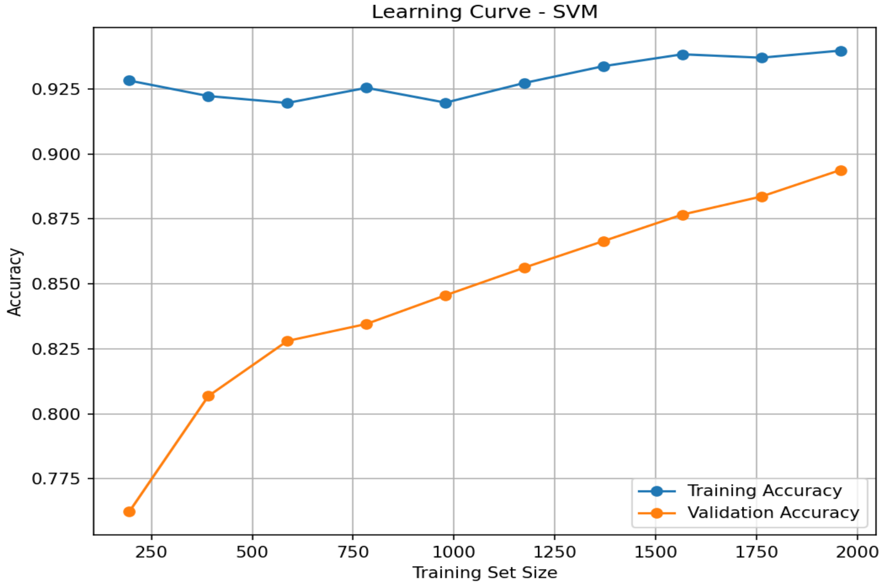
Y-randomization Results as validation for
best models Randomforest, SVM and ANN.

MODEL LEARNING BEHAVIOR ASSESSMENT

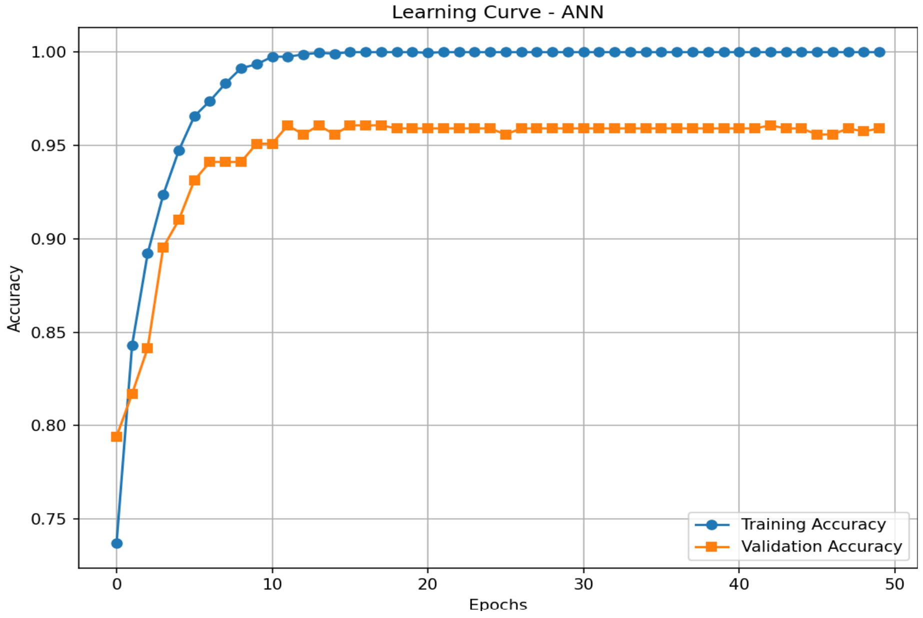
(A)



(B)



(C)



DISCUSSION

Model Effectiveness

- **ANN** showed highest test accuracy (97%) and perfect sensitivity (100%), indicating excellent detection of high-risk cases.
- **Random Forest** achieved perfect precision and specificity (100%), making it optimal for avoiding false positives.
- **SVM** showed strong balance but slightly lower metrics in precision and AUC.

Clinical Impact

- **ANN's high sensitivity** ensures that no severe case is missed—ideal for critical care scenarios.
- **Random Forest’s precision and specificity** make it suitable for reducing overdiagnosis and unnecessary interventions.

Validation & Reliability

- **Bootstrap t-tests** confirmed statistically significant superiority of RF and ANN over SVM ($p < 0.0001$).
- **Y-randomization** showed drastic AUC drop under shuffled labels (RF: 0.508, ANN: 0.512), affirming model robustness.

Learning Behavior

- ANN learning curve demonstrated rapid convergence, stable generalization, and minimal overfitting.
- RF and SVM also showed strong generalization but with slightly different learning dynamics.

CONCLUSION

•This study demonstrated the application of **supervised ML/DL models** for myocardial infarction severity prediction.

•**Random Forest** emerged as the most robust and interpretable model, with 95.4% accuracy, 100% precision, and 0.990 AUC.

•**ANN** achieved the highest accuracy (97%) and perfect sensitivity (100%), ideal for identifying all high-risk cases.

•**Model validations** including **bootstrap analysis**, **paired t-tests**, and **Y-randomization** ensured statistical significance and reliability.

•**Clinical risk stratification** into low, moderate, and high categories supports real-time, personalized treatment decisions.

•These ML/DL models offer a scalable, objective alternative to traditional clinical judgment—poised to enhance triage, intervention planning, and healthcare efficiency.

•**Future Work:** Extend validation to multi-center datasets, improve model interpretability, and integrate with real-time clinical decision systems.

REFERENCES

[1]. Reddy, K., Khaliq, A. and Henning, R.J., 2015. Recent advances in the diagnosis and treatment of acute myocardial infarction. *World journal of cardiology*, *7*(5), p.243.

[2]. Alanazi, A., 2022. Using machine learning for healthcare challenges and opportunities. Informatics in Medicine Unlocked, 30, p.100924. https://doi.org/10.1016/j.imu.2022.100924.

[3]. Porto, B.M., 2024. Improving triage performance in emergency departments using machine learning and natural language processing: a systematic review. *BMC Emergency Medicine*, *24*(1), p.219.

[4]. Ali, H., 2022. Reinforcement learning in healthcare: optimizing treatment strategies, dynamic resource allocation, and adaptive clinical decision-making. *Int J Comput Appl Technol Res*, *11*(3), pp.88-104.

[5]. Golovenkin, S.E., Bac, J., Chervov, A., Mirkes, E.M., Orlova, Y.V., Barillot, E., Gorban, A.N. and Zinovyev, A., 2020. Trajectories, bifurcations, and pseudo-time in large clinical datasets: applications to myocardial infarction and diabetes data. *GigaScience*, *9*(11), p.giaa128.