Explainable Machine Learning For Personalized Treatment and Lifestyle Recommendations In Cardiovascular Care

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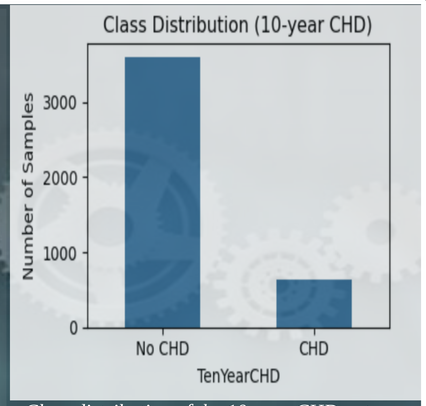
I. INTRODUCTION

- Cardiovascular disease (CVD) remains one of the leading causes of death globally, emphasizing the need for effective predictive and preventive strategies.
- This study develops a machine learning–driven framework for personalized cardiovascular risk modeling and lifestyle guidance using clinical data.
- This work is summarized: a classification based prediction model is implemented to predict the CVD risk, and the generative adversarial network (GAN) is incorporated to learn the underlying relationship between risk factors.

II. DATA SET

- Clinical data obtained from Kaggle, contains 4.3k samples
  - Features: Demographic, clinical, lifestyle
  - Target: 10-year CHD event
- Models were trained and evaluated using 10-fold cross-validation.



Class distribution of the 10-year CHD outcome

III. METHODS

Overall proposed methodology

Raw Data → Prediction models of CVD risks → Lifestyle recommendation with GAIN

Data Preprocessing:

Dataset → KNN Imputation, Scaling/Normalization → Feature Engineering → Feature Selection / PCA → Imbalance handling → Original / PCA → 10-fold Cross-Validation → Training Models

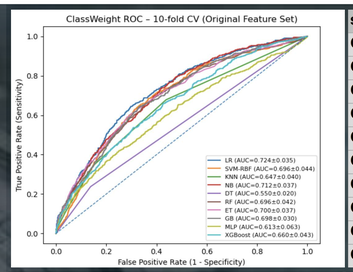
IV. PREDICTIVE MODELS

- **Linear & Distance-based Models**
  - Logistic Regression, SVM, KNN
  - Interpretable baselines for cardiovascular risk prediction
- **Tree-based Ensembles**
  - Decision Tree, Random Forest, Extra Trees, Gradient Boosting, XGBoost
  - Capture nonlinear interactions among clinical risk factors
- **Neural Network**
  - Multi-layer Perceptron (MLP)
  - Learns nonlinear feature representations

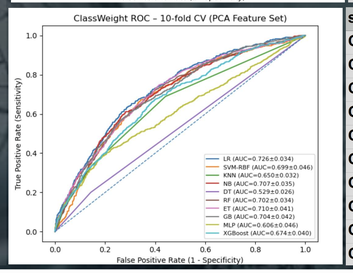
V. EVALUATION AND RESULTS

- **Original Feature Set:** Nonlinear and ensemble-based models outperform linear baselines, highlighting the importance of modeling complex feature interactions.
- **PCA Feature Set:** PCA maintains predictive performance while improving model stability across folds.

***Across all features representations:** Model performance remains consistent across both Original and PCA representations, indicating robust and generalizable learning patterns.



strategy	dataset	model	ROC_AUC (mean±std)	F1 (mean±std)	ACC (mean±std)
ClassWeight	Original	Logistic Regrssion	0.724 ± 0.035	0.378 ± 0.026	0.667 ± 0.017
ClassWeight	Original	Naive Bayes	0.712 ± 0.037	0.318 ± 0.036	0.801 ± 0.012
ClassWeight	Original	Extremely Randomized Trees	0.700 ± 0.037	0.117 ± 0.040	0.852 ± 0.005
ClassWeight	Original	Gradient Boosting	0.698 ± 0.030	0.148 ± 0.043	0.849 ± 0.007
ClassWeight	Original	Support Vector Machine	0.696 ± 0.044	0.371 ± 0.041	0.693 ± 0.022
ClassWeight	Original	Random Forest	0.696 ± 0.042	0.052 ± 0.046	0.849 ± 0.005
ClassWeight	Original	Extreme Gradient Boosting	0.660 ± 0.043	0.313 ± 0.038	0.749 ± 0.018
ClassWeight	Original	K-Nearest Neighbors	0.647 ± 0.040	0.163 ± 0.055	0.833 ± 0.009
ClassWeight	Original	Multilayer Perceptron	0.613 ± 0.063	0.256 ± 0.050	0.801 ± 0.016
ClassWeight	Original	Decision Tree	0.550 ± 0.020	0.236 ± 0.035	0.767 ± 0.019



strategy	dataset	model	ROC_AUC (mean±std)	F1 (mean±std)	ACC (mean±std)
ClassWeight	PCA	Logistic Regrssion	0.726 ± 0.034	0.381 ± 0.023	0.676 ± 0.017
ClassWeight	PCA	Naive Bayes	0.710 ± 0.041	0.061 ± 0.045	0.849 ± 0.005
ClassWeight	PCA	Extremely Randomized Trees	0.707 ± 0.035	0.236 ± 0.051	0.828 ± 0.007
ClassWeight	PCA	Gradient Boosting	0.704 ± 0.042	0.124 ± 0.039	0.845 ± 0.006
ClassWeight	PCA	Support Vector Machine	0.702 ± 0.034	0.018 ± 0.021	0.847 ± 0.003
ClassWeight	PCA	Random Forest	0.699 ± 0.046	0.369 ± 0.040	0.690 ± 0.021
ClassWeight	PCA	Extreme Gradient Boosting	0.674 ± 0.040	0.313 ± 0.042	0.775 ± 0.022
ClassWeight	PCA	K-Nearest Neighbors	0.650 ± 0.032	0.184 ± 0.047	0.835 ± 0.010
ClassWeight	PCA	Multilayer Perceptron	0.606 ± 0.046	0.260 ± 0.025	0.797 ± 0.012
ClassWeight	PCA	Decision Tree	0.529 ± 0.026	0.200 ± 0.045	0.757 ± 0.025

VI. GENERATIVE ADVERSARIAL IMPUTATION NETWORKS

- GAIN learns conditional dependencies among cardiovascular risk factors to enable realistic lifestyle simulations.

GAIN Models → Generation: High Risk Individual → Applicable Lifestyle Modification → Recommended Optimal Lifestyle Modification

- Variable groups in GAIN:

Variable	Features
X^U - Unchangeable Variables	Sex, Age, Education, stroke history
X^D - Directly Changeable Variables	Smoking, Medication, Cholesterol, BMI
X^I — Indirectly Changeable Variables	Blood Pressure, Heart rate

- GAIN performs two tasks:
  - Generate applicable alternative lifestyle behaviors for the high-risk patients.
  - Simulate feasible physiological responses (e.g., blood pressure, heart rate) associated with lifestyle changes for the high-risk patients.

High-Risk Individual → GAIN ($X^U \rightarrow X^D \rightarrow X^I$) → Simulated Lifestyle → Risk Evaluation

VII. CONCLUSION/ FUTURE WORK

- Tree-based ensemble models achieve the strongest and most stable predictive performance for cardiovascular risk prediction across multiple feature representations. These models provide a reliable foundation for personalized risk simulation.
- This is most likely because the dataset is noisy, and a tree-based approach, by taking the average outcome, reduces variance error, and results in a better outcome.
- Future work (a) will complete the full GAIN-based lifestyle recommendation pipeline, including alternative lifestyle generation, indirect physiological variable simulation, and expected utility–based optimization to select personalized lifestyle interventions, (b) collection of a less noisy and larger dataset.

VIII. REFERENCES

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