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Peer Review

Review of: "FGSCare: A Feature-driven Grid Search-based Machine Learning Framework for Coronary Heart Disease Prediction"

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The paper titled "FGSCare: A Feature-driven Grid Search-based Machine Learning Framework for Coronary Heart Disease Prediction" presents a comprehensive framework for predicting coronary heart disease (CHD) using both traditional machine learning models and deep learning techniques, with an emphasis on feature selection and interpretability.

Strengths:

1. Introduces a feature-driven grid search-based approach to improve coronary heart disease (CHD) prediction by optimizing feature selection and model performance.
2. Systematic evaluation of feature selection methods, highlighting their significant impact on model accuracy and generalization.
3. Evaluates both traditional machine learning (e.g., Decision Trees, Gradient Boosting) and deep learning models (e.g., MLP, KAN), offering a balanced comparison.
4. Uses SHAP values to enhance model transparency and explainability, which is crucial for clinical adoption.

Weaknesses:

1. While the paper provides an overview of the models used, their hyperparameters, and their performance, it does not delve deeply into each method's architecture or implementation details. For example, the deep learning models (MLP, Transformer, KAN) are described in terms of their

parameters but lack detailed descriptions of their layer structures, activation functions, or how the layers are connected.

2. The selection of features might be more complex than simply removing features based on correlation coefficients. In particular, nonlinear relationships, interaction terms, and higher-order feature combinations are not fully explored. Consider more advanced feature selection techniques to conduct experiments with.
3. The focus on SHAP values is insightful, but its utility might be limited when applied to very complex models. Incorporate LIME for a more local understanding of model decisions, especially for deep learning models like ResNet or Transformers.
4. By evaluating the model on only a single dataset, the paper does not explore the potential for overfitting to the specific characteristics of the Framingham dataset. The performance metrics might be overly optimistic and may not generalize well to real-world clinical data.
5. Grid search can become prohibitive in terms of computational time and resources, especially when dealing with complex models and large datasets. Future work should explore alternative hyperparameter optimization techniques, such as Bayesian optimization, random search, or genetic algorithms, which are more efficient and could reduce computational cost while improving performance.

Declarations

Potential competing interests: No potential competing interests to declare.

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