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Algorithm-Sensitive Feature Weighting using Mutual Information and ReliefF for Heart Disease Classification

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Abstract

Heart disease remains a critical global health issue requiring reliable early prediction for clinical decision-making. This study evaluates the effect of feature selection and feature weighting on the performance of machine learning models with different learning mechanisms, namely K-Nearest Neighbors (KNN), Naïve Bayes (NB), and Logistic Regression (LR), for heart disease prediction. An algorithm-sensitive comparative framework was applied using global feature relevance estimation (Mutual Information), local feature relevance estimation (ReliefF), feature selection, and feature weighting, with raw features as baseline. Experiments were conducted on the Cleveland Heart Disease dataset using stratified 5-fold cross-validation. The results show that ReliefF-based feature weighting achieves the best performance for Naïve Bayes (accuracy = 0.8085; F1-score = 0.7774), while Logistic Regression attains the highest overall performance under the baseline (accuracy = 0.8547; F1-score = 0.8324). Feature selection improves KNN performance due to reduced sensitivity to irrelevant features. These findings indicate that the effectiveness of feature importance strategies depends on model-specific learning behavior, where feature weighting benefits probabilistic models, while feature selection is more effective for distance-based models. This study contributes an algorithm-sensitive evaluation perspective for aligning feature importance strategies with machine learning model characteristics to improve heart disease prediction performance.

Keywords: classification; feature weighting; heart disease; mutual information; relieff

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INTRODUCTION

Cardiovascular disease remains one of the leading causes of mortality worldwide, with global deaths increasing from 12.33 million in 1990 to 19.42 million in 2021 (Wang et al., 2024). This rise is associated with lifestyle changes, unhealthy dietary habits, reduced physical activity, and population aging. Beyond mortality, cardiovascular disease significantly contributes to healthcare expenditure, long-term disability, and reduced quality of life. These challenges highlight the need for reliable early risk prediction systems to support preventive interventions and improve clinical decision-making.

Machine learning techniques have been widely applied to heart disease classification due to their ability to extract meaningful patterns from structured clinical data. Iacobescu et al. (2024) showed that classical algorithms such as K-Nearest Neighbors, Naive Bayes, and Logistic Regression remain widely used due to their interpretability and computational efficiency. Victor et al. (2024) further demonstrated that these algorithms can achieve reliable performance when supported by appropriate preprocessing strategies. However, their reported performance varies across studies, suggesting that results are highly dependent on experimental settings. This indicates that algorithm selection alone does not guarantee consistent performance.

The performance of these models is strongly influenced by preprocessing and feature engineering techniques. Sayadi et al. (2022) demonstrated that feature selection significantly improves classification accuracy in medical datasets. Sarra et al. (2022) showed that statistical methods such as Chi-Square are effective in identifying relevant features. In contrast to these findings, other studies report varying performance when similar methods are applied under different experimental conditions, indicating inconsistency in the effectiveness of preprocessing techniques.

Feature selection methods based on Mutual Information and ReliefF have been widely used to identify relevant features. Li & Fard (2022) demonstrated that Mutual Information effectively captures statistical dependency between features and the target variable. Recent studies further confirm its effectiveness in complex data scenarios, where Mutual Information is used to reduce noise and extract informative features from high-dimensional data (Huang et al., 2024). Kidambi Raju et al. (2023) confirmed that Mutual Information-based selection improves predictive performance in medical datasets. Khan Mamun & Elfouly (2023) showed that feature selection improves classification performance in cardiovascular prediction tasks. Xi et al. (2023) further demonstrated that ReliefF enhances classification accuracy by capturing local data structure. Recent studies also indicate that ReliefF improves robustness by considering neighborhood-based differences and reducing the impact of noise in feature evaluation (Pau et al., 2023). However, these studies evaluate the methods under different experimental settings, making direct comparison difficult and limiting the generalizability of their findings. This indicates that conclusions regarding their effectiveness remain inconsistent and context dependent.

Bhatt et al. (2023) demonstrated the effectiveness of machine learning models in large scale healthcare datasets, indicating their applicability in complex environments. Pau et al. (2023) highlighted the role of feature preprocessing in IoT-based health monitoring systems, emphasizing the importance of data quality in predictive performance. Talaat et al. (2024) proposed a hybrid AI model that improves prediction accuracy in cardiovascular risk assessment. However, these studies focus on different application settings and evaluation strategies, making it difficult to draw consistent conclusions regarding the effectiveness of feature relevance methods**.** In contrast to these approaches, Fira et al. (2025) showed that the effectiveness of feature selection methods varies significantly across datasets. This indicates that no single method consistently outperforms others under different conditions.

Although previous studies have shown that feature selection can improve classification performance, their findings remain inconsistent across datasets and algorithms, indicating that the effectiveness of feature relevance methods is model dependent. Most studies focus primarily on feature selection, while the comparative effect of feature weighting and feature selection across classifiers with different learning mechanisms remains underexplored. In addition, prior studies generally evaluate these methods separately, without a unified framework that systematically examines their interaction with classifier specific learning behavior. This limitation restricts both theoretical understanding and practical guidance for selecting appropriate feature relevance strategies.

Therefore, this study conducts a comparative evaluation of feature weighting and feature selection using Mutual Information and ReliefF across K-Nearest Neighbors, Naive Bayes, and Logistic Regression. By evaluating both strategies within a unified experimental framework, this study addresses limitations in previous findings and provides a structured comparison under controlled experimental conditions. This approach enables a clearer understanding of model-dependent behavior and offers more reliable guidance for selecting appropriate feature relevance strategies in heart disease prediction.

METHOD

This study adopted a quantitative experimental design based on the Knowledge Discovery from Data (KDD) framework, consisting of data preprocessing, feature relevance estimation, feature transformation, model training, and evaluation. Feature relevance was computed using Mutual Information (MI) and ReliefF and applied in both feature selection and feature weighting scenarios. The transformed features were evaluated using K-Nearest Neighbors (KNN), Naive Bayes (NB), and Logistic Regression (LR), representing distance-based, probabilistic, and linear learning mechanisms. This framework ensures each stage is systematically controlled, enabling consistent comparison of feature relevance strategies across classifiers.

The Cleveland Heart Disease dataset was used due to its clinical relevance and widespread use in cardiovascular prediction studies. The dataset consists of 303 samples, 13 input features, and 1 target variable indicating the presence or absence of heart disease. The class distribution is relatively balanced, with approximately 54% positive cases and 46% negative cases, reducing bias from class imbalance. This dataset provides sufficient variability in clinical attributes while allowing comparability with prior research.

Data preprocessing was explicitly defined to ensure reproducibility and data quality. Duplicate records were removed, and missing values were handled using mode-based imputation for categorical variables. Outliers in numerical features were treated using the 1.5 × IQR method to reduce the influence of extreme values. Categorical variables were transformed using one-hot encoding, while numerical features were standardized using z-score normalization. All preprocessing steps were performed within each cross-validation fold using training data only to prevent information leakage.

Feature relevance was estimated using two complementary approaches. Mutual Information captured global statistical dependency between features and the target variable, while ReliefF captured local feature importance based on nearest neighbor differences ($k = 10$). In the feature selection setting, the top 60% of ranked features were retained to reduce redundancy while preserving informative attributes. In contrast, feature weighting retained all features and assigned weights based on normalized relevance scores. Baseline models using original features were included to enable direct comparison of feature transformation effects.

The selection of classifiers was explicitly justified based on their distinct learning mechanisms. KNN was selected as a distance-based model sensitive to feature scaling and local structure, suitable for evaluating feature weighting effects. Naive Bayes was chosen as a probabilistic model assuming feature independence, enabling analysis of feature relevance on probability estimation. Logistic Regression was selected as a linear model providing interpretable coefficients and capturing global relationships. This combination allows evaluation of whether feature relevance strategies produce consistent or model-dependent results.

Model evaluation was conducted using stratified 5-fold cross-validation ($k = 5$) to preserve class distribution across folds, with a fixed random seed of 42 to ensure reproducibility. Performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC, with metrics computed for each fold and averaged. Statistical significance was assessed using paired Wilcoxon signed-rank tests at a 95% confidence level. All experiments were implemented in Python using scikit-learn, ensuring reproducibility, minimizing bias, and enabling fair comparison across feature selection, feature weighting, and baseline configurations.

RESULTS AND DISCUSSION

Results

The classification performance obtained from the experimental evaluation is summarized in Table 1. The results are reported using Accuracy, Precision, Recall, and F1-score to provide a comprehensive evaluation of model performance. These metrics are computed using stratified k-fold cross-validation. This approach ensures a reliable estimation of model performance across different data splits.

Table 1. Classification performance under different feature processing strategies

Model	Accuracy	Precision	Recall	F1-score
NB Baseline	0.8019	0.8269	0.718	0.7642
NB MI Selection	0.7921	0.8099	0.7323	0.7599
NB ReliefF Selection	0.7856	0.765	0.7839	0.7719
NB MI Weighting	0.7955	0.822	0.7183	0.7612
NB ReliefF Weighting	0.8085	0.8215	0.7468	0.7774
LR Baseline	0.8547	0.8767	0.7976	0.8324
LR MI Selection	0.825	0.8365	0.7762	0.8022
LR ReliefF Selection	0.8349	0.8456	0.7833	0.8119
LR MI Weighting	0.8054	0.8197	0.7548	0.7819
LR ReliefF Weighting	0.8448	0.8491	0.805	0.8244
KNN Baseline	0.8186	0.8287	0.7772	0.7974
KNN MI Selection	0.812	0.8303	0.7407	0.783
KNN ReliefF Selection	0.8086	0.8244	0.7476	0.7816
KNN MI Weighting	0.7953	0.7968	0.7479	0.7706
KNN ReliefF Weighting	0.8052	0.8412	0.7119	0.7695

Table 1 shows that Logistic Regression achieves the highest overall performance in the baseline configuration, with an accuracy of 0.8547 and an F1-score of 0.8324. In contrast, Naïve Bayes benefits from ReliefF-based weighting, improving its F1-score from 0.7642 to 0.7774. However, the comparison between the baseline and ReliefF weighting is not statistically significant ($p = 0.152$), although it shows a relatively large effect size (Cohen's $d = 0.79$), indicating a meaningful practical gain.

Logistic Regression and KNN, comparisons between the baseline and their respective feature processing strategies also show no statistically significant differences ($p = 0.6338$ and $p = 0.7125$), with small effect sizes (Cohen's $d = -0.23$ and -0.18), suggesting minimal impact of feature transformation. Meanwhile, KNN performs more consistently under feature selection rather than weighting. These results confirm that feature relevance strategies have model-dependent effects and do not consistently yield statistically significant improvements.

For clearer comparison of model performance, the results are also presented in graphical form. Figure 1 presents the accuracy comparison across models and feature processing strategies. Logistic Regression consistently achieves the highest accuracy, particularly in the baseline configuration. Naïve Bayes improves under ReliefF-based weighting, while KNN performs more consistently with feature selection and declines under weighting. These results indicate that probabilistic models benefit from weighting, whereas distance-based models benefit from feature selection, supporting the trends observed in Table 1.

Figure 2 presents the F1-score comparison across models, reflecting the balance between precision and recall. Logistic Regression achieves the highest F1-score in the baseline configuration, indicating strong overall performance. Naïve Bayes improves under ReliefF weighting, mainly due to increased recall, while KNN performs better with feature selection and declines under weighting. These results confirm that feature processing influences both performance and error characteristics.

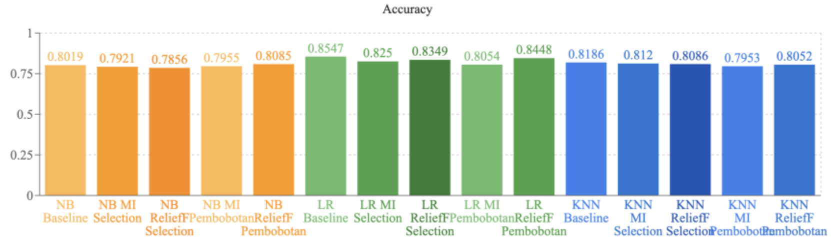

Figure 1. Accuracy comparison across models

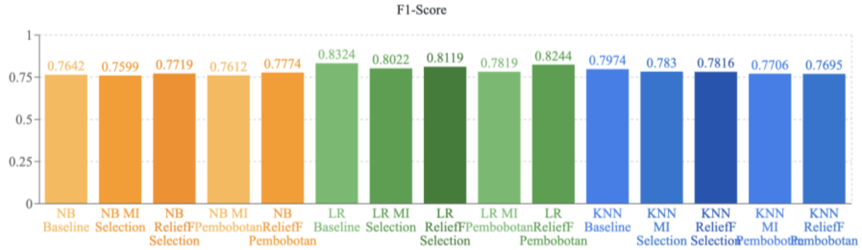

Figure 2. F1-score comparison across models

A more detailed error analysis is is performed using confusion matrices from a hold-out test set (80% training, 20% testing) to examine the trade-off between false positives (FP) and false negatives (FN). Figure 3 shows that Logistic Regression (Baseline) achieves balanced performance, with 29 true negatives and 25 true positives, along with 4 false positives and 3 false negatives.

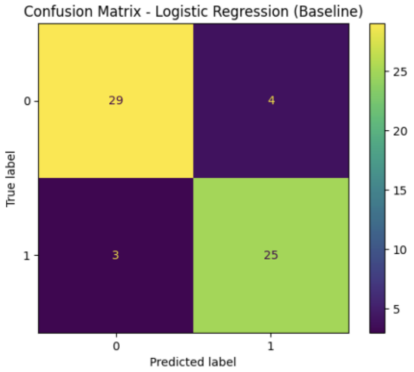

Figure 3. Confusion matrix – logistic regression (baseline)

Following the baseline model, Figure 4 shows the confusion matrix of Naïve Bayes with ReliefF weighting, illustrating the impact of feature weighting on classification performance. The model correctly classifies 28 TN and 25 TP, with 5 FP and 3 FN. This indicates relatively balanced performance, with a slight increase in false positives suggesting higher sensitivity and improved detection of positive cases at the cost of reduced specificity.

The next confusion matrix presents the performance of the KNN model with Mutual Information (MI) feature selection. Figure 5 shows the confusion matrix of KNN with MI-based feature selection, highlighting the effect of feature selection on classification performance. The model correctly classifies 29 TN and 27 TP, with 4 FP and only 1 FN. The very low FN indicates strong sensitivity and effective detection of positive cases. Overall, feature selection improves class separation while maintaining a good balance between sensitivity and specificity..

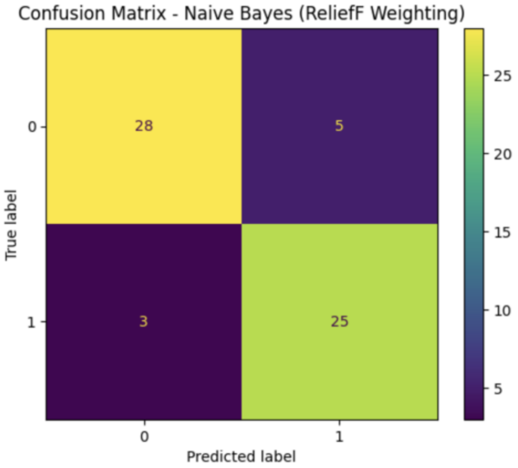

Figure 4. Confusion matrix – naive bayes (relieff weighting)

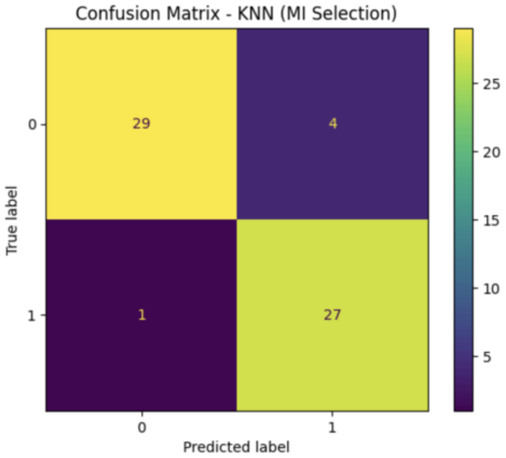

Figure 5. Confusion matrix – knn (mi selection)

Complementing the previous analysis, ROC curves are used to evaluate classification performance across different decision thresholds. Unlike confusion matrices, ROC analysis provides a threshold-independent view of the trade-off between sensitivity and specificity. The Area Under the Curve (AUC) is used to quantify the overall discriminative ability of each model. Higher AUC values indicate better class separation. The following figure presents the ROC curve for the Naïve Bayes model.

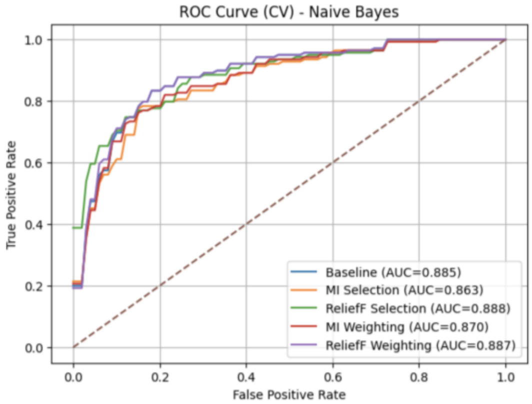

Figure 6. ROC curve (cv) – naïve bayes

The ROC curve for the Naïve Bayes model shows strong classification performance, with all AUC values above 0.86. The baseline achieves an AUC of 0.885, while ReliefF-based methods slightly improve performance, with the highest AUC of 0.888. In contrast, MI Selection produces the lowest AUC (0.863), indicating a slight decline. All configurations perform well above random classification. Overall, ReliefF approaches provide the most consistent results.

A further analysis is presented through the following ROC curve, which shows the performance of the Logistic Regression model across different feature processing strategies. This model is included due to its strong performance in the baseline configuration. The ROC analysis illustrates how well the model distinguishes between classes under various scenarios. It also enables comparison of the impact of feature selection and feature weighting.

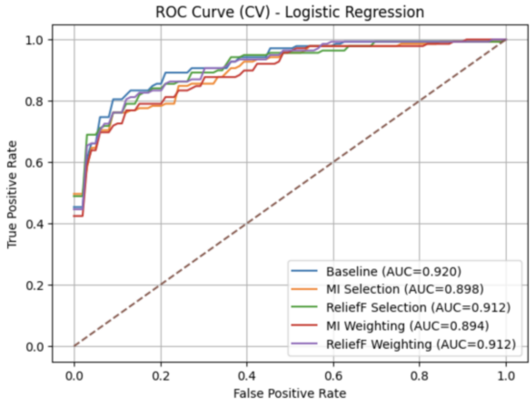

Figure 7. ROC curve (cv) – logistic regression

The ROC curve for the Logistic Regression model shows excellent performance, with all AUC values close to or above 0.89. The baseline achieves the highest AUC of 0.920, indicating very strong class discrimination. ReliefF-based methods also perform competitively with AUC values around 0.912. In contrast, MI-based approaches show slightly lower results, with AUC values below 0.90. Overall, all configurations outperform random classification, with the baseline remaining the most optimal.

The following ROC curve presents the performance of the KNN model under different feature processing strategies. This model is included to examine the behavior of distance-based learning in relation to feature representation. The ROC analysis illustrates how well the model discriminates between classes across various scenarios. It also highlights the impact of feature selection and weighting on classification performance.

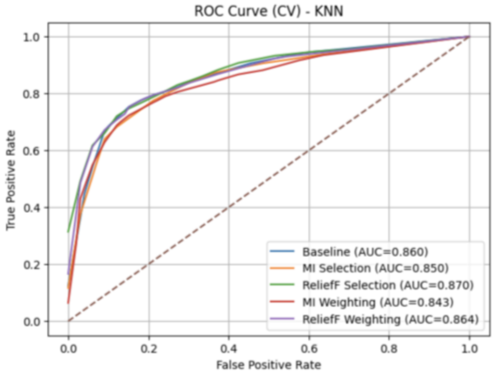

Figure 8. ROC curve (cv) – knn

The ROC curve for the KNN model shows moderate performance, with AUC values ranging from 0.843 to 0.870. ReliefF Selection achieves the highest AUC (0.870), indicating improved discriminative ability. The baseline model follows with an AUC of 0.860, while MI-based methods yield slightly lower results. MI Weighting produces the lowest AUC (0.843). Overall, KNN performs above random classification but remains lower than Logistic Regression and Naïve Bayes.

These findings can be interpreted through the lens of the bias variance trade-off and feature representation. Feature selection reduces variance by eliminating irrelevant attributes, which is particularly advantageous for high-variance models such as KNN. In contrast, feature weighting refines the relative importance of predictors without reducing dimensionality, making it more compatible with probabilistic models such as Naïve Bayes. Logistic Regression, which inherently optimizes feature importance during training, exhibits only marginal gains from additional transformation.

These findings align with prior studies while also showing that feature relevance strategies are not universally effective. Their impact depends on compatibility with the underlying learning mechanism. In particular, weighting may fail in KNN due to the persistence of irrelevant features in distance calculations. Feature selection is more suitable for distance-based models, while weighting benefits probabilistic models. However, this study is limited to a single dataset, and future work should validate these results on larger and more diverse datasets.

Discussion

The findings demonstrate that the effectiveness of feature relevance strategies is fundamentally contingent upon classifier-specific learning mechanisms rather than being universally applicable. Logistic Regression achieves optimal performance under the baseline configuration, indicating that its internal optimization process sufficiently captures feature importance. As noted by Hassan et al. (2024), coefficient estimation inherently encodes feature relevance, thereby limiting the added value of external transformations.

In contrast, the performance improvement observed in Naïve Bayes under ReliefF-based weighting reflects the sensitivity of probabilistic models to feature scaling. Chen et al. (2023) explain that probabilistic inference depends on accurate estimation of conditional probabilities, where feature weighting enhances discriminative capacity by adjusting attribute contributions. Furthermore, Pau et al. (2023) highlight that locality-aware approaches such as ReliefF improve robustness by incorporating neighborhood information, which explains its consistent performance gains.

A different pattern is evident in KNN, where feature weighting does not improve performance due to the persistence of irrelevant features in distance calculations. Zhang et al. (2024) emphasize that distance-based models are highly sensitive to noise, while Wild et al. (2024) show that feature selection improves class separability by eliminating redundant dimensions. This indicates that dimensionality reduction is more critical than feature rescaling for distance-based learning.

These findings can be interpreted through the bias–variance trade-off framework. Tiwari et al. (2024) argue that feature selection reduces variance by simplifying the feature space, whereas feature weighting redistributes importance without reducing dimensionality, making it more suitable for probabilistic models. Additionally, the stronger performance of ReliefF compared to Mutual Information can be attributed to its ability to capture local feature interactions, as demonstrated by Yan et al. (2025), particularly in datasets with non-linear structures.

Collectively, this study advances the understanding of feature engineering by positioning feature relevance strategies as model-aware processes. Rather than serving as generic preprocessing steps, their effectiveness depends on alignment with algorithmic assumptions and learning behavior. Practically, feature weighting is more appropriate for probabilistic models, feature selection for distance-based models, and additional transformation provides limited benefit for optimization-based models.

However, several methodological considerations remain. The dataset is moderate in size and may not fully represent real-world clinical variability. In addition, the study is limited to classical machine learning approaches, whereas Talaat et al. (2024) show that advanced models such as hybrid and deep learning architectures can yield superior performance. The absence of systematic hyperparameter optimization also constrains performance maximization.

Future work should evaluate the proposed framework on larger and more diverse datasets to improve generalizability. It should also incorporate advanced models and optimization techniques to enhance performance and provide a more comprehensive comparison. Furthermore, future studies should consider real world deployment aspects, including computational efficiency, scalability, and inference time.

CONCLUSION

This study shows that the effectiveness of feature relevance strategies depends on their alignment with model-specific learning mechanisms rather than being universally applicable. Empirical results indicate that Logistic Regression achieves the best overall performance in the baseline configuration (accuracy = 0.8547; F1-score = 0.8324), while Naïve Bayes benefits from ReliefF-based weighting, improving its F1-score by 1.32%. In contrast, feature selection is more effective for KNN due to its sensitivity to irrelevant features in distance computation. The main contribution of this study lies in demonstrating that feature weighting and selection produce different effects across probabilistic, optimization-based, and distance-based models. This finding highlights that feature relevance strategies should be treated as model aware processes rather than generic preprocessing steps. However, the study is limited to a single dataset with moderate dimensionality. Future work should evaluate this framework on high-dimensional and heterogeneous datasets, as well as explore hybrid feature selection weighting approaches and stability analysis across different data distributions.

REFERENCES

Bhatt, C. M., Patel, P., Ghetia, T., & Mazzeo, P. L. (2023). Effective heart disease prediction using machine learning techniques. *Algorithms*, *16*(2), 88. https://doi.org/10.3390/a16020088

Chen, W., Cai, Y., Li, A., Su, Y., & Jiang, K. (2023). EEG feature selection method based on maximum information coefficient and quantum particle swarm. *Scientific Reports*, *13*(1), 14515. https://doi.org/10.1038/s41598-023-41682-5

Fira, M., Goras, L., & Costin, H. N. (2025). Evaluating sparse feature selection methods: A theoretical and empirical perspective. *Applied Sciences*, *15*(7), 3752. https://doi.org/10.3390/app15073752

Hassan, W., Hussain, G. A., Wahid, A., Safdar, M., Khalid, H. M., & Jamil, M. K. M. (2024). Hassan, W., Hussain, G. A., Wahid, A., Safdar, M., Khalid, H. M., & Jamil, M. K. M. (2024). Optimum feature selection for classification of PD signals produced by multiple insulation defects in electric motors. *Scientific Reports*, *14*(1), 23446. https://doi.org/10.1038/s41598-024-73196-z

Huang, L., Zhou, X., Shi, L., & Gong, L. (2024). Time series feature selection method based on mutual information. *Applied Sciences*, *14*(5), 1960. https://doi.org/10.3390/app14051960

Iacobescu, P., Marina, V., Anghel, C., & Anghele, A. D. (2024). Evaluating binary classifiers for cardiovascular disease prediction: enhancing early diagnostic capabilities. *Journal of*

Cardiovascular Development and Disease, *11*(12), 396. https://doi.org/10.3390/jcdd11120396

Kidambi Raju, S., Ramaswamy, S., Eid, M. M., Gopalan, S., Karim, F. K., Marappan, R., & Khafaga, D. S. (2023). Evaluation of mutual information and feature selection for SARS-CoV-2 respiratory infection. *Bioengineering*, *10*(7), 880. https://doi.org/10.3390/bioengineering10070880

Li, K., & Fard, N. (2022). A novel nonparametric feature selection approach based on mutual information transfer network. *Entropy*, *24*(9), 1255. https://doi.org/10.3390/e24091255

Khan Mamun, M. M. R., & Elfouly, T. (2023). Detection of cardiovascular disease from clinical parameters using a one-dimensional convolutional neural network. *Bioengineering*, *10*(7), 796. https://doi.org/10.3390/bioengineering10070796

Pau, S., Perniciano, A., Pes, B., & Rubattu, D. (2023). An evaluation of feature selection robustness on class noisy data. *Information*, *14*(8), 438. https://doi.org/10.3390/info14080438

Sarra, R. R., Dinar, A. M., Mohammed, M. A., & Abdulkareem, K. H. (2022). Enhanced heart disease prediction based on machine learning and χ2 statistical optimal feature selection model. *Designs*, *6*(5), 87. https://doi.org/10.3390/designs6050087

Sayadi, M., Varadarajan, V., Sadoughi, F., Chopannejad, S., & Langarizadeh, M. (2022). A machine learning model for detection of coronary artery disease using noninvasive clinical parameters. *Life*, *12*(11), 1933. https://doi.org/10.3390/life12111933

Talaat, F. M., Elnaggar, A. R., Shaban, W. M., Shehata, M., & Elhosseini, M. (2024). CardioRiskNet: a hybrid AI-based model for explainable risk prediction and prognosis in cardiovascular disease. *Bioengineering*, *11*(8), 822. https://doi.org/10.3390/bioengineering11080822

Tiwari, A. K., Saini, R., Nath, A., Singh, P., & Shah, M. A. (2024). Hybrid similarity relation based mutual information for feature selection in intuitionistic fuzzy rough framework and its applications. *Scientific Reports*, *14*(1), 5958. https://doi.org/10.1038/s41598-024-55902-z

Victor, O. A., Chen, Y., & Ding, X. (2024). Non-invasive heart failure evaluation using machine learning algorithms. *Sensors*, *24*(7), 2248. https://doi.org/10.3390/s24072248

Wang, Y., Wang, X., Wang, C., & Zhou, J. (2024). Global, regional, and national burden of cardiovascular disease, 1990-2021: results from the 2021 global burden of disease study. *Cureus*, *16*(11). https://doi.org/10.7759/cureus.74333

Wild, R., Sozio, E., Margiotta, R. G., Dellai, F., Acquasanta, A., Del Ben, F., ... & Laio, A. (2024). Maximally informative feature selection using Information Imbalance: Application to COVID-19 severity prediction. *Scientific Reports*, *14*(1), 10744. https://doi.org/10.1038/s41598-024-61334-6

Xi, J., Jiang, Q., Liu, H., & Gao, X. (2023). Lithological mapping research based on feature selection model of ReliefF-RF. *Applied Sciences*, *13*(20), 11225. https://doi.org/10.3390/app132011225

Yan, X., Shang, S., Li, D., & Dang, Y. (2025). An efficient and interactive feature selection approach based on copula entropy for high-dimensional genetic data. *Scientific Reports*, *15*(1), 30100. https://doi.org/10.1038/s41598-025-15068-8

Zhang, L., Lin, G., Wei, L., & Kou, Y. (2024). Feature subset selection for multi-scale neighborhood decision information system via mutual information. *Artificial Intelligence Review*, *57*(1), 15. https://doi.org/10.1007/s10462-023-10626-w