Journal of Electrical Technology UMY (JET-UMY), Vol. 8, No. 2, December 2024
ISSN 2550-1186 e-ISSN 2580-6823

Advancing Cardiovascular Risk Prediction: A Review of Machine Learning Models and Their Clinical Potential

Rona Regen*, Hendra Setiawan

Master Program of Electrical Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia
Yogyakarta, Indonesia
*Corresponding author, e-mail: 23925006@students.uii.ac.id

Abstract – *This study conducts a systematic literature review on the application of machine learning technology in predicting heart disease risk. A total of 20 recent articles were identified and analyzed to evaluate the most used algorithms and their performance. The results show that Random Forest, Logistic Regression, Support Vector Machine, Decision Tree, and K-Nearest Neighbors are the most frequently applied models, with average accuracies of 89.56%, 83.14%, 83.14%, 82.57%, and 79.40%, respectively. In addition to comparing accuracy, this review also evaluates the strengths, weaknesses, and potential challenges of implementing each algorithm in clinical applications. The analysis reveals that RF demonstrates high stability and accuracy, making it the leading candidate for large-scale clinical heart disease risk prediction applications. These findings are expected to provide new insights for the development of more accurate, reliable, and clinically deployable machine learning predictive models to support medical decision-making.*

Keywords*: Machine Learning, Heart Disease Risk Prediction, Clinical Applications, Predictive Modeling, Early Detection*

I. Introduction

Cardiovascular diseases, including heart disease, are the leading cause of death worldwide, accounting for approximately 17.9 million deaths annually, or 32% of global deaths [1]. In this context, early detection and prevention of heart disease play a crucial role in reducing mortality rates. Machine learning (ML) technology has become a key tool in analyzing heart disease risks due to its ability to handle complex and large datasets, as well as its capability to produce more accurate predictions compared to traditional methods [2], [3].

This study aims to provide a comprehensive overview of the most frequently used ML models for predicting heart disease risk. We evaluate the performance of algorithms such as Random Forest (RF), Logistic Regression (LR), Supervised vector machine (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN), and analyze their strengths and limitations to provide guidance for clinical applications.

While numerous studies have explored the performance of machine learning algorithms in predicting heart disease risk, this study offers unique contributions in several key aspects. It not only compares the accuracy of widely used algorithms such as RF, LR, and SVM, but also evaluates their stability and consistency across diverse clinical datasets. Additionally, this study emphasizes the strengths and limitations of these models, focusing on their suitability for real-world clinical applications. Clear visual comparisons are also provided to help readers better understand the findings and their practical implications.

II. Research Methods

This study employs a structured methodology focusing on the selection of relevant articles and the analysis of their data to examine the application of machine learning in predicting heart disease risk.

Manuscript received October 2024, revised November 2024

II.1. *Article Selection*

To identify relevant studies, a comprehensive search was conducted using Google Scholar with the keywords "Predictive Modeling Heart Disease Machine Learning." The initial search yielded a substantial number of articles. These were systematically screened to ensure only the most relevant and high-quality studies were included.

The selection process followed a structured approach with several inclusion criteria. First, only fully accessible articles with complete datasets were considered. Second, studies had to be published in reputable journals or conference proceedings to maintain research quality. Third, only articles published within the last five years were included to ensure relevance to current technological advancements.

Additionally, studies were required to implement at least one machine learning model specifically for predicting heart disease risk. Through this multi-stage screening process, the initial pool of articles was gradually narrowed down to a final set of 20 studies. These selected studies were then analyzed in detail, with Table 1 summarizing the included articles and the machine learning models they employed.

TABLE 1
LIST OF SELECTED PAPERS

Title	year	ref	Machine Learning Model	Models count
Application of Machine Learning for Cardiovascular Disease Risk Prediction	2023	[4]	QUEST, RF, Neural Network (NN), Bayesian Network (BN), C5.0	5
Comparison of machine learning algorithms for clinical event prediction (risk of coronary heart disease)	2019	[5]	DT, Boosted Decision Tree (BDT), RF, SVM, NN, LR	6
Explainable machine learning model for predicting the occurrence of postoperative malnutrition in children with congenital heart disease	2022	[6]	LR, SVM, adaptive boosting, multilayer perceptron, Extreme Gradient Boosting (XGB)	5
Heart disease classification based on ECG using machine learning models	2023	[7]	Gaussian Naïve Bayes (GNB) RF, LR, Linear Discriminant Analysis, Dummy Classifier	5
Human heart health prediction using GAIT parameters and machine learning model	2024	[8]	LR, SVM, Artificial NN	3
IoT-based patient monitoring system for predicting heart disease using deep learning	2023	[9]	Convolutional NN, KNN,	4

			Linear SVM, Modified Social Spider Optimization - Adaptive Neuro-Fuzzy Inference System	
Using a machine learning-based risk prediction model to analyze the coronary artery calcification score and predict coronary heart disease and risk assessment	2022	[10]	RF, SVM, Kernel Ridge Regression, Radial Basis Function NN, KNN	5
Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques	2019	[11]	Naive Bayes (NB), Generalized Linear Model, LR, DT, RF, Gradient Boosted Trees, SVM	7
HDPM: An Effective Heart Disease Prediction Model for a Clinical Decision Support System	2020	[12]	NB, LR, Multilayer Perceptron, SVM, DT, RF	6
Effective Feature Engineering Technique for Heart Disease Prediction with Machine Learning	2023	[13]	Linear regression, RF, SVM, DT, XGB, NB, KNN, Multilayer Perceptron, Gradient Boosting (GB)	9
Efficient Prediction of Cardiovascular Disease Using Machine Learning Algorithms with Relief and LASSO Feature Selection Techniques	2021	[14]	DT, RF, KNN, GB	4
HDPF: Heart Disease Prediction Framework Based on Hybrid Classifiers and Genetic Algorithm	2021	[15]	LR, SVM, KNN, DT, RF,	5
Machine learning-based approach to the diagnosis of cardiovascular vascular disease using a combined dataset	2023	[16]	DT, RF, GB, XGB, SVM, Multilayer Perceptron, KNN, LR	8
An ensemble method based multilayer dynamic system to predict cardiovascular disease using machine learning approach	2021	[17]	XGB, LR, SVM, KNN, DT	5

Intelligent Cardiovascular Disease Prediction Empowered with Gradient Descent Optimization	2021	[18]	SVM, KNN NB, RF	4
Heart Disease Identification Method Using Machine Learning Classification in E-Healthcare	2020	[19]	LR, KNN, NB, DT. SVM	5
Heart disease prediction using entropy-based feature engineering and ensembling of machine learning classifiers	2022	[20]	LR, DT. RF, NB, KNN SVM	6
Early prediction of high-cost inpatients with ischemic heart disease using network analytics and machine learning	2022	[21]	LR, DT. NN, RF, XGB	5
Machine learning based heart disease prediction system for Indian population: An exploratory study done in South India	2021	[22]	KNN, NB, LR, AdaBoost, RF	5
A machine learning approach for risk factors analysis and survival prediction of Heart Failure patients	2023	[23]	DT Regressor XGB DT. GB RF	5

II.2. *Data Analysis*

The analysis of the selected articles was carried out with the primary aim of identifying the machine learning algorithms utilized and evaluating their effectiveness in predicting the risk of heart disease. This involved an in-depth examination of the models described in each study, focusing on their methodologies, implementations, and outcomes. Emphasis was placed on comparing the predictive accuracy of various algorithms, as accuracy is a critical measure of a model's performance in medical applications, especially when predicting complex conditions like heart disease [10].

To facilitate this comparison, statistical measures were calculated for each machine learning model. These included the minimum, maximum, average, and standard deviation of accuracy, providing a comprehensive overview of how each model performed across different datasets and conditions. This statistical analysis not only highlighted the variations in performance between algorithms but also provided insights into their reliability and consistency [24]. The application of these quantitative methods ensured that the evaluation process was objective, reproducible, and scientifically robust.

The findings from this analysis indicated that some algorithms were employed more frequently than others in the studies reviewed. Specifically, RF, LR, SVM, DT, and KNN emerged as the top five most commonly used models. These algorithms were consistently featured across multiple studies due to their proven efficacy and adaptability in handling structured data, which is typical in heart disease prediction tasks.

The prevalence of these algorithms is illustrated in Figure 1, which depicts the frequency distribution

of machine learning models employed in the reviewed studies. RF is the most frequently utilized algorithm, appearing in 16 studies, followed closely by LR with 15 occurrences, SVM with 14, DT with 13, and KNN with 11. These five algorithms dominate the field, reflecting their popularity and effectiveness in predictive modeling. Other algorithms, such as NB, NN, and XGB, are used less frequently, with frequencies ranging between 6 and 8. Rarely used algorithms, such as QUEST, BDT, and GB, appear fewer than three times. This distribution underscores the diversity of approaches in the field while highlighting the algorithms most trusted by researchers for heart disease prediction.

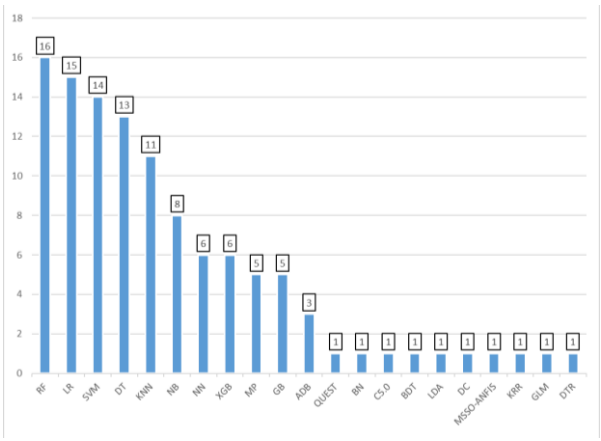

Fig. 1. Frequency distribution of machine learning algorithms employed in the reviewed studies

The significance of these five algorithms lies in their ability to represent the current advancements in machine learning applications within the healthcare domain. Each of these models offers distinct advantages; for example, RF is valued for its ensemble learning approach and high accuracy, while LR remains popular for its simplicity and interpretability in clinical settings [25], [26]. Similarly, SVM are known for their robust performance on complex, high-dimensional datasets, and DTs offer an intuitive decision-making process that aligns well with medical diagnostics [27].

By focusing on these algorithms, this study highlights the state-of-the-art techniques driving innovation in predictive modeling for cardiovascular health. The statistical and graphical analyses provide a foundation for understanding the strengths and limitations of various machine learning approaches, paving the way for future research and development in this critical domain.

III. Results and Discussion

This section elaborates on the models under investigation, namely KNN, DT, SVM, LR, and RF. The discussion includes an explanation of how the models work, their strengths, weaknesses, and performance based on accuracy analysis.

III.1. *K-Nearest Neighbor*

KNN is one of the oldest machine learning algorithms, introduced around the 1960s [28]. It classifies test data based on the majority class or average value of K nearest neighbors in the sample space [29]. The algorithm calculates the distance between each data point in the test set and training data points using metrics like Euclidean distance (1)

$$D_e = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

KNN (KNN) is a straightforward and intuitive algorithm that excels in simplicity and ease of implementation. However, its performance is significantly affected by the choice of the parameter K, which determines the number of neighbors considered during classification or regression. Additionally, KNN is highly sensitive to noise in the data, as outliers can disproportionately influence predictions. The algorithm also relies on proper scaling of features to ensure meaningful distance calculations, making preprocessing a critical step for its effective application.

Advantages: KNN is simple, easy to implement, and well-suited for scenarios where interpretability and minimal algorithmic complexity are desired.

Disadvantages: Its sensitivity to noise, dependence on the choice of K, and need for feature scaling can pose challenges, particularly for high-dimensional or noisy datasets.

III.2. *Decision Tree*

DT is a tree-structured algorithm that systematically partitions a dataset into smaller subsets through a series of recursive splits [28]. It organizes decision-making logic into a hierarchical structure, with the root node at the top, internal nodes representing decision points, and leaf nodes signifying predictions[30], [31]. This intuitive structure makes DT highly interpretable and easy to visualize, making it a popular choice for simple tasks. However, its flexibility often leads to overfitting, particularly when dealing with complex or noisy datasets, unless appropriate regularization techniques are applied.

Advantages: DT is highly interpretable, easy to visualize, and effective for analyzing small datasets or datasets with clear patterns.

Disadvantages: It is prone to overfitting, especially in the absence of regularization techniques such as pruning or setting a maximum depth.

III.3. *Supervised Vector Machine*

SVM is a powerful algorithm designed to identify the optimal hyperplane that separates data classes or forms a robust decision boundary. It excels in handling high-dimensional datasets and is particularly effective for tasks requiring precise classification. The optimization process, expressed mathematically in (2), ensures a maximized margin between data classes, enhancing generalization. However, SVM requires careful tuning of parameters such as the kernel, regularization, and margin, which can be computationally intensive. This complexity makes SVM less scalable for large datasets.

$$f(\theta) = \sum_{j=1}^{n} \theta_j^2 \qquad (2)$$

Advantages: SVM delivers high accuracy, especially for small, high-dimensional datasets, and is effective in tasks with complex boundaries.

Disadvantages: Parameter tuning is intricate, often involving multiple iterations to find optimal settings. Additionally, SVM can be computationally expensive and slower for large-scale datasets due to its reliance on complex optimization algorithms.

III.4. *Logistic Regression*

LR, despite its name, is a statistical and machine learning algorithm primarily used for binary classification tasks. It predicts the probability of an event occurring by modeling the relationship between one or more independent variables and a dependent variable using a logistic function [32]. LR is valued for its simplicity, computational efficiency, and ease of implementation. However, it struggles to capture complex or non-linear relationships within the data, limiting its effectiveness in such scenarios.

Advantages: LR is fast, easy to implement, and highly effective for binary classification problems with linear relationships between variables.

Disadvantages: It is less suitable for complex datasets with non-linear patterns, as it lacks the capacity to model intricate relationships without additional transformations or feature engineering.

III.5. *Random Forest*

RF is a robust ensemble learning algorithm that combines predictions from multiple DT to improve stability, accuracy, and generalization [25]. By aggregating outputs from various trees, RF reduces the risk of overfitting and delivers consistent performance, even on high-dimensional datasets. Additionally, it offers valuable insights through feature importance estimates, aiding in the interpretability of complex models. However, these advantages come at the cost of increased computational requirements, particularly for large datasets.

Advantages: RF is highly stable, resistant to overfitting, and excels in handling high-dimensional data while providing feature importance for interpretability.

Disadvantages: It is computationally intensive, requiring substantial processing power and memory, and performs best when trained on large datasets to ensure robust predictions.

III.6. *Performance Summary*

The performance of the models based on accuracy, standard deviation, and other factors is summarized

in Table 2, Table 3 and visualized in Figures 2 and 3.

TABLE 2
AVERAGE ACCURATION ML MODELS

Model	Average Accuracy (%)	Standard Deviation (%)
RF	89.56	7.21
LR	83.14	7.47
SVM	83.14	10.12
DT	82.57	10.91
KNN	79.40	11.77

TABLE 3
STRENGTHS & WEAKNESSES ML MODELS

Model	Strengths	Weaknesses
RF	High stability; robust	Requires large datasets
LR	Simple and fast	Ineffective for complex data
SVM	Accurate for small datasets	Parameter tuning complexity
DT	Easy to interpret	Prone to overfitting
KNN	Simple to implement	Sensitive to noise

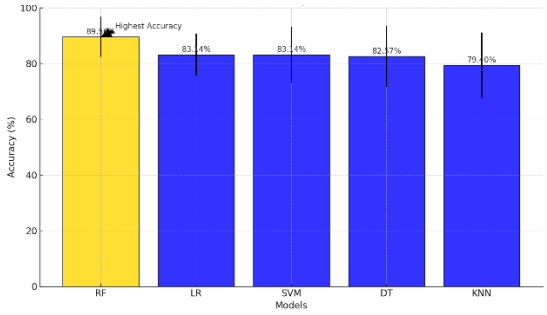

Fig. 2. Averages accuracy for five models

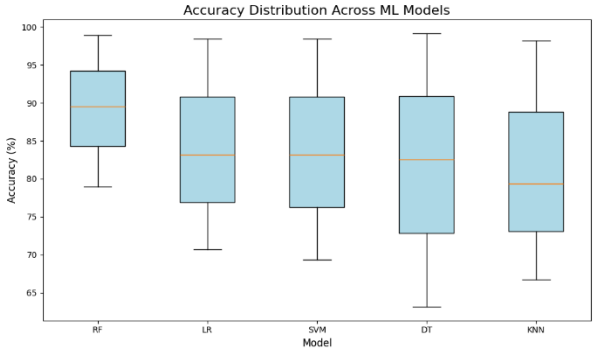

Fig. 3. Distribution of accuracies across the models

III.7. Critical Analysis and Recommendations

From the visualization and analysis:

- RF stands out with the highest average accuracy (89.56%) and the lowest standard deviation (7.21%), indicating both reliability and robustness. It is recommended for large and complex datasets.
- KNN has the lowest average accuracy (79.40%) and the highest standard deviation (11.77%), reflecting its sensitivity to noise and parameter dependence.
- For simple tasks or smaller datasets, LR and SVM are viable choices. However, SVM requires careful parameter tuning, making it less practical for large-scale applications.

Future research should explore ensemble methods combining multiple models to leverage their respective strengths, potentially achieving higher accuracy and robustness in heart disease risk prediction.

IV. Conclusion

This systematic literature review provides an insightful analysis of the use of machine learning algorithms for predicting heart disease risk, focusing on commonly employed models such as RF, LR, SVM, DT, and KNN. Among these, RF demonstrates superior performance with the highest average accuracy of 89.56% and the lowest variability, showcasing its reliability for large and complex datasets. LR and SVM, while effective for smaller datasets, present limitations such as reduced applicability to complex data patterns and intensive parameter tuning, respectively. KNN, though simple and intuitive, is less reliable due to its sensitivity to noise and dependence on parameter selection. DT, valued for their interpretability, often face challenges with overfitting, especially in more complex datasets.

To further advance this field, future research should explore the integration of deep learning-based approaches, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have shown promise in handling large-scale and high-dimensional data.

Additionally, the development of hybrid models that combine the strengths of multiple algorithms could further improve predictive accuracy and robustness. These innovations could pave the way for broader clinical deployment, offering enhanced decision-making support in cardiovascular disease management.

References

[1] "Cardiovascular diseases (CVDs)." Accessed: Mar. 12, 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[2] H. Wang, Q. Zu, J. Chen, Z. Yang, and M. A. Ahmed, "Application of Artificial Intelligence in Acute Coronary Syndrome: A Brief Literature Review," *Adv. Ther.*, vol. 38, no. 10, pp. 5078–5086, Oct. 2021, doi: 10.1007/s12325-021-01908-2.

[3] M. P. Cote, J. H. Lubowitz, J. C. Brand, and M. J. Rossi, "Artificial intelligence, machine learning, and medicine: a little background goes a long way toward understanding," *Arthroscopy: The Journal of Arthroscopic & Related Surgery*, vol. 37, no. 6. Elsevier, pp. 1699–1702, 2021. Accessed: May 24, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0749806321003856

[4] S. Dalal *et al.*, "Application of Machine Learning for Cardiovascular Disease Risk Prediction," *Comput. Intell. Neurosci.*, vol. 2023, p. e9418666, Mar. 2023, doi: 10.1155/2023/9418666.

[5] J.-J. Beunza *et al.*, "Comparison of machine learning algorithms for clinical event prediction (risk of coronary heart disease)," *J. Biomed. Inform.*, vol. 97, p. 103257, Sep. 2019, doi: 10.1016/j.jbi.2019.103257.

[6] H. Shi *et al.*, "Explainable machine learning model for predicting the occurrence of postoperative malnutrition in children with congenital heart disease," *Clin. Nutr.*, vol. 41, no. 1, pp. 202–210, Jan. 2022, doi: 10.1016/j.clnu.2021.11.006.

[7] S. Matin Malakouti, "Heart disease classification based on ECG using machine learning models," *Biomed. Signal Process. Control*, vol. 84, p. 104796, Jul. 2023, doi: 10.1016/j.bspc.2023.104796.

[8] P. Singh, P. S. Kourav, S. Mohapatra, V. Kumar, and S. K. Panda, "Human heart health prediction using GAIT parameters and machine learning model," *Biomed. Signal Process. Control*, vol. 88, p. 105696, Feb. 2024, doi: 10.1016/j.bspc.2023.105696.

[9] G. Ramkumar, J. Seetha, R. Priyadarshini, M. Gopila, and G. Saranya, "IoT-based patient monitoring system for predicting heart disease using deep learning," *Measurement*, vol. 218, p. 113235, Aug. 2023, doi: 10.1016/j.measurement.2023.113235.

[10] Y. Huang *et al.*, "Using a machine learning-based risk prediction model to analyze the coronary artery calcification score and predict coronary heart disease and risk assessment," *Comput. Biol. Med.*, vol. 151, p. 106297, Dec. 2022, doi: 10.1016/j.compbiomed.2022.106297.

[11] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques," *IEEE Access*, vol. 7, pp. 81542–81554, 2019.

[12] N. L. Fitriyani, M. Syafrudin, G. Alfian, and J. Rhee, "HDPM: an effective heart disease prediction model for a clinical decision support system," *IEEE Access*, vol. 8, pp. 133034–133050, 2020.

[13] A. M. Qadri, A. Raza, K. Munir, and M. Almutairi, "Effective feature engineering technique for heart disease prediction with machine learning," *IEEE Access*, 2023, Accessed: May 25, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10138551/

[14] P. Ghosh *et al.*, "Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques," *IEEE Access*, vol. 9, pp. 19304–19326, 2021.

[15] S. E. Ashri, M. M. El-Gayar, and E. M. El-Daydamony, "HDPF: heart disease prediction framework based on hybrid classifiers and genetic algorithm," *Ieee Access*, vol. 9, pp. 146797–146809, 2021.

[16] K. M. Mohi Uddin, R. Ripa, N. Yeasmin, N. Biswas, and S. K. Dey, "Machine learning-based approach to the diagnosis of cardiovascular vascular disease using a combined dataset," *Intell.-Based Med.*, vol. 7, p. 100100, Jan. 2023, doi: 10.1016/j.ibmed.2023.100100.

[17] M. N. Uddin and R. K. Halder, "An ensemble method based multilayer dynamic system to predict cardiovascular disease using machine learning approach," *Inform. Med. Unlocked*, vol. 24, p. 100584, Jan. 2021, doi: 10.1016/j.imu.2021.100584.

[18] M. S. Nawaz, B. Shoaib, and M. A. Ashraf, "Intelligent cardiovascular disease prediction empowered with gradient descent optimization," *Heliyon*, vol. 7, no. 5, 2021, Accessed: May 25, 2024. [Online]. Available: https://www.cell.com/heliyon/pdf/S2405-8440(21)01051-3.pdf

[19] J. P. Li, A. U. Haq, S. U. Din, J. Khan, A. Khan, and A. Saboor, "Heart disease identification method using machine learning classification in e-healthcare," *IEEE Access*, vol. 8, pp. 107562–107582, 2020.

[20] R. Rajendran and A. Karthi, "Heart disease prediction using entropy based feature engineering and ensembling of machine learning classifiers," *Expert Syst. Appl.*, vol. 207, p. 117882, Nov. 2022, doi: 10.1016/j.eswa.2022.117882.
[21] P. Yang, H. Qiu, L. Wang, and L. Zhou, "Early prediction of high-cost inpatients with ischemic heart disease using network analytics and machine learning," *Expert Syst. Appl.*, vol. 210, p. 118541, Dec. 2022, doi: 10.1016/j.eswa.2022.118541.
[22] E. Maini, B. Venkateswarlu, B. Maini, and D. Marwaha, "Machine learning–based heart disease prediction system for Indian population: An exploratory study done in South India," *Med. J. Armed Forces India*, vol. 77, no. 3, pp. 302–311, Jul. 2021, doi: 10.1016/j.mjafi.2020.10.013.
[23] Md. M. Ali *et al.*, "A machine learning approach for risk factors analysis and survival prediction of Heart Failure patients," *Healthc. Anal.*, vol. 3, p. 100182, Nov. 2023, doi: 10.1016/j.health.2023.100182.
[24] T. M. Mitchell and M. Learning, "Mcgraw-hill science," *Engineering/Math*, vol. 1, p. 27, 1997.
[25] L. Breiman, "RFs," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.
[26] D. W. Hosmer Jr, S. Lemeshow, and R. X. Sturdivant, *Applied LR*. John Wiley & Sons, 2013. Accessed: Dec. 12, 2024. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=bRoxQBIZRd4C&oi=fnd&pg=PR13&dq=Hosmer,+D.+W.,+Lemeshow,+S.,+%26+Sturdivant,+R.+X.+(2013).+Applied+Logistic+Regression.+Wiley&ots=kM3Opu7Wd5&sig=9vZfiqVamRxGCuxdwB5uz8HwhoI
[27] J. M. Moguerza and A. Muñoz, "SVM with applications," 2006, Accessed: Dec. 12, 2024. [Online]. Available: https://projecteuclid.org/journals/statistical-science/volume-21/issue-3/Support-Vector-Machines-with-Applications/10.1214/088342306000000493.short
[28] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Trans. Inf. Theory*, vol. 13, no. 1, pp. 21–27, 1967.
[29] S. M. M. Hasan, M. A. Mamun, M. P. Uddin, and M. A. Hossain, "Comparative analysis of classification approaches for heart disease prediction," in *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, IEEE, 2018, pp. 1–4. Accessed: May 25, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8465594/
[30] M. M. Ali, B. K. Paul, K. Ahmed, F. M. Bui, J. M. W. Quinn, and M. A. Moni, "Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison," *Comput. Biol. Med.*, vol. 136, p. 104672, Sep. 2021, doi: 10.1016/j.compbiomed.2021.104672.
[31] J. R. Quinlan, "Induction of DTs," *Mach. Learn.*, vol. 1, no. 1, pp. 81–106, Mar. 1986, doi: 10.1007/BF00116251.
[32] S. Uddin, A. Khan, M. E. Hossain, and M. A. Moni, "Comparing different supervised machine learning algorithms for disease prediction," *BMC Med. Inform. Decis. Mak.*, vol. 19, no. 1, p. 281, Dec. 2019, doi: 10.1186/s12911-019-1004-8.

Authors' information

Rona Regen current Master's student in Electrical Engineering with academic focus lies in radar, control systems, IoT, and machine learning.

Dr. Hendra Setiawan is an Associate Professor in Electrical Engineering with a research focus on signal processing, IC design, FPGA, physical layer wireless communication, and renewable energy. He is currently residing in Yogyakarta, Indonesia