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Artificial Intelligence and Machine Learning Algorithms in Modern Cardiology

Anita Petreska[1]*, Daniela Slavkovska[2]

[1]Faculty of Information and Communication Technologies, Bitola, University "St. Kliment Ohridski"- Bitola, Republic of North Macedonia; [2]University Children's Hospital, Skopje, Republic of North Macedonia

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***Correspondence:** Anita Petreska, Faculty of Information and Communication Technologies, Bitola, University "St. Kliment Ohridski"- Bitola, Republic of North Macedonia. E-mail: petreska.anita@uklo.edu.mk
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Abstract

BACKGROUND: Recent years have witnessed the widespread adoption of machine learning (ML) and deep learning techniques in various health-care applications. Artificial intelligence and ML algorithms using big medical data make it possible to predict diseases and enable the development of personalized treatments for patients. Heart diseases are one of the most common chronic diseases affecting human health, and early detection can reduce the mortality rate.

AIM: We aimed to review different types of ML techniques and their applications in heart disease risk detection.

METHODS: For different cardiovascular diseases, the choice of algorithms should be tailored based on their accuracy and efficiency

RESULTS: The research presented highlights the critical global issue of heart disease and its impact on public health. The urgency to address this global problem is emphasized, as heart disease has become a significant factor in the increasing mortality rate worldwide. The introduction of ML in the prognosis of heart disease is a significant step toward realizing predictive, preventive, and personalized health care and reducing health-care costs. In this study, a comparative evaluation of ML models was made: Logistic regression, decision tree, random forest, and support vector machine. The quality of the data, as well as the choice of an appropriate algorithm, is key factors in the assessment of heart diseases.

CONCLUSION: Despite the impressive performance of ML, there are doubts about its robustness in traditional health-care systems due to many security and privacy issues.

Introduction

According to the World Health Organization, heart disease is a major contributor to high mortality rates. To solve this global problem, researchers are actively working to predict heart diseases at an early stage to provide timely and appropriate treatments that will save many lives. The use of advanced technologies, including data mining, has become a powerful tool in the detection and prediction of heart disease. Part 2 reviews the role of artificial intelligence and data mining in health care. In part 3, the role of machine learning (ML) in health care and the challenges in choosing ML models in health care are given. Section 4 presents the integration of artificial intelligence in cardiology, performing a comparative analysis between four commonly used ML algorithms to discover patterns and anomalies that are crucial in the detection and diagnosis of heart disease risk. The methodology used, data collection, data pre-processing, exploratory data analysis (EDA), evaluation metrics, limitations, and challenges faced by ML algorithms used for heart disease detection are presented. In section 5, the advantages of ML in the prognosis of heart diseases are presented; in section 6, the disadvantages of ML in the prognosis of heart diseases are presented. Section 7 presents the conclusions and future challenges.

The Role of Artificial Intelligence and Data Mining in Health care

The potential of artificial intelligence in health-care [1] lies in its ability to solve tasks such as diagnostics, treatment planning, precision diagnostics, personalized treatment plans, improved decision-making processes, and overall advances in patient care. Artificial intelligence, with its capabilities for ML, data analytics, and pattern recognition, is of great importance in analyzing complex data sets. Dealing with huge and complex data sets requires innovative methods and technologies that play a key role in handling, analyzing, and extracting meaningful patterns from the vast amounts of available data. While data mining [2] has been successfully applied in other sectors such as marketing, e-business, and retail, its adoption in the health-care sector is still developing. Despite the abundance of data in the health-care system, there is a lack of tools that can accurately discover and exploit

data connections, and inefficiencies through analytics, and implement best practices to improve treatment and reduce costs. Medical data mining offers a lot of potential for discovering hidden patterns in medical data sets and serves as an important tool in the medical sector, providing and comparing existing data for future courses of action. It can be used to identify inherent inefficiencies and best practices that can lead to improved diagnosis, better medicine, and more successful treatment, helping in the early detection and prevention of disease outbreaks by searching medical databases for relevant information. Physicians can benefit from a computer-aided diagnostic system in making sound medical judgments. Medical professionals are very interested in automating the diagnosis process by integrating ML techniques with the expertise of doctors. The application of data mining techniques in health care has enormous potential to revolutionize the prediction of heart disease and bridge the information and knowledge gap in the health-care sector, leading to more effective prevention, early detection, and treatment of cardiovascular disease.

ML and its Role in Health care

A key component of artificial intelligence is ML, which encompasses three main types: Supervised learning, unsupervised learning, and reinforcement learning. ML [3] is often perceived as a sophisticated technology accessible only to highly trained experts, which prevents many doctors and biologists from using this tool in their research. This paper aims to eliminate this outdated perception with the implementation of artificial intelligence in cardiology. Emphasis is placed on traditional ML algorithms illustrating the diverse range of AI solutions. The best models should be recommended to doctors in health organizations to help them predict heart disease at an early stage. It is necessary to establish legal, ethical, and methodological frameworks for the application of artificial intelligence models in medicine. ML, as a significant branch of artificial intelligence, enables the development of systems that learn from retrospective data. Unlike traditional statistics, which focus on scoring systems, ML contributes to the creation of automated clinical decision-making systems, already applied in screening and diagnostic models. Implementing ML algorithms in health care is a multi-step process that begins with defining goals, collecting data, preparing and exploring data, and defining training models. ML algorithms enable the discovery of patterns in complex data, making them invaluable for interpreting results and guiding personalized clinical decisions [4].

Challenges in choosing ML models

The complexity of real-world data poses challenges in selecting appropriate ML models [5]. The presence of different sources, diverse formats, and dynamic information requires careful consideration. Maintaining data quality requires meticulous attention and continuous control throughout the data lifecycle. Biases in data collection can exacerbate social inequalities, thus requiring fairness and an understanding of the contextual implications of the data. Biased training data can lead to discriminatory predictions, highlighting the need for strategies to identify and correct biases in data preprocessing. Maintaining data quality throughout the lifecycle of ML models emphasizes the importance of continuous monitoring and adjustment. Model interpretation becomes a challenge when data quality affects the transparency of decisions. Choosing models that offer clear explanations for their results is essential for building trust and understanding. Balancing the trade-off between model complexity and simplicity is a constant challenge, as complex models can capture complex patterns but risk over fitting, while overly simplistic models can lead to generalization. Ethical considerations arise from the impact of data collection on individuals and societies. Data heterogeneity poses challenges, especially in multimodal datasets, requiring models to adapt to different data types for stable performance across different information sources. Tuning hyperparameters requires careful consideration to optimize model performance, striking the right balance for desired results. Ensuring fairness and mitigating bias in data collection is an ongoing challenge. Fair sampling and data representation strategies are essential to prevent biases from affecting model predictions. Class imbalance in datasets raises reliability concerns for ML models. Models must be selected or designed to provide accurate estimates of uncertainty, increasing the reliability of predictions. Data privacy emerges as a challenge when handling sensitive information. Striking a balance between using valuable data and protecting individual privacy is critical when choosing an ML model [6]. Addressing these challenges requires a holistic approach, combining technical expertise, ethical considerations, and constant vigilance throughout the ML lifecycle.

Integration of Artificial Intelligence in Cardiology

The integration of artificial intelligence in cardiology [7] is not just a technological advance, but a fundamental change in the way we approach cardiovascular care. It creates a synergy between human expertise and ML capabilities, offering a path to more accurate, efficient, and personalized health care. Although challenges and ethical considerations must be navigated, the potential benefits for patients and the health-care system are enormous. Responsible use of AI in cardiology [8] could lead to a future where cardiovascular disease is diagnosed earlier, treatments are more tailored, and overall patient outcomes

are significantly improved. Collaboration among health-care professionals, technologists, policymakers, and the public is needed to ensure that the power of artificial intelligence is ethically and effectively used to improve cardiovascular medicine.

Comparison of ML algorithms in cardiology

ML algorithms [9] have shown great promise in the field of cardiology, offering innovative solutions for diagnosis, risk prediction, and personalized treatment, ML algorithms in cardiology. The most commonly used ML algorithms [10] are presented: Logistic regression, decision tree, random forest, and support vector machine (SVM).

Logistic regression models predict a patient's likelihood of developing cardiovascular disease based on various risk factors such as age, gender, and blood pressure. Useful for identifying high-risk patients who may benefit from targeted interventions. Decision trees classify patients based on cardiovascular risk factors, aiding in personalized treatment plans. Decision support systems help physicians make informed decisions about patient care. Random forests are an ensemble learning method that combines multiple decision trees for more accurate prediction models. It identifies important risk factors and helps develop effective treatment plans. SVM are used in risk prediction models, analyzing various patient data to stratify individuals based on their risk of cardiovascular events, contributing to personalized treatment strategies [11].

Most commonly used algorithms of ML for predicting heart diseases

The primary objectives of this study are centered on the development of an efficient ML algorithm for predicting heart disease [12]. The study aims to improve accuracy rates, optimize feature selection, use advanced feature extraction techniques, and evaluate model performance. The paper reviews different types of ML techniques and their applications in heart disease risk detection. For different cardiovascular diseases, the choice of algorithms should be tailored based on their accuracy and efficiency [12].

Methodology

This study aims to estimate the probability of a patient experiencing a heart attack, proposing ML methods to help doctors diagnose heart disease more efficiently. The methodology includes three phases. In the initial phase, data are collected and prepared, followed by a reprocessing phase by addressing missing values, cleaning, and standardization. The third stage involves applying a classifier to construct an ML model, using four algorithms: Logistic regression, decision tree, random forest, and SVM [9], [13]. The heart disease risk prediction process involves loading data from the Kaggle database, cleaning it, extracting significant features, and then splitting the database into training and test sets (80% and 20%). Subsequently, the data is used to train and test the five ML models, and the results are comprehensively evaluated and compared, evaluating the efficiency of the proposed methodology based on accuracy, precision, recall, and F1 score [14], [15].

Data collection

In this research, we use a database from Kaggle [16] that contains 4238 records, covering 16 attributes. Among these attributes, 15 serve as input parameters, while one serves as an objective attribute, indicating the presence or absence of heart disease. Table 1 illustrates all 16 attributes, including demographic details, behavior, medical history information, current health information, and the target predictor variable.

Table 1: Data set

Feature	Description	Characteristic representation	Specific
Sex	Demographic	Male or female	(Nominal)
Age	Demographic	Age of the patient	[Continuous]
Current smoker	Behavioral	Whether or not the patient is a current smoker	(Nominal)
Cigs per day	Behavioral	The number of cigarettes that the person smoked on average in 1 day	[Continuous]
BP meds	Medical (history)	Whether or not the patient was on blood pressure medication	(Nominal)
Prevalent stroke	Medical history	Whether or not the patient had previously had a stroke	(Nominal)
Prevalent Hyp	Medical history	Whether or not the patient was hypertensive	(Nominal)
Diabetes	Medical history	Whether or not the patient had diabetes	(Nominal)
Tot chol	Medical (current)	Total cholesterol level	[Continuous]
Sys BP	Medical (current)	Systolic blood pressure	[Continuous]
Dia BP	Medical (current)	Diastolic blood pressure	[Continuous]
BMI	Medical (current)	Body mass index	[Continuous]
Heart rate	Medical (current)	Heart rate	[Continuous]
Glucose	Medical (current)	Glucose level	[Continuous]

Data pre-processing

Ensuring the quality of the final ML model requires effective data preprocessing, which involves multiple steps: identifying and addressing missing data; differentiating continuous and categorical features; recognizing ordinal categorical features; encoding them with integers based on their inherent ordered relationships; as well as identifying nominal categorical features and encoding them accordingly. Perform feature scaling to align all feature values within a similar dynamic range. Conduct feature selection, a process that involves selecting appropriate features and discarding those that contribute minimally to the prediction of the target variable. This not only reduces training time but also improves overall performance.

EDA

EDA [17] is a fundamental step in ML-based prediction of heart disease, to discover and understand

essential insights and patterns in a database. Performed systematically, EDA includes both visual and statistical investigations, fostering a deep understanding of the data and laying the foundation for the development of accurate and relevant models [18]. Visual representations including histograms offer a comprehensive understanding of data distributions, feature significance, and model performance metrics. In the field of predicting heart disease through ML, data visualization is proving essential, making it easier to understand the complex relationships between factors such as age, cholesterol levels, blood pressure, and their impact on heart disease risk. Figure 1 visually illustrates the mean values of all attributes for cases with and without heart disease risk.

Correlation analysis was conducted to reveal potential relationships between variables, to clarify

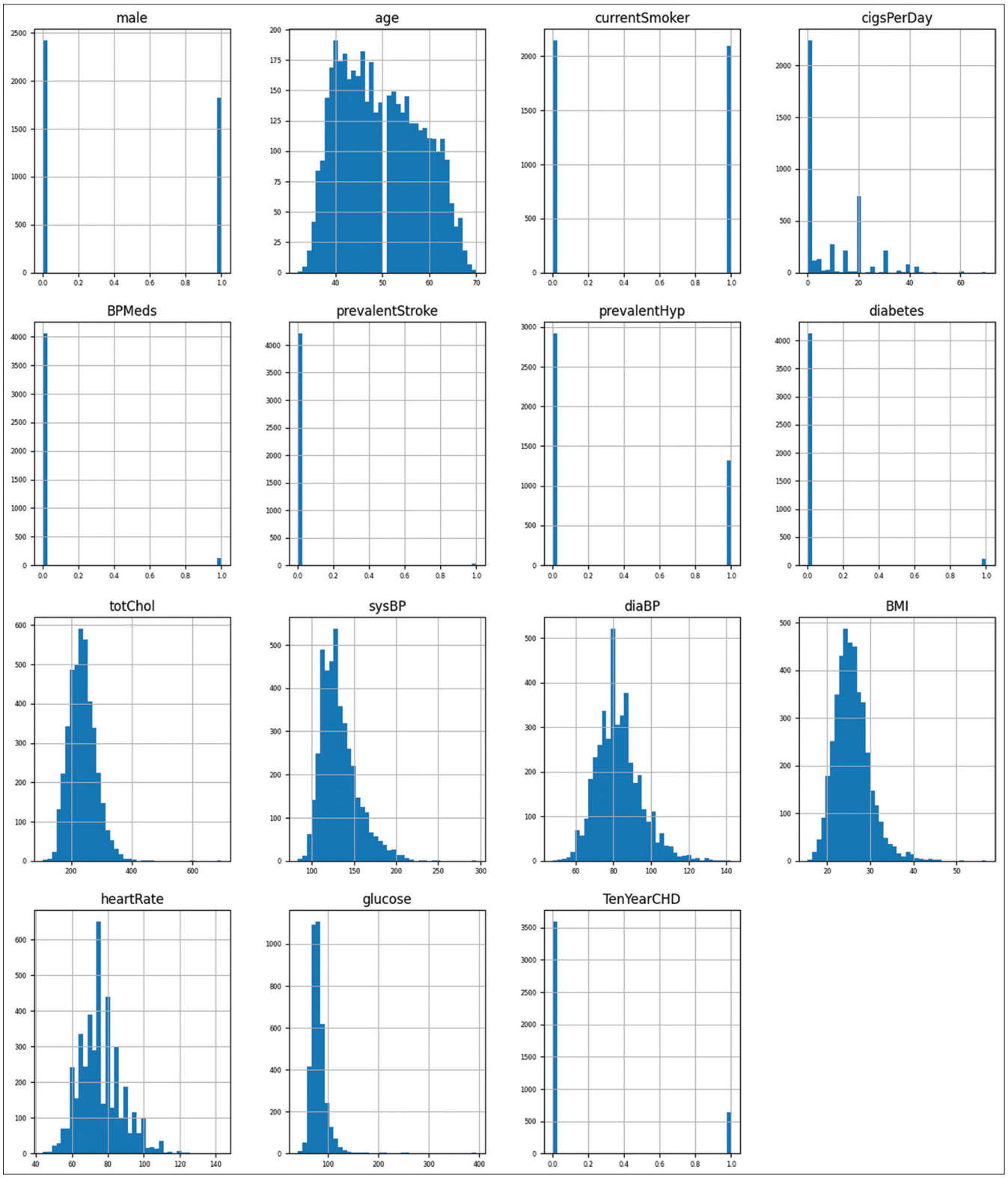


Figure 1: Attribute distribution

interactions and dependencies within the dataset. This review offers valuable insights into the possible impact of variables and their collective impact on heart disease risk. The correlation matrix shown in Figure 2 reveals whether the characteristics are positively or negatively correlated with each other and with the target variable.

Comparison of results

Table 2 shows the evaluation scores of the five considered ML algorithms by evaluating their performance in terms of accuracy, precision, recall, and F1 score to build a model for predicting heart diseases [9], [19].

Figure 3 shows the accuracy values from the used ML models on the barplot.

The presented results (Figure 3) offer a comprehensive evaluation of four ML algorithms – logistic regression, decision tree, random forest, and SVM – in the context of a task that likely involves medical diagnostics, such as heart disease prognosis. Let's delve into a narrative interpretation and comparative analysis of these results:

Table 2: Accuracy, precision, recall, F1 score for different ML models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Logistic regression	86	86	99	92
Decision tree	77	87	86	87
Random forest	86	86	99	92
Support vector machine	85	86	95	91

The logistic regression model exhibits strong performance across all key metrics. With an accuracy of 86%, it correctly classifies instances, showcasing its overall effectiveness. The precision of 86% indicates a high correctness rate when predicting positive cases, while the outstanding recall of 99% underscores the model's ability to capture a substantial majority of actual positive instances. The F1 score, at 92%, highlights a well-balanced trade-off between precision and recall, making logistic regression a robust choice for the given task.

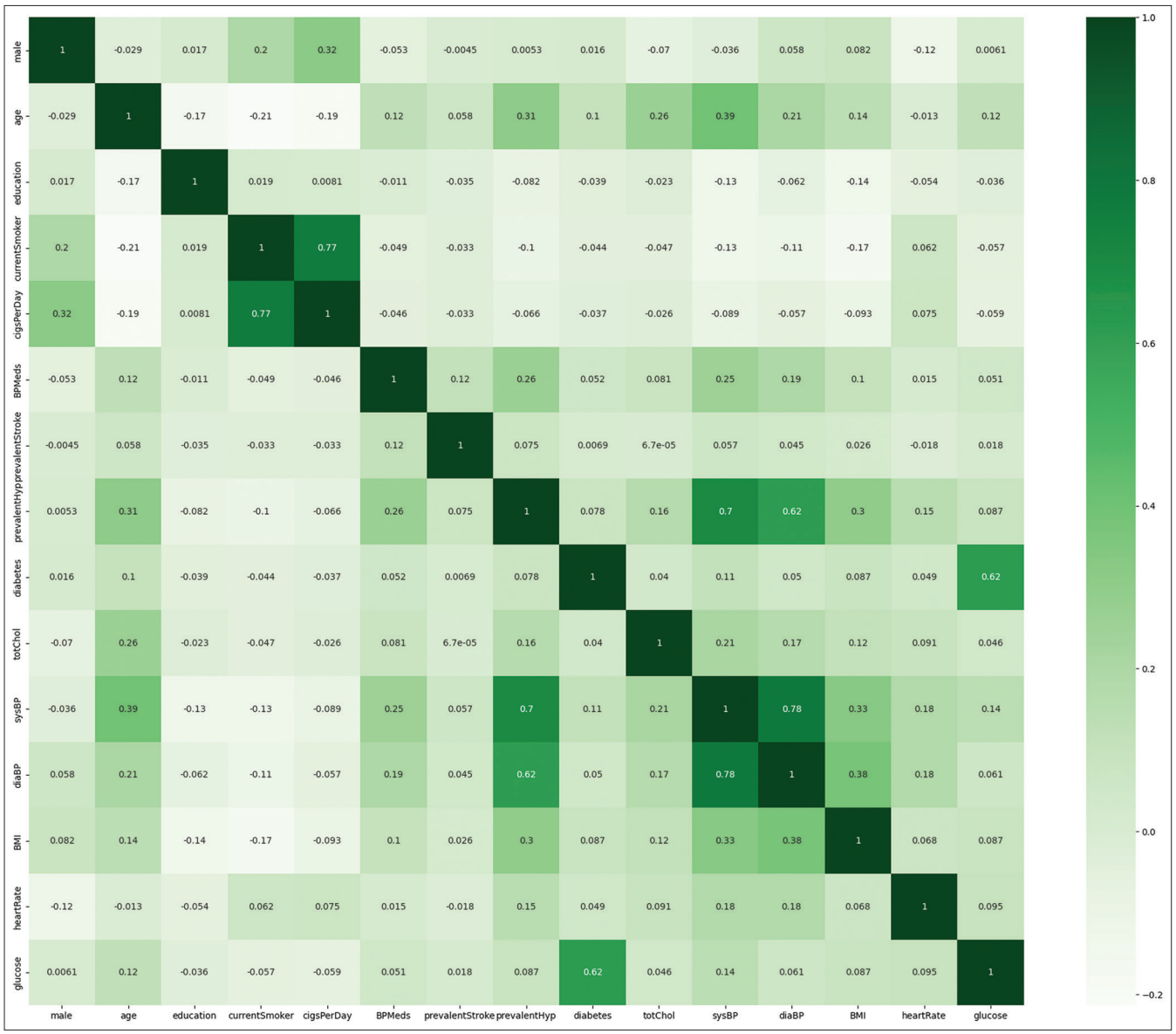


Figure 2: Correlation matrix

The decision tree model demonstrates good performance, achieving an accuracy of 77%. Its precision of 87% signifies a high correctness rate in positive predictions, and the recall of 86% indicates effective identification of actual positive instances. The F1 score, standing at 87%, reflects a harmonious balance between precision and recall. While slightly behind logistic regression, the decision tree model showcases competent predictive capabilities, especially in its interpretability and ease of understanding.

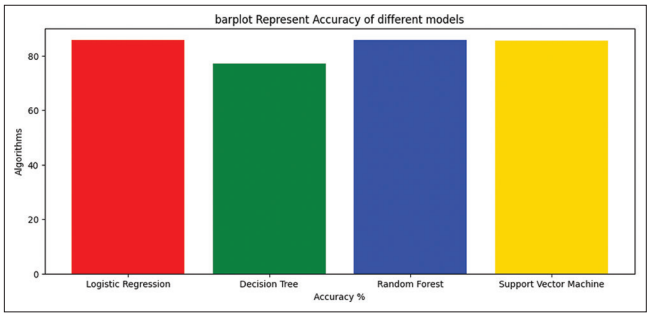


Figure 3: Barplot represents the accuracy of different models

The random forest model mirrors the performance of logistic regression with an accuracy of 86%. It shares a precision of 86%, an exceptionally high recall of 99%, and an F1 score of 92%. These metrics collectively underscore the model's proficiency in accurately identifying positive cases while maintaining a balanced precision-recall trade-off. Random forest, known for its ensemble learning approach, demonstrates resilience against overfitting and robust generalization.

The SVM model delivers commendable performance, with an accuracy of 85%. Its precision of 86% indicates a high correctness rate in positive predictions, while the recall of 95% showcases its effectiveness in capturing a significant proportion of actual positive instances. The F1 score, at 91%, reflects the model's ability to strike a balance between precision and recall. SVM, leveraging its capacity to find optimal decision boundaries, proves to be a valuable contender in the task.

Comparative analysis

Accuracy

Logistic regression and random forest share the highest accuracy at 86%, followed closely by SVM at 85% and decision tree at 77%.

Precision

Decision tree exhibits the highest precision at 87%, closely followed by logistic regression, random forest, and SVM, all at 86%.

Recall

Random forest and logistic regression both achieve an outstanding recall of 99%, while SVM follows with 95% and decision tree with 86%.

F1 score

Logistic regression and random forest tie with the highest F1 score at 92%, followed by SVM at 91% and decision tree at 87%.

In summary, all evaluated models demonstrate strong predictive capabilities, each with its own set of advantages. Logistic regression and random forest emerge as particularly robust choices, excelling in accuracy, precision, recall, and F1 score. The decision tree model, while slightly less accurate, offers interpretability, making it valuable for applications where model transparency is crucial. SVM, with its effective balance between precision and recall, proves to be a competitive choice in the lineup. The selection among these models depends on specific task requirements, interpretability needs, and the importance of different performance metrics in the given context.

The selection of the best model relies on the particular needs of the application and the significance of the defined metrics in the field of heart disease prediction. Continuous refinement and improvement of the methodology is essential, allowing the inclusion of additional factors such as echocardiographic data and medical records in future models being developed.

Advantages of ML in Prognosis of Heart Diseases

Classical ML algorithms, despite their limitations, offer several advantages in the context of cardiac disease prognosis. Here are some key advantages [20], [21], [22], [23].

Classical algorithms such as decision trees and logistic regression are often more interpretable compared to complex models such as neural networks. This interpretability can be crucial in the medical domain, as it allows health professionals to understand the factors that influence predictions.

The decision process of classical algorithms is transparent and easy to follow. This transparency is important in medical applications, where understanding why a particular prediction was made is essential to gaining trust and acceptance.

Classical algorithms often provide insight into the importance of features. Knowing which characteristics contribute most to predictions can help health-care professionals identify critical factors for heart disease prognosis.

Classical algorithms usually have a shorter training time compared to more complex models. This can be advantageous in scenarios where fast predictions are needed, making them suitable

for real-time or near-real-time applications. Some classical algorithms, such as decision trees, are robust to noisy data. They can handle datasets with outlying or incomplete information without significantly affecting their performance.

Classical algorithms can perform well on smaller datasets, making them suitable for applications were obtaining large amounts of labeled data is challenging. This scalability is particularly relevant in medical domains where acquiring large datasets can be difficult. Implementing classical ML algorithms is often straightforward. They do not require the complexity and computational resources associated with deep learning models, making them affordable and feasible for deployment in a variety of health-care settings.

Classical algorithms tend to produce simpler models, which can be advantageous in scenarios where a less complex model is preferred, such as when the goal is to understand and communicate the model to non-experts. They are part of well-established frameworks, and extensive libraries and tools are available for their implementation. This wealth of resources simplifies their adoption and integration into existing health systems. They are well suited for binary classification tasks, such as predicting the presence or absence of a particular condition. In cardiac disease prognosis, where identifying the presence of disease is often the primary concern, these algorithms can be effective.

Although classical ML algorithms may not capture the full complexity of heart disease prognosis, their advantages make them valuable tools, especially in scenarios where interpretability, simplicity, and ease of implementation are critical considerations.

Disadvantages of ML in Heart Disease Prognosis

Classical ML algorithms, although powerful and widely used, come with certain drawbacks when applied to heart disease prognosis [24], [25], [26], [27], [28].

Classic ML algorithms, such as decision trees and linear regression, struggle to capture the complex, non-linear relationships present in heart disease data. This limitation can result in suboptimal performance when dealing with complex patterns.

The success of classical algorithms often relies on hand-crafted features. Identifying features relevant to the prognosis of heart disease can be challenging, and the effectiveness of these algorithms largely depends on the quality of the features selected.

Classical algorithms are sensitive to noise and outliers in the data. In the context of heart disease prognosis, noisy data or outliers may be present due to various factors, potentially leading to inaccurate predictions. Some classical algorithms, especially those based on exhaustive search or optimization may face scalability problems when dealing with large datasets. As health-care datasets continue to grow, scalability becomes of key importance.

Classical algorithms can handle missing data efficiently. In health-care datasets, missing values are not uncommon, and inappropriate handling of such missing information can lead to biased or unreliable predictions. They often require manual tuning of hyperparameters, and their ability to adapt to changing data distributions is limited. This lack of ML may make them less adept at dealing with evolving patterns in heart disease data.

While interpretability is often considered an advantage, in some cases, classical algorithms may provide overly simplistic models that lack the depth needed to fully understand the underlying complexities of heart disease prognosis.

Heart disease datasets can show class imbalance, with fewer cases of certain conditions. Classical algorithms may struggle to provide accurate predictions in such scenarios, especially when a minority class is of significant interest, such as identifying rare heart diseases.

Classical algorithms are prone to overfitting (capturing noise in the training data) or underfitting (oversimplifying the model). Achieving the optimal balance can be challenging, especially when dealing with heterogeneous and dynamic cardiac disease datasets. Many classical algorithms inherently do not account for temporal dynamics in the data. In heart disease prognosis, where disease progression over time is crucial, the lack of temporal awareness can be a significant limitation.

Heart disease datasets often include a large number of variables, and classical algorithms may struggle to efficiently handle high-dimensional data, leading to increased computation time, and potential information loss.

While classical ML algorithms are valuable in various domains, understanding their limitations is essential, especially in complex and dynamic health applications such as heart disease prognosis. Advances in deep learning and more advanced techniques have been developed to address some of these challenges in recent years.

Conclusion and Future Challenges

The development of artificial intelligence aims to benefit patients by improving diagnostic accuracy and

offering personalized therapy. The surge in computing power has made it possible to analyze huge data sets, with the results of artificial intelligence meant to complement the expertise of doctors. The expansion of artificial intelligence in medicine requires the establishment of international standards covering legal, ethical, and methodological aspects. Although guidelines have been introduced, many critical questions remain unanswered. Overcoming challenges in algorithm standardization, reproducibility, explanation, and ethical accountability are critical to the widespread adoption of AI in medicine. Data quality is a significant challenge, emphasizing the importance of reliable, unbiased, and non-discriminatory electronic health record databases.

Data challenges center on acquisition methods and security. The unauthorized transfer of patient data is punishable by strict European data protection regulations, such as the General Data Protection Regulation, addressing privacy concerns.

The use of ML and deep learning models for clinical applications has great potential to transform traditional health-care delivery. However, to ensure the reliable and robust application of these models in clinical settings, various privacy and security challenges need to be addressed. ML models should be trained and validated on different datasets to ensure their effectiveness in different populations. Standardized practices for data sharing and rigorous reevaluation of models are critical to maintaining the reliability and accuracy of ML applications. Promoting interoperability ensures the seamless integration of ML technologies into existing health-care systems.

Individuals should be in control of their health data, emphasizing the importance of privacy and empowering patients to manage their health information. Clinicians need to understand the strengths and limitations of ML, recognize when it can and cannot be applied, and interpret the model's recommendations in the broader clinical context for each patient. Rather than replacing clinicians, ML is seen as a complementary tool to enhance human-led decision-making and improve care delivery.

Collaboration among stakeholders, including clinicians, researchers, patients, and industry partners, is essential to build trust in ML and digital health. It also plays a key role in shaping the future of cardiovascular disease prevention. Establishing ethical frameworks, ensuring inclusiveness, and fostering collaboration will be key to its successful integration into health-care systems. Continued development is key to realizing the full potential of these approaches.

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