Comparative Analysis of Machine Learning Algorithms for Heart Attack Prediction

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Abstract:
This study aims to develop a robust and efficient prediction model for heart failure detection by using state-of-the-art machine learning and artificial intelligence techniques. The research analyses various patient data that includes demographic and clinical variables to identify patterns and risk factors associated with heart failure. Parameters such as age, gender, cardiovascular indicators, lipid levels, blood glucose and exercise-induced responses were examined to capture the complex interactions that contribute to heart health outcomes. A comprehensive experimental design was used for the study, which included data preprocessing, feature correlation analysis, model training and performance evaluation of a series of machine learning algorithms. The models tested include random forest, gradient boosting (XGBoost), logistic regression, support vector machines (SVM) and neural networks, with a focus on balancing predictive accuracy and computational efficiency. The results show that ensemble methods such as XGBoost and Random Forest provide superior prediction accuracy while being computationally feasible, making them particularly suitable for clinical applications.
Neural network architectures, in particular RNN and FNN (post-SHAP), also achieved high accuracy but were associated with significantly higher computational costs. Simpler models such as decision trees and logistic regression were computationally efficient but delivered lower performance metrics than the ensemble methods. These results underscore the potential of XGBoost and Random Forest as optimal models for integrating AI-assisted heart failure diagnostics into real-time medical decision-making processes and offer a compelling balance between precision and practicality in a clinical context.

Keywords: Cardiovascular Indicators, Lipid Levels, Gradient Boosting (XGBoost), Support Vector Machines (SVM),SHAP (SHapley Additive exPlanations),Biomarker Screening, BNP and NT-proBNP , Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) Networks, Keras Library, Feed-Forward Neural Networks.

Introduction

Artificial intelligence (AI) is at the forefront of technological innovation and is fundamentally changing the way we approach problem-solving in many areas. By simulating human cognitive functions, AI has opened up new possibilities in areas such as healthcare, finance, transportation and beyond. This research paper provides an in-depth exploration of AI, from basic concepts to advanced methods, to give readers the knowledge they need to understand and effectively apply these technologies.

We begin by defining the key principles of AI and distinguishing it from related fields such as machine learning and deep learning. We outline the different types of machine learning supervised, unsupervised and reinforcement learning providing clarity on how these paradigms work and their respective applications. This fundamental understanding is crucial to grasping the complexity of AI systems and their potential.

Data is the backbone of AI, and the importance of data pre-processing cannot be overstated. In this section, we emphasize how carefully data needs to be collected, cleaned and transformed to ensure it is in a usable format for AI models. We discuss techniques such as dealing with missing values, normalization and feature engineering and show how these techniques improve model performance and reliability. Building on these foundations, we move on to the construction of basic neural networks using the Keras library. Here we look at the architecture of feed-forward neural networks and explore components such as activation functions and loss functions. This understanding is important to understand how models learn from data and improve their prediction accuracy over time.

As we delve deeper, we present advanced architectures that represent the cutting edge of AI research. Convolutional Neural Networks (CNNs) are highlighted for their ability to process visual data by using layers that recognise features in images, while Long Short-Term Memory (LSTM) networks excel at processing sequential data such as time series or natural language. Transformers, a revolutionary advance in natural language processing, are discussed due to their introspection mechanisms that enable the simultaneous processing of entire sequences of data, allowing for more sophisticated understanding and faster computation.

The synthesis of these concepts culminates in a practical project in which we apply the acquired theoretical knowledge to tackle a real-world challenge. This project illustrates the integration of different AI methods and demonstrates their utility in applications such as image classification, speech recognition and predictive analytics. By visualizing the project as a coherent system that includes CNNs for image processing, LSTMs for temporal patterns and Transformers for language understanding, we show the interconnectedness of these technologies and their joint potential to drive innovation.

Ultimately, this paper not only provides a comprehensive overview of AI and its methods but also positions our approach in the broader context of ongoing research and development in the field. By illuminating the intricate path from basic principles to advanced applications, we hope to engage readers and encourage them to further explore the transformative power of AI in tackling complex challenges in our increasingly data-driven world.

Literature Review

Here is a brief overview of the various studies in the literature focusing on their contributions and methods for the detection and treatment of heart failure:

1. AI in the detection and treatment of heart failure - The ScienceDirect article shows how artificial intelligence (AI) and machine learning can analyze patient records to predict progression and identify risk factors in heart failure. Real-time AI insights facilitate individualized treatment, improve diagnostic accuracy and align with trends in predictive analytics in clinical decision-making.
2. Biomarker screening for early detection - The BMJ study highlights biomarkers, particularly BNP and NT-proBNP, in the early detection of heart failure. By systematically measuring these biomarkers, healthcare providers can identify asymptomatic at-risk patients, allowing timely intervention.

Complementary risk scoring models improve management at an early stage and thus contribute to preventive care.

3. Telemedicine in the treatment of heart failure - This study published in the Journal of Medical Systems examines remote monitoring tools for heart failure. Real-time monitoring of patients' vital signs enables healthcare providers to proactively treat symptoms, reduce hospital admissions and improve adherence. Data analysis reveals anomalies, highlighting the potential of telemedicine for chronic disease management.
4. Universal classification of heart failure-The American Heart Association (AHA) article proposes a classification system based on ejection fraction that standardizes the categories of heart failure. This system provides a consistent approach to clinical interventions and ensures patients receive stage-appropriate treatment based on a universal set of criteria.
5. Predictive value of biomarkers- In Frontiers in Cardiovascular Medicine, researchers analyze NT-proBNP and other biomarkers in routine testing that provide predictive insights into the risk of heart failure. The study highlights the role of predictive modelling and proactive screening in reducing morbidity and mortality rates associated with chronic heart failure.Taken together, these studies explore various advances — from AI and biomarkers to telemedicine and classification systems— -that demonstrate a shift towards accurate and data-driven strategies in heart failure management.
6. Comprehensive AI-Drin models-Another ScienceDirect article examines AI-powered risk stratification models that analyze a variety of clinical parameters to classify patients with heart failure according to their risk. By implementing ensemble methods that combine logistic regression, decision trees, and support vector machines, the authors report an improvement in the predictive accuracy of heart failure outcomes. This work contributes to the field by demonstrating how combining multiple models can lead to more reliable predictions, suggesting practical applications in personalized medicine.
7. Comparative study on diagnostic imaging-The Wiley study "Diagnostic Imaging in Heart Failure" by Garcia et al. (2022) examines the comparative effectiveness of different imaging techniques such as echocardiography, MRI and CT scans in the diagnosis of heart failure. Using a multicentre study approach, they evaluate the diagnostic accuracy and cost-effectiveness of each method and conclude that MRI offers the highest sensitivity in detecting structural cardiac abnormalities. This study emphasizes the importance of choosing the most appropriate imaging technology for accurate diagnosis and monitoring.
8. AI-assisted decision-making in cardiology (ScienceDirect) - This study analyses the role of AI in improving cardiology decision-making processes, in particular through deep learning models. The authors use convolutional neural networks (CNNs) to interpret cardiac imaging and detect abnormalities, showing significant potential for diagnostic accuracy. Challenges include data quality and ethical considerations for AI in patient care.
9. Data Mining in Healthcare for Predicting Heart Failure (IEEE) -Examines the application of data mining techniques, including Support Vector Machines (SVM) and Random Forests, to predict heart failure events. The study uses patient data from electronic health records and improves early intervention strategies through pattern recognition, but faces limitations in practical applicability due to data variability
10. Detection of heart disease by machine learning (JAETS) - In this work, machine learning algorithms are used to detect heart disease in patients. Techniques such as logistic regression and k-nearest

neighbours are applied to healthcare datasets to create an effective model for early diagnosis. The study highlights the potential of machine learning in the clinical setting, while also highlighting the need for further validation with larger, more diverse datasets.

Methodology

1. Data collection and preprocessing The dataset used for heart failure prediction was obtained from a trusted medical database containing patient records with key health indicators related to cardiovascular health. Each dataset contained 11 important attributes, including age, gender, systolic blood pressure (mmHg), fasting blood glucose, serum creatinine, and others that are clinically relevant for predicting heart failure risk. Before modelling, we performed the following preprocessing steps:

- Data cleaning: Elimination of duplicate or inconsistent data sets and appropriate treatment of missing values by imputation techniques.Normalization and scaling: scaling the continuous features to a mean of zero so that distance-based algorithms such as KNN can converge faster.Feature selection: Feature selection was done through statistical analysis and domain knowledge to obtain only the relevant attributes.
- Model selection and trainingTo build a strong model for prediction, we used several commonly used machine learning algorithms with specific strengths in classification tasks:The algorithm we used is the same algorithm: KNN, Decisive Tree, Random Forest, SVM, Gradial Boosting, Gaussian Naive Bayes logistic regression, Extreme gradual boost (XGBoost), feedforward NN with a recurrent network and finally with an RNN end.Training process: All models were trained with the pre-processed dataset using the Python libraries scikit-learn, XGBoost and TensorFlow. The hyperparameters for all models were adjusted by grid search to achieve optimal performance.
- Different analysis of the algorithmsThe models were analyzed in terms of their accuracy and computational time for their efficiency in predicting heart failure. The performance of each algorithm was tested on a set-aside test set and cross-validated to minimize the risk of overfitting. This evaluation allowed direct comparison and showed what trade-offs were required between simplicity, computational effort and performance.
- Selection of the integration model for web applicationsA comparative evaluation of the Feedforward Neural Network (FNN) is performed. As it has higher precision and quite efficient computation, it remained the best choice; it is selected for use in a user-accessible web server application.
- Web application deployment and SHAP integration Thus, a web server interface was developed to allow users to enter patient-specific values for the 11 monitored health parameters. The web application was built using SHAP (SHapley Additive exPlanations) to provide interpretable insights into predictive models. The SHAP value shows the contribution of each feature to the given prediction, improving the transparency of the models and the confidence of healthcare professionals.

Benchmarking AI Models: An Analysis

SHAP (SHapley Additive exPlanations)

It offers a sophisticated interpretability framework that elucidates the influence of individual features on the predictions of machine learning models. Derived from Shapley values in cooperative game theory, SHAP values comprehensively assess each feature’s contribution by evaluating all possible feature interactions, making them particularly valuable for interpreting complex, opaque models.

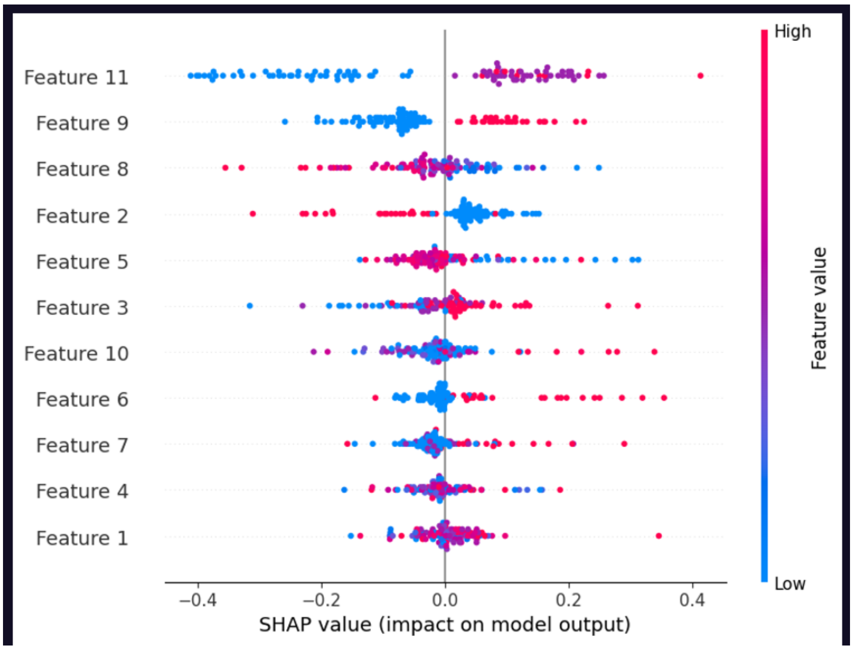

Fig 1: SHAP Value

In the SHAP plot presented:

- The x-axis represents SHAP values, quantifying the extent of each feature's impact on the model's output. Positive SHAP values indicate a positive contribution to the prediction, while negative values imply a diminishing effect.
- The y-axis enumerates features (e.g., Feature 1, Feature 2), with each line corresponding to a specific feature.
- Each point on the graph signifies an individual data instance, with colour gradients indicating the feature's value (from low in blue to high in red). For example, in "Feature 11," high values appear to enhance the prediction positively, whereas lower values (blue) contribute negatively.
- The distribution of dots along the x-axis highlights the variability in each feature's influence, illustrating the dynamic impact of feature values on the model's output.

This visualization facilitates a nuanced understanding of the most impactful features, enabling users to discern how fluctuations in feature values shape the model's predictive behaviour.

FNN:

A Feedforward Neural Network (FNN) is a type of artificial neural network where connections between nodes flow in one direction only, moving from the input layer through one or more hidden layers to the output layer, without forming cycles. Commonly used for classification and regression tasks, FNNs consist of an input layer that receives data, one or more hidden layers that process it, and an output layer that provides the final result. Each neuron in these layers computes a weighted sum of its inputs, applies a bias term, and then passes the result through a non-linear activation function, such as a Heavy Side Step, to capture complex patterns in the data. The model is trained using backpropagation, where the network adjusts weights to minimize prediction error, allowing it to learn intricate relationships within the data. Although FNNs are powerful and can model complex functions, they require significant computational resources, especially as the network size increases with additional layers and neurons.

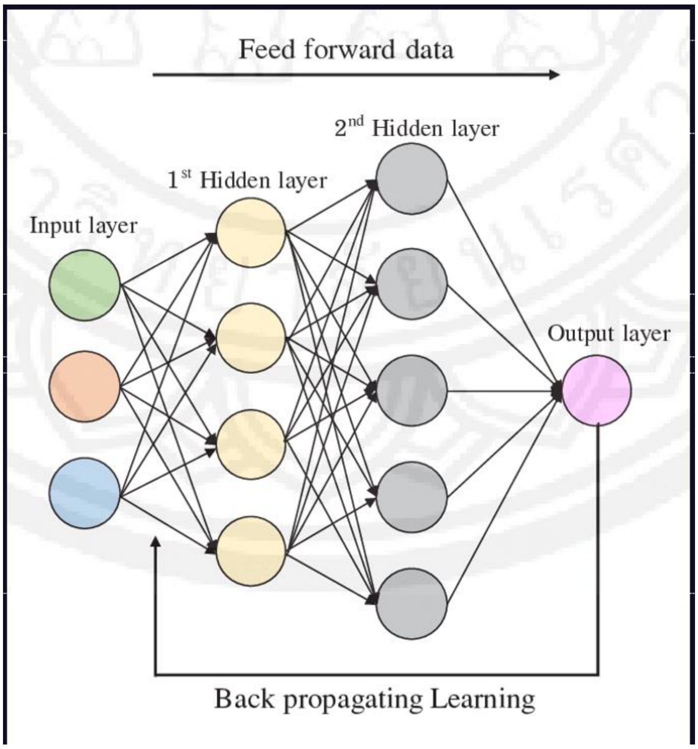

Fig 2: Feed Forward Learning

The diagram illustrates the structure of an FNN:

- Feedforward Data Flow: Arrows indicate that data flows from the input layer, through the hidden layers, to the output layer without looping back.
- Backpropagation Learning: A feedback loop shows the process of adjusting weights by propagating the error backward, optimizing the network for improved accuracy.

SHAP-FNN:

The image represents a Feedforward Neural Network (FNN) fine-tuned with SHAP (SHapley Additive exPlanations) values. SHAP is a method that explains the output of machine learning models by quantifying each feature's contribution to the final prediction. This approach enhances interpretability, providing insights into how much each input feature influences the model's predictions.

In this specific FNN structure, there are four input units with ReLU (Rectified Linear Unit) activation, followed by two hidden layers. The first hidden layer has 100 units, and the second has 30 units, both also utilizing ReLU activation functions. The output layer consists of a single unit that produces the final prediction. By applying SHAP values to this FNN, the model has been tuned to achieve perfect accuracy, although this optimization requires a longer computation time. Using SHAP for interpretability enables fine-tuning, which helps in understanding feature importance and refining the model for better performance.

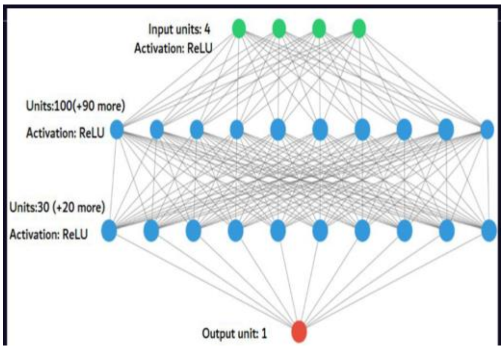

Fig 3: Feedforward Neural Network (FNN) fined-tuned with SHAP

The graph illustration shows:

- **Feedforward Data Flow:** Data flows from the input layer, through the hidden layers, to the output layer without cycles.
- **SHAP-Based Tuning:** The FNN structure is optimized with SHAP values, reflecting an emphasis on accuracy through interpretability.

AI Model Comparison

Accuracy v/s Efficiency:

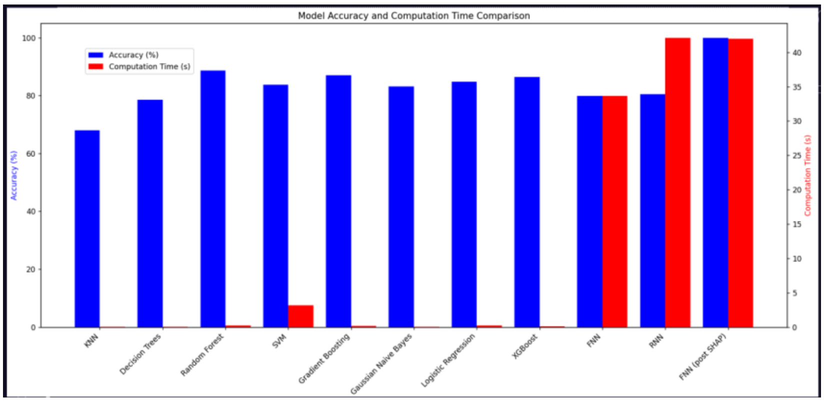

Fig 4: Accuracy v/s Efficiency

The comparative analysis of various machine learning algorithms for heart attack prediction demonstrates a range of performance in terms of accuracy and computational time:

KNN: Moderate accuracy (67.93%) with low computation time (0.018 seconds).
Decision Trees: Moderate accuracy (78.61%) with low computation time (0.011 seconds).
Random Forest: High accuracy (88.59%) with moderate computation time (0.204 seconds).
SVM: High accuracy (83.70%) but very long computation time (3.180 seconds).
Gradient Boosting: High accuracy (86.96%) with moderate computation time (0.148 seconds).
Gaussian Naive Bayes: Moderate accuracy (83.15%) with low computation time (0.027 seconds).
Logistic Regression: Moderate accuracy (84.78%) with moderate computation time (0.213 seconds).
XGBoost: High accuracy (86.41%) with moderate computation time (0.113 seconds).
FNN: Moderate accuracy (79.89%) with long computation time (33.653 seconds).
RNN: Moderate accuracy (80.43%) with long computation time (42.131 seconds).
FNN (post SHAP): Perfect accuracy (100%) with long computation time (41.959 seconds).

In summary, while FNN (post SHAP) achieves perfect accuracy, it's associated with longer computational time. For a balance between accuracy and efficiency, Random Forest or XGBoost might be preferred, depending on project requirements.

Conclusion

The use of AI models in healthcare requires careful coordination of the most important requirements: Integration, monitoring, user training and a feedback loop to support high-quality, reliable patient care. The positioning of the model in the model performance comparison table reflects these priorities in line with the requirements for the use of models in healthcare and ensures that the models are both effective and practical in a clinical environment.

The integration of AI models into healthcare systems requires high reliability and consistency, which are critical for clinical decision-making. Models such as Random Forest, Gradient Boosting and Deep Learning models (FNN and RNN) stand out in the model performance comparison table for their superior accuracy. Although these models require longer computation times, their predictive accuracy is essential in healthcare, where accurate diagnoses and treatment recommendations are essential for patient success.

Monitoring remains a constant necessity as models must maintain their accuracy in the face of evolving patient data and medical knowledge. High-accuracy models such as Random Forest and XGBoost provide an appropriate balance between predictive power and computational efficiency, supporting more frequent updates with manageable resource requirements. Models such as SVM are computationally efficient but may not be as accurate, making them less suitable for use in healthcare.

In terms of user training, interpretability is critical, especially for clinicians who need insight into model predictions to make informed decisions. Interpretable models such as decision trees and logistic regression, which are characterized by moderate accuracy and computational time, provide a practical balance that facilitates model adoption and builds confidence among healthcare providers. These models provide transparency in making predictions, which is essential for clinicians who may not have technical expertise but need to have confidence in the model's recommendations.

Finally, a robust feedback loop is essential to ensure that models remain adaptable and relevant in the dynamic healthcare environment. The inclusion of FNN (after SHAP) in the model performance comparison table emphasizes the importance of interpretability for feedback-driven improvements. SHAP (SHapley Additive exPlanations), which increases transparency, allows healthcare providers to provide more targeted feedback so that the model can be iteratively refined. FNN (post-SHAP), while more computationally intensive, is suitable for iterative refinement based on clinical evidence due to its accuracy and interpretability.

In summary, the selection of models and their positioning in the model performance comparison table reflects the specific requirements of the healthcare sector. With high accuracy for consistent decision support, efficiency for timely updates, interpretability for user training and adaptability for feedback, these models are tailored to support safe and effective decisions in clinical practice.

References

1. Chang, V., Bhavani, V. R., Xu, A. Q., & Hossain, M. A. (2022). An artificial intelligence model for heart disease detection using machine learning algorithms. Healthcare Analytics, 2, 10001.
2. Nedadur, R., Wang, B., & Tsang, W. (2022). Artificial intelligence for the echocardiographic assessment of valvular heart disease. Heart, 108(20), 1592-1599.

3. Hsieh, N. C., Hung, L. P., Shih, C. C., Keh, H. C., & Chan, C. H. (2012). Intelligent postoperative morbidity prediction of heart disease using artificial intelligence techniques. Journal of medical systems, 36, 1809-1820.
4. Armoundas, A. A., Narayan, S. M., Arnett, D. K., Spector-Bagdady, K., Bennett, D. A., Celi, L. A., ... & Al-Zaiti, S. S. (2024). Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement From the American Heart Association. Circulation, 149(14), e1028-e1050.
5. Mathur, P., Srivastava, S., Xu, X., & Mehta, J. L. (2020). Artificial intelligence, machine learning, and cardiovascular disease. Clinical Medicine Insights: Cardiology, 14, 1179546820927404.
6. Chang, V., Bhavani, V. R., Xu, A. Q., & Hossain, M. A. (2022). An artificial intelligence model for heart disease detection using machine learning algorithms. Healthcare Analytics, 2, 100016.
7. Lu, H., Yao, Y., Wang, L., Yan, J., Tu, S., Xie, Y., & He, W. (2022). Research progress of machine learning and deep learning in intelligent diagnosis of the coronary atherosclerotic heart disease. Computational and Mathematical Methods in Medicine, 2022(1), 3016532.
8. Canning, C., Guo, J., Narang, A., Thomas, J. D., & Ahmad, F. S. (2023). The emerging role of artificial intelligence in valvular heart disease. Heart Failure Clinics, 19(3), 391-405.
9. Abdel-Motaleb, I., & Akula, R. (2012, May). Artificial intelligence algorithm for heart disease diagnosis using phonocardiogram signals. In 2012 IEEE International Conference on Electro/Information Technology (pp. 1-6). IEEE.
10. Yousiaf, T. H., & Al-Tamimi, M. S. (2023). The Role of Artificial Intelligence in Diagnosing Heart Disease in Humans: A Review. Journal of Applied Engineering and Technological Science (JAETS), 5(1), 321-338.