# Heart Attack Diagnosis System Based on Artificial Intelligence and Optimization Algorithms

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**Abstract**

Heart attacks, or myocardial infarctions, are a primary cause of mortality worldwide, underscoring the importance of early and accurate diagnosis to improve patient outcomes. This paper reviews various Artificial Intelligence (AI) and Machine Learning (ML) techniques for heart attack diagnosis, focusing on both traditional algorithms and more complex models. The traditional algorithms are Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Decision Trees (DT). More complex models are Convolutional Neural Networks (CNN), Extreme Gradient Boosting (XGBoost), Auto-encoders, Artificial Neural Networks (ANN), and TSK Fuzzy Inference System (TANFIS). Additionally, the integration of optimization techniques, including the Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Jellyfish Optimization Algorithm (JOA) is explored to enhance model accuracy by selecting the most important features. Our findings indicate that ensemble and hybrid models, which combine ML with metaheuristic optimization, show significant potential in improving diagnostic performance and reducing overfitting. However, challenges remain, particularly regarding computational complexity and interpretability. This study provides insights into the strengths and limitations of different AI-based diagnostic models, contributing to the advancement of automated heart disease prediction systems.

**Keywords:** Diagnosis system; Feature selection; Heart attack; Optimization algorithms; Artificial Intelligence

## 1. Introduction

Heart attacks, also known as myocardial infarctions, are a leading cause of mortality worldwide. Early and accurate detection of heart attacks is crucial for timely medical intervention and improving patient outcomes. Machine learning techniques have shown great potential in assisting healthcare professionals in the early diagnosis and classification of heart attacks, enabling personalized treatment plans for patients. Given the increasing availability of electronic health records and advancements in data science, machine learning has the potential to revolutionize the field of cardiovascular medicine by providing accurate and automated classification models for heart attacks.



DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

In conclusion, machine learning algorithms offer promising tools for the accurate classification of heart attacks, aiding in early diagnosis and personalized treatment. While challenges persist, ongoing research and advancements in this field hold great potential for improving patient outcomes and reducing the burden of heart disease on the healthcare system [1].

Traditional diagnostic methods for heart disease have typically relied on statistical models and rule-based systems, but these approaches face limitations in handling complex, high-dimensional datasets. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) offer a transformative potential to enhance diagnostic accuracy and efficiency by automating feature selection and learning directly from patient data. New AI methods, such as deep learning, can leverage vast amounts of medical data to provide real-time insights and predictions, supporting early intervention and improving patient outcomes [2,3]. Given the global rise in heart disease, there is an urgent need for AI-powered diagnostic tools that can handle complex clinical scenarios and contribute to better resource allocation and treatment planning [4].

AI techniques combined with optimization approaches are increasingly being used to refine diagnostic models for heart disease. AI models, including Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs), are often paired with optimization algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to enhance model performance by prioritizing the most relevant features and reducing computational complexity [5,6,7]. These optimization methods enable more accurate predictions, helping healthcare providers better identify patients at risk. The integration of AI and optimization also addresses challenges such as overfitting and interpretability, making these tools highly valuable for precise and reliable medical diagnosis [8,9].

This paper is structured as follow, the related work that includes the recent studies on hybrid and ensemble models that integrate various AI and optimization methods are reviewed in Section 2. Next, the overview of heart attack diseases has been described in Section 3. Section 4 includes the overview of AI models commonly used for heart disease diagnosis. The conclusions with a discussion on current limitations and future research directions has been mentioned in Section 5.

## 2. Related Work

In this section, many recent diagnosis models are presented. The Artificial Intelligence (AI) methods and models employed in [10] are Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), Naive Bayes (NB), Decision Tree (DT), and extreme gradient boosting (XGBoost). These models are a component of a heterogeneous ensemble learning framework that combines heuristic–metaheuristic optimization with feature selection utilizing the Grey Wolf Optimizer (GWO) and the Pearson Correlation Coefficient (PCC). The proposed ensemble many advantages such as improving diagnostic accuracy where the ensemble method outperforms individual machine learning models by aggregating multiple learners. Additionally, the integration of PCC with GWO ensures optimal feature subsets for each base learner, improving model performance. The ensemble approach improves model robustness and reduces overfitting. On the other hand, the disadvantages of the proposed ensemble model are computational complexity and also it becomes more complex and harder to interpret.

In [11], Machine Learning (ML) algorithms such as SVM in combination with the Jellyfish Optimization Algorithm (JOA) for feature selection was proposed to predict heart disease. In fact, ML techniques offer low-cost and accurate diagnosis of heart disease and also feature selection using the JOA helps in improving model performance by reducing overfitting. Although these advantages, there are many disadvantages such as the need for expertise in implementing ML algorithms and optimization techniques and interpretability of the ML model may be a challenge. Additionally, the generalizability of the model to different populations or datasets might be limited. Overall, the study demonstrates the effectiveness of employing ML techniques like SVM along with innovative optimization algorithms for heart disease prediction, showcasing high accuracy and performance.

As presented in [12], various AI techniques, focusing on Gradient Boosting (GB) models, Hyperparameter Optimization (HyperOpt), and the Least Absolute Shrinkage Selection Operator (LASSO) feature selection method, were used to diagnose heart disease. LASSO was used to identify the most informative feature subset from clinical data. The GB is an ensemble learning technique that combines multiple weak learners to create a strong learner and enhance predictive accuracy while HyperOpt was used to optimize the GB model's hyperparameters. These models achieved a high accuracy in predicting heart disease, which is crucial for early detection and treatment based on the most relevant features selected by LASSO. On the other hand, the implementation of these models is complex.



DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

According to [13], a hybrid diagnosis model that includes several AI techniques were employed for classifying medical datasets. This model combines various deep learning approaches such as Convolutional Neural Networks (CNN) and auto encoder and also Particle Swarm Optimization (PSO) algorithm. This model achieved dimensional reduction by using PSO and high accuracy rates by using deep learning methods. Although these benefits, it has a high complexity and deep learning models can sometimes be seen as "black boxes," making it challenging to interpret how the model arrives at a particular decision.

According to [14], Tuned Adaptive Neuro-Fuzzy Inference System (TANFIS) has been used to predict heart disease efficiently after optimizing TANFIS using Moth Flame Optimization (MFO) and Grasshopper Optimization Algorithm (GOA). The proposed method represents a new hybrid model that offers high accuracy in predicting heart disease. It depends on population diversity to avoid premature convergence and local optima issues. Additionally, it used Internet of Things (IoT) for data acquisition and fog computing for storage to contribute real-time monitoring and alert in abnormal situations. There are many issues of implementing this proposed method where implementing hybrid AI models may introduce complexity in understanding and tuning the system. Additionally, the computational requirements for optimization algorithms like MFO and GOA may be intensive. Hybrid models might lack interpretability compared to simpler models like decision trees or logistic regression.

In [15], hybrid diagnosis model that includes feature selection and Naïve Bayes (NB) as a diagnosis model was used to enhance accuracy on diagnosis heart attack disease. The implementation of this model is simple and also it is easy to interpret. Additionally, backward elimination can enhance the accuracy of the classification model. However, NB assumes that features are independent, which may not hold true in real-world datasets. NB may not capture complex relationships in the data as effectively as more advanced algorithms, and not suitable for large datasets. NB may not perform well on very large datasets or datasets with highly correlated features.

According to [16], wavelet denoising and Artificial Neural Networks (ANN) have been used for heart condition detection. This work aims to improve detection accuracy in the presence of noise in ECG signals. In fact, the use of wavelet denoising can enhance the accuracy of heart abnormality detection, especially in the presence of noise. Additionally, wavelet denoising helps in reducing noise interference in ECG signals, leading to more precise classification results. The integration of ANN for signal classification enables the system to learn and distinguish between different heart conditions based on ECG signal features. Although these benefits, selecting the optimal parameters for the wavelet denoising algorithm may require extensive experimentation. ANN's performance is highly dependent on the quality and quantity of training data available. Insufficient data may lead to suboptimal performance.

**Table 1:** Many Recent Medical Diagnostic Models.

| Paper | AI Techniques | Optimization/ Feature Selection | Accuracy | Advantages | disadvantages |
|---|---|---|---|---|---|
| Ensemble Heuristic–Metaheuristic Feature Fusion Learning [10 ] | SVM, KNN, LR, RF, NB, DT, XGBoost | GWO, PCC | Cleveland: 91.8% Statlog: 88.9% | High diagnostic accuracy, efficient feature selection | Computational complexity, longer training time |
| Prediction of Heart Disease with Jellyfish Optimization [11 ] | SVM | Jellyfish optimization | 98.47% | Low-cost, high sensitivity and specificity | Requires expertise, limited interpretability |
| HypGB Classifier [12 ] | Gradient Boosting | HyperOpt, LASSO | Cleveland: 97.32% Kaggle: 97.72% | High accuracy, optimized feature selection | Complexity, data dependency |
| Hybrid ML with Deep Learning and Meta-Heuristic Algorithms [13 ] | CNN, SVM, Autoencoder | PSO | COVID-19: 99.76% Brain tumour: 99.51% | High accuracy, dimensionality reduction | Complexity, interpretability |



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| TANFIS Classifier [14] | TANFIS | Moth Flame, Grasshopper Optimization | 99.76% | High efficiency, IoT integration | High computational overhead, interpretability challenges |
| Naïve Bayes with Feature Selection [15 ] | Naïve Bayes | Backward Elimination | 94.89% | Simplicity, ease of interpretability | Assumption of feature independence, less expressive |
| Wavelet Denoising with ANN [16 ] | ANN | Wavelet Denoising | 97.05 | Improved noise reduction in ECG signals | Sensitive to SNR changes, tuning complexity |

## 3. Overview of Heart Attack Diseases

Heart attack diseases are a significant global health concern, affecting millions of individuals worldwide. These conditions involve the disruption of blood flow to the heart, leading to potentially devastating consequences if not promptly addressed. A heart attack, also known as a myocardial infarction, occurs when the blood flow to a part of your heart is blocked [17]. Without blood flow, part of your heart muscle can't get oxygen and begins to die. There are many common heart attack diseases such as coronary artery disease, myocardial infarction, and aortic dissection [18]. Coronary artery disease represents the most common type of heart attack, caused by plaque buildup in the coronary arteries that supply the heart muscle with oxygen and nutrients. Myocardial infarction, also known as a heart attack, occurs when blood flow to part of the heart muscle is blocked, causing damage or death of heart tissue. Aortic dissection occurs by a serious condition in which the inner layer of the aorta, the large blood vessel branching off the heart, tears. This can lead to life-threatening bleeding [19]. The common warning signs and symptoms of a potential heart attack. Is clutching their chest in apparent discomfort, which is one of the primary symptoms. Surrounding this, additional symptoms are highlighted: chest discomfort, indigestion, anxiety, irregular heartbeat, dizziness or fainting, upper body pain, shortness of breath, cold sweat, nausea or vomiting, and fatigue. These symptoms, which vary in type and intensity, serve as important indicators. Recognizing these signs early is crucial for timely intervention and could be life-saving, as some individuals may experience only a few of these symptoms without the classic chest pain as shown in Figure 1.


**Figure 1.** The Common Symptoms of Heart Attacks



DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

## 4. Overview of Diagnosis Models

In this section, many different AI techniques used in heart attack diagnosis system will be described. These techniques are Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Logistic Regression (LR), Random Forest (RF), and Naïve Bayes (NB). Also, Decision Tree (DT), Extreme Gradient Boosting (XGBoost), Convolutional Neural Network (CNN), Auto encoder, TSK Fuzzy Inference System (TANFIS), and Artificial Neural Network (ANN). These techniques will be described in the following subsections.

1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm that excels at binary classification tasks by identifying the optimal hyperplane that separates different classes. In heart attack diagnosis, SVM uses patient data features, such as cholesterol levels, blood pressure, and age, to distinguish between patients at high risk and low risk. SVM works by selecting data points (support vectors) that define the boundaries of each class, maximizing the margin between them to improve accuracy. In practice, SVM can handle high-dimensional data and works well when there's a clear margin of separation, making it effective for analysing complex medical datasets. However, it can be computationally intensive and may struggle with overlapping data. [20].

2. K-Nearest Neighbours (KNN)

K-Nearest Neighbours (KNN) is an instance-based learning algorithm used for both classification and regression. For heart attack diagnosis, KNN operates by finding the 'k' most similar cases within a dataset and predicting the patient's diagnosis based on the majority class among these neighbours. KNN is easy to understand and implement, especially in a clinical setting, as it classifies new cases by directly comparing them to past instances. Its main drawback is computational complexity; as the dataset size grows, it becomes more challenging to calculate the nearest neighbours efficiently. Still, KNN remains widely used due to its simplicity and effectiveness in cases with sufficient labelled examples [21].

3. Logistic Regression (LR)

Logistic Regression is one of the most popular statistical models for binary classification, where it estimates the probability of a binary outcome using a logistic (sigmoid) function. In heart attack diagnosis, Logistic Regression helps predict the likelihood of a patient having a heart attack based on various clinical features. It is widely used because it's computationally efficient, interpretable, and well-suited for initial screenings where risk assessment is essential. Logistic Regression models are relatively simple but can effectively handle linearly separable data. However, it may struggle with complex, non-linear relationships without additional modifications [22].

4. Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and merges their predictions to improve classification accuracy and reduce overfitting. In heart attack diagnosis, Random Forest leverages various patient data features to predict the likelihood of heart disease. It builds each tree on a random subset of data and combines their outcomes through majority voting, making it robust against overfitting and enhancing generalizability. This method works well with complex data, where multiple factors contribute to the diagnosis, as it can capture feature interactions. However, the model complexity makes it challenging to interpret, which can be a drawback in healthcare settings [23].

5. Naive Bayes (NB)

Naive Bayes is a probabilistic classifier based on Bayes' theorem. It calculates the probability of each class given the input features and classifies based on the highest posterior probability. Despite the "naive" assumption of feature independence, Naive Bayes is effective in many applications, including heart attack prediction. It processes input features, such as age, cholesterol, and blood pressure, independently to determine a patient's risk of heart attack. Naive Bayes is computationally efficient and suitable for real-time diagnosis but may struggle with more complex, dependent feature relationships [24].

6. Decision Tree (DT)

Decision Trees are interpretable, tree-structured models used for classification and regression tasks. Each internal node represents a decision based on a feature (e.g., blood pressure), each branch represents the outcome, and each leaf node represents a class label (e.g., heart disease present or absent). Decision Trees are easily understood by clinicians and can highlight key contributing factors to heart disease. However, they are prone to overfitting on complex data. Combining Decision Trees into ensembles, such as Random Forests, can mitigate this limitation [25].

7. Extreme Gradient Boosting (XGBoost)



DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

XGBoost is an advanced gradient boosting algorithm that iteratively builds decision trees to minimize errors from previous models. It's especially valued in heart attack diagnosis for its high accuracy, efficiency, and ability to handle missing values, which are common in medical data. XGBoost optimizes feature importance, capturing complex feature interactions and improving the model's predictive performance. While effective, it requires significant computational resources and careful tuning of hyperparameters to avoid overfitting [26].

8. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are widely used for image-based medical diagnosis, especially in analysing ECG and echocardiogram images. CNNs use convolutional layers to detect features such as edges and shapes in images, helping to identify abnormalities indicative of heart disease. CNNs excel at learning hierarchical features, capturing fine details that traditional algorithms might miss, making them highly effective for image diagnostics. However, CNNs require large amounts of labelled data and significant computational resources, which can be a challenge in some healthcare settings [27].

9. Auto encoder

Auto-encoders are neural networks designed for unsupervised learning, typically used for dimensionality reduction and feature learning. In heart attack diagnosis, autoencoders can help extract the most important features from large, noisy patient datasets, removing irrelevant information. By encoding and then reconstructing data, autoencoders can capture essential patterns and identify anomalies. These models are particularly useful in identifying rare cases or abnormalities that traditional methods might overlook [28].

10. TSK Fuzzy Inference System (TANFIS)

The Takagi-Sugeno-Kang (TSK) Fuzzy Inference System, or TANFIS, applies fuzzy logic to manage uncertainty in data, making it well-suited for medical applications where data may be imprecise. In diagnosing heart attacks, TANFIS models patient data as a set of fuzzy rules, accommodating uncertainties such as approximate cholesterol levels or borderline blood pressure readings. It combines fuzzy logic with rule-based decision-making, enhancing interpretability and accuracy in uncertain clinical environments [29].

11. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are inspired by the structure of the human brain, consisting of interconnected layers of neurons that learn complex patterns in data. In heart attack diagnosis, ANNs analyze diverse patient data inputs, such as blood pressure, age, and ECG readings, to predict heart disease risk. ANNs can model complex relationships between features, offering high accuracy but often lacking interpretability. They are versatile and can be fine-tuned for various diagnostic tasks, but training them requires extensive data and computational power [30].

## 5. Conclusion

The integration of AI and ML techniques in heart attack diagnosis represents a significant advancement in the field of cardiovascular medicine. As this paper has demonstrated, various algorithms, including Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN), have shown promising results in improving diagnostic accuracy and efficiency. The combination of these algorithms with optimization techniques, such as Particle Swarm Optimization (PSO) and Jellyfish Optimization Algorithm (JOA), enhances feature selection and reduces overfitting, there by yielding more robust predictive models. Despite the progress made, challenges remain, particularly in terms of computational complexity and the interpretability of models. As AI systems become more complex, the need for transparency in decision-making processes becomes paramount, especially in clinical settings where understanding model behaviour is crucial for healthcare professionals. Future research should focus on developing hybrid models that leverage the strengths of various algorithms while addressing their limitations. Additionally, the exploration of transfer learning and federated learning could enhance the generalizability of models across diverse populations and datasets. As the healthcare landscape continues to evolve, ongoing collaboration between data scientists and medical practitioners will be essential to harness the full potential of AI in improving patient outcomes.

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DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

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Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024

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DOI: https://doi.org/10.54216/JAIM.080203
Received: March 27, 2024 Revised: June 03, 2024 Accepted: November 05 2024