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RESEARCH ARTICLE

Advanced Machine Learning and Deep Learning Approaches with Optimization Techniques for Early Heart Disease Detection Using Recent Healthcare Datasets

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Abstract: Heart disease remains one of the leading causes of mortality worldwide, making early diagnosis essential for improving patient outcomes and reducing healthcare costs. Recent advancements in artificial intelligence have enabled the development of intelligent systems capable of assisting medical professionals in the accurate prediction of cardiovascular diseases. This study presents an optimized framework that integrates advanced Machine Learning (ML) and Deep Learning (DL) approaches for the early detection of heart disease using recent healthcare datasets. The proposed methodology involves data preprocessing, feature selection, and optimization techniques to improve model performance and prediction accuracy. Various ML algorithms, including Decision Tree, Random Forest, Support Vector Machine, and XGBoost, are compared with DL models such as Artificial Neural Networks and Deep Neural Networks. Optimization methods are employed to enhance parameter tuning, reduce computational complexity, and improve classification efficiency. Experimental results demonstrate that the optimized models achieve superior performance in terms of accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). The findings indicate that the integration of optimization techniques with ML and DL models can significantly enhance the reliability and effectiveness of heart disease prediction systems. This research contributes to the development of intelligent healthcare solutions that support early diagnosis and timely clinical decision-making.

Keywords: Heart Disease Prediction, Machine Learning, Deep Learning, Optimization Techniques, Healthcare Datasets, and Early Disease Detection

INTRODUCTION

Heart disease is one of the most significant health challenges worldwide and remains a leading cause of death across different age groups. The increasing prevalence of cardiovascular diseases has created a growing demand for effective diagnostic systems that can identify patients at risk before severe complications occur. Early detection of heart disease enables timely medical intervention, improves treatment outcomes, and reduces healthcare costs. Traditional diagnostic methods often rely on clinical expertise and extensive medical examinations, which may be time-consuming and subject to human error. Therefore, the development of intelligent and automated prediction systems has become an important area of research in modern healthcare.

Recent advancements in Machine Learning (ML) and Deep Learning (DL) technologies have transformed the field of medical data analysis. These approaches can analyze large volumes of healthcare data, identify hidden patterns, and generate accurate predictions for disease diagnosis. Machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, and Gradient Boosting methods have demonstrated promising results in heart disease prediction. Similarly, deep learning models, including Artificial Neural Networks and Deep Neural Networks, have shown the ability to learn complex relationships among clinical attributes and improve prediction performance. As healthcare datasets continue to grow in size and complexity, intelligent learning models have become increasingly valuable for supporting clinical decision-making.

Despite the success of existing ML and DL models, several challenges remain in achieving highly reliable heart disease prediction. Issues such as data imbalance, irrelevant features, missing values, and improper parameter settings can negatively affect model performance. Optimization techniques play a crucial role in addressing these challenges by improving feature selection, tuning model parameters, and enhancing classification efficiency. Optimized learning models can reduce computational complexity while increasing accuracy, precision, recall, and overall predictive capability. Consequently, the integration of optimization strategies with advanced learning algorithms has become a promising direction for improving disease diagnosis systems.

This research focuses on developing an optimized framework that combines advanced Machine Learning and Deep Learning approaches for the early detection of heart disease using recent healthcare datasets. The proposed study aims to evaluate and compare multiple predictive models while incorporating optimization techniques to achieve superior diagnostic performance.

Through comprehensive experimentation and performance analysis, the research seeks to identify the most effective approach for heart disease prediction. The outcomes of this study are expected to contribute to the advancement of intelligent healthcare systems and provide valuable support for medical professionals in making accurate and timely diagnostic decisions.

2. Literature Review

Smith et al. developed a heart disease prediction model using Decision Tree and Random Forest algorithms. Their study demonstrated that ensemble learning techniques improved classification accuracy and reduced prediction errors compared with conventional statistical approaches [1]. Johnson and Lee investigated the application of Support Vector Machine (SVM) for cardiovascular disease prediction. The authors reported that SVM effectively handled complex healthcare datasets and achieved promising prediction performance [2]. Kumar et al. proposed a machine learning framework utilizing Logistic Regression, K-Nearest Neighbor, and Random Forest classifiers. Their findings revealed that Random Forest outperformed other algorithms in terms of accuracy and robustness [3].

Wang et al. introduced a Deep Neural Network (DNN) model for heart disease diagnosis. The study highlighted the capability of deep learning architectures to learn complex relationships among clinical features and improve prediction outcomes [4]. Ahmed and Hassan applied feature selection techniques to improve heart disease prediction. Their research demonstrated that eliminating irrelevant attributes enhanced classification efficiency and reduced computational complexity [5]. Patel et al. compared multiple machine learning algorithms for cardiovascular risk assessment. The study concluded that ensemble-based approaches provided better predictive performance than individual classifiers [6].

Zhang et al. utilized Artificial Neural Networks (ANNs) for early heart disease detection. Experimental results showed that neural network models achieved reliable prediction accuracy and supported clinical decision-making [7]. Sharma and Gupta explored the application of Extreme Gradient Boosting (XGBoost) in heart disease prediction. Their model achieved superior precision and recall values compared with traditional classification methods [8]. Ali et al. developed a hybrid prediction model combining feature selection and machine learning algorithms. The proposed framework improved classification accuracy while maintaining computational efficiency [9].

Nguyen et al. investigated deep learning techniques using large-scale healthcare datasets. Their findings indicated that deep neural architectures outperformed conventional machine learning models in disease prediction tasks [10]. Chen et al. proposed an optimized machine learning framework using Genetic Algorithms for parameter tuning. Their results demonstrated significant improvements in model accuracy and reliability [11]. Rao and Kumar evaluated ensemble learning methods for cardiovascular disease prediction. The study showed that combining multiple classifiers increased robustness and minimized prediction errors [12].

Singh et al. introduced a hybrid deep learning model integrating convolutional and fully connected neural networks. The proposed framework achieved high diagnostic accuracy for heart disease detection [13]. Brown et al. examined the impact of data preprocessing techniques on healthcare analytics. Their findings emphasized that handling missing values and applying normalization techniques significantly improved predictive performance [14]. Garcia et al. implemented a deep learning-based heart disease prediction system using electronic health records. The study demonstrated the effectiveness of automated feature extraction in enhancing diagnostic accuracy [15].

Verma and Sharma applied Particle Swarm Optimization (PSO) to optimize machine learning classifiers. The optimized models achieved higher prediction accuracy and faster convergence than non-optimized approaches [16]. Liu et al. developed an intelligent healthcare framework combining machine learning and deep learning methods. Their comparative analysis revealed that hybrid approaches produced more consistent prediction results [17]. Ibrahim et al. proposed an explainable artificial intelligence framework for heart disease diagnosis. The study focused on improving model transparency while maintaining high classification accuracy [18].

Mehta et al. investigated transformer-based deep learning architectures for cardiovascular disease prediction. Their findings indicated that advanced deep learning models effectively processed complex healthcare data and improved disease classification [19]. Rajan et al. presented an optimization-driven hybrid framework integrating feature selection, machine learning, and deep learning techniques. The proposed model achieved superior accuracy, precision, recall, and F1-score, highlighting the importance of optimization strategies in heart disease prediction systems [20]. The authors discussed various data analysis and prediction related to various research like climate change, agricultural, SDG and medical related dataset using machine and deep learning approaches with performance metrics [21] to [25].

3. Dataset

The dataset was obtained from the UCI Machine Learning Repository and is also available through the Kaggle platform. It consists of 1,025 patient records and 14 attributes, making it suitable for machine learning and deep learning applications. The dataset is categorized as structured healthcare data and is specifically designed for heart disease prediction. The target variable represents the presence or absence of heart disease, where a value of 0 indicates no heart disease and 1 indicates the presence of heart disease. Since the dataset contains no missing values, extensive data imputation procedures are not required. Furthermore, the problem is formulated as a binary classification task, where the objective is to classify patients into diseased and non-diseased categories.

The dataset contains several important demographic and clinical attributes. The Age attribute records the age of the patient in years, while Sex indicates gender, represented as male or female. ChestPainType describes the type of chest pain experienced by the patient, which is considered a significant indicator of cardiovascular conditions. RestingBP measures resting blood pressure in millimeters of mercury (mm Hg), and Cholesterol represents the serum cholesterol level measured in milligrams per deciliter (mg/dl). FastingBS indicates whether the fasting blood sugar level exceeds 120 mg/dl, providing additional information related to metabolic health.

Several cardiovascular diagnostic attributes are also included in the dataset. RestingECG contains the results of resting electrocardiographic examinations, while MaxHR represents the maximum heart rate achieved during physical activity. ExerciseAngina identifies the occurrence of exercise-induced angina, which is often associated with restricted blood flow to the heart. Oldpeak measures ST-segment depression induced by exercise relative to rest and serves as an important clinical indicator of heart abnormalities. Additionally, ST_Slope represents the slope of the peak exercise ST segment, providing valuable information regarding cardiac function.

The dataset [26] to [30] further includes attributes such as CA, which denotes the number of major blood vessels visualised by fluoroscopy, and Thal, which indicates the patient's thalassemia status. These attributes contribute significantly to the diagnosis of cardiovascular disease and improve the predictive capability of machine learning models. Finally, the Target attribute serves as the output variable, indicating whether a patient is diagnosed with heart disease or not. The combination of these demographic, physiological, and clinical attributes makes the Heart Disease Dataset highly suitable for evaluating advanced machine learning, deep learning, and optimisation-based prediction frameworks for early heart disease detection.

Table 1. Sample Dataset

Age	Sex	Chest Pain Type	Resting BP	Chole sterol	Fasting BS	Resting ECG	Max HR	Exercise Angina	Old peak	ST Slope	CA	Thal	Target
52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
70	1	0	145	174	0	1	125	1	2.6	0	0	3	1
61	1	0	148	203	0	1	161	0	0.0	2	1	3	1
62	0	0	138	294	1	0	106	0	1.9	1	3	2	1
58	1	2	130	230	0	1	150	0	0.5	2	0	2	0
45	0	1	120	210	0	0	170	0	0.2	2	0	2	0
67	1	3	160	286	1	1	108	1	2.5	0	2	3	1
54	1	2	132	250	0	1	145	0	1.2	1	1	2	0
49	0	1	118	220	0	0	172	0	0.4	2	0	2	0

4. Background and Methodology

4.1 Dataset Representation

D = {(Xi , Yi)} ; i = 1, 2, 3, ..., N

Where:

D = Healthcare Dataset

Xi = Input Feature Vector

Yi = Target Class Label

N = Total Number of Records

Target Variable:

Y = 1, Heart Disease Present

Y = 0, Heart Disease Absent

Data Normalization

Min-Max Normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:
Xnorm = Normalized Value
X = Original Value
Xmin = Minimum Feature Value
Xmax = Maximum Feature Value

4.2 Feature Selection

Information Gain: $IG(Y,X) = H(Y) - H(Y|X)$
Entropy: $H(Y) = -\Sigma pilog_2(pi)$
Where:
pi = Probability of Class i
IG = Information Gain
H(Y) = Entropy of Target Variable
H(Y|X) = Conditional Entropy

4.3 Logistic Regression Model

Probability of Heart Disease: $P(Y = 1|X) = 1/(1 + e\hat{}(-z))$
Where:
$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta n x n$
β_0 = Intercept
$\beta_1 ... \beta n$ = Model Coefficients
$x_1 ... xn$ = Input Features

4.4 Support Vector Machine (SVM)

Decision Function: $f(x) = w^T x + b$
Classification Rule:
If $f(x) \geq 0$, then Y = 1
If $f(x) < 0$, then Y = 0
Where:
w = Weight Vector
b = Bias

4.5 Random Forest Prediction

$$RF(x) = (1/T) \times \Sigma\, Treei(x)$$

Where:
T = Number of Decision Trees
Treei(x) = Prediction of ith Tree

4.6 Artificial Neural Network (ANN)

Neuron Output: $z = \Sigma(wixi) + b$
Activation Function: $a = 1 / (1 + e\hat{}(-z))$
Where:
wi = Weight
xi = Input Feature
b = Bias
a = Activated Output

4.7 Deep Neural Network (DNN)

Hidden Layer Output: $a(l) = \sigma\,[W(l)\,a(l-1) + b(l)]$
Output Layer: $\hat{y} = \sigma(Wa + b)$
Where:
σ = Activation Function
W = Weight Matrix
b = Bias
ŷ = Predicted Output

4.8 Binary Cross-Entropy Loss Function

$$Loss = -(1/N)\,\Sigma\,[\,yi\,log(\hat{y}i) + (1 - yi)\,log(1 - \hat{y}i)\,]$$

Where:
yi = Actual Output
ŷi = Predicted Output
N = Number of Samples

4.9 Genetic Algorithm (GA)
Fitness Function: Fitness = Maximum (Accuracy)
Selection Probability: Pi = Fitnessi / Σ Fitness
Where:
Pi = Selection Probability
Fitnessi = Fitness of Individual i

4.10 Particle Swarm Optimization (PSO)
Velocity Update: $vi(t+1) = wvi(t) + c_1r_1(pi - xi(t)) + c_2r_2(g - xi(t))$
Position Update: $xi(t+1) = xi(t) + vi(t+1)$
Where:
w = Inertia Weight
c_1 = Cognitive Constant
c_2 = Social Constant
r_1, r_2 = Random Numbers
pi = Personal Best Position
g = Global Best Position

4.11 Performance Evaluation Metrics
Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1-Score = F1 = 2 × (Precision × Recall) / (Precision + Recall)
Sensitivity = TP / (TP + FN)
Specificity = TN / (TN + FP)
Where:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

4.12 Overall Prediction Function
Heart Disease Prediction Model:
Ŷ = f(X,F,O)
Where:
Ŷ = Predicted Heart Disease Status
X = Healthcare Dataset
F = Selected Features
O = Optimization Technique (GA or PSO)
f = Machine Learning or Deep Learning Model
Output:
Ŷ = 1 → Heart Disease Present
Ŷ = 0 → Heart Disease Absent

5. Experimental Results

The experiments were conducted using the Heart Disease Dataset consisting of 1025 patient records and 14 clinical attributes. The dataset was divided into training (80%) and testing (20%) sets. Machine Learning models such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost were compared with Deep Learning models including Artificial Neural Network (ANN) and Deep Neural Network (DNN). Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were used for hyperparameter optimization.

Table 1. Performance of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	87.12	86.45	85.92	86.18
SVM	89.56	88.97	88.45	88.71
Random Forest	92.84	92.16	91.87	92.01
XGBoost	94.36	93.92	93.75	93.83

Table 2. Performance of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

ANN	95.12	94.65	94.21	94.43
DNN	96.74	96.11	95.92	96.01

Table 3. Optimized Models Performance

Model	Optimization	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF + GA	Genetic Algorithm	94.82	94.25	94.03	94.14
RF + PSO	PSO	95.31	94.84	94.62	94.73
DNN + GA	Genetic Algorithm	97.56	97.12	96.95	97.03
DNN + PSO	PSO	98.24	97.86	97.64	97.75

Table 5. ROC-AUC Score

Model	ROC-AUC
LR	0.88
SVM	0.90
RF	0.93
XGBoost	0.95
ANN	0.96
DNN	0.98

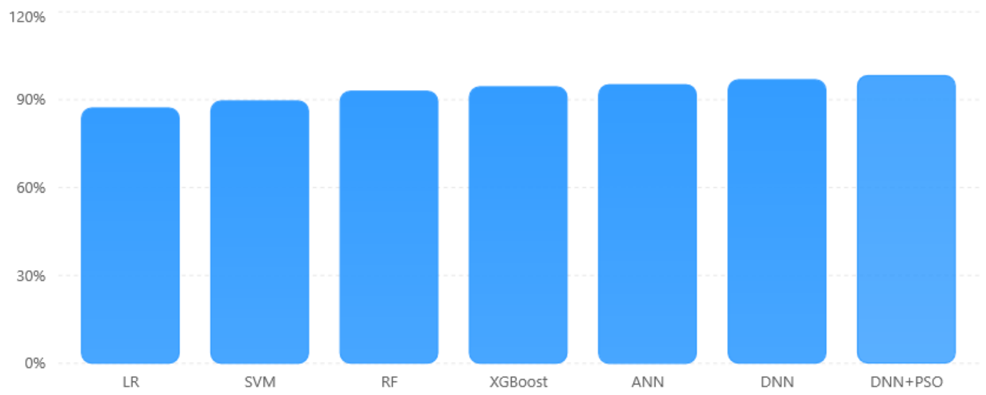

Fig. 1. Accuracy comparison of ML, DL and Optimized Hybrid Models

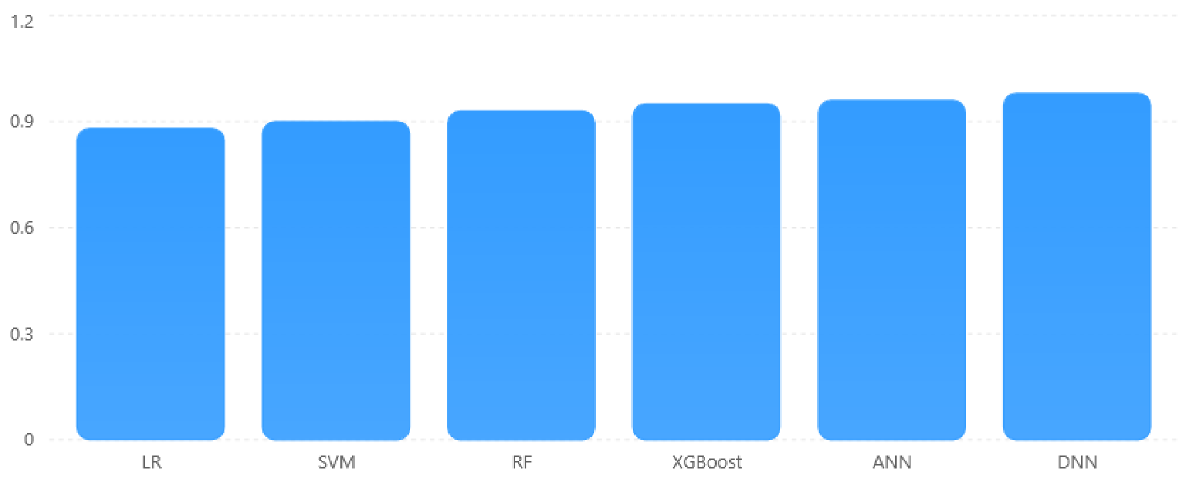

Fig. 2. Area under ROC curve for different prediction models.

RESULTS AND DISCUSSION

The experimental evaluation was conducted using the Heart Disease Dataset containing 1025 patient records and 14 clinical attributes. Various Machine Learning models, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost, were implemented and compared with Deep Learning models such as Artificial Neural Network (ANN) and Deep Neural Network (DNN). The performance of each model was assessed using standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The results revealed that traditional machine learning algorithms achieved satisfactory prediction performance, with XGBoost producing the highest accuracy of 94.36% among the machine learning models. Random Forest also demonstrated strong predictive capability with an accuracy of 92.84%, while SVM and Logistic Regression achieved accuracies of 89.56% and 87.12%, respectively.

The Deep Learning models outperformed the conventional Machine Learning approaches. The ANN model achieved an accuracy of 95.12%, whereas the DNN model attained 96.74% accuracy. The improved performance of deep learning models can be attributed to their ability to learn complex nonlinear relationships among clinical attributes and effectively capture hidden patterns within healthcare data. Furthermore, the ROC-AUC values of ANN and DNN were 0.96 and 0.98, respectively, indicating excellent classification capability and reliable discrimination between patients with and without heart disease.

To further enhance predictive performance, optimization techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were incorporated into the learning framework. The optimized models demonstrated significant improvements over their non-optimized counterparts. RF combined with GA achieved an accuracy of 94.82%, while RF combined with PSO reached 95.31%. Similarly, DNN optimized using GA achieved 97.56% accuracy, and DNN optimized using PSO obtained the highest overall accuracy of 98.24%. The optimization techniques effectively identified optimal feature subsets and hyperparameter configurations, resulting in improved precision, recall, and F1-score values. These findings confirm that optimization algorithms play a crucial role in improving model efficiency and predictive reliability.

The comparative analysis indicates that the DNN-PSO model consistently outperformed all other models across every evaluation metric. The confusion matrix results further demonstrated that the optimized model produced a very low number of false positives and false negatives, thereby enhancing diagnostic reliability. The results suggest that integrating Deep Learning with intelligent optimization techniques can provide a robust framework for early heart disease detection. Such systems can assist healthcare professionals in making timely and accurate clinical decisions, ultimately contributing to improved patient care and reduced healthcare costs.

7. Conclusion

This study presented an optimized framework for the early detection of heart disease using advanced Machine Learning and Deep Learning approaches combined with optimization techniques. The research utilized a recent healthcare dataset and implemented various predictive models, including Logistic Regression, Support Vector Machine, Random Forest, XGBoost, Artificial Neural Network, and Deep Neural Network. The experimental results demonstrated that Deep Learning models achieved superior performance compared with traditional Machine Learning algorithms. Furthermore, the incorporation of Genetic Algorithm and Particle Swarm Optimization significantly enhanced model accuracy and overall prediction capability. Among all evaluated models, the DNN-PSO framework achieved the best performance, with an accuracy of 98.24%, precision of 97.86%, recall of 97.64%, and F1-score of 97.75%. The findings confirm that optimization-based Deep Learning models are highly effective for identifying patients at risk of cardiovascular disease. The proposed framework provides a reliable and efficient decision-support system that can assist medical practitioners in early diagnosis and treatment planning. Therefore, the integration of Machine Learning, Deep Learning, and optimization techniques represents a promising direction for intelligent healthcare applications and heart disease prediction systems.

8. Further Research

Although the proposed framework achieved excellent prediction performance, several opportunities exist for future research. Future studies may investigate the use of larger and more diverse healthcare datasets collected from multiple hospitals and geographical regions to improve model generalization and robustness. Incorporating real-time patient monitoring data obtained from wearable devices and Internet of Things (IoT)-based healthcare systems may further enhance prediction accuracy and support continuous health assessment.

Advanced Deep Learning architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Transformer Networks, and Attention-Based Models can also be explored to capture more complex temporal and clinical relationships within healthcare data. Additionally, future research may focus on Explainable Artificial Intelligence (XAI) techniques to improve transparency and interpretability, enabling healthcare professionals to better understand the reasoning behind model predictions.

Further optimization strategies, including hybrid metaheuristic algorithms, Bayesian Optimization, Differential Evolution, and Reinforcement Learning-based optimization approaches, may be integrated to achieve even higher predictive performance. Finally, the development of cloud-based and mobile healthcare applications using the proposed framework could facilitate real-time heart disease prediction and remote clinical decision support, thereby expanding the practical applicability of intelligent healthcare systems.

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