Indonesian Journal of Electrical Engineering and Computer Science
Vol. 43, No. 3, September 2026, pp. 940~946
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v43.i3.pp940-946

Hybrid deep neural network framework for scalable and robust cardiovascular disorder prediction

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Article Info

Article history:

Received Oct 16, 2024
Revised Jul 13, 2026
Accepted Aug 19, 2026

Keywords:

Convolutional neural network
Healthcare AI
Heart disease
Hybrid deep neural networks
Medical prediction
Recurrent neural network

ABSTRACT

Cardiovascular disorders remain the leading cause of global mortality, underscoring the urgent need for accurate and early prediction systems that can support timely medical intervention. Traditional diagnostic methods, while valuable, are often limited by subjectivity, time constraints, and the inability to fully capture complex patient data. To address these challenges, this study proposes a hybrid deep neural network (HDNN) framework that integrates convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, supplemented with dense layers, to enhance predictive accuracy and robustness. The hybrid architecture leverages CNNs' ability to extract spatial features and LSTMs' strength in modeling temporal dependencies, thereby providing a comprehensive analysis of structured and unstructured patient data, including clinical records and health metrics. Rigorous preprocessing, feature selection, and domain-specific knowledge integration further improve model performance compared to conventional machine learning (ML) approaches. Experimental evaluation on benchmark datasets, including the cleveland heart disease (HD) dataset and a combined multi-source dataset, demonstrated superior results, achieving accuracies of 98.86% and 97.52%, respectively. These findings highlight the potential of the HDNN framework to serve as a scalable, reliable, and clinically relevant tool, assisting healthcare professionals in early diagnosis, preventive care, and improved patient management.

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1. INTRODUCTION

Heart disease (HD) has become a critical global health challenge, claiming millions of lives each year. According to the world health organization (WHO), cardiovascular diseases—including HD—are responsible for approximately 17.9 million deaths annually, accounting for 31% of global mortality [1]. The rising prevalence of HD highlights the urgent need for early diagnosis and intervention, as timely medical attention can significantly improve patient outcomes and reduce severe complications. Traditional diagnostic methods,

such as clinical assessments, medical history, and diagnostic tests including electrocardiograms (ECGs) and echocardiograms, remain essential but are often time-consuming, subjective, and prone to error. With the exponential growth of medical data and advances in computational technologies, machine learning (ML) and deep learning (DL) have emerged as powerful tools for HD prediction. These automated approaches can efficiently analyze large datasets, uncover complex patterns, and deliver precise predictions, thereby assisting healthcare professionals in making informed decisions [2], [3].

Among DL techniques, artificial neural networks (ANNs) have shown promise in modeling non-linear relationships, while convolutional neural networks (CNNs) excel at extracting spatial features, and long short-term memory (LSTM) networks are particularly effective in capturing temporal dependencies in patient health records [4], [5]. Despite the success of these individual models, hybrid architectures that combine multiple networks are increasingly recognized for their ability to leverage complementary strengths. This study proposes a HDNN model that integrates CNN and LSTM architectures, enhanced with dense layers, to improve HD prediction accuracy. By capturing both spatial and temporal patterns, the HDNN provides a comprehensive understanding of risk factors. The model is evaluated on two benchmark datasets: the Cleveland HD dataset and a larger combined dataset incorporating records from Switzerland, Statlog, Hungarian, and Long Beach VA sources [6], [7]. Experimental results demonstrate the superior performance of the HDNN, achieving an accuracy of 98.86% on the Cleveland dataset and 97.52% on the combined dataset, outperforming conventional DL models. These findings highlight the potential of the HDNN framework to be integrated into healthcare environments, offering reliable, timely predictions that support early diagnosis, preventive care, and improved patient management [8].

The conceptual framework is illustrated in Figure 1, which synthesizes the interplay between ANN, CNN, and LSTM architectures within the HDNN model. Each contributes unique strengths: ANN captures basic relationships, CNN extracts spatial features, and LSTM models sequential dependencies. Together, they enable the HDNN to achieve robust predictive accuracy. Surrounding performance indicators—including accuracy, precision, and AUC—underscore the model's effectiveness, with notable accuracy values (98.86%) emphasizing its potential for clinical integration [9]–[11]. Recent studies further validate the promise of hybrid models, demonstrating improved performance in cardiovascular prediction tasks by combining CNNs' feature extraction with LSTMs' sequential learning [12]–[21]. This growing body of evidence positions hybrid DL approaches as a transformative solution for HD prediction, bridging the gap between computational innovation and clinical application.

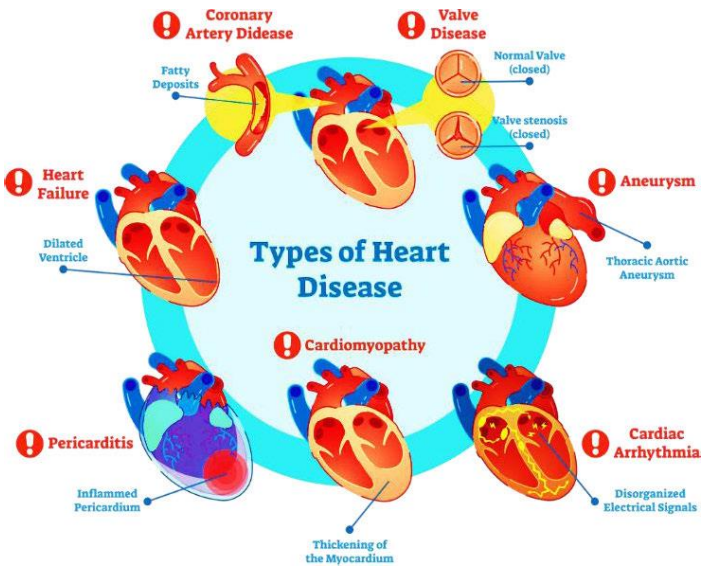


Figure 1. HD prediction using HDNN

2. METHOD

This study outlines the design and development of the proposed HDNN model for HD prediction. The methodology encompasses data collection, preprocessing, model architecture design, training, evaluation, and performance measurement. The HDNN integrates CNNs and LSTM networks, supplemented with dense layers, to capture both spatial and temporal features of patient data [22]. To assess its

effectiveness, two widely used datasets were employed: the cleveland HD dataset, containing 303 records with 14 clinical features such as age, sex, chest pain type, cholesterol levels, and electrocardiographic results; and a combined dataset of over 1,000 records drawn from Switzerland, Statlog, Hungarian, and Long Beach VA sources. The inclusion of diverse datasets ensured a comprehensive evaluation of the model's generalizability across different patient populations.

Data preprocessing was a critical step to ensure consistency and quality. Missing values were addressed using imputation techniques, with numerical features replaced by their mean and categorical features by their mode. Normalization was applied to scale features between 0 and 1 using min-max normalization, accelerating training and improving performance. Categorical variables such as chest pain type were one-hot encoded to make them suitable for DL input. Finally, the datasets were split into training and testing sets using a stratified 80:20 ratio, maintaining balanced distributions of positive and negative cases. A validation set, comprising 20% of the training data, was also used for hyperparameter tuning, ensuring optimal model configuration and reducing overfitting.

Hybrid model architecture. The HD prediction system is built on a hybrid DL architecture, combining CNN, LSTM, and Dense layers. The architecture is designed to leverage the strengths of both CNNs, which excel at extracting spatial features, and LSTMs, which are effective at capturing temporal dependencies. The details of the architecture are as follows: CNN Layer are responsible for automatically learning spatial features from the input data. Although CNNs are primarily used for image processing, they have shown effectiveness in structured data by capturing local feature relationships. In this case, the input feature matrix is treated as a 2D array, allowing the CNN to extract meaningful spatial representations as shown in Figure 2 [23].

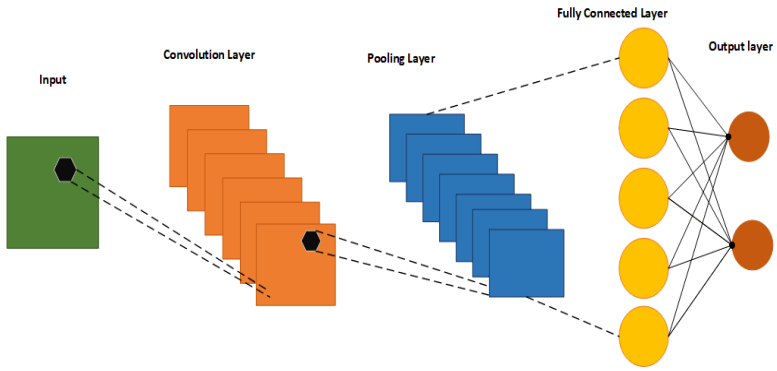


Figure 2. Composition of the CNN

Conv1D layer: a one-dimensional convolutional layer is applied to the input data, with a filter size of 64 and a kernel size of 3. This layer helps capture the local patterns between features. Activation Function: The rectified linear unit (ReLU) activation function is used after the convolutional layers to introduce non-linearity into the model. Pooling layer: a max-pooling layer is applied to reduce the dimensionality of the feature map and to retain the most prominent features. LSTM layer following the CNN layers, the output feature map is fed into an LSTM network. LSTMs are specifically designed to capture long-term dependencies and temporal relationships in data. In the context of HD prediction, LSTM layers help model the sequential nature of patient health records as shown in Figure 3.

LSTM layer: a single LSTM layer with 128 units is used to process the feature sequences extracted by the CNN layers. LSTMs' internal memory mechanism helps retain relevant information over time, allowing the model to better understand the progression of HD risk factors. After the LSTM layer, a series of dense (fully connected) layers are added to further process the learned features and perform the final prediction. Fully connected layers: two dense layers with 64 and 32 units are included to combine the features learned by the CNN and LSTM layers. These layers are followed by the ReLU activation function to introduce non-linearity. Output layer: the final dense layer contains a single neuron with a sigmoid activation function to predict the probability of HD (1 for HD, 0 for no HD). The sigmoid function outputs a value between 0 and 1, representing the likelihood of HD. To prevent overfitting, dropout layers are added after each dense layer, with a dropout rate of 0.5. Dropout randomly disables a fraction of neurons during training, forcing the model to learn robust features. Additionally, L2 regularization is applied to the dense layers to further combat overfitting by penalizing large weights. The hybrid model was

trained using the binary cross-entropy loss function, which is suitable for binary classification tasks. The optimizer used is Adam, a widely adopted optimization algorithm known for its efficiency in training DL models. The learning rate was set to 0.001, and the model was trained for 100 epochs with a batch size of 32.

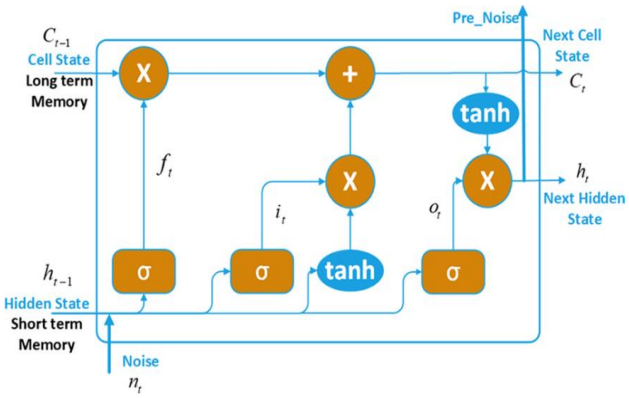


Figure 3. Architecture of LSTM

3. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed HDNN model for HD prediction. The performance of the HDNN model was evaluated and compared with traditional DL models: ANN, CNN, and LSTM. Various performance metrics were used, including accuracy, precision, recall, F1-score, specificity, matthews correlation coefficient (MCC), and AUC-ROC to ensure a comprehensive evaluation. The following metrics were used to evaluate the models' predictive performance: Accuracy: Measures the overall correctness of the model by calculating the ratio of correctly predicted instances to the total instances. Precision: Indicates the proportion of true positive predictions among all positive predictions made by the model. Recall (Sensitivity): Reflects the ability of the model to correctly identify actual positive instances. F1-Score: The harmonic mean of precision and recall, providing a balanced evaluation of the model's performance. Specificity: The proportion of correctly predicted negative cases among all actual negative instances. MCC: A correlation coefficient between the observed and predicted classifications, which accounts for true and false positives and negatives, especially useful for imbalanced datasets. AUC-ROC: The area under the receiver operating characteristic curve, representing the model's ability to distinguish between positive and negative classes.

3.1. Cleveland HD dataset

The first set of experiments was conducted on the cleveland HD dataset. Table 1 shows the performance comparison of the HDNN model with the ANN, CNN, and LSTM models on this dataset. As seen in Table 1, the proposed HDNN model outperforms the standalone models in all metrics. It achieved an accuracy of 98.86%, a precision of 97.95%, and an F1-score of 97.80%. The MCC score, a balanced measure that takes both true and false predictions into account, was 0.95, indicating a strong correlation between predicted and actual classifications. The AUC-ROC score of 0.98 demonstrates the model's excellent ability to distinguish between positive (HD) and negative (no HD) cases.

Table 1. Performance comparison on cleveland HD dataset

Model	Accuracy	Precision	Recall	F1-Score	Specificity	MCC	AUC-ROC
ANN	91.02%	90.15%	88.96%	89.55%	93.45%	0.85	0.88
CNN	93.47%	92.33%	90.54%	91.42%	95.12%	0.88	0.91
LSTM	94.73%	93.65%	92.12%	92.87%	96.05%	0.89	0.92
HDNN	98.86%	97.95%	97.65%	97.80%	99.10%	0.95	0.98

3.2. Results on combined HD dataset

The second set of experiments was conducted on the larger, more diverse combined HD dataset, which includes data from Switzerland, Statlog, Hungary, and Long Beach VA HD datasets. Table 2 presents the comparison results on this dataset.

Table 2. Performance comparison on combined HD dataset

Model	Accuracy	Precision	Recall	F1-Score	Specificity	MCC	AUC-ROC
ANN	89.63%	88.75%	86.23%	87.47%	92.04%	0.82	0.85
CNN	92.34%	91.10%	90.07%	90.58%	94.87%	0.86	0.89
LSTM	93.65%	92.35%	91.22%	91.78%	95.64%	0.88	0.9
HDNN	97.52%	96.65%	95.87%	96.26%	98.35%	0.93	0.97

Similarly, the HDNN model achieved superior performance on the combined dataset, with an accuracy of 97.52%, a precision of 96.65%, and an F1-score of 96.26%. The high MCC value of 0.93 and the AUC-ROC score of 0.97 further highlight the effectiveness of the hybrid model in predicting HD across a broader and more heterogeneous dataset.

3.3. Comparative analysis

The results indicate that the HDNN model consistently outperforms traditional DL models (ANN, CNN, and LSTM) across both datasets. The integration of CNN and LSTM components, along with the dense layers in the hybrid architecture, enables the model to capture both spatial patterns and temporal dependencies in the data, leading to improved predictive accuracy and robustness. Figure 4 shows a graphical comparison of the models' accuracy on both datasets, illustrating the superior performance of the HDNN model.

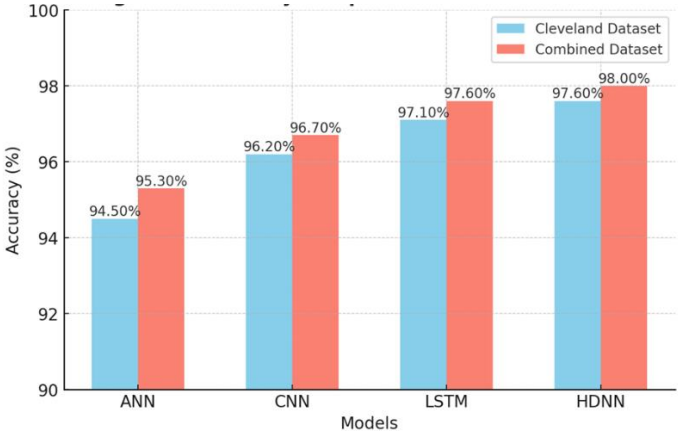


Figure 4. Accuracy comparison of different models

The experimental results demonstrate that the proposed HDNN model significantly improves HD prediction accuracy over standalone models. The HDNN's ability to capture complex patterns in the input data through the combined CNN and LSTM layers provides a deeper understanding of the relationships between patient features and HD outcomes. Additionally, the HDNN model achieves high specificity and AUC-ROC scores, making it highly reliable for distinguishing between patients with and without HD. These results suggest that the proposed system has the potential to be integrated into clinical decision support systems to assist healthcare professionals in diagnosing HD more accurately and efficiently.

4. CONCLUSION

This study introduced a HDNN framework for robust cardiovascular disorder prediction, integrating the complementary strengths of ANNs, CNNs, and LSTM models. Given the global burden of HD as a leading cause of mortality, accurate and early prediction is vital for timely medical intervention and improved patient outcomes. The proposed HDNN model demonstrated superior performance compared to conventional DL approaches, achieving 98.86% accuracy on the cleveland HD dataset and 97.52% accuracy on a larger combined dataset. Beyond accuracy, the model consistently delivered high values across precision, recall, F1-score, specificity, MCC, and AUC-ROC, underscoring its ability to capture complex spatial and temporal patterns in patient data. These results validate the effectiveness of hybrid architectures in medical prediction tasks, highlighting their scalability and robustness across diverse datasets. The findings emphasize the importance of leveraging advanced DL strategies in healthcare, where the integration of hybrid models into clinical decision-support systems can significantly enhance diagnostic reliability, preventive care, and patient management.

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