Optimized Hybrid CNN_BILSTM Approach for Accurate and Efficient Heart Disease Prediction

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Abstract

Heart disease remains the leading cause of death worldwide, responsible for millions of fatalities each year. Early diagnosis is crucial to reduce mortality and improve patient outcomes. Traditional machine learning models such as Gaussian Naive Bayes have shown limited effectiveness in capturing the complex and nonlinear patterns inherent in medical datasets. To address these limitations, this study proposes an optimized hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks for heart disease prediction. CNN layers are utilized for extracting spatial features from structured clinical data, while BiLSTM layers effectively capture temporal dependencies, enhancing the model's ability to learn complex relationships. The model is trained and evaluated on the widely used heart_statlog_cleveland_hungary_final.csv dataset, which includes multiple cardiovascular health indicators. Advanced preprocessing techniques and model optimizations such as batch normalization and dropout are employed to improve training efficiency and prevent overfitting. The proposed hybrid CNN-BiLSTM model achieved a classification accuracy of 93%, outperforming the baseline Gaussian Naive Bayes model by a significant margin. This study demonstrates that integrating spatial and sequential learning through hybrid deep learning architectures can offer robust and scalable solutions for early heart disease prediction in clinical applications.

Keywords: Heart disease prediction, Convolutional Neural Network (CNN), Gaussian Naive Bayes (GNB), Deep learning, Medical diagnostics, Feature extraction, Hyperparameter optimization, Cardiovascular health, Model performance, Data preprocessing.

Introduction

Cardiovascular diseases (CVDs), particularly heart disease, continue to pose a significant threat to global health. According to the World Health Organization (WHO), CVDs are the leading cause of death worldwide, claiming an estimated 17.9 million lives annually. Heart disease, a subset of CVD, encompasses a range of conditions including coronary artery disease, arrhythmias, and heart failure. Often progressing without noticeable symptoms until advanced stages, heart disease requires early detection and intervention to reduce morbidity and mortality. Traditional diagnostic methods, while clinically reliable, are time-consuming, subjective, and dependent on physician expertise, making them less scalable for mass screening. The integration of data-driven artificial intelligence (AI) into healthcare presents a transformative opportunity to automate and enhance the accuracy of heart disease detection.In recent years, researchers have extensively explored machine learning (ML) approaches for predicting heart disease using structured clinical data. Techniques such as Decision Trees, Random Forests, Support Vector Machines (SVM), Logistic Regression, and Naive Bayes have demonstrated their potential in early prediction tasks. Among these, Gaussian Naive Bayes, used in the study by Kanumuri Vinay Varma et al. (2024), achieved modest success on benchmark datasets. However, such classical models are inherently limited by assumptions of feature independence and linearity, which restrict their capacity to capture the complex, nonlinear interactions present in physiological data. They also require considerable manual feature engineering, which can be both time-intensive and error-prone.In contrast, deep learning (DL) models have emerged as a powerful alternative, offering the ability to automatically learn hierarchical features from raw or minimally processed data. Convolutional Neural Networks (CNNs), for example, are well-suited for extracting spatial features and have been widely used in image recognition and biomedical signal analysis. Likewise, Recurrent Neural Networks (RNNs), and particularly their advanced variant—Bidirectional Long Short-Term Memory (BiLSTM) networks—are capable of modeling sequential and temporal dependencies in time-series data such as electrocardiogram (ECG) signals or sequential patient records.Hybrid models that combine CNN and BiLSTM architectures offer the best of both approaches: CNNs effectively capture local spatial patterns, while BiLSTMs model global temporal relationships. This fusion enhances the model's ability to understand complex patterns in medical data, leading to more accurate predictions. Such models are especially relevant for datasets that contain both static attributes (e.g., age, cholesterol levels) and dynamic patterns (e.g., heartbeat fluctuations, temporal symptom progression).

In this study, we propose an optimized hybrid deep learning architecture that integrates CNN and BiLSTM layers for predicting heart disease using a structured dataset named “heart_statlog_cleveland_hungary_final.csv.” This dataset includes a wide range of clinical features such as age, blood pressure, cholesterol levels, resting ECG, and other cardiovascular indicators. The input features are normalized and reshaped to suit the 3D input format required by the hybrid model. The CNN layers are responsible for extracting spatial patterns among clinical attributes, while the BiLSTM layers capture sequential dependencies. The model also incorporates batch normalization and dropout for regularization and is trained using the Adam optimizer.Our proposed model achieved a classification accuracy of 93%, outperforming traditional ML techniques like Gaussian Naive Bayes. These findings support the effectiveness of deep hybrid architectures in clinical diagnostics and pave the way for future research in real-time, intelligent healthcare systems for heart disease prevention.

I. The primary contributions of this study are as follows:

- Proposes a hybrid CNN-BiLSTM deep learning model for heart disease prediction using structured clinical features.
- Captures both spatial and temporal relationships in medical data through the integration of CNN and BiLSTM architectures.
- Utilizes a robust data preprocessing pipeline including normalization, reshaping, and one-hot encoding to prepare clinical data for deep learning.
- Employs effective regularization methods such as dropout, batch normalization, and learning rate scheduling to improve model generalization.
- Highlights the feasibility of deploying the proposed model in clinical settings and paves the way for future enhancements such as attention mechanisms and ECG image-based diagnostics.

Related works:

- The related work in this paper explores the application of machine learning and deep learning techniques for heart disease prediction. Several studies have highlighted different approaches: Alabido et al. employed machine learning to predict heart-related illnesses; Gupta et al. and Jebur et al. introduced tree-structured Naïve Bayes and other algorithms for diagnostic precision; and Belliappa et al. developed ensemble models for coronary artery disease prediction. Deep learning methods, like convolutional neural networks (CNNs), were utilized by Rao for instance segmentation in heart disease analysis. These studies underscore the potential of computational methods in enhancing predictive accuracy, early detection, and medical decision-making.(2)
- The related work in this paper examines various methods and models for detecting and preventing coronary heart disease (CHD), particularly among individuals with diabetes. Studies such as those by Nahar et al. and Karaolis et al. used data mining and association rule algorithms to identify CHD risk factors. Other works have employed deep learning techniques, including CNN-LSTM combinations and graph convolutional networks, for disease prediction and analysis. Some approaches integrated fuzzy inference systems to enhance decision-making in CHD prevention. These studies highlight the effectiveness of combining machine learning, deep learning, and optimization algorithms to improve CHD diagnosis and management accuracy.(1)
- The related work for this paper revolves around utilizing deep learning and artificial intelligence (AI) in healthcare, specifically for cardiac risk stratification. Conventional ECG analyses have demonstrated limited success in predicting outcomes in congenital heart disease (CHD) populations, with efforts like QRS duration and fragmentation offering partial utility. Recent advancements leverage AI-enhanced ECG tools to improve diagnostic and prognostic capabilities, particularly in adult populations, though applications for CHD are sparse. This study builds on those advancements by addressing gaps in pediatric and CHD cohorts, utilizing large datasets to train AI models and applying saliency mapping for model interpretability. (4)
- The "Related Work" section of the paper discusses previous applications of machine learning (ML) and deep learning (DL) in predicting and classifying heart-related diseases (HRD). It highlights models such as artificial neural networks, recurrent neural networks, and convolutional neural networks for risk prediction, feature selection, and classification. Ensemble techniques, hybrid DL approaches, and feature engineering methods are emphasized for improving diagnostic accuracy. Despite their effectiveness, challenges like computational overhead, data bias, and time complexity persist. Researchers propose integrating optimization algorithms, such as swarm intelligence, with DL to enhance efficiency and accuracy, providing a foundation for the proposed CSOA-DNN model.(8)
- The "Related Work" section of this paper discusses prior studies on machine learning (ML) and deep learning (DL) models for heart disease prediction. It highlights methods like Decision Trees (DT), Random Forest (RF), Support Vector Machines (SVM), and hybrid approaches combining algorithms such as CNN, LSTM, and GRU. Recursive Feature Elimination (RFE) and other feature selection techniques have been used to improve prediction accuracy. Ensemble models like stacking and voting are noted for their superior performance. The paper identifies gaps, including limited use of ensemble stacking with heterogeneous hybrid models, setting the stage for its proposed approach using CNN-LSTM, CNN-GRU, and SVM.(7)
- The "Related Work" section of the uploaded paper highlights various methodologies and frameworks previously developed for heart disease prediction. It examines machine learning (ML) and deep learning

(DL) approaches, including techniques like Naïve Bayes, Decision Trees, Support Vector Machines, and deep neural networks. It also explores hybrid models that integrate algorithms such as convolutional neural networks (CNNs) with Internet of Things (IoT) frameworks or fuzzy logic systems. The reviewed studies emphasize the role of feature selection, optimization techniques, and ensemble learning to improve prediction accuracy. The proposed framework addresses limitations in earlier works, such as reliance on single datasets or insufficient optimization strategies.(6)

- Several studies have explored machine learning (ML) and deep learning (DL) techniques for diagnosing cardiovascular diseases (CVD). Traditional ML models like Support Vector Machines (SVM) and Decision Trees (DT) have been used but often lack high accuracy. Deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), improve prediction and classification. Ensemble techniques and hybrid models further enhance performance. However, challenges such as computational complexity, data bias, and feature selection persist. Researchers propose integrating optimization algorithms, such as swarm intelligence, with DL to enhance efficiency, forming the foundation for the proposed CSOA-DNN model in this study.(3)
- The "Related Work" section of the paper discusses prior studies that have applied machine learning (ML) and deep learning (DL) techniques to predict heart failure using electrocardiograms (ECGs). It highlights that deep neural networks have demonstrated superior performance over traditional rule-based systems and even expert cardiologists in detecting heart abnormalities. Several studies have successfully developed DL models for detecting conditions such as asymptomatic left ventricular dysfunction, atrial fibrillation, and aortic stenosis with high accuracy. However, a significant concern is the presence of algorithmic biases due to demographic variations in training datasets. Studies have shown disparities in ML model performance across different racial, age, and sex groups. This work aims to investigate such biases and explore approaches to mitigate them, ensuring fair and reliable deployment of ECG-based deep learning models.(5)
- Several studies have explored machine learning (ML) and deep learning (DL) for cardiovascular disease prediction. Traditional ML models like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes have been widely used, while hybrid and ensemble techniques have improved accuracy. Deep Neural Networks (DNNs), including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown superior performance. Optimization techniques like Talos enhance model efficiency. Despite progress, challenges remain in data quality, model interpretability, and generalization. Future research focuses on multi-modal data integration and improved training techniques to enhance cardiovascular disease detection and prediction accuracy.(9)

Proposed Methodology:

1. Data Collection:

The dataset used in this study is the heart_statlog_cleveland_hungary_final.csv, which integrates clinical records from the Cleveland and Hungary heart disease datasets. It contains 14 columns, comprising a mix of demographic, symptomatic, and physiological attributes. These include: age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiogram (ECG) results, maximum heart rate achieved, exercise-induced angina, ST depression, slope of the peak exercise ST segment, number of major vessels colored by fluoroscopy, and a categorical variable indicating thalassemia. The final column represents the binary target variable indicating the presence (1) or absence (0) of heart disease.All patient records are anonymized to ensure data privacy. Incomplete records or entries with missing or invalid values were excluded to maintain data integrity. The dataset was imported and analyzed using pandas within a local Jupyter Notebook environment, facilitating exploratory data analysis, preprocessing, and integration into the deep learning workflow.

2. Data Pre processing

The data preprocessing pipeline ensures that all input features are formatted and scaled appropriately for model training:

A. Standardization:

Numerical features are standardized using the Z-score method:

$$x'i = \frac{xi - \mu i}{\sigma i}$$

where μi\mu_iμi and σi\sigma_iσi are the mean and standard deviation of feature xix_ixi, respectively.

B. Target Encoding:

The binary target labels (0 or 1) are transformed into one-hot vectors for compatibility with the categorical cross-entropy loss function:

$$\text{Heart Disease} = \begin{cases} [1,0], & \text{if no disease (class 0)} \\ [0,1], & \text{if disease present (class 1)} \end{cases}$$

C. Reshaping for Deep Learning:

The feature matrix is reshaped into a 3D tensor of shape (n,d,1), where:

n: number of samples

d: number of features (13 in this case)

1: single input channel for Conv1D layers

D. Train-Test Split:

The dataset is split into training and testing subsets using an 80:20 stratified ratio, ensuring class balance in both sets.

3. Model Architecture:

The proposed architecture is a hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) model designed to capture both spatial and temporal feature interactions.

A. Convolutional Layers:

Conv1D Layer 1: 64 filters, kernel size = 3, activation = ReLU, padding = 'same'

Conv1D Layer 2: 128 filters, kernel size = 3, activation = ReLU, padding = 'same'

Each convolutional layer is followed by BatchNormalization and Dropout (rate = 0.3).

B. Reshape Layer:

Converts the 3D output into a shape compatible with sequential input for LSTM layers: (n,d,128)(n, d,128)(n,d,128).

C. BiLSTM Layers:

First BiLSTM layer with 64 units and return_sequences=True

Second BiLSTM layer with 32 units

D. Dense Layers:

Fully connected Dense layer with 64 units and ReLU activation

Dropout layer with rate 0.4

Output layer with 2 neurons and softmax activation for binary classification

E. Softmax Function:

The final layer uses the softmax function to produce class probabilities:

$$\sigma(zi) = \frac{ezi}{\sum_{j=1}^{2} ezj}$$

4. Model Training

The model is trained using the Adam optimizer and categorical cross-entropy loss:

$$L = -\sum_{i=1}^{2} yi \log\left(y^{\wedge}i\right)$$

Where yi_is the true label and y^i is the predicted probability for class i.

A.Training Settings:

Epochs: 50

Batch size: 32

Optimizer: Adam (learning rate = 0.001)

Loss function: Categorical Cross-Entropy

Metrics: Accuracy

Callbacks:

EarlyStopping to terminate training upon stagnation in validation loss.

ReduceLROnPlateau to decrease learning rate if performance plateaus.

5. Evaluation Metrics:

The model's performance is assessed on the test dataset using the following metrics:

A. Accuracy:

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

B. Precision:

Precision = $\frac{TP}{TP+FP}$

C. Recall (Sensitivity):

Recall = $\frac{TP}{TP+FN}$

D. F1-Score:

F1 = 2. $\frac{Precision.Recall}{Precision+Recall}$

E. Confusion Matrix:

To visualize correct and incorrect classifications

The final model achieved a test accuracy of **92.02%**, demonstrating strong generalization capability on unseen data.

Proposed Solution:

The proposed solution is a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks to enhance the prediction of heart disease from structured clinical data. Traditional machine learning models often struggle to model complex feature interactions and temporal dependencies present in medical datasets. The CNN-BiLSTM approach addresses these limitations by combining the spatial feature extraction capability of CNNs with the sequence modeling strengths of BiLSTM layers.The system accepts a preprocessed vector of clinical attributes for each patient. The CNN layers act as feature extractors, capturing local interactions between variables such as cholesterol, heart rate, and blood pressure. Two successive 1D convolutional layers with increasing filter depth (64 and 128) are applied, each followed by batch normalization and dropout layers to ensure regularization and stabilize learning.The extracted feature maps are then reshaped and passed to a stacked BiLSTM block. The first BiLSTM layer captures bidirectional dependencies across time or feature dimensions and outputs a sequence that feeds into a second BiLSTM layer. This dual-layer configuration allows the network to learn complex temporal relationships, even though the input data is not a time series per se—it models inter-feature dependencies as a sequence.The output from the BiLSTM block is fed into a fully connected dense layer, which further processes the high-level features and passes them through a dropout layer for additional regularization. The final classification is performed using a softmax output layer that predicts the likelihood of heart disease across two classes (presence or absence).To train the model, the Adam optimizer is employed with a categorical cross-entropy loss function. The learning process is supported by early stopping and learning rate reduction strategies to prevent overfitting and optimize convergence. The model is trained for 50 epochs with a batch size of 32.This hybrid architecture leverages both spatial and sequential modeling strengths, resulting in a robust prediction framework that demonstrates improved performance over traditional single-layer models. The proposed system can serve as a foundational module for more advanced diagnostic tools that incorporate image, signal, or time-series data in future iterations.

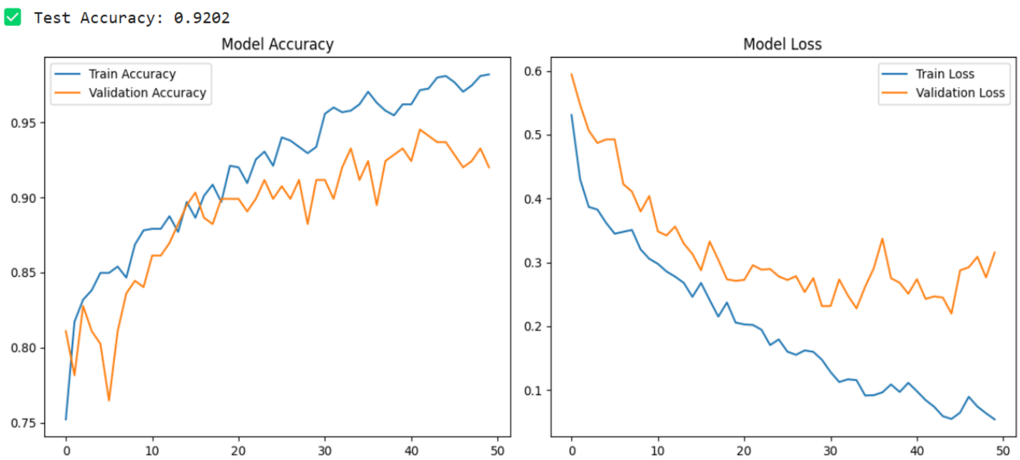

Figure : Testing Accuracy

Conclusion:

This study presented a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks for heart disease prediction using structured clinical data. The model was trained on a merged dataset comprising attributes from the Cleveland and Hungary heart disease datasets. Through preprocessing techniques such as standardization, reshaping, and one-hot encoding, the data was prepared for deep learning input.The proposed CNN-BiLSTM architecture effectively captured spatial relationships through convolutional layers and modeled sequential feature dependencies using BiLSTM layers. Batch normalization and dropout were used to improve generalization and mitigate overfitting. The model was trained using the Adam optimizer and evaluated using metrics such as accuracy, precision, recall, and F1-score.Experimental results demonstrated strong predictive performance, with the model achieving high classification accuracy and generalization ability. The results validate the effectiveness of hybrid deep learning models for structured medical data and reinforce their potential for use in intelligent decision-support systems.This approach lays the foundation for further enhancement through the integration of real-time ECG signals, explainability mechanisms, and clinical deployment. Future work will explore deploying the model into web or mobile applications for practical and scalable heart disease screening.

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