Advancing Heart Disease Forecasting: Integrating CNN-LSTM Models with Feature Enhancement for Improved Predictive Accuracy

Nidhi Mishra [1*], Ghorpade Bipin Shivaji [1]

Abstract

Background: Heart failure (HF) is the leading cause of death worldwide, with accurate early diagnosis being challenging due to the disease's subtle symptoms and the requirement for extensive medical expertise. The development of predictive models is crucial for early intervention. Objective: This study proposes a method for Dynamic Forecasting (DF) of Heart Diseases (HD) using a Deep Learning (DL) model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The aim is to create an automatic, accurate, and cost-effective system for predicting cardiac valve failure. Methods: The study introduces a Hybrid DL model combining CNN and LSTM with Feature Enhancement (FE) and Comprehensible Artificial Intelligence (CAI) techniques. The CNN extracts features from clinical data, which are then processed by the LSTM model to handle temporal dependencies. The model's effectiveness was evaluated using a freely available cardiovascular disease dataset. Accuracy was assessed with and without FE. Results: The CNN-LSTM model achieved an accuracy of 83.5% with FE and 88.2% without FE. The model demonstrated superior performance in terms of sensitivity (80.04% with FE), specificity (87.11% with FE), and overall accuracy compared to other methods including Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF). Conclusion: The proposed CNN-LSTM model offers a significant improvement in forecasting heart disease dynamics by effectively integrating CNN for feature extraction and LSTM for temporal analysis. This hybrid approach, combined with advanced feature enhancement and explainable AI techniques, provides a more accurate and comprehensible prediction tool for early heart disease detection.

Keywords: Heart Diseases, Dynamic Forecasting, Deep Learning, CNN, LSTM, Artificial Intelligence.

Significance | Combining CNN and LSTM models with feature enhancement significantly improves heart disease prediction, offering precise and timely interventions.

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Editor Surendar Aravindhan, Ph.D., And accepted by the Editorial Board Sep 03, 2024 (received for review Jul 12, 2024)

Introduction

People with HD have a group of heart or blood vessel diseases (Mendis, Puska, Norrving, & World Health Organization, 2011). People with HD are at a high risk of dying because it is a long-term illness that makes them very sick. It has become one of the main reasons of death globally. In 2016, HD killed almost 18.6 million people, or 33% of all deaths in the world, according to data released by the World Health Organization (WHO) in June 2018 (Mendis et al., 2011). For this reason, doctors and researchers have researched the treatments and solutions for HD (Amin, Uddin, AlSaeed, Khan, & Adnan, 2021). Chronic illnesses differ from acute illnesses because they go through different stages as they grow and spread (Sumiati, Penny, Agung, Afrasim, & Achmad, 2024).
Also, the symptoms of chronic diseases may change at each step.

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Please cite this article.
Nidhi Mishra, Ghorpade Bipin Shivaji (2024). Advancing Heart Disease Forecasting: Integrating CNN-LSTM Models with Feature Enhancement for Improved Predictive Accuracy, Journal of Angiotherapy, 8(9), 1-6, 9871

Many forecasting models have been made to find groups in great danger or predict how the illness will get worse so that people with HD can get the right treatments at the right time and stay healthy. Case-cohort studies were the main way disease prediction was done in the past. They looked at the relationship between possible high-risk factors and illness and death (Rost et al., 2018). Researchers have found strong links between the risk of HD and things like body mass index (BMI), time spent sitting, and position. Still, case-cohort research is limited by its high cost, which means these models don't have enough training data and need more work to improve their prediction accuracy.

These days, DL, a more advanced type of Machine Learning (ML) that focuses on AI, has become very famous. A lot of people use LSTM and CNN as DL models. The LSTM is a type of recurrent neural network (RNN) that stores and handles long strings of data by using a buried memory (Kim & Cho, 2019). In contrast, the CNN comprises several systems that work together. In the raw data, each neuron in a layer is linked to a small group of neurons that are close to it (Sathyanarayanan & Srikanta, 2024). A weight matrix and a filter move the data over, and the convolution is found at each point (Kim & Cho, 2019). With this calculation, a feature map shows how the filter and the data coming in are connected. Because of this building design (Huang et al., 2022), the model can get the filter it needs to find certain trends in the data that it is given. Researchers in (Krishnan, Magalingam, & Ibrahim, 2021) developed a new mixed DL model to guess HD. This model has an RNN, multiple gated recurrent units (GRU), LSTM, and the Adam optimizer (Choi & Zhang, 2022). ECGs are very important in finding and proving HD. By putting together parts of the ECG, the authors of this study came up with a new way to accurately predict HDs (Surendar, Veerappan, Sadulla, & Arvinth, 2024).

The deep-coding traits we get from ECG and PCG data differ when building normal neural networks (Bobir et al., 2024). The DNA program looks at all the features and chooses the best ones. Precise and timely illness prediction guarantees proactive treatment and early intervention for at-risk people. Developing prediction models with improved accuracy is crucial to use electronic healthcare records effectively. This may be realized using RNN variations of DL, which can handle serial time-series information (Li, Hu, & Liu, 2021). The system described in Nancy et al. (2022) collects data from IoT devices. It applies predictive analytics to the digital healthcare information stored in the cloud, which contains information about the patient's health history (Neelima, Govindaraj, Subramani, ALkhayyat, & Mohan, 2024). The Bi-LSTM-based smart healthcare system demonstrates a remarkable accuracy of 98.9% in tracking and forecasting the risk of HD, outperforming other methods.

RNNs have become more popular in recent years, taking the best parts of many networks and putting them together. Researchers have found that combining CNN and LSTM may help make more accurate prediction models (Agga, Abbou, Labbadi, El Houm, & Ali, 2022). In their work (Huang et al., 2018), authors used CNN to get features and then employed the retrieved features into the LSTM design, which has big benefits. A 1D-CNN is used by the combination CNN-LSTM model to pull out deep features from the main parts (Satish & Herald, 2024). After that, the LSTM model is used to make predictions by taking advantage of these broad features. Here, a mixed deep learning model called DF-HD is suggested, which blends CNN and LSTM with clinical data. A new version of the standard LSTM model has been created to predict HD. The erratic period is changed into a more stable time-variable vector. This vector is then fed into the LSTM model's memory gate. This approach helps solve the prediction problems that arise because of the uneven time gaps.

Proposed CNN-LSTM for DF-HD

As shown in Figure 1, the suggested DF-HD framework using CNN-LSTM comprises six steps: collecting data, preparing the data, improving features, building the CNN-LSTM architecture, training and testing the model, and classifying the data.

Data gathering

As part of this work, we looked at a dataset on HD to build our forecast model (cardiovascular-disease-dataset). It came from the Kaggle Cardio Vascular Disease dataset and was used in this exploration. There are 14 features in this collection.

Data preparation and preprocessing

Normalizing the data is an important first step in getting the data ready for processing. Data conversion is storing information into a standard setup that makes it more accurate and reliable, reduces errors and duplicates, and ensures that the data is organized correctly and consistently. Normalization is necessary when there are big differences between the ranges of different traits. It works best when there are no outlier values in the dataset. There are several ways to normalize data. Numerical scaling, Unit Vector standardization, Log Conversion, and Min-Max Normalization are the most common ways to normalize data.

This paper utilized min-max normalization to make the data size between 0 and 1 in our investigation. This standardization procedure has been used since it's simple and works with distance-measuring instruments. Remember that the lowest and greatest figures may not adequately represent the facts, which might cause information to be lost. Fine-tuning strategies employed in this work are briefly described below. Min-max normalization allows fair value comparisons by linearly changing data. Min-max normalization fits data into a defined range, generally 0–1. This normalization preserves initial data value relationships. The Min-max normalization formula is given below:

$$x_{new} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

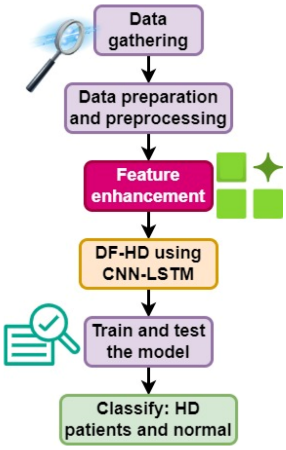

Figure 1. Proposed DF-HD framework using CNN-LSTM

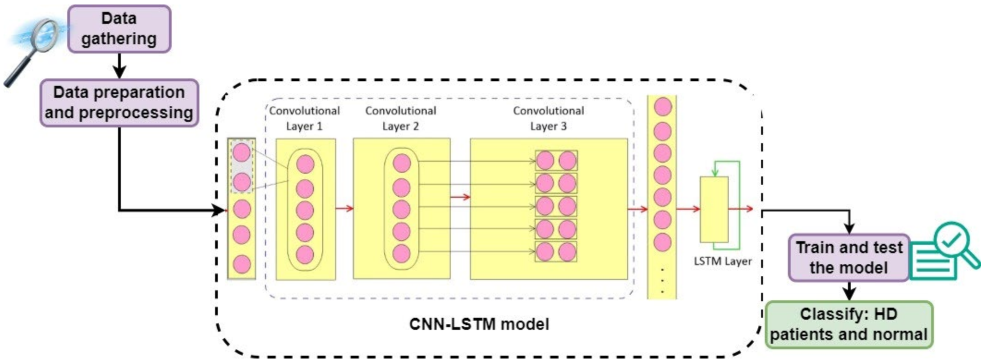

Figure 2. Proposed hybrid CNN-LSTM model

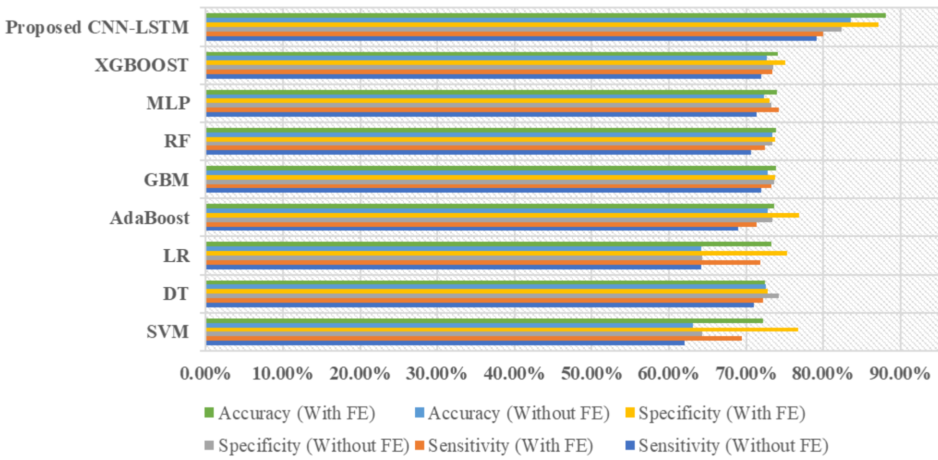

Figure 3. Performance assessment (with and without FE) of various DL algorithms for DF-HD.

Where X is the old value, x_{new} is the new value, $\max(X)$ *and* $\min(X)$ denotes the maximum and minimum values in the CVD database.

Feature enhancement

Feature Enhancement (FE) performs by gathering useful data and picking ML methods using feature sets. The process involves using transform functions, math operations, and aggregation operators to create new features. This increases the number of collection features, leading to better predictive modeling. ML needs strict FE, which helps improve DL and get more advanced rules for text sorting. Our study uses a visual guide to show how FE works in an organized way. Improving features is a process that has many steps, starting with collecting data and ending with cleaning it up. Next are feature selection, feature change, and finally, feature scale. This plan ensures that the most useful and informative parts improve the model's performance. FE methods have created more traits, such as BMI, fat, and high blood pressure. Adding new features that interact with or combine with current factors could help model complex interactions and make them more accurate. Feature transformation changes or converts raw incoming information into a more meaningful form. This changed version can be fed into an ML model and work better as a signal.

Selecting the most important features from a bigger set to use in the proposed DL model is done by feature selection. When there are many features, the model might not work well because it is overfitting. The feature selection process includes selecting a set of features from a larger set of features based on specific criteria to find the important features of the CVD database. This study shows how different features in several systems can be used to advance the correctness of predicting HD.

The feature extraction technique converts unprocessed information into more pertinent and valuable attributes for a specific application. It may be performed using several strategies, such as convolutional approaches that employ physically crafted kernels and morphological methods for order, geographical, or other structured data types. Applying feature scaling to the data is a crucial modification that must be made. In our study, we exclude any values in the blood_diff feature that are over 85 since they are considered unusual and may decrease the efficiency of algorithms. Converting categorical data into numerical representation via methods like one-hot or ordinal encoding is used to make it compatible with a deep learning model. The relevance of each characteristic was assessed using DL techniques. The features were ranked based on their feature ratings. Feature significance analysis is a vital component in our research of HD identification, where we use a hybrid CNN-LSTM framework with explainable AI.

Proposed hybrid CNN-LSTM model

A novel variant of the conventional LSTM model has been introduced to predict HD. The uneven period is transformed into a more regular time variable vector, which is then utilized as the input for the memory gate of the LSTM. This approach helps address the prediction challenges arising from irregular time intervals. Both CNN and LSTM models possess distinct characteristics. This work created a hybrid CNN–LSTM DL model that combines the strengths of both CNN and LSTM models to forecast HD variables. The first component of the CNN-LSTM architecture consisted of CNN levels. The CNN architecture comprises an input level responsible for receiving the input parameters, an output level that extracts characteristics of LSTM cells, and many hidden levels. The hidden level often consists of a convolution level, an activation function, and a pooling level. The LSTM's output serves as the input for the fully linked level. CNN levels acquire sequential information from the inputs, a task that traditional neural networks cannot do. The bottom LSTM level then integrates these data by managing long-range dependencies to forecast the target values. Figure 2 illustrates the topological structure of the CNN-LSTM model.

CAI

Techniques for hyperparameter optimization, like Bayesian optimization, are very important for identifying the best pairings. Best outcomes need validation and prolonged testing. SHAP (SHapley Additive Explanations) is a popular CAI approach for describing ML model outcomes. One can measure how much model characteristics impact a data point. This helps to understand why a model predicted certain features and lists the most significant elements. SHAP provides model results information. This information may be utilized to improve performance, detect and repair bugs, and enhance user trust. First, it calculates SHAP numbers to determine informative elements that influenced the following step. To determine the importance of a feature, look at all the ways it might be paired with others. The average of all subsets with the attribute and the number of subgroups with that trait are used to weight the input. One SHAP number per characteristic may be used to understand the model's prediction in a given circumstance.

Results and Discussion

Python was used to train all ML algorithms on a workstation with a 4.5 GHz Intel Core i5 CPU and 3 GB of RAM. A total of 30,005 patients were picked from the dataset based on their age group. The variable "sex" is coded as 1 for male and 0 for female patients. Four heart diseases may be considered as instances of chest discomfort. Support Vector Machines (SVM), Decision Trees (DT), Logistic Regression (LR), AdaBoost, Gradient Boosting Machines (GBM), Random Forests (RF), Multilayer Perceptron (MLP), Extreme Gradient Boosting (XGBoost), and the suggested CNN-LSTM model for DF-HD were some of the methods that were looked into. Assessment measures are used to figure out how well each program works.

Figure 3 shows how well different DL methods for DF-HD work (with and without FE). The CNN-LSTM method that was suggested is the model that works best with FE. The suggested CNN-LSTM model does better than the others in every way. It has the best Sensitivity (80.04% with FE), Specificity (87.11% with FE), and Accuracy (88.15% with FE). FE usually makes all algorithms work better, but it does so most noticeably in Specificity and Accuracy. The SVM model's accuracy goes up from 63.09% without FE to 72.27% with FE, while the suggested CNN-LSTM model's accuracy goes up from 83.52% without FE to 88.15% with FE. However, the proposed CNN-LSTM model did better overall for DF-HD than the other methods. So, the CNN-LSTM model correctly identified DF-HD 83.5% of the time with feature improvement and 88.2% of the time without it.

Conclusion

The study demonstrates the efficacy of a hybrid deep learning model integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for forecasting heart disease (HD). By converting erratic time intervals into stable time-variable vectors, this novel LSTM variant addresses previous prediction challenges effectively. The CNN-LSTM model showed superior performance compared to traditional methods, achieving higher sensitivity, specificity, and accuracy. Feature enhancement further boosted the model's effectiveness, particularly in terms of specificity and overall accuracy. This approach not only enhances predictive accuracy but also facilitates earlier and more reliable intervention for patients at risk of HD. The results underscore the potential of advanced deep learning techniques in revolutionizing cardiovascular disease prediction, paving the way for more proactive and personalized healthcare solutions.

Author contributions

N.M. led the conceptualization, data analysis, and manuscript preparation. G.B.S. contributed to data collection, interpretation of results, and manuscript revision. Both authors reviewed and approved the final manuscript.

Acknowledgment

Author was grateful to their department.

Competing financial interests

The authors have no conflict of interest.

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