COMPUTER RESEARCH AND MODELING
2024 VOL. 16 NO. 7 P. 1651–1666
DOI: 10.20537/2076-7633-2024-16-7-1651-1666

Ки&М

SPECIAL ISSUE

UDC: 004.8

Efficient diagnosis of cardiovascular disease using composite deep learning and explainable AI technique

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Received 29.10.2024, after completion — 03.12.2024
Accepted for publication 03.12.2024

During the last several decades, cardiovascular disease has surpassed all others as the leading cause of mortality in both high-income and low-income countries. The mortality rate from heart disorders may be lowered with early identification and close clinical monitoring. However, it is not feasible to adequately monitor patients every day, and 24-hour consultation with a doctor is not a feasible option, since it requires more sagacity, time, and knowledge than is currently available.

In this study, we examine the Explainable Artificial Intelligence (XAI) technique, namely, the SHAP interpretability approach, in order to educate the medical professionals about the Explainable AI (XAI) methods that can be helpful in healthcare. The XAI methods enhance the trust and understandability of both practitioners and Health Researchers in AI Models. In this work, we propose a composite Deep Learning model: Bi-LSTM+CNN model to effectively predict heart disease from patient data. After balancing the dataset, the Bi-LSTM+CNN model was used. In contrast to other studies, our proposed hybrid deep learning model produced excellent experimental results, including 99.05 % accuracy, 99 % precision, 99 % recall, and 99 % F1-score.

Keywords: explainable AI, cross-validation, backward elimination, REFCV, cardiovascular disease, healthcare

Citation: *Computer Research and Modeling*, 2024, vol. 16, no. 7, pp. 1651–1666.

КОМПЬЮТЕРНЫЕ ИССЛЕДОВАНИЯ И МОДЕЛИРОВАНИЕ 2024 Т. 16 № 7 С. 1651–1666
DOI: 10.20537/2076-7633-2024-16-7-1651-1666

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СПЕЦИАЛЬНЫЙ ВЫПУСК

УДК: 004.8

Эффективная диагностика сердечно-сосудистых заболеваний с использованием композиционного глубокого обучения и техники объяснимого искусственного интеллекта

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Получено 29.10.2024, после доработки — 03.12.2024
Принято к публикации 03.12.2024

Сердечно-сосудистые заболевания на протяжении последних десятилетий представляют собой серьезную угрозу здоровью населения во всем мире, независимо от уровня развития страны. Ранняя диагностика и постоянный медицинский контроль могли бы значительно снизить смертность от этих заболеваний. Однако существующие системы здравоохранения зачастую не в состоянии обеспечить необходимый уровень мониторинга пациентов из-за ограниченных ресурсов.

В рамках нашего исследования мы использовали метод SHAP для объяснения работы модели глубокого обучения Bi-LSTM+CNN, разработанной для прогнозирования сердечно-сосудистых заболеваний. Путем балансировки данных и применения кросс-валидации мы достигли высокой точности (99,05 %), полноты (99 %) и F1-меры (99 %) модели. Интерпретируемость модели, обеспечиваемая методом SHAP, повышает доверие медицинских специалистов к полученным результатам и способствует более широкому внедрению искусственного интеллекта в клиническую практику.

Ключевые слова: объяснимый ИИ, обратное исключение, REFCV, сердечно-сосудистые заболевания, здравоохранение, глубокое обучение

Introduction

As the life standard of people improves their stress levels also rise resulting in an increase in the number of people with CVD to an alarming rate. Cardiovascular disease is globally still one of the leading fatal diseases, CVD include coronary artery disease, atrial fibrillation, and other cardiac or vascular conditions [Aryal et al., 2020]. Additionally, low-income nations are not able to afford the primary devices such as CT scan electrocardiograms used for detecting cardiovascular disease. Therefore, the early detection of cardiovascular disease plays a key role in lessening its physical and social burden on patients.

Heart disease ranks high among the top killers in the US. According to the National Health and Nutrition Examination Survey (NHANE's) data from 2013 to 2016, the prevalence of CVD (including hypertension, coronary heart disease, stroke and heart failure) in adults 20 years of age or older is 48 % (121.5 million in 2016) [Mozaffarian et al., 2016]. Cardiovascular disease has a wide variety of possible causes, which makes diagnosis challenging. Among the many clinical indications that fall within this category are age, cholesterol, diabetes, and hypertension. Latest data available (2018 World Life Expectancy) shows that Pakistan has one of the world's highest mortality rates from cardiovascular disease, ranking 18th overall. The country has 237.98 fatalities per 100 000 inhabitants. Therefore, making accurate CVD forecasts is of the utmost importance for many reasons, including preventing severe health outcomes. Medication mistakes seem to be the biggest killer on a global scale; a little misunderstanding might accelerate death. If more accurate disease prediction could be made using supervised learning algorithms, healthcare providers may make fewer errors of this sort. Based on the research done by [Bashir, Qamar, Khan, 2016], scientists have come up with several supervised learning strategies to improve healthcare accuracy. Using data mining (DM) approaches to the huge amount of data generated in the medical field one can uncover the hidden pattern for early clinical prediction. Conducting innovative research in the past decades proved that DM plays an essential role in the medical field. For effective disease prediction, the available medical data must be collected and made available for further study. The attributes including blood pressure, cholesterol, blood sugar and abnormal pulse rate must be considered while diagnosing heart disease [Mohan, Thirumalai, Srivastava, 2019]. Medical data scientists are very interested in creating tools that might help with the early diagnosis of heart problems [Bashir et al., 2021]. The issue of CVD categorization into "Yes" and "No" is addressed in this research. [Ahmad et al., 2023] Suggested a method for categorization that made use of Hybrid Deep Learning. On the other hand, these models often do not provide practical means of accurately predicting the onset of cardiac disease. As a result, we classified CVD presence using several deep-learning methods.

Research objectives

We aim to achieve the following research objectives to accurately predict the onset of cardiovascular disease (CVD).

1. The objective of this work is to use the Bi-LSTM and CNN deep learning methods to analyze the data on cardiovascular disease and predict the probability of cardiovascular events.

2. This study aims to assess the proposed Bi-LSTM and CNN methods for predicting cardiovascular disease, comparing them to the current cutting-edge techniques in the domains of deep learning and machine learning.

3. The objective of this study is to assess the predictive efficacy of the suggested techniques in comparison to previous studies.

Research questions

This work considers following research questions: 1) How to predict CVD by applying a hybrid deep learning model to analyze the heart disease dataset? 2) What is the efficacy of DL models for CVD prediction in comparison to other traditional ML classifiers and benchmark studies?

Problem statement

Cardiovascular diseases (CVDs) remain a leading cause of mortality worldwide, necessitating accurate and efficient diagnostic methods. Artificial neural networks (ANNs) have demonstrated exceptional accuracy in data mining for cardiac diagnosis, but there remains significant potential for enhancing their predictive capabilities. This research focuses on exploring various diagnostic approaches to optimize predictions and address the growing burden of CVDs.

Significance of the research

Our research presents a novel approach to CVD prediction that leverages deep learning methods. By prioritizing the most salient features and employing a hybrid Bi-LSTM-CNN architecture, we effectively capture spatial dependencies in patient health data. Our methodology demonstrates significant potential in accurately predicting CVD, thereby enabling early intervention and improved patient outcomes.

Research gap

Even though deep neural networks and traditional models of machine learning have turned out to be effective and are often used for cardiovascular disease diagnosis, most past studies have struggled to increase categorization levels. Furthermore, selecting the incorrect layers and settings affects the neural network model's performance. In this study, we introduced a novel Hybrid deep learning model combination of Bi-LSTM+CNN for CVD prediction with high accuracy. Also, there has been no study with combination of Bi-LSTM+CNN augeument with Explainable AI methods. The objective of this research is to give significant insight into the effectiveness of various architectures in diagnosing CVD by experimenting with various parameter configuration settings of the proposed hybrid DL model and comparing their results with benchmark studies. A proposed model for detecting cardiovascular disease from the provided data is presented, which combines a CNN and a BI-LSTM models.

Literature review

Cardiovascular disease (CVD) refers to any condition that affects the cardiovascular system. Coronary artery disease (e. g., angina, heart attack), heart failure, hypertensive heart disease, rheumatic heart disease, cardiomyopathy, arrhythmia, congenital heart disease, valvular heart disease, carditis, aortic aneurysms, peripheral artery disease, and thromboembolic disease all fall under the umbrella of cardiovascular disease. Most closely related to coronary artery disease (CAD) is heart failure (HF). Previously, [Preethi, Selvakumar, 2020] predicted and identified individuals with heart disease, and it was found that heart failure (HF) is often caused by narrowing or blocking of the coronary arteries. Traditional machine learning algorithms, including Support Vector Machines, K-Nearest Neighbors, Random Forests, and Artificial Neural Networks, have been widely applied to predict cardiovascular disease. These techniques have demonstrated promising results in extracting meaningful patterns from complex medical data. However, to further enhance predictive accuracy and interpretability, recent research has explored the potential of deep learning models, particularly those based on neural networks. This study focuses on leveraging advanced machine learning and deep learning techniques to improve the prediction of cardiovascular disease. By investigating various diagnostic approaches and exploring the potential of big data analytics, we aim to develop a robust and accurate predictive model that can aid in early detection and intervention.

Machine learning-based hearth disease prediction

Heart failure is a complex clinical condition that can now affect a larger population. Cardiac centers and hospitals are significantly dependent on ECG as among the most effective solutions in the diagnostic process. When applied to the problem of identifying heart disease from relatively small test datasets, classifiers and popular approaches for encoding categorical data using machine learning have shown a wide range of surprising outcomes. For example, convolutional neural networks (CNN) were utilized to extract features without having to learn and understand sequence information. [Ahmad et al., 2023] presented a deep learning-based system, namely, a convolutional neural network (CNN) with bidirectional long/short-term memory, for accurately predicting cardiovascular disease from patient data. By prioritizing and selecting highly rated characteristics in the provided dataset, feature selection ensured that only the most relevant features were picked. Cardiovascular disease was predicted using CNN+BiLSTM. Achieved accuracy was reported at 94.507 %. This model is the base model of the current contribution. This research work aims to improve the work by employing more datasets to improve accuracy.

A variety of machine-learning models for heart disease prediction have been developed over the years. A wide variety of machine learning methods such as Logistic regression, Support Vector Classifiers (SVC), K Neighbour Classifiers, Decision Tree Classifier, Random Forest Classifier, and Gradient Boosting Classifier. Random Forest Classifier was top-ranked with an accuracy of about 86 %. Use of better datasets can enhance accuracy of such models. [Nagavelli, Samanta, Chakraborty, 2022] described several heart disease detection machine-learning methods. They used Naïve Bayes, SVM, XG Boost. Finally, they used a clinical decision support system for heart disease prediction. They mainly focused on XGBoost to compare several decision tree classification algorithms in an effort to enhance the accuracy which is now reported at around 95 %. The use of more attributes can improve the overall performance. [Patel et al., 2021] reported utilization of various machine-learning techniques for heart disease prediction. Decision Tree, SVM, ANN, Naïve Bayes, Random Forest, and KNN are the machine learning methods covered. They achieved an accuracy of 91 %. It is proposed that use of more complex hybrid models can improve overall accuracy.

CVD prediction using supervised and unsupervised learning

[Gupta et al., 2022] conducted research on heart disease prediction using supervised learning techniques. K-Nearest Neighbour, Decision Tree, Logistic Regression, Naïve Bayes, and a support vector machine (SVM) model are just a few of the supervised learning methods used to predict cardiac illness using a dataset obtained from the UCI repository. Findings show, that Logistic regression outperformed the other supervised classifiers. Since the number of false negatives in this model is quite low in comparison to that of other models (based on the overall confusion matrix). The ensemble techniques, on the other hand, can improve the classifier's accuracy. Logistic Regression achieved the highest accuracy of 92 %. Detailed algorithm analysis was proposed as a possible venue to improve overall performance of the method. [Chen et al., 2022] conducted research on data collected from the National Center of Biotechnology Information (NCBI). According to the findings, the primary risk variables for hypertension were body mass index, age, genetics, and waist circumference. Compared to the other machine learning model's validation results indicated that Random Forest performed better than other predictors. Accuracy achieved through RF was reported at 82 %. Overall, among ML's many other benefits, its ability to process vast amounts of clinical data based on a well-defined algorithm helps physicians make decisions in the clinic and ameliorate patients' outlook in recovery.

CVD prediction using feature selection techniques

Wrapper methods (forward, backward, and stepwise), filter methods (ANOVA, Pearson correlation, variance thresholding), and embedded methods (Lasso, Ridge, Decision Tree) are the three main categories of feature selection techniques. [Dissanayake, Md Johar, 2021] reported on heart disease prediction using feature selection techniques. The algorithms applied to the Cleveland heart disease dataset achieved an accuracy of 88.52 %. The use of hybrid (assemble) techniques was proposed to improve overall heart disease prediction results. [Pescatello et al., 2021] presented a new hybrid feature selection technique to pinpoint the most crucial characteristics. The study included a comparison of standard feature selection algorithms, including maximum relevance and minimum redundancy (mRMR), Relief, agentic algorithm, and least absolute shrinkage and selection operator (LASSO). Numerous classifiers were used. The accuracy of the random forest algorithm was 89.8 %. More accuracy can be achieved by employing hybrid feature selection techniques.

[Alim et al., 2022] performed a study related to Principal Component Analysis and Classification Techniques, tried to improve the overall performance of heart disease prediction algorithms by utilizing multiple PCA-based methods. The K Nearest neighbor and Random Forest models are applied to the datasets by the authors, who then assess the model's performance with and without PCA, to determine which strategy produces the best results. The Random Forest (RF) method combined with principal component analysis (PCA) reduction yielded a higher classification score of 91 %.

Combined reinforcement multitask progressive time-series networks

[Li et al., 2022] proposed a heart disease prediction model based on combined reinforcement multitask progressive time-series networks. Experimental findings demonstrate that the model's

Table 1. Summary of studies, methods, results, and limitations

Study	Methods	Results	Limitations
Ahmad et al. 2023	CNN+BiLSTM	94 %	Requires additional embedding techniques (e. g., Word2vec)
Joshi et al. 2023	Logistic regression, Support Vector Classifiers (SVC), K Neighbour Classifiers, Decision Tree, Random Forest, Gradient Boosting	86 %	Insufficient features can limit the model's ability to capture complex patterns
Nagavelli et al. 2022	Naïve Bayes, SVM, XGBoost	95 %	Performance may degrade with insufficient features
Patel et al., 2020	Decision Tree, SVM, ANN, Naïve Bayes, Random Forest, KNN	91 %	Hybrid models are needed to further enhance prediction accuracy
Gupta et al. 2022	K-Nearest Neighbour, Decision Tree, Logistic Regression, Naïve Bayes, SVM	92 %	Requires detailed algorithm analysis for optimized performance
Chen et al. 2022	K-Nearest Neighbour, Decision Tree, Logistic Regression, Naïve Bayes, SVM	82 %	Limited feature set impacts model accuracy
Dissanayake et al. 2021	Filter methods (ANOVA, Pearson correlation, variance thresholding), embedded methods (Lasso, Ridge, Decision Tree)	88.52 %	Combining hybrid techniques is critical for better predictive performance
Linda et al. 2021	mRMR, Relief, agentic algorithm, LASSO	89.9 %	Hybrid techniques require careful parameter tuning for improved prediction
Alim et al. 2022	K-Nearest Neighbour, Random Forest	91 %	Accuracy depends heavily on larger, high-quality datasets
Wenqi et al. 2022	Combined Reinforcement Multitask Progressive time-series networks	93 %	Complexity may limit generalization and real-world applicability

numerous tasks interact with each other to provide superior outcomes compared to other state-of-the-art approaches following deep reinforcement learning. The accuracy achieved was reported at 93 %. By exchanging parameters among models doing different tasks, the models may learn from each other and improve their performance.

Methodology

The proposed framework employs a hybrid deep learning architecture, combining the strengths of Bidirectional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Networks (CNNs), to accurately predict the onset of cardiovascular disease (CVD). The dataset, initially collected and preprocessed, undergoes balancing techniques to address potential class imbalances and feature scaling to ensure numerical stability. The trained model is evaluated using a suite of metrics, including accuracy, precision, recall, and F1-score, to assess its predictive performance. To enhance the model's interpretability and trustworthiness, Explainable AI techniques are applied, enabling a better understanding of the decision-making process and promoting transparency in the clinical application of the model.

Dataset

In this work, the "heart disease" dataset is accessed through the UCI machine learning repository. In total, four datasets are utilized in this research. Some of the data i. e., Cleveland, Hungary, Switzerland, and Long Beach V, date back to 1988. All reported tests pertain to employing a selected number of 14 of its 76 features, including the anticipated attribute. The patient's cardiovascular status is shown in the "target" column. It has two integer values: 0 indicates no illness and 1 indicates presence of the disease.

The dataset utilized in this study consists of 1025 instances, each characterized by 14 real-valued attributes. These attributes, outlined in Table 2, encompass a range of clinical and demographic factors, including age, sex, chest pain type, resting blood pressure, serum cholesterol levels, fasting blood sugar, electrocardiographic results, maximum heart rate, exercise-induced angina, ST depression, ST slope, number of major vessels, and thallium stress test results. The dataset is notably free of missing values, confirming data integrity and facilitating robust model training. To ensure model evaluation and prevent overfitting, the dataset was partitioned into training, validation, and testing sets. The training set, comprising 80 % of the data, was utilized to train the machine learning models. The remaining 20 % of the original dataset was reserved as a testing set for unbiased evaluation of the final model's performance.

Table 2. Heart disease dataset attributes

No.	Attributes (description)
1	Age
2	Sex
3	Chest pain type (4 values)
4	Resting blood pressure
5	Serum cholesterol in mg/dl
6	Fasting blood sugar > 120 mg/dl
7	Resting electrocardiographic results (values 0, 1, 2)
8	Maximum heart rate achieved
9	Exercise induced angina
10	Oldpeak = ST depression induced by exercise relative to rest
11	The slope of the peak exercise ST segment
12	Number of major vessels (0–3) colored by flourosopy
13	Thal: 0 = normal; 1 = fixed defect; 2 = reversable defect

Data preprocessing

To ensure optimal model performance, data pre-processing is a crucial step. Feature scaling, a technique that normalizes data to a common scale, is applied to the dataset. This process involves standardizing the features using the following formula:

$$c_i = \frac{x_i - \overline{x}}{\sigma},$$

where c_i is the standardized value, x_i is the original value, $\overline{x}$ is the mean, and σ is the standard deviation.

To address the class imbalance issue, where the number of instances in the majority class significantly outweighs the minority class, we employ an oversampling technique. This technique involves replicating instances from the minority class to achieve a more balanced distribution. By balancing the dataset, we mitigate the risk of the model being biased towards the majority class.

To effectively predict CVD, we propose a hybrid deep learning model that combines the strengths of Bi-LSTM and CNN architectures. This hybrid model leverages the ability of Bi-LSTM to capture long-range dependencies in sequential data and the ability of CNN to extract relevant features from the input data.

Bi-directional LSTM layer

Recently, there has been much interest in the Bi-LSTM model due to its increased ability to retain sequence information by accounting for both historical and future information, all of which are equally significant [Asghar et al., 2021]. Because traditional RNNs suffer from the vanishing gradient problem, limiting their ability to capture long-term dependencies, and LSTMs, while addressing this issue, still struggle with bidirectional context understanding, Bi-LSTMs have emerged as a powerful solution [Alghazzawi et al., 2021]. The BiLSTM network consists of both backward and forward-looking LSTM subnetworks. Using a supplied sequence of $(n_1, n_2, n_3, \ldots, n_n)$ words, the BiLSTM generates both “ahead” and “in reverse” hidden layer vector. Concatenating the left and right sequence representations $\overrightarrow{H} = \overleftarrow{H}, \overrightarrow{H}$ yields the output sequence $(H_1, H_2, H_3, \ldots, H_t)$. Then, concatendated vectors can be used in the top layer, which is responsible for making predictions for each input [Asghar et al., 2021].

The forward and backward LSTM layers are computed as follows:

Forward LSTM:

$$F_g = \sigma(N_a M_g + W_a q_{g-1} + K_a), \tag{1}$$

$$I_g = \sigma(N_b M_g + W_b q_{g-1} + K_b), \tag{2}$$

$$O_g = (N_c M_g + W_c q_{g-1} + K_c), \tag{3}$$

$$\widetilde{C}_G = (N_d W_g + W_d q_{g-1} + M_d), \tag{4}$$

$$C_g = F_g \odot C_{g-1} + I_g \odot \widetilde{C}_G, \tag{5}$$

$$H_g = O_g \odot C_g. \tag{6}$$

Backward LSTM:

$$F_g = \sigma(N_a M_g + W_a q_{g+1} + K_a), \tag{7}$$

$$I_g = \sigma(N_b M_g + W_b q_{g+1} + K_b), \tag{8}$$

$$O_g = (N_c M_g + W_c q_{g+1} + K_c), \tag{9}$$

$$\widetilde{C}_G = (N_d W_g + W_d q_{g+1} + K_d), \tag{10}$$

$$C_g = F_g \odot C_{g+1} + I_g \odot \widetilde{C}_G, \tag{11}$$

$$H_g = O_g \odot C_g. \tag{12}$$

Here, m is the size of the input value and n is the size of the cell state. M_g stands for the size of the vector. N_a, N_b, N_d, and N_d are the initial values of the weights in the input matrix. W_a, W_b, W_d, and W_d denote the matrix weights of the output gate. K_a, K_b, K_d, and K_d serve as the bias vector representations. The activation function (sigmoid) is denoted by σ.

Dropout layer

The purpose of the dropout layer is to stop the neural network from overfitting data and generalize better. The dropout parameter, or rate, covers a range from 0 to 1, and its value usually set to 0.2. A dropout layer can arbitrarily block or erase neuron activity, depending on how it is applied to the Bi-LSTM layer.

Convolutional Neural Networks (CNN)

Convolutional neural networks (CNN) models consist of three key layers: a flatten layer, which converts the output of the pooling layer into a one-dimensional feature vector; a max pooling layer, which reduces the dimensionality of the input data while retaining its most important information; and the convolutional layer, which extracts relevant features from the input through convolutional operations. These layers work together to progressively learn and represent spatial hierarchies in the data, enabling CNNs to effectively perform tasks like image classification and pattern recognition.

SHAP

One of the Explainable AI approaches, Shapley Additive Explanations (SHAP), is utilized to calculate the importance of features [Lee et al., 2023]. This method is used to calculate the SHAP value for each and every attribute in the deep learning model to understand the contribution of each feature on the target value. The conditional expected value of deep learning is utilized to calculate the SHAP value for each feature. A Shapley value from cooperative game theory allocates the total benefit that is achieved through cooperation among game contestants based on the contributions of each member. One can calculate the SHAP value using the formula below (in practical setting SHAP values are sampled to reduce computational complexity) [Lundberg, 2017]:

$$\phi_i(f) = \sum_{S \subseteq \{1, \ldots, M\} \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} [f(S \cup \{i\}) - f(S)],$$

where $\phi_i(f)$ is the SHAP value of attribute or feature i for the model f, M is the total number of features, S is a subset of features excluding feature i, $|S|$ denotes the cardinality of the subset S, $f(S)$ is the output of the model when considering only the features in S, and $f(S \cup \{i\})$ is the output of the model when including feature i in addition to the features in S.

Process for the SVD prediction model

The CVD Prediction Model follows a structured approach to classify whether a person has cardiovascular disease (CVD) based on the input features. First, the dataset is prepared by loading the CVD data in CSV format, splitting it into training and testing sets (we've used standard functions from Scikit-Learn), and converting the data into integer sequences to be used by the model. Pre-processing steps, such as normalization, are performed to ensure the data is ready for training.

Next, the model is constructed using a sequential architecture. A Bidirectional LSTM layer is added to capture both past and future sequence information, which is useful in time-series or sequential data. A Dropout layer is introduced to prevent overfitting by randomly disabling neurons during training. The Conv1D layer is applied to extract meaningful features from the input sequences, followed by a MaxPooling1D layer. The output from these layers is then flattened into a vector, which is passed through a Dense layer with a sigmoid activation function to classify the data into one of two categories: "yes" (CVD present) or "no" (CVD absent). The model then is compiled with an appropriate loss function, optimizer, and performance metrics.

Finally, the model is evaluated using the test data, and the CVD prediction is returned. This model leverages the strengths of both LSTM for sequence modeling and CNN for feature extraction, providing an efficient approach for CVD prediction. Overall representation of the process is shown in the algorithm 1 below.

Algorithm 1. CVD prediction model

```
Input: Heart Disease CVD dataset in .csv format.
Output: CVD prediction ("yes" or "no").
1. Data preparation:
   1.1. Load the CVD dataset.
   1.2. Split the dataset into training and testing sets.
   1.3. Create a vocabulary to map CVD data points to integers.
   1.4. Convert data streams to integer sequences.
   1.5. Perform data pre-processing steps.
2. Model construction:
   2.1. Initialize a Sequential model.
   2.2. Add a Bidirectional LSTM layer.
   2.3. Add a Dropout layer to prevent overfitting.
   2.4. Add a Conv1D layer.
   2.5. Add a MaxPooling1D.
   2.6. Flatten the output from the previous layers.
   2.7. Add a Dense layer with a sigmoid activation function.
   2.8. Compile the model with appropriate loss function, optimizer, and metrics.
3. Model evaluation:
   3.1. Evaluate the model using the test data.
   3.2. Return the CVD prediction: "yes" or "no".
```

Results and discussion

In this section, we present the results of experiments from a variety of studies to address the questions listed in the introduction of this article.

Research question #1: How can cardiovascular disease be predicted using the heart disease dataset with a hybrid deep learning model?

We have examined and analyzed various deep learning (DL) models before proposing a hybrid Bi-LSTM+CNN model for diagnosing CVD. This approach allowed us to effectively address the first research question. Different hyperparameters related to the layers were modified to generate the Bi-LSTM+CNN models. To identify CVD, Bi-LSTM+CNN models with varying parameter values were utilized. Several studies were conducted under different settings. Table 2 presents the various parameters that were used to develop the proposed Bi-LSTM+CNN model.

Ten alternative Bi-LSTM+CNN models were created using different parameter combinations for "filter number", "filter size", and "unit of Bi-LSTM layers" (see Table 3).

The Bi-LSTM-+CNN-10 model, outperformed all other models in terms of accuracy (99.5 % according to experiments), when there 16 #filters, 6 #filter sizes, and 64 Bi-LSTM units. A number of models, each with its own set of parameters (see Table 4).

Accuracy, recall, precision, F-score were determined using the standard formulae. Among the many Bi-LSTM+CNN models compared in Table 4 for accuracy, recall, precision, and F1 score,

Table 3. Various parameters of Bi-LSTM+CNN model

Parameters	Values	Parameters	Values
Input size	1025	The number of filters	6, 9, 16, 4, 8
Input features	13	Filter size	2, 3, 4, 6
Input dimension	9 to 64	Dropout	0.3
Bi-LSTM unit size	64, 9, 16, 24, 40, 32	Activation function	Sigmoid
Number of CNN layers	1	No. of epochs	40, 20, 120, 150
Number of hidden layers	3	Batch size	32, 64

Table 4. 10 different Bi-LSTM+CNN models parameters

Model	No. of filters	BiLSTM unit size	No. of filter size
Bi-LSTM+CNN-1	8	16	2
Bi-LSTM+CNN-2	8	64	2
Bi-LSTM+CNN-3	6	64	2
Bi-LSTM+CNN-4	16	16	4
Bi-LSTM+CNN-5	6	9	2
Bi-LSTM+CNN-6	4	32	4
Bi-LSTM+CNN-7	9	16	4
Bi-LSTM+CNN-8	9	24	3
Bi-LSTM+CNN-9	9	24	4
Bi-LSTM+CNN-10	16	64	6

Table 5. Accuracy, Re-Call, Precision, and F1-score from 10 different Bi-LSTM+CNN models

Model	Accuracy	Precision	Recall	F1-score
Bi-LSTM+CNN-1	0.781	0.78	0.78	0.78
Bi-LSTM+CNN-2	0.838	0.84	0.84	0.84
Bi-LSTM+CNN-3	0.838	0.84	0.84	0.84
Bi-LSTM+CNN-4	0.857	0.86	0.86	0.86
Bi-LSTM+CNN-5	0.857	0.86	0.85	0.86
Bi-LSTM+CNN-6	0.867	0.87	0.86	0.87
Bi-LSTM+CNN-7	0.909	0.91	0.91	0.91
Bi-LSTM+CNN-8	0.933	0.93	0.93	0.93
Bi-LSTM+CNN-9	0.957	0.96	0.96	0.96
Bi-LSTM+CNN-10	0.9905	0.99	0.99	0.99

the "Bi-LSTM+CNN-10" model achieved the best results with 99.5 % accuracy, 99 % precision, 99 % F-score.

To examine the effectiveness of our proposed model, the accuracy versus epochs and Loss versus epochs plots is illustrated in Fig. 1, respectively. The plot accuracy versus epochs shows the capability of the model to correctly classify over a training set and provide information about model convergence, and the ability for overfitting or underfitting. Also, loss versus epochs plot gives insight into model's optimization and model's capability to reduce mistakes in prediction.

To enhance the interpretability of the proposed model, we employed Shapley Additive Explanations (SHAP). SHAP provides a powerful framework for understanding the impact of individual features on model predictions. By calculating the average marginal contribution of each feature to the model's output, SHAP enables identification of most influential factors driving the prediction. This information allows us to gain insights into the underlying mechanisms of the model. Moreover, SHAP also allows us to visualize feature importance both globally and locally, providing a comprehensive understanding of the model's behavior.

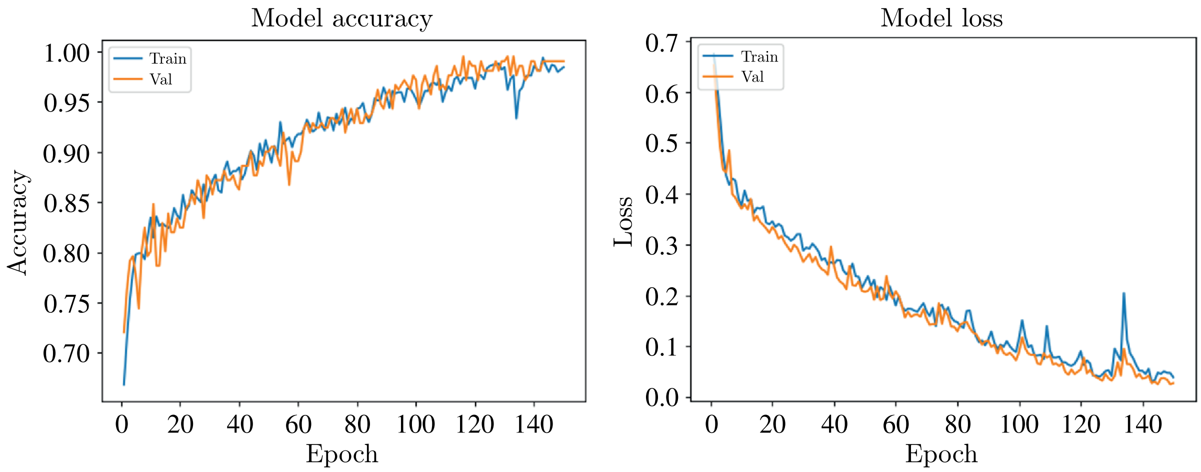

Figure 1. Proposed model accuracy and loss vs epoch plot

As shown in Fig. 2, slop = 2, thal = 3, and oldpeak = 0 are the most important feature values influencing the opinion of model that the patient has a heart problem. The feature values influencing the decision of the model that the patient does not have a heart problem are ca = 1. This is possibly the most important factor, as it shows that the patient has no blocked vessels.

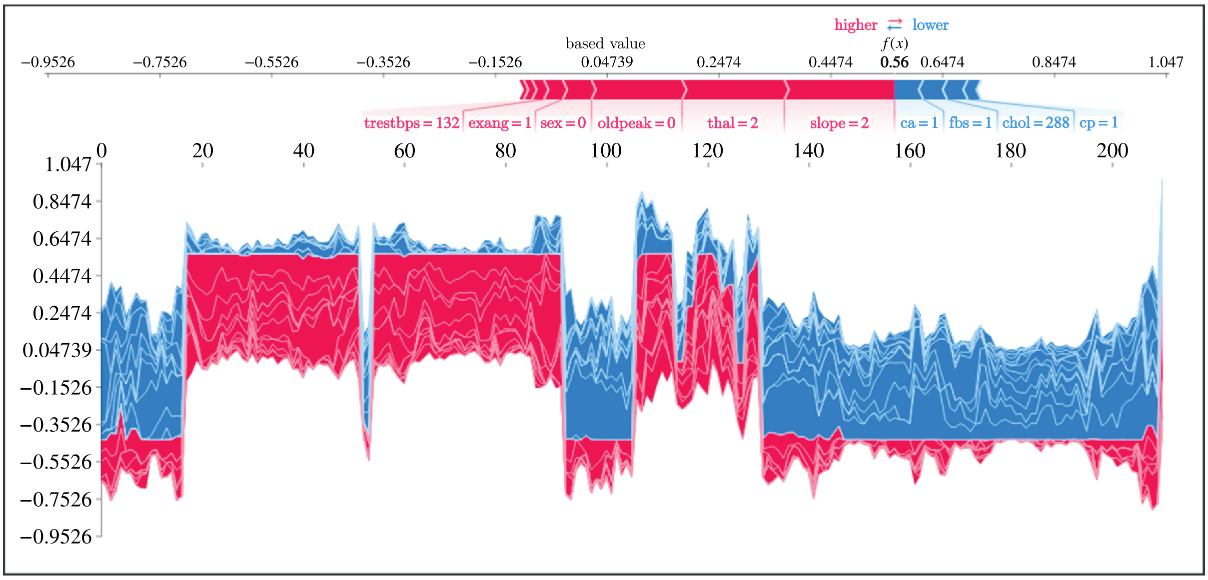

Figure 2. SHAP plot generated Local (top) and Global (bottom) explanation of signal instance

Global predictions made by the model can be seen in Fig. 2. Using the SHAP Values, the base value was determined to be −0.1526. Accordingly, the patient is considered to be suffering from the disease if the total value is greater than −0.1526, and not to have the disease if it is lower than −0.15266. The red portion of the graph causes the prediction to rise, while the blue portion pushes it downward. Accordingly, the cases where a person has a lot more red-colored features are typically 1 means they have a disease and vice versa. At diverse values the impact of attributes on the prediction is visualized by using a summary plot graph as shown in Fig. 3. The attributes or features that add more value to the model than the bottom values are on top. The value of attributes is visualized by colour such that blue indicates low, purple indicates medium and red indicates high.

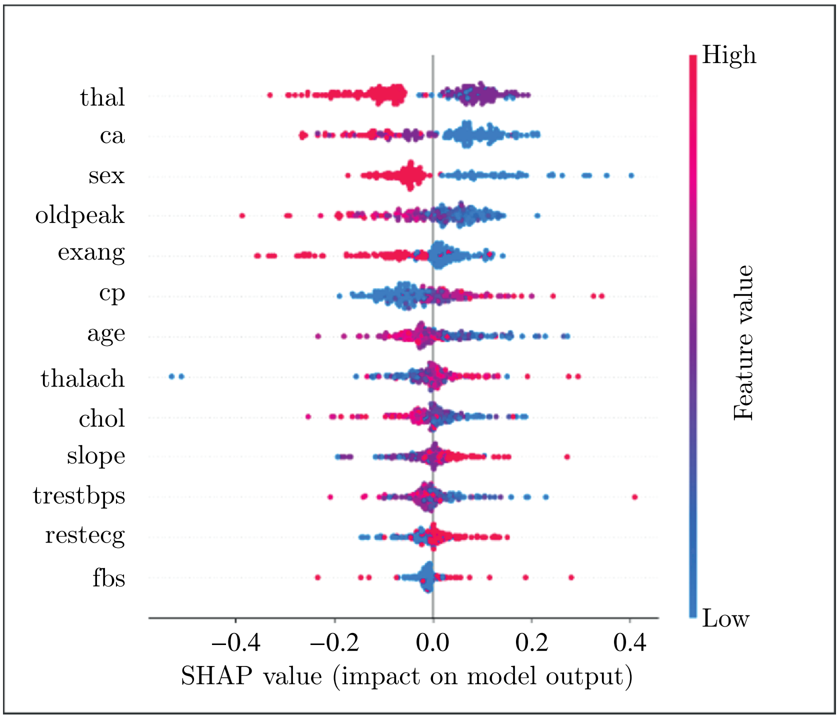

Figure 3. Summary plot using SHAP explanation

Research question #2: To what extent can deep learning models can demonstrate efficacy in predicting CVD in comparison to other traditional ML classifiers and benchmarks studies? In order to answer the second study question, the effectiveness of the developed Bi-LSTM+CNN model for CVD prediction was compared to that of various traditional ML classification algorithms and deep learning classifiers.

Proposed Bi-LSTM-CNN model vs. Machine Learning models

Using patient data, we have compared the recommended hybrid DL model to typical machine learning approaches. The F1 score, together with precision, accuracy, and recall, was used to evaluate their performance. With an accuracy rate of more than 87 %, SVM was the most effective of the machine learning models tested. The outcomes of the suggested model and conventional machine learning classifiers are summarized in the Table 6.

Table 6. Traditional ML models Vs Suggested model (Bi-LSTM+CNN)

ML model	Accuracy	Precision	Recall	F1-score
SVM	0.87	0.87	0.87	0.87
NB	0.79	0.80	0.79	0.79
K-NN	0.81	0.82	0.82	0.82
DT	0.81	0.82	0.82	0.82
RF	0.82	0.83	0.83	0.83
Proposed (BiLSTM+CNN)	0.9905	0.99	0.99	0.99

Proposed model (Bi-LSTM+CNN) vs. Deep Learning

In order to effectively detect CVD based on patient information, our suggested DL model is compared to existing deep learning approaches comprising Bi-LSTM, RNN, CNN, and LSTM. The F1 score, recall, accuracy, precision, and other measures are used to assess their performance. Table 7 summarizes the outcomes of all investigated models.

Table 7. DL models Vs Bi-LSTM+CNN model (proposed)

Name of model	Accuracy	Precision	Recall	F1-score
Bi-LSTM	0.83	0.83	0.83	0.83
CNN	0.83	0.84	0.84	0.84
RNN	0.87	0.87	0.87	0.87
LSTM	0.85	0.85	0.85	0.85
Proposed (Bi-LSTM+CNN)	0.9905	0.99	0.99	0.99

The aforementioned comparative studies indicate that with respect to accuracy, f1score recall, and precision, the recommended Bi-LSTM+CNN deep learning model outperforms along with other DL models like RNN, LSTM, CNN, and BILSTM. Reliability in classification is enhanced by combining feature selection techniques with two different DL algorithms.

Baseline research and the suggested model for CVD prediction evaluation

In order to evaluate performance of our model, we compare the proposed DL method to the precision of the baseline research. By comparing the proposed Bi-LSTM+CNN deep learning algorithm to the methods from existing literature, we were able to determine its effectiveness. We compare the proposed model using several benchmarking approaches to see how well it works. By comparing it with benchmark studies, it shows how our suggested BILSTM+CNN model outperforms it (see below). However, there are a number of reasons why it could be difficult to conduct an in-depth analysis of published procedures and provide a comprehensive comparison. Due to utilization of distinct datasets, and pre-processing procedures it can be challenging to compare various methods. For example, [Ahmad et al., 2023] use hybrid deep learning to detect CVD. CNN+Bi-LSTM analysis was performed on the dataset related to heart illness. Among the models, the CNN+Bi-LSTM model demonstrates great accuracy (94 %) and efficacy. Another study [24] employed three distinct models in their work on the diagnosis of cardiac disease; of these three approaches, neural networks performed best, with an accuracy of 93 %.

The work proposed (our model) — a hybrid network, the Bi-LSTM+CNN along with Explainable AI, is used by the suggested method to classify the CVD. Table 7 compares the performance of the developed Bi-LSTM+CNN model with similar techniques established for CVD diagnosis. Balanced data, feature scaling, hypermeter tuning, and the Bi-LSTM+CNN model have all been linked to our performance in detecting CVD. By utilising the Bi-LSTM layer, historical context may be kept. The classification of CVD was done using the hybrid model of Bi-LSTM+CNN.

Table 8. Comparison of techniques for CVD diagnosis

Study	Techniques	Accuracy
Ahmad et al., 2023	Diagnosing CVD with Deep learning	0.94
Salhi et al., 2021	Diagnosing CVD with Machine Learning and Neural Network	0.93
Proposed approach (BiLSTM-CNN)	CVD diagnosis using a hybrid deep learning model (Bi-LSTM+CNN)	0.99

Conclusions

The amount of healthcare data has increased dramatically, making it more important than ever to gather and examine this information in order to timely identify people who have CVD. In this work, we provide an innovative model for CVD detection. The study used a hybrid model, namely, BiLSTM+CNN, to accurately detect and categorize cardiovascular disease (CVD) using the available dataset, data processing techniques, and classification methods. In addition, we also augmented the classification with Explainable AI (SHAP) technique to better understand the predictions made by the model. We used the cardiac disease dataset to evaluate and train the suggested model. To diagnose CVD, a hybrid Bi-LSTM+CNN model was used. According to the examination of the Bi-LSTM+CNN model, the recommended model performs better than the presently employed conventional machine learning approaches in terms of accuracy, precision, recall, and F1-score. The evaluation of our model demonstrated that the recommended approach produces the most optimal outcomes with regard to recall, precision, F-score, and accuracy in contrast to other well-known classical ML systems that are already in use. The research yielded superior accuracy of 99.05 %, precision of 99 %, recall of 99 %, and F1-score of 99 % in comparison to the baseline studies. These results are optimistic.

Here, we also need to outline limitations: First, the analysis was conducted using only a single dataset, which may limit the generalizability of the results. Additionally, a Bi-LSTM layer was used in place of pre-trained embeddings, potentially impacting the model's efficiency and effectiveness. Furthermore, the experiments focused exclusively on the Bi-LSTM+CNN deep learning model without exploring other possible combinations of deep learning architectures.

In future work, we plan to incorporate additional datasets to evaluate the performance and robustness of the proposed model more comprehensively. Employing diverse feature selection methods could further enhance the model's predictive accuracy. Additionally, integrating pre-trained algorithms such as Word2Vec, GloVe, or fastText in lieu of the BiLSTM layer could improve model efficiency. We also aim to explore and develop additional hybrid deep learning models to advance the field. Finally, expanding the analysis to include patient data from diverse regions may provide deeper insights into cardiovascular disease (CVD) and its prediction.

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