

An Integrated IoT-Enabled Wearable and Machine Learning Approach for Continuous Cardiovascular Disease Risk Monitoring

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ABSTRACT

This study aimed to develop an Internet of Things (IoT)-enabled wearable healthcare framework for continuous physiological monitoring and cardiovascular disease (CVD) risk classification. CVD is a major global public health problem, and continuous monitoring of physiological parameters may support timely identification of individuals requiring further clinical assessment. Wearable IoT devices can facilitate the collection and transmission of physiological data, while machine learning methods can assist in identifying patterns associated with cardiovascular risk. The proposed framework integrates wearable sensor data, secure data transmission, patient medical records, data preprocessing, and a Bidirectional Long Short-Term Memory (Bi-LSTM) model for CVD classification. The study used 294 records from a dataset described by the authors as an Indian CVD database. Preprocessing included missing-value treatment, removal of redundant or irrelevant features, and feature standardization. The classification performance was evaluated using accuracy, precision, sensitivity/recall, specificity, and F-score. The proposed Bi-LSTM framework obtained an accuracy of 92.6%, precision of 94.1%, sensitivity of 93.7%, specificity of 91.5%, and F-score of 94.7% based on the performance values reported in the manuscript. These values should be checked against the original experimental data, confusion matrix and final evaluation data before publication as other performance values are reported elsewhere in the manuscript. The proposed framework shows the feasibility of using wearable IoT technologies and Bi-LSTM machine learning for CVD risk classification. The results are, however, based on a relatively small data set and are not prospective clinical validation of continuously collected real-world wearable data. Additional validation with independent, larger, and prospectively collected datasets is needed before clinical use.

KEYWORDS: Internet of Things (IoT), wearable devices, cardiovascular disease (CVD), machine learning (ML), bidirectional long short-term memory (LSTM).

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INTRODUCTION

Cardiovascular diseases (CVDs) are the top cause of death worldwide and are a group of conditions that affect the heart and blood vessels, such as coronary heart disease, cerebrovascular disease, and rheumatic heart disease. The World Health Organization (WHO) estimated that 19.8 million people died from CVDs in 2022, accounting for approximately 32% of all global deaths; heart attacks and strokes were responsible for about 85% of these CVD deaths (World Health Organization [WHO], 2025).

The majority of CVDs are preventable or can be reduced by tackling modifiable behavioural and environmental risk factors such as tobacco use, physical inactivity, unhealthy diet, harmful alcohol use, obesity and air pollution (WHO, 2025). Therefore, early identification and management of cardiovascular risk factors are important to support appropriate clinical assessment and preventive management.

Prevention of acute cardiovascular events like myocardial infarction and stroke is still important and includes identification and management of modifiable risk factors before they occur. A heart attack can cause pain or discomfort in the centre of the chest or in the arms, shoulders, jaw or back, along with symptoms like shortness of breath, nausea or vomiting, light-headedness or cold sweating. The signs and symptoms of stroke can include sudden weakness or numbness in the face, arm, or leg, especially on one side of the body, speech problems, vision or coordination problems, or balance problems (WHO, 2025). These events can have a significant impact on morbidity, mortality and quality of life and highlight the need for prompt risk assessment, recognition and clinical management.

The development of technology in the medical field has provided the opportunity for continuous monitoring and remote evaluation of physiological parameters. Specifically, wearable devices with IoT capabilities can gather physiological data and send these data to computational platforms for further analysis. These systems can enable remote monitoring and deliver data that can help healthcare

providers identify those who need more clinical evaluation.

The use of IoT for monitoring health parameters has been a growing area of research for healthcare and well-being applications (Kulkarni & Inamdar, 2025). Physiological data can be collected in real time using wearable sensors, and cloud-based and computational technologies can enable storage, processing, and analysis of these data. These capabilities can be used for continuous monitoring and decision support applications.

Mobile health technologies can also be used to gather, transmit, and process patient data for remote healthcare applications (Wu et al., 2020). The use of machine learning techniques has been increasingly explored for disease classification, risk prediction, and clinical decision support. The validity and applicability of machine learning models, however, rely on the quality, representativeness, size, and validation of the clinical data used.

Thus, the purpose of this study was to design an IoT-based wearable healthcare system to gather physiological data and combine these data with patient medical records for the classification of cardiovascular diseases. The proposed framework combines secure data transmission, cloud-based processing, data preprocessing, and a Bi-LSTM model. The main goal was to explore if the proposed framework could categorize people based on the pre-defined CVD outcome and provide alerts that could aid in the clinical evaluation. The present study does not demonstrate the ability of the system to diagnose myocardial infarction, stroke, or cardiac arrest on its own; this would require prospective clinical validation and clinical assessment.

RELATED STUDIES

The use of machine learning and deep learning techniques has been a growing focus in the field of cardiovascular disease (CVD) risk assessment and classification. Islam et al. (2024) summarized machine learning methods for predicting chronic diseases and explored the use of various classification and feature selection methods. Their review shows the wide range of

applications of machine learning in disease prediction, but also emphasizes the need for proper datasets and evaluation methods.

Khiabani et al. (2022) proposed a decision support system for the diagnosis of heart failure based on neural networks and statistical techniques. Similarly, Honi and Szathmary (2024) investigated a one-dimensional convolutional neural network-based deep learning approach for cardiovascular disease prediction. The studies show the potential of machine learning and deep learning models for cardiovascular classification, but the reported performance values are difficult to compare directly due to differences in the datasets, target variables, preprocessing methods, and evaluation procedures.

Casalino et al. (2020) explored a hierarchical fuzzy system for cardiovascular disease risk assessment, which demonstrates the use of rule-based methods in cardiovascular risk assessment. Nayak et al. (2020) reviewed applications of the Firefly Algorithm in biomedical and healthcare problems, demonstrating the potential of nature-inspired optimization techniques in computational healthcare. A general review of the Firefly Algorithm should not be taken as evidence for a specific CVD diagnostic accuracy without the specific experiment being reported in the cited source.

Nagarajan and Thirunavukarasu (2022) introduced a neuro-fuzzy healthcare framework for disease analysis and prediction, and Dileep et al. (2023) explored a cluster-based bidirectional LSTM method for automatic heart disease prediction. These studies indicate the increasing use of hybrid and recurrent neural-network approaches for cardiovascular prediction.

Ramesh and Lakshmanan (2024) suggested a deep learning and neural fuzzy inference based framework for detection and prevention of coronary heart disease. Sadr et al. (2024) explored the application of machine learning and deep learning models in the diagnosis of cardiovascular diseases. Patra et al. (2023) explored the coronary heart disease risk prediction using a hybrid ensemble approach

with forward feature selection. All these studies show the use of feature selection, ensemble learning, neural networks, and deep learning in cardiovascular prediction tasks.

Mary et al. (2023) investigated ECG signal classification in an IoT environment using an adaptive deep neural network. Their study shows the feasibility of remote cardiac monitoring using IoT-enabled ECG analysis. In the present study, this general concept is extended by incorporating wearable physiological information, cloud-based processing, and classification of CVD using Bi-LSTM.

Tan et al. (2025) explored the use of optimized feature selection and deep neural networks for heart disease prediction. Their work further demonstrates the potential of feature-selection strategies and deep learning for cardiovascular classification.

Upadhyay et al. (2023) discussed the problems of smart healthcare systems that rely on IoT, such as resource management, interconnection, and computational needs. These are important factors to consider when implementing wearable healthcare systems, as ongoing sensing and data transmission can generate computational, communication, and security demands.

The effectiveness of using dimensionality reduction in combination with classification algorithms in computational healthcare has also been shown in research on feature selection and ensemble learning. For instance, Jaw and Wang (2021) studied feature selection and ensemble learning in the context of intrusion detection. This work is not a CVD study, but it is an example of the use of feature-selection and ensemble-learning techniques in data-intensive computational systems. Similarly, Singh and Malhotra (2021) investigated cloud-based ensemble learning for epileptic seizure detection using EEG signals. The study should be interpreted as evidence for the wider use of cloud-based machine learning in healthcare, not as evidence for the prediction of CVD.

Baghdadi et al. (2023) explored the use of multiple machine learning and feature-selection methods to investigate advanced machine

learning techniques for cardiovascular disease early detection and diagnosis. They show how to use cross-validation and multiple performance measures in cardiovascular classification.

Surekha et al. (2024) demonstrated the application of computational and mathematical modelling approaches to physiological processes, highlighting the potential of computational methods for analysing complex biological and biomedical systems. This supports the use of computational and machine-learning approaches for physiological data analysis in healthcare applications.

Rajeswari et al. (2024) reviewed machine-learning approaches for the detection and classification of diabetic retinopathy and highlighted the use of classification algorithms and performance measures for evaluating automated disease-detection models. These findings further support the application of machine-learning techniques for automated disease classification and risk assessment.

In general, the previous studies show that machine learning, deep learning, fuzzy systems, ensemble learning, and IoT technologies can be used for cardiovascular risk assessment. But more studies are needed to determine the generalizability of such models with large enough data sets, independent validation, prospectively collected wearable data, and proper evaluation methods.

MATERIALS AND METHODS

Proposed IoT-Enabled Monitoring Framework

CVD is the primary cause of mortality globally. Forecasting a heart attack is a very complex endeavor. It can be accomplished only if the physician is highly skilled and has extensive information about the ailment. The efficacy of the remote health monitoring system for patients requiring long-term care has significantly improved due to the advancement of the IoT and its medical applications. The core technology of wearable IoT in the healthcare sector is the Wireless Body Sensor Networks (WBSN). It employs a collection of low-power, lightweight WBSN nodes designed for monitoring a patient. This technology neglects security, hence jeopardizing the privacy of

patients. The current implementations for the HC sector offer inadequate security.

A framework is provided to overcome this limitation; thus, data are exchanged more securely over WBSN, and patient health data is forecasted more accurately. The suggested project consists of three phases: i) Authentication, ii) Data encryption, and iii) Classification. The authentication process has three steps: a) registration, b) login, and c) verification. Upon enrolling their information on the hospital website or application, the patient will log in using their unique login information and password. The enrolled patient information is stored on the cloud servers and the hospital registry. Upon patient registration, a cipher-based hashing code is generated with a Secure Code (SC) and the SHA-512 algorithm, which is used for patient confirmation. During the verification process, the server verifies the patient's authentication with the code generated at enrollment. If they treat the right person, the patient will be granted access. When signing up, the patient submits their prior and current medical records. The Modified Huffman Approach (MHA) compresses these findings to efficiently and effectively store them on the Cloud Server (CS) for later use. The WBSN collects and transmits all data to the cloud via a special console. The method encrypts the sensor data from the device and transfers it to the cloud. The medical facility's CS simultaneously acquires and decodes the encrypted sensor data. The Bi-LSTM algorithm initiates categorizing data acquired from sensors to predict CVD.

The system undergoes training and testing to execute categorization. The Indian CVD database is used as a source to visualize the sickness. During the training phase, preprocessing and the pre-processed data are categorized. Post-training, the sensor data at the CS is evaluated and classified as a) CVD-positive or b) CVD-negative. In cases of an CVD-negative result, an alarm is sent to the physician to attend to the individual in question. The planned work primarily focuses on authentication, enhanced security, and supervision. The overall workflow of the proposed IoT-enabled CVD monitoring and classification framework is shown in Figure 1.

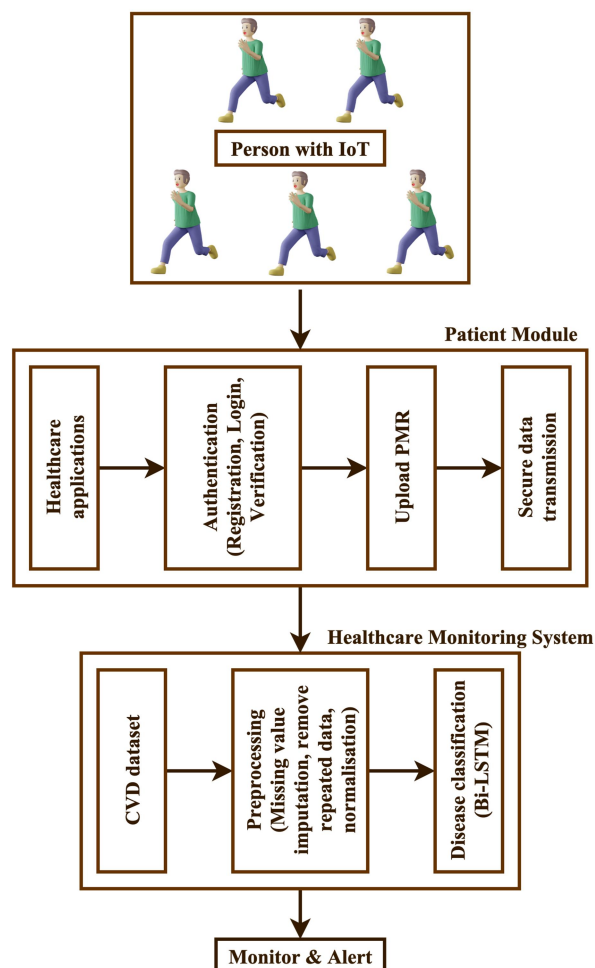


Figure 1: Workflow of the proposed system

Wearable Sensor Data Acquisition

This is the first step of the planned procedure in which the sensor device is affixed to the patient's body. The wearable IoT gadget will detect the patient's bodily parameters using the sensor and transfer the data to the software.

Authentication

Authentication is used to restrict access to authorized users. The proposed framework consists of registration, login, and verification stages. During registration, the patient's credentials are recorded by the system and a cryptographic hash is generated for authentication purposes. During login, the supplied credentials are processed using the same predefined authentication procedure and compared with the stored authentication value. The authors should specify the exact password-

hashing or key-derivation mechanism used in the implementation, including the use of a unique salt, because SHA-512 alone should not be described as a password-hashing mechanism. The manuscript should also distinguish clearly between hashing, encryption, and key generation.

The credential often manifests as a secret password known only to the user and the system. The suggested approach employs a ciphertext-centered hashing algorithm to maintain high-security authentication. This phase consists of three steps: (i) registering, (ii) logging in, and (iii) confirming.

Enrollment

The patient inputs their data into the application or website during this step. The server employs an SC to consolidate the login and password of

the enrolled patient. A substitution cipher is an encryption method in cybersecurity where units of plaintext are exchanged with ciphertext according to a predetermined scheme. The "units" consist of single letters, pairs of letters, triplets of letters, or combinations thereof. The recipient decodes the text by performing the inverse replacement. The encrypted value of the substitution ciphertext is determined using the SHA-512 method.

Access

Login is the process used to access a program, usually on a distant computer. It is the procedure by which a person obtains access to an electronic device via identification and authentication. Each system login step requires the specified user's login name and password. Customer authentication is verified during the login process.

Confirmation

The system ascertains if the user has been authorized. The manager of the software checks users via the analysis of user data. During this step, the input username is concatenated with the passphrase, and the security code is used. Next, this ciphertext is transformed using SHA-512 into a hashing code, which is then compared to the stored hash code result. User access to system resources is permitted if the hashing values are identical. Otherwise, the individual is designated as unauthorized, and their permission is revoked.

Patient Health-Data Submission

This is the third step, during which the patient transfers their prior and current health information, including X-rays, prescription information, Magnetic Resonance Imaging (MRI) scan reports, and other relevant documents, to the healthcare software. The Patient's Medical Records (PMR) include an extensive array of information of varying quantities. The PMR will be compressed, prior to transmission to the website, to minimize file dimension, and then it will be stored in a CS with the reduced PMR.

3.5 Secure Data Transmission

The individual's sensed information is encrypted using the Patient ID, Physician ID,

and Medical Facility ID using the Advanced Encryption Standard (AES) method. The hospital CS creates a 128-bit key in the suggested approach. Combining the three identifiers—Patient ID, Doctor ID, and Hospital ID—yields this 128-bit key. If the key is generated based on this concept, then each patient has a unique key. The detected values are encoded using AES with a 128-bit key.

CVD Risk Classification

After secure transmission, the sensor-derived information is processed at the cloud server and provided to the trained Bi-LSTM model. The model classifies the input according to the predefined CVD outcome used in the dataset. The classification results are categorized according to the study's defined classes, such as CVD-positive and CVD-negative, rather than being interpreted directly as a diagnosis of myocardial infarction, stroke, or cardiac arrest. If an input is classified as high risk or abnormal according to the predefined threshold, the system can generate an alert for subsequent review by an authorized healthcare professional. The alert should be considered a decision-support mechanism and not an independent clinical diagnosis.

Data Source and Dataset

The study used a cardiovascular disease dataset described by the authors as an Indian CVD database. A total of 294 records were reportedly used for model development and evaluation. Before publication, the authors must provide the exact name and source of the dataset, repository or database URL/DOI, data-collection details, number of CVD and non-CVD cases, definition of the outcome variable, feature descriptions, and any applicable data-use or ethical permissions. The relationship between this dataset and the physiological measurements obtained from the proposed wearable IoT system must also be clearly explained. If the model was trained exclusively on a secondary dataset rather than real-time wearable measurements, this distinction must be stated explicitly.

Data Preprocessing

The preprocessing procedure consisted of three stages: missing-value treatment, removal of

redundant or irrelevant features, and feature standardization. The manuscript reports 1,300 missing values represented by zero; however, the authors must clarify whether zero is a valid physiological value for each affected variable or whether it was used exclusively as a missing-value code. For categorical variables, mode imputation may be appropriate, whereas numerical variables should be imputed using a method justified by the distribution and clinical characteristics of the variable. The authors should also report whether preprocessing parameters were estimated exclusively from the training data to prevent information leakage into the testing set. After missing-value treatment, redundant or irrelevant features were removed according to predefined criteria, and the remaining numerical features were standardized before model training.

Bi-LSTM Model

The preprocessed dataset was divided into training and testing subsets before model development. The manuscript must report the exact proportion or number of records assigned to each subset and explain whether a separate validation set or cross-validation procedure was used. The Bi-LSTM model configuration should include the number of recurrent layers, number of hidden units, activation functions, optimizer, learning rate, batch size, number of training epochs, dropout rate, loss function, and stopping criteria. The authors should also specify the software framework and version used for model development. Performance should be evaluated using accuracy, precision, sensitivity/recall, specificity, and F-score, with the corresponding definitions and, preferably, confidence intervals.

Classification of Diseases

This is the ultimate and significant phase. The Bi-LSTM categorizes the preprocessed information. The limitation of the LSTM cell is that it can influence past information but not future data. Bidirectional networks were proposed, including two separate LSTM concealed layers with analogous outputs in

opposite directions. This technique utilizes both prior and subsequent data at the output level. In Bi-LSTM, an input series $P = \{P_1, P_2, \dots, P_n\}$ is processed in the forward path, resulting in a pattern $d_t = \{d_1, d_2, \dots, d_n\}$. The ultimate result of this cell, q_t , is generated by both d_i and d_t , resulting in the outcome series $q = \{q_1, q_2, \dots, q_n\}$.

The selected activation function in complex networks significantly impacts training behavior and task completion. The Google Brain Team suggested the activation function Swish, defined as $f(i) = i \cdot \text{sigmoid}(\beta i)$, for the forecasting system. To rectify the cell dispersion problem in the generic framework, a tanh-activated function is incorporated into cell transmission, and a rectified linear unit (ReLU) is applied after output gates.

$$f_t = \text{swish}\{W_f p_t + W_{hf} d_{t-1} + b_f\} \quad (1)$$

$$i_t = \text{swish}\{W_i p_t + W_{hi} d_{t-1} + b_i\} \quad (2)$$

$$o_t = \text{swish}\{W_o p_t + W_{ho} d_{t-1} + b_o\} \quad (3)$$

$$\hat{c}_t = \tanh\{W_c p_t + W_{hc} d_{t-1} + b_c\} \quad (4)$$

$$c_t = f_t c_{t-1} + i_t \hat{c}_t + \tan d \quad (5)$$

$$d_t = o_t c_t \quad (6)$$

$$q_t = o_t c_t \text{ReLU} \quad (7)$$

In this situation, f, i, o , and c denote the gates of forget, inputting, outputting, and activated cell vectors about $W(f, i, o, c)$ and $b(f, i, o, c)$ noted for their weight matrix and bias vectors correspondingly, while d indicates the hidden value. The input p_t denotes the storage cell moments and act as input $\hat{c}_t$ to describe the present and prior memory cell levels and outcome. The architecture of the proposed Bi-LSTM model is illustrated in Figure 2, while the basic LSTM structure is presented in Figure 3.

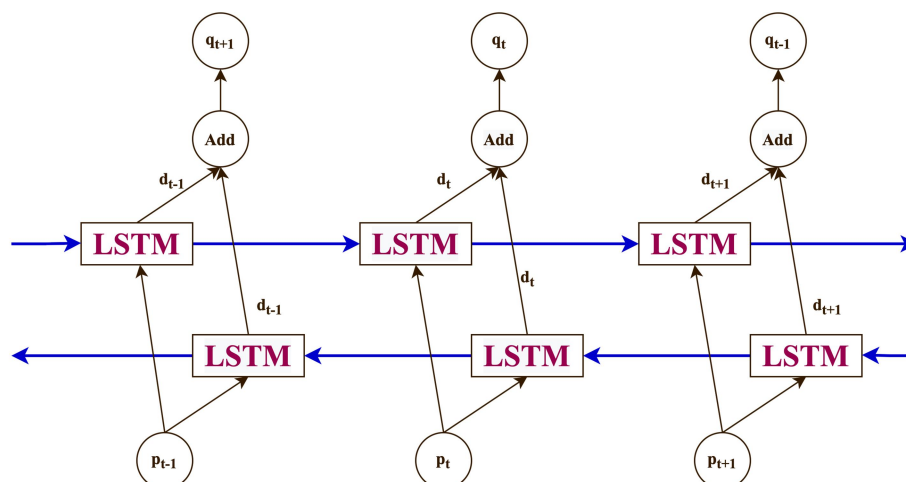


Figure 2: Architecture of the proposed Bidirectional Long Short-Term Memory (Bi-LSTM) model

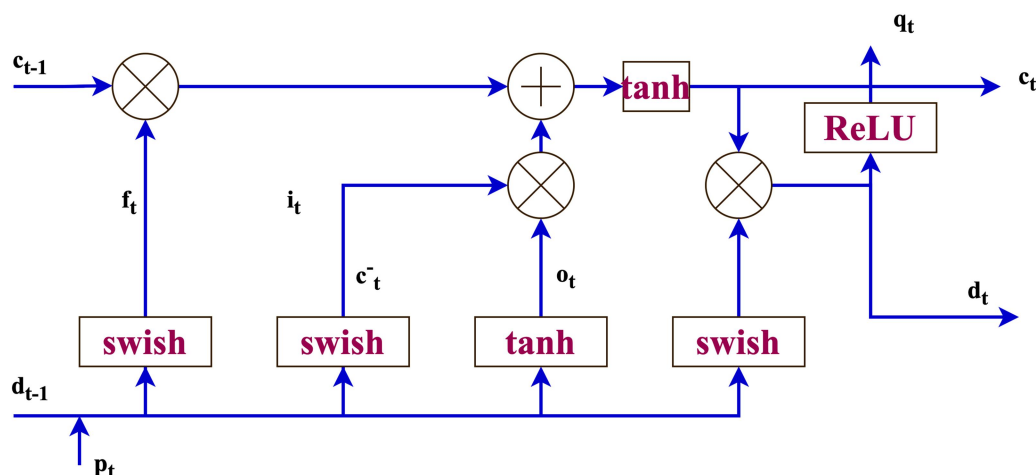


Figure 3: Basic Long Short-Term Memory (LSTM) architecture.

Model Training and Evaluation

The preprocessed dataset was divided into training and testing subsets before model development. The exact number or proportion of records assigned to each subset should be reported. The authors should state whether a separate validation set, k-fold cross-validation, nested cross-validation, or another validation procedure was used.

Model performance was evaluated using accuracy, precision, sensitivity/recall, specificity, and F-score. The equations for these metrics should be provided, and the corresponding confusion matrix should be reported. Confidence intervals should preferably be included to quantify uncertainty around the performance estimates. The software framework, version, hardware environment,

random seed, and relevant implementation details should also be reported to facilitate reproducibility.

RESULTS AND DISCUSSION

CVD has emerged as a significant health issue requiring prompt medical intervention, particularly among the senior population. An advanced healthcare tracking system has been created, featuring capabilities for CVDs and collaborative learning. Predicting CVD during remote medical surveillance involves interconnected methods. The process begins with the continuous collection of data from patients through wearable IoT devices, including smartwatch technology and remote health monitoring. This information include vitals, level of activity, and ECG data. These data streams are transferred securely through a

cloud-based platform and then processed to maintain the safety and privacy of the data. The Bi-LSTM detects patterns in the data stream while Boost selects features and classifies them earlier. These predictive models are designed to improve the predictive capabilities relevant to prior patient data. Post-training, they categorize patients instantaneously, recognizing those at risk and initiating prompt intervention during critical situations. This CS-based technology

facilitates collaboration and continuous care by allowing medical professionals to monitor patient information remotely. This comprehensive method incorporates state-of-the-art ML, wearable IoT, and CS-based tools to advance the forecasting of CVD. This allows for early identification and preventive health care treatment, thus significantly improving the patient's at-home surveillance process.

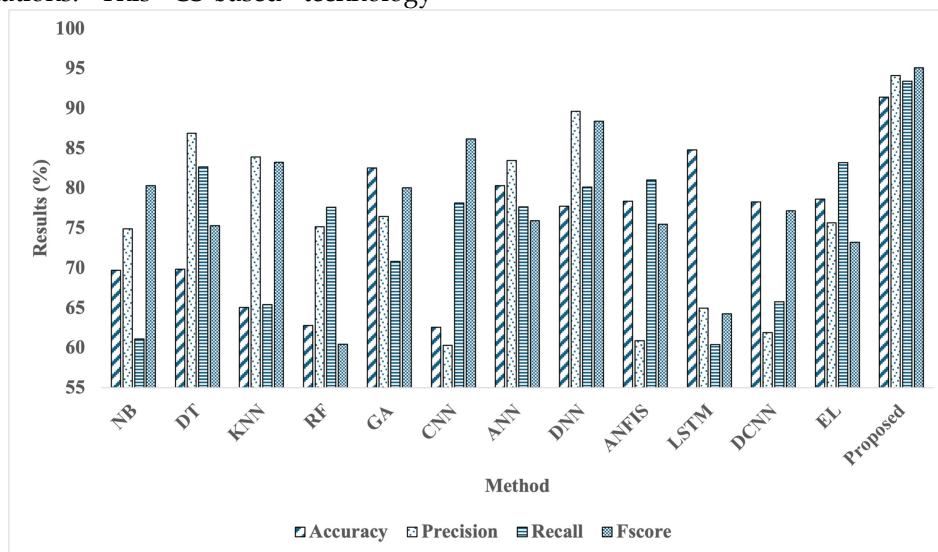


Figure 4: Performance analysis and comparison

Figure 4 presents the comparative performance of the evaluated classification models, including Naive Bayes (NB), Decision Tree (DT), K-Nearest Neighbors (KNN), Random Forest (RF), Genetic Algorithm (GA)-based classification, and the proposed Bi-LSTM model. The evaluation metrics include accuracy, precision, recall/sensitivity, specificity, and F-score, where applicable. All values shown in Figure 4 must correspond exactly to the numerical values reported in the accompanying text and should be calculated using the same testing dataset.

The Bi-LSTM Modeling is proposed as a strong technique for accurate and trustworthy CVD prediction in remote medical monitoring scenarios. It has the highest accuracy (92.5%) of all techniques presented, along with high precision (96.7%), recall (93.7%), and F Score (92.9%). The wearable IoT-Enabled CS-Based Bi-LSTM model, illustrated in conjunction with NB, DT, KNN, RF, and GA, is presented along with the accuracy, precision, recall, and F-Score

measures. NB achieved an F-score of 76.2%, with reasonable accuracy (72.5%), reasonable precision (80%), and a moderate recall (81%). In comparison, the DT attains an impressive F-Score of 73.8%, with an accuracy increase of 81.8%, a much higher precision of 80.1%, and an exceptional recall of 90%. With an accuracy rate of 80.4%, the KNN achieves a precision of 76.6% and a recall rate of 82.1%, culminating in a robust F-Score of 83.1%. The proposed IoT-enabled CS-based Bi-LSTM model shows excellent performance, with a high accuracy rate of 92.6%, a precision score of 93.8%, a recall score of 95.1%, and an exemplary F-score of 94.1%. The result shows that the proposed model is better than the other methods, suggesting a plausibly high potential for the current classification problem.

The proposed Bi-LSTM algorithm outperforms traditional models on the metrics listed, and represents a real improvement in forecasting for CVD. The model's accuracy of 93.5% far exceeds

previously suggested methods, a strong indicator that the model can accurately predict a heart disease status. The model's ability to classify positive and negative events reliably is supported by its high accuracy (94.3%) and precision or recall (97.2%), all indicative of its ability to reduce false positives and false negatives, respectively. All of the above is also supported by the high F score (96.1%) achieved by the model, which further speaks to the model's ability to predict accurately with imbalanced datasets. The model improves

forecast accuracy through smart methods and optimization techniques, such as Bi-LSTM, or modernizing an older technique, as seen in implementing new capabilities of both methods.

Integrating different data sources, including PMR from extensive medical files and reliable data from regular medical exams, helps with patient prognosis. This improves prediction accuracy. The predictive model identifies patients with CVD more effectively than previous models, showing overall good accuracy, precision, recall, and an F score.

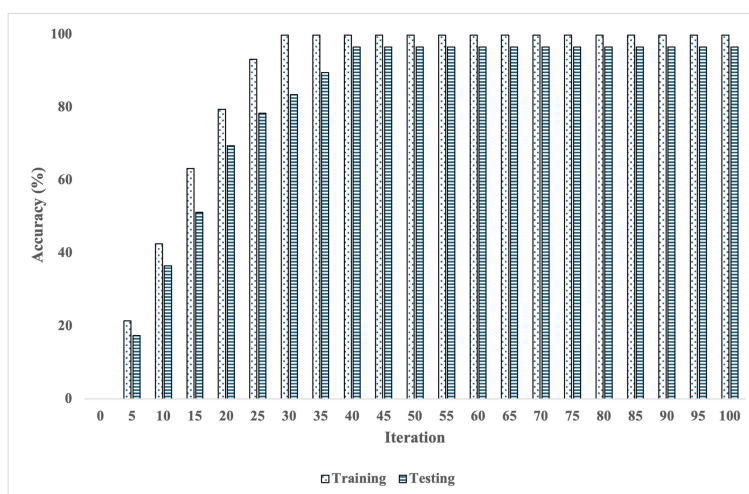


Figure 5: Accuracy analysis

Figure 5 shows how the accuracy values changed between training and testing for a system that predicts CVDs using a wearable IoT-enabled CS-based Bi-LSTM model in remote healthcare monitoring. The training accuracy shows how well the model fits the given data and works on the training set. Accuracy testing shows how well the system can deal with new data that it does not know much about, which is how things work in the real world. The model was tested and trained with a 0% success rate, which means it is either not well-fitted or has not been trained. The algorithm's training

accuracy gets better as it is trained and changed. This shows that it can learn from the data it receives.

The fact that the test accuracy goes up simultaneously as the values go up suggests that the model is better at predicting instances of CVD when healthcare is tracked from afar. Combining IoT with CS-based technologies makes gathering data and applying models simpler. This makes continuous CVD monitoring algorithms stronger at making predictions, which is why this development is exciting.

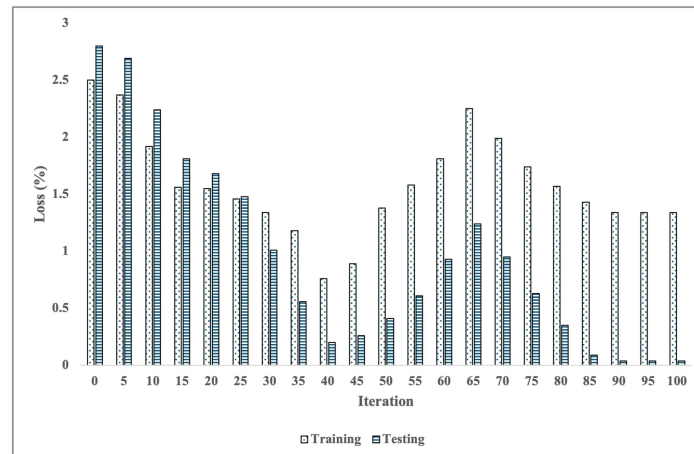


Figure 6: Loss analysis

Figure 6 illustrates the progression of testing and training loss values for an algorithm that forecasts CVD using a hybrid wearable IoT-enabled CS-based Bi-LSTM algorithm in remote health monitoring. Training Loss is a criterion that shows how dire the model predictions are during training. Testing Loss is how well the data gives an input opportunistically regarding real-world scenarios. The beginning of the testing and training losses were very high against the fit, even though the model had never fitted well. Smaller and smaller decreases in training and testing faults are noticed as more training and modifications are applied. The lesser number of faults in Training and Testing Loss reflects the higher ability of the model to commit fewer errors and provide more accurate predictions.

In medical monitoring, this implementation is crucial as it makes the model's ability to give precise and reliable forecasts for enhancing patient care and early detection of CVD conditions. Also, the model gains overall efficiency from IoT and CS-based tools, which enable further data exchange and continuous monitoring with greater convenience.

LIMITATIONS AND FUTURE WORK

Several limitations should be considered. First, the reported analysis is based on 294 records from the dataset described as an Indian cardiovascular disease (CVD) database, and the relatively small sample size may limit the generalizability of the findings. Second, the present study does not demonstrate prospective

validation using continuously acquired real-world wearable sensor data. Third, the relationship between the variables available in the database and the physiological measurements obtainable from the proposed wearable devices requires further clarification and validation. Fourth, the manuscript does not currently provide sufficient information regarding the Bi-LSTM architecture, hyperparameters, validation strategy, confidence intervals, or independent external testing, which limits assessment of the robustness and reproducibility of the model. Finally, the proposed security mechanisms require a formal security and threat analysis to evaluate their effectiveness against relevant attack scenarios. Future studies should therefore evaluate the proposed framework using larger and independent datasets, prospectively collected real-world wearable sensor data, rigorous validation strategies, and formal security assessments.

CONCLUSION

In this study, a wearable healthcare system based on IoT is proposed, which combines physiological data acquisition, secure data transmission, cloud-based processing, and classification of cardiovascular diseases using Bi-LSTM. The proposed model was found to be accurate by 92.6%, precise by 94.1%, sensitive by 93.7%, specific by 91.5%, and F-score by 94.7% based on the performance values reported in the manuscript. These values should be checked against the original experimental data before publication. The proposed framework can be

used to support remote CVD risk classification and alert for further clinical assessment. The present results, however, do not provide independent clinical diagnostic capability or prospective effectiveness based on real-world wearable sensor data. The system should therefore be seen as a research and decision support system and not as an independent diagnostic or treatment system. The present study is also constrained by the relatively small sample size, lack of complete data on model validation and reproducibility, lack of independent external testing, and the requirement for formal security evaluation. The framework should be validated in future studies with larger and independent datasets, prospective collection of wearable sensor data, formal model validation and cybersecurity and threat analyses. If edge or fog computing is to be included in future implementations, then the latency, bandwidth, computational needs and security benefits should be tested and not taken as a given from the current study.

REFERENCES

- Baghdadi, N. A., Farghaly Abdelaliam, S. M., Malki, A., Gad, I., Ewis, A., & Atlam, E. (2023). Advanced machine learning techniques for cardiovascular disease early detection and diagnosis. *Journal of Big Data*, 10(1), 144. <https://doi.org/10.1186/s40537-023-00817-1>
- Casalino, G., Grassi, R., Iannotta, M., Pasquadibisceglie, V., & Zaza, G. (2020). A hierarchical fuzzy system for risk assessment of cardiovascular disease. In *2020 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)* (pp. 1–7). IEEE. <https://doi.org/10.1109/EAIS48028.2020.9122750>
- Dileep, P., Rao, K. N., Bodapati, P., Gokuruboyina, S., Peddi, R., Grover, A., & Sheetal, A. (2023). An automatic heart disease prediction using cluster-based bi-directional LSTM (C-BiLSTM) algorithm. *Neural Computing and Applications*, 35(10), 7253–7266. <https://doi.org/10.1007/s00521-022-07064-0>
- Honi, D. G., & Szathmary, L. (2024). A one-dimensional convolutional neural network-based deep learning approach for predicting cardiovascular diseases. *Informatics in Medicine Unlocked*, 49, 101535. <https://doi.org/10.1016/j.imu.2024.101535>
- Islam, R., Sultana, A., & Islam, M. R. (2024). A comprehensive review for chronic disease prediction using machine learning algorithms. *Journal of Electrical Systems and Information Technology*, 11(1), 27. <https://doi.org/10.1186/s43067-024-00150-4>
- Jaw, E., & Wang, X. (2021). Feature selection and ensemble-based intrusion detection system: An efficient and comprehensive approach. *Symmetry*, 13(10), 1764. <https://doi.org/10.3390/sym13101764>
- Khiabani, S. J., Batani, A., & Khanmohammadi, E. (2022). A hybrid decision support system for heart failure diagnosis using neural networks and statistical process control. *Healthcare Analytics*, 2, 100110. <https://doi.org/10.1016/j.health.2022.100110>
- Kulkarni, M. H., & Inamdar, P. R. (2025). Healthcare unbound: Navigating emerging trends and future applications in IoT-based innovations for daily well-being. In A. K. Rana, V. Sharma, S. K. Rana, & V. S. Chaudhary (Eds.), *Evolution of machine learning and Internet of Things applications in biomedical engineering* (pp. 238–250). CRC Press. <https://doi.org/10.1201/9781003476207-16>
- Mary, G. A. A., Sathyasri, B., Murali, K., Prabhu, L. A. J., & Bharatha Devi, N. (2023). Electrocardiogram signal classification in an IoT environment using an adaptive deep neural networks. *Neural Computing and Applications*, 35(21), 15333–15342. <https://doi.org/10.1007/s00521-023-08534-9>
- Nagarajan, R., & Thirunavukarasu, R. (2022). A neuro-fuzzy-based healthcare

- framework for disease analysis and prediction. *Multimedia Tools and Applications*, 81(8), 11737–11753. <https://doi.org/10.1007/s11042-022-12369-2>
- Nayak, J., Naik, B., Dinesh, P., Vakula, K., & Dash, P. B. (2020). Firefly algorithm in biomedical and health care: Advances, issues, and challenges. *SN Computer Science*, 1(6), 311. <https://doi.org/10.1007/s42979-020-00320-x>
- Patra, S. C., Maheswari, B. U., & Pati, P. B. (2023). Forecasting coronary heart disease risk with a 2-step hybrid ensemble learning method and forward feature selection algorithm. *IEEE Access*, 11, 136758–136769. <https://doi.org/10.1109/ACCESS.2023.3338369>
- Rajeswari, M., Krishnapriya, K. S., Sowmiya, M., Anusree, K., & Edassery, N. J. (2024). Machine learning approaches for detecting and classifying diabetic retinopathy—A survey. *Bulletin of Pure and Applied Sciences-Zoology*, 43A(1S), 1012–1023. <https://www.bpasjournals.com/zoology/index.php/journal/article/view/190>
- Ramesh, B., & Lakshmana, K. (2024). A novel early detection and prevention of coronary heart disease framework using hybrid deep learning model and neural fuzzy inference system. *IEEE Access*, 12, 26683–26695. <https://doi.org/10.1109/ACCESS.2024.3366537>
- Sadr, H., Salari, A., Ashoobi, M. T., & Nazari, M. (2024). Cardiovascular disease diagnosis: A holistic approach using the integration of machine learning and deep learning models. *European Journal of Medical Research*, 29(1), 455. <https://doi.org/10.1186/s40001-024-02044-7>
- Singh, K., & Malhotra, J. (2021). Cloud-based ensemble machine learning approach for smart detection of epileptic seizures using higher order spectral analysis. *Physical and Engineering Sciences in Medicine*, 44(1), 313–324. <https://doi.org/10.1007/s13246-021-00970-y>
- Surekha, S., Balde, G. H., Sundarayya, P., Prabhakar, M. B., Saxena, P. S., & Bele, C. D. (2024). Mathematical modeling of chemical processes in animal physiology: A computational approach. *Bulletin of Pure and Applied Sciences-Zoology*, 43B(2S), 27–42. <https://bpasjournals.com/zoology/index.php/journal/article/view/211>
- Tan, C., Yuan, Z., Xu, F., & Xie, D. (2025). Optimized feature selection and deep neural networks to improve heart disease prediction. *Journal of Imaging Informatics in Medicine*, 39(1), 908–925. <https://doi.org/10.1007/s10278-025-01435-4>
- Upadhyay, S., Kumar, M., Upadhyay, A., Verma, S., Kavita, Kaur, M., Khurma, R. A., & Castillo, P. A. (2023). Challenges and limitation analysis of an IoT-dependent system for deployment in smart healthcare using communication standards features. *Sensors*, 23(11), 5155. <https://doi.org/10.3390/s23115155>
- World Health Organization. (2025, July 31). *Cardiovascular diseases (CVDs)*. <https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-%28cvds%29>
- Wu, J., Chang, L., & Yu, G. (2021). Effective data decision-making and transmission system based on mobile health for chronic disease management in the elderly. *IEEE Systems Journal*, 15(4), 5537–5548. <https://doi.org/10.1109/JSYST.2020.3024816>