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ORIGINAL

An Innovative algorithm framework for cardiovascular risk assessment based on ECG data

Un innovador marco de algoritmos para la evaluación del riesgo cardiovascular basado en datos de ECG

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ABSTRACT

Introduction: cardiovascular disease (CVD) is a primary universal physical problem, with conventional prediction systems frequently being persistent and expensive. Modern advancements in machine learning (ML)offer a hopeful option for accurate CVD risk assessment by leveraging multifaceted relations among diverse risk factors.
Objective: their search proposes a novel deep learning (DL) system, Dynamic Owl Search algorithm-driven Adaptive Long Short-Term Memory (DOS-ALSTM), to enhance cardiovascular risk prediction utilizing electrocardiogram (ECG) data.
Method: the study utilizes ECG data from a diverse population group to train and assess the proposed model. Data is cleaned and normalized employing standard techniques to handle lost values and ensure reliability. Relevant features are extracted using statistical and signal processing technique to detain crucial features from the ECG data. The DOS-ALSTM system integrates a DOS optimization algorithm for optimized parameter regulation and ALSTM networks to detain sequential dependencies in ECG data for accurate risk prediction. The recognized method is evaluated using Python software.
Results: the DOS-ALSTM system demonstrates superior performance with superioraccuracy of 99 %, recall of 98 %, F1-Score of 97,9 % and Precision of 98,8 % in CVD risk assessment compared to traditional methods.
Conclusions: the DOS-ALSTM method gives a robust forecast for non-invasive, accurate cardiovascular risk assessment, leveraging sophisticated DL methods and optimized algorithms.

Keywords: Cardiovascular Disease (CVD); Risk Assessment; Dynamic Owl Search Algorithm-Driven Adaptive Long Short-Term Memory (DOS-ALSTM); ECG Data.

RESUMEN

Introducción: la enfermedad Cardiovascular (ECV) es un problema físico universal primario, siendo los sistemas convencionales de predicción frecuentemente persistentes y costosos. Los avances modernos en el aprendizaje automático (ML) ofrecen una opción esperanzadora para la evaluación precisa del riesgo de ECV al aprovechar las relaciones multifacéticas entre diversos factores de riesgo.
Objetivo: su búsqueda propone un nuevo sistema de aprendizaje profundo (DL), un algoritmo de búsqueda de búho dinámico dirigido por algoritmos de memoria adapta de corto plazo (DOS-ALSTM), para mejorar la predicción de riesgo cardiovascular utilizando datos de electrocardiograma (ECG).
Método: el estudio utiliza datos ECG de un grupo poblacional diverso para entrenar y evaluar el modelo propuesto. Los datos son limpiados y normalizados empleando técnicas estándar para manejar valores perdidos

y asegurar la confiabilidad. Las características relevantes se extrautilizando técnicas estadísticas y de procesamiento de señales para detener características cruciales de los datos del ECG. El sistema DOS-ALSTM integra un algoritmo de optimización de DOS para la regulación de parámetros optimiy redes ALSTM para detener dependencias secuenciales en los datos de ECG para la predicción de riesgo precisa. El método reconocido es evaluado usando software Python.
Resultados: el sistema DOS-ALSTM demuestra un rendimiento superior con una precisión superior del 99 %, un recuerdo del 98 %, una puntuación F1 del 97,9 % y una precisión del 98,8 % en la evaluación del riesgo de ECV en comparación con los métodos tradicionales.
Conclusiones: el método DOS-ALSTM ofrece un pronóstico robusto para la evaluación precisa y no invasiva del riesgo cardiovascular, aprovechando métodos de DL sofisticados y algoritmos optimizados.

Palabras clave: Enfermedad Cardiovascular (ECV); Evaluación del riesgo; Algoritmo Dinámico de Búsqueda de Búhos - Memoria Corta Larga Adaptativa Dirigida (DOS-ALSTM); Datos de ECG.

INTRODUCTION

Cardiovascular Disease (CVD) is the major problem of morbidity and fatality worldwide. It includes a variety of settings troubling the blood and heart arteries, like coronary disease, strokes, arrhythmias and heart attacks. Gooding et al. compute cardio function and identify anomalies, electrocardiograms (ECG), echocardiograms, stress tests, blood tests, imaging tests and angiography are regularly used in the diagnosis process.[1] Treatment consists of anti-hypertensives, anti-platelet medications, statins and anticoagulants. In addition, lifestyle changes like eating a heart-healthy diet, exercising frequently and quitting smoking are employed to manage symptoms and avoid difficulties. Angioplasty and stenting, valve replacement and coronary artery bypass grafting (CABG) are examples of operational procedures. Heart treatment programs intervention programs, therapy, and exercise to progress heart health and support continued monitoring with therapeutic professionals to ensure capable disease management.[2] ECG readings are necessary since they give concurrent information on heart movement, which helps to identify CVD. They make individualized exploit regimens, risk stratification for severe processes, and early defect identification easier. ECG is critical for well-organized monitoring and cure of cardiovascular health while advances in data analytics also expand diagnosis accuracy. It consists of key mechanisms like the P wave (atrial depolarization), the T wave (ventricular repolarisation) and the QRS complex (ventricular depolarization).[3] Figure 1 shows the CVD risk assessment using ECG data.

When estimating CVD with ECG data, the electrical motion of the heart is monitored, noise is isolated from the signals through preprocessing, and significant characteristics like heart rate irregularity and QRS interval are extracted. Intelligent machine learning (ML) algorithms classify ECG patterns to forecast cardiovascular risk, facilitating punctual activities and steady monitoring to get better liberal outcomes.[4] The utilization of ECG data for CVD evaluation has diverse benefits, like non-invasiveness, immediate monitoring, and early detection of CVD. It provides widespread information on heart health and is realistically valued. Technological advancements also enhance the accuracy of analysis, enabling longitudinal estimation and quick patient-centered therapies.[5] The susceptibility of ECG data to artifacts can cause mistaken readings, and its slender analytic sequence can cause structural issues to be ignored. Harmonizing tests are vital for a systematic cardiovascular assessment due of the selection in understanding among physiologists, the possibility of false positives or negatives, and the requirement for focused guidance.[6] Study objective is to develop and assess a new DL technique, the Dynamic Owl Search algorithm-driven Adaptive Long Short-Term Memory (DOS-ALSTM), which enhances the capability to estimate cardiovascular risk by capably interpreting ECG data. This research improves the predicted accuracy and offers sensible insights for the cure of cardiovascular health.

Karthik et al.[7] provided an automated deep learning-based model for ECG signal detection, to diagnose cardiovascular illnesses. Preprocessing, deep belief network feature extraction, optimizer tuning using an enhanced swallow swarm technique and Extreme Gradient Boosting (XGBoost) classification are all included. Better diagnostic performance is shown via simulations using the Physialisch-Technische Bundesanstalt eXtended Large ECG dataset (PTB-XL) dataset.

Liu et al.[8] presented a scalable framework for clinical ECG recognition. One technique for converting 2D ECG wave images into 1D signals is a bi-directional connection. In comparison to modern techniques, Convolutional Recurrent Transformer Network (CRT-Net), a deep neural network (DNN), achieved better performance on public datasets by integrating traditional methods to extract ECG waveform properties.

Golande et al.[9] employed a cross-feature engineering method. The suggested method improves the categorization of heart illness based on ECG data. It used a long short-term memory (LSTM) classifier, pre-processes to eliminate interference, and combined traditional ECG beat extraction with CNN-based characteristics. In comparison to current techniques, simulation findings demonstrated fewer diagnostic errors and quicker classification.

Khanna et al.[10] presented the Internet of Things (IoT) and healthcare illness diagnosis (HDD) model, which used deep learning and ECG, signals to diagnose CVD. The artificial flora technique optimizes Bi-directional LSTM for feature extraction, and a fuzzy DNN is used for classification. The model's accuracy was 93,452 %.

Mewada[11] suggested a 2D deep CNN that combines temporal CNN features with wavelet-based spectral features for ECG classification. The model outperformed existing models, simplifying preprocessing and enhancing categorization utilizing multi-spectral feature integration. It was examined using the Massachusetts Institute of Technology - Beth Israel Hospital (MIT-BIH) dataset. Wasimuddin et al.[12] created a condensed CNN-based classifier that used ECG wave images to identify different arrhythmia types in real-time. The three-layer Mat lab model was constructed and simulated for portable devices. When tested against the European ST-T database, it outperformed the majority of current solutions.

Madan et al.[13] developed a cross 2D-CNN-LSTM system that presented a 1D ECG into 2D Scalogram images for automatic clatter filtering and characteristics were extracted. High sensitivity and specificity are established by tentative results utilized in the arrhythmia database, which capitulate accuracy rates for dissimilar cardiac disorders. Ahmed et al.[14] utilized real and clatter-removed ECG data from the MIT-BIH dataset to initiate a single1D-CNN for the categorization of cardiac disease. The system outperformed the limitations of the conventional ECG and performs well, given that a rapid an alytical substitute.

Abdullah et al.[15] provided a CNN-LSTM method that does not need handcrafted features for dependable ECG categorization and monitoring. Tested on the PTB and MIT-BIH datasets, the method performs better than present techniques, with a 98,1 % accuracy rate for myocardial infarction and a 98,66 % accuracy rate for arrhythmia classification. Chen et al.[16] described a mechanical system that employed an incorporated broad DNN to differentiate between abnormal and normal ECG data. The end-to-end model achieved high rates of gratitude with an ECG dataset, utilized convolutional layers for feature extraction and incorporated LSTM and concentration methods. Rath et al.[17] evaluated four DL methods to predict coronary artery disease (CAD) using ECG signals. Utilized the MIT-BIH and PTB-ECG datasets, the autoencoder (AE)system surpasses the others with outstanding accuracy and F1 scores.

Parveen et al.[18] utilized synthetic minority oversampling technique (SMOTE) to stabilize the samples and smooth fresh signals, the suggested method improves ECG classification. It utilized an XGB classifier for heartbeat categorization and a new 1D-Residual Deep Convolutional AE(RDCAE) for feature extraction. It surpassed existing methods with 99,9 % accuracy and 99,8 % specificity, representing improvements in medical cardiac care systems.

METHOD

The methodology begins with collection of ECG data from an assorted population group, further cleaned and normalized to address missing values and reliability. Standard pre-processing techniques, namely interpolation and scaling are used to prepare the data for analysis. After that, meaningful features are extracted using statistical methods and signal processing techniques which capture the important characteristics present in the ECG signals. The DOS-ALSTM system is provided with the support of the incorporated Dynamic Owl Search optimization algorithm for the best possible regulation of parameters that enhance the model. Adaptive Long Short Term Memory networks are employed to catch the sequential dependencies in the data ECG. This new holistic approach with such an ability means making accurate cardio vascular risk predictions with the strengths of the advanced machine learning techniques. Figure 1 demonstrates the flow for the suggested method.

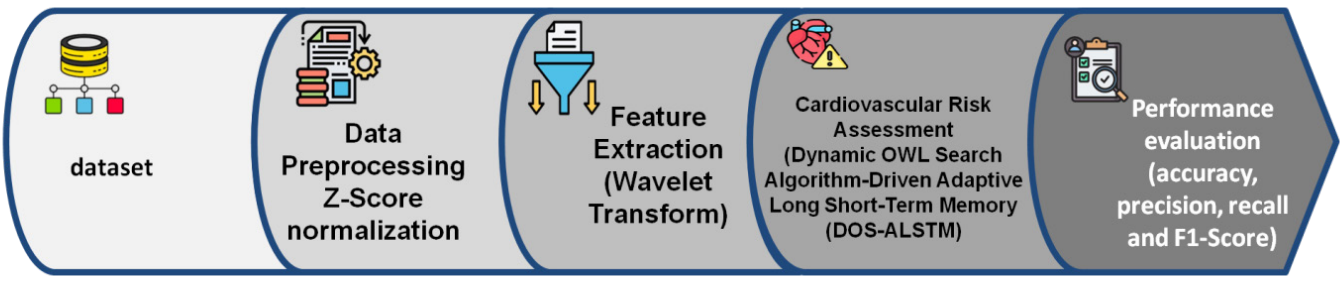

Figure 1. Flow of suggested method

Data collection

The ECG data is gathered from Kaggle (https://www.kaggle.com/datasets/devavrat atripathy/ecg-dataset). It contains ECG readings from patients, with every admission representative a whole ECG collected of 140 data points. These data points reproduce the electrical action of the heart over instance. Additionally, the data includes a tag that categorizes every ECG as also normal or abnormal, allowing for the assessment of CVD risk conditions. The data provides an expensive source for training methods toaim at identifying and assessing heart disease.

Data preprocessing

The process of finding and eliminating error, inconsistencies and inaccuracies from data to enhance its quality and dependability for analysis is known as data cleaning. By utilizing a statistical method called Z-Score normalization, values in ECG data can be complete into a separation with a mean of and a deviation of 1. This process aids in ensuring that diverse characters make an identical contribution to the analysis, a necessary phase of data modeling and ML. By allowing only a meticulous incidence range to pass through, bandpass filtering efficiently eliminates high-frequency noise and low-frequency drift, which are regularly present in ECG data. The Z-Score for a data point Y_J is computed with equation (1).

$$Z_j = \frac{Y_J - \mu}{\sigma} \qquad (1)$$

Z_j is the data point, Y_J is the velocity of the data point, μ average of the ECG data and σ is the deviation of the ECG data. When Z-Score normalization and Bandpass Filtering are utilized together, noise is removed from the data and values are normalized, which enhances the method's performance. It finally contributes to more reliable and explicable outcomes by making it easier to recognize outliers, ensuring consistency across data, and assisting superior comparisons in the evaluation of cardiovascular risk.

Feature extraction

After pre-processing, noise-isolated data characters were extracted utilizing wavelet transform. It is a signal processing method that decomposes the ECG signals into several incidence bands, enabling complete analysis of both time and frequency fields. After performing wavelet decomposition, statistical characters like variance, mean and skewness are computed from the wavelet coefficients, combining both statistical and signal processing techniques. The wavelet transform decomposes the signal into diverse sub-bands of dissimilar resolutions, capturing brief characters like the QRS complex using equation (2).

$$X_y(b,a) = \frac{1}{\sqrt{b}} \int_{\infty}^{\infty} y(s)\psi\left(\frac{s-a}{b}\right) cs \qquad (2)$$

X_y represents the wavelet transform, y(s) is the ECG data, ψ is the wavelet gathering, b is the frequency and a is the time, and cs is the infinitesimal increment of s.

The ECG signal is decomposed into wavelet coefficients at dissimilar scales and then the statistical features were extracted. Equation (3) gives the standard energy in every frequency band.

$$\mu = \frac{1}{m} \sum_{j=1}^{m} X_y\ (b_j, a_j) \qquad (3)$$

μ represents the mean value, m is the sum of data points, and theextent of energy across the wavelet coefficients, representing signal inconsistency is measured using equation (4).

$$\sigma^2 = \frac{1}{m} \sum_{j=1}^{m} \left(X_y\left(b_j, a_j\right) - \mu\right)^2 \qquad (4)$$

σ is the variance, and j is the index of wavelet coefficients. Using skewness equation (5), the irregularity of wavelet coefficients that capture anomalies in the signal can be measured.

$$skewness = \frac{\frac{1}{m} \sum_{j-1}^{m} \left(X_y\left(b_j, a_j\right) - \mu\right)^3}{\sigma^3} \qquad (5)$$

The method gives a broad analysis of the ECG data by capturing both time-localized features and statistical patterns. It is mainly efficient in detecting transient actions in CVD, while also quantifying overall signal behavior, making it very useful for cardiovascular risk assessment.

Cardiac risk assessment using Dynamic Owl Search algorithm-driven Adaptive Long Short-Term Memory (DOS-ALSTM)

A new approach DSO-ALSTMmethod with ECG data is analyzed to determine CVD risk assessment. This method makes use of the DOS algorithm's optimization powers to improve the ALSTM method training procedure.

Adaptive Long Short-Term Memory (ALSTM)

After the feature extraction decomposed ECG signals were assessed using ALSTM. It is an improved edition of the conventional LSTM method that introduces adaptive mechanisms to develop recital in sequence modeling tasks. ALSTM is specially intended to regulate its interior parameters dynamically in response to changing input situations, making it more flexible and capable than conventional LSTM models.

Forgot gate: it explains how the previous cell state should be discarded and is described by equation (6).

$$e_s = \sigma(X_e.[g_{s-1}, y_s] + a_e) \qquad (6)$$

σ is the sigmoid activation function. It outputs values between 0 and 1. X_e is the weight matrix, g_{s-1}, and y_s is the concatenation of the previous secreted state g_{s-1} and the present input y_s. This concatenation allows the forget gate to consider both past information and current context. a_e is a bias phrase.

Input gate: this maintains how much of the new data from the present input y_s must be further to the cell state computed by equation (7).

$$j_s = \sigma(X_j.[g_{s-1}, y_s] + a_j) \qquad (7)$$

This stage is similar to the forget gate, it provides a vector of values between 0 and 1, where superior j deals show that more of the new information will be incorporated into the memory.

Cell state update: it incorporating both retained and new information was added using equation (8). i_s. tanh demonstrates the new data being added to the cell state.

$$D_s = e_{s-1} + i_s.\tanh\,(X_D.[g_{s-1}, y_s] + a_D \qquad (8)$$

The tanh function is used to transform the linear combination of past hidden state and current input into a range suitable for memory addition.

Output gate: it determines the fraction of the cell state Ds will be outputted as the recent hidden state g_s is given in equation (9).

$$p_s = \sigma(X_p.[g_{s-1}, y_s] + a_p \qquad (9)$$

The output p_s is a vector of value between 0 to 1. When multiplied by tanh, it controls which parts of the cell state are sent to the secreted state. The ALSTM model greatly improves sequential data analysis's predictive power, especially when it comes to assessing cardiovascular risk using ECG data. ALSTM enhances accuracy and adaptability through dynamic memory management, facilitating enhanced anomaly identification and well-informed decision-making in healthcare environments.

Dynamic Owl Search (DOS) algorithm

Predicted data were optimized using the DOS algorithm for increasing robustness. DSO is an optimization algorithm inspired by the hunting behavior of owls, particularly their ability to dynamically adjust their position and movement while searching for prey. DOS is designed to solve complex optimization problems by mimicking how owls locate their prey using both exploration and exploitation capabilities. The only random value in the standard DOS is the parameter. When random values are used every iteration, the system converges too soon. A process known as chaotic mappingis employed. This method transforms lowering value is expressed as equation (10).

$$\propto (s) = \propto_{initial} \times e^{-\lambda s} \qquad (10)$$

The issue of mature convergence in DOS, Le is a commonly used method in bio-inspired optimization algorithms to achieve premature alignment. The main element of this method for appropriately managing local searches is σ random walk is calculated using equation (11).

$$Le(x) = x^{-1-\Gamma}, x = \frac{B}{|A|^{1/\Gamma^2}}, \ \sigma^2 = \left\{ \frac{\Gamma(1+\tau)}{\tau\Gamma({(1+\Gamma)}/{2})} \frac{\sin({\pi\tau}/{2})}{2^{(1+\Gamma)/2}} \right\} \qquad (11)$$

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Where x is the stepsize, τ indicates the LFindex between 0 and 2, Β and Α denote the $N(0,\sigma^2)$, and ɼ(.) indicates the Gamma function. Using the algorithm below, new owl positions can be obtained depending on the circumstances mentioned in equation (12).

$$O_j^{s+1} = \begin{cases} O_j^s + \beta \times D_J \times \left| \propto M - O_j^s \right| \times Le(\delta), < 0.5 \\ O_j^s + \beta \times D_J \times \left| \propto M - O_j^s \right| \times Le(\delta), \geq 0.5 \end{cases} \quad (12)$$

DOS is an efficient solution for intricate, multi-dimensional optimization issues, due to its dynamic adjustment process. Large search spaces can benefit from the algorithm's ability to avoid local minima through a dynamic balance between exploration and exploitation.

DSO-ALSTM optimizes performance in time series prediction problems by merging the advantages of the DSO and ALSTM networks. By dynamically balancing exploration and exploitation based on the fitness of prospective solutions, DSO effectively searches the search space for optimal solutions. By integrating DOS, ALSTM's hyper-parameters are optimized, guaranteeing that they are tailored for particular datasets and allowing for dynamic adaptation to shifting data patterns. Algorithm 1 shows the DSO-ALSTM algorithm.

Algorithm 1: Dynamic Owl Search Algorithm-driven Adaptive Long Short Term Memory (DOS-ALSTM)
START
Step 1: initialization parameters: weight matrices and bias terms.
Step 2: input ECG data
Step 3: implement ALSTM workflow for each time step s times.

- Compute forget gate: $e_s=\sigma(X_e.[g_{s-1},y_s]+a_e)$
- Update the cell state: $D_s=e_{s-1}+i_s.\tanh(X_D.[g_{s-1},y_s]+a_D$

Step 4: initialize DSO parameter: τ,ɼ,β,λ
Step 5: optimized prediction using DSO, for each iteration 's'

- chaotic map for adjusting parameters: $\propto(s)=\propto_{initial}\times e^{-\lambda s}$

Step 6: update owl search parameters based on exploration and exploitation.

$$O_j^{s+1} = \begin{cases} O_j^s + \beta \times D_J \times \left| \propto M - O_j^s \right| \times Le(\delta), < 0.5 \\ O_j^s + \beta \times D_J \times \left| \propto M - O_j^s \right| \times Le(\delta), \geq 0.5 \end{cases}$$

Step 7: output prediction.
END

RESULTS

Python 3.10 is utilized to evaluate the DOS-ALSTM in predicting CVD risk. The method's performance is estimated utilizing various metrics like F1-score, precision, accuracy and recall. DOS-ALSTM system is compared with existing methods such as CNN with Extreme Gradient Boosting (CNN-XG-Boost) Sekhar et al.[19] and DNN Alqahtani et al.[20]. Table 1 evaluates the performance of the suggested method.

The results demonstrated that the DOS-ALSTM system fares significantly better compared with traditional methods of cardiovascular risk assessment in terms of increased accuracy and predictability. This superior performance indicates its capacity for providing more reliable and non-invasive appraisal of cardiovascular health.

Table 1. Evaluation of the performance of the suggested method

Method	Precision (%)	Accuracy (%)	F1-score (%)	Recall (%)
CNN-XG-BOOST[19]	98	98,7	96,98	97,9
DNN[20]	97,77	87,59	65,54	76,27
DOS-ALSTM (Proposed)	98,8	99	97,9	98

Accuracy: by computing the percentage of true positives (TP) and true negatives (TN) among all examples evaluated, accuracy evaluates a model's overall reliability. It is calculated by equation (13).

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \quad (13)$$

It is assessed by false positive (FP), false negative (FN), TP and TN. With 99 %, the DOS-ALSTM model surpasses traditional models, achieving accuracies of 98,7 % and 87,59 % for CNN-XG-Boost and DNN, respectively. The model produces an accuracy score nearly around meaning that it has a high general capability of identifying the patients at risk for cardiovascular disease correctly.

Precision: the precision of a model is measured by the ratio of its genuine positive forecasts to its overall positive predictions. It indicates the accuracy of the positive predictions and is given by equation (14).

$$precision = \frac{TP}{TP+FP} \quad (14)$$

Demonstrating a precision of 98,8 %, the DOS-ALSTM model outperforms its counterparts, which show a precision of 98 % for CNN-XG-Boost and 97,77 % for DNN. Figure 2 depicts the evaluation of accuracy and precision. This is the precision score, the number of correct true positives among all the positive predictions done by this model. This means that only the identified high-risk patients are really at risk.

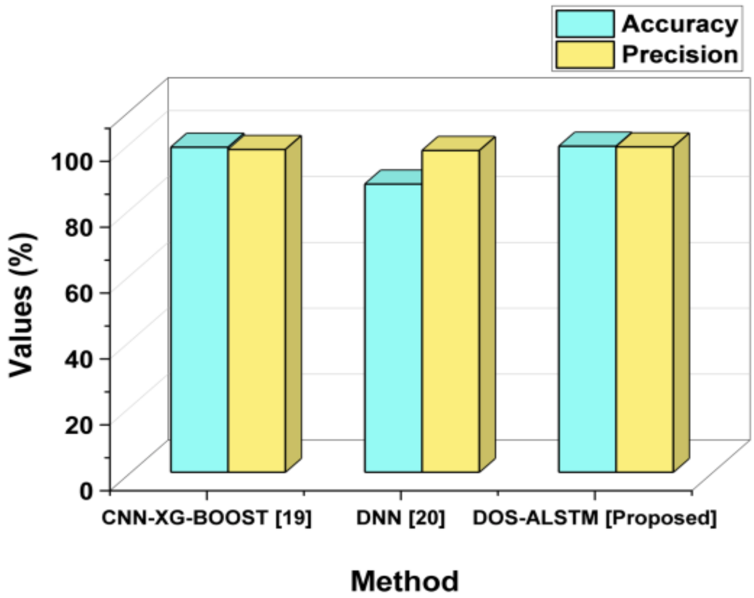

Figure 2. Estimation of precision and accuracy

Recall: it estimates a method's capability to establish all applicable variables in data. It is evaluated by the equation (15). With a recall of 98 %, the DOS-ALSTM model excels compared to CNN-XG-Boost and DNN, which have recall rates of 97,9 % and 76,27 %, respectively.

$$recall = \frac{TP}{TP+FN} \quad (15)$$

This is a metric measuring the ability of the model to capture all actual positive cases. It emphasizes its ability to identify individuals who are at an increased risk.

F1-Score: it is computed as the typical precision and recall by balancing the two measures. In unbalanced datasets where one class can predominate, it is especially helpful. It is computed as equation (16).

$$F1 - Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (16)$$

Achieving an F1-Score of 97,98 %, the DOS-ALSTM model leads in performance, while CNN-XG-Boost and DNN follow with 96,9 % and 65,54 %. Figure 3 demonstrates the evaluation of recall and F1-Score. The F1 score will give the average measure between precision and recall for the given model. This provides an overall measure of how well the model is able to correctly classify cardiovascular risk by minimizing false positives and false negatives.

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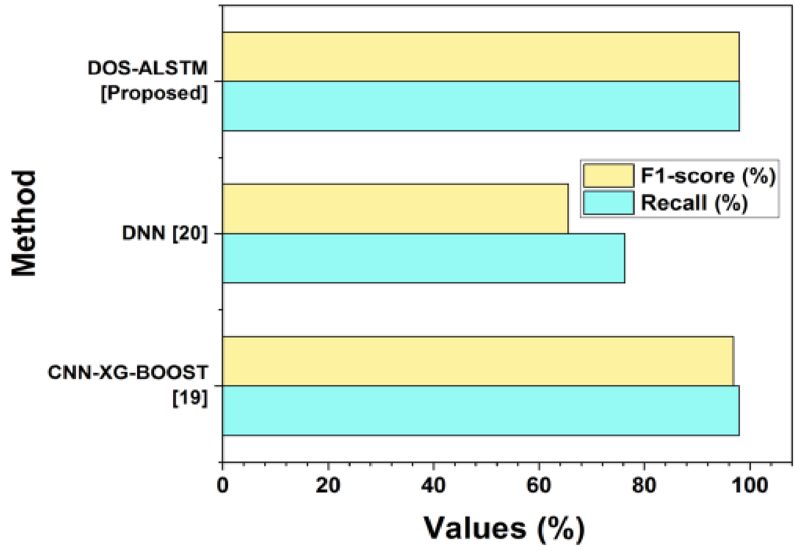

Figure 3. Outcomes of F1-Score and Recall

The training accuracy and loss graph gives significant information about how well the DOS-ALSTM method performs for cardiovascular risk assessment. The accuracy graph indicates that the approach detects cardiovascular irregularities in ECG data with a reliable rising trend. Meanwhile, the loss graph gives a decreased trend, reflecting reductions in forecast error. When taken as a whole, these graphs reveal the method's superior accuracy and robustness, representing its efficacy in correctly diagnosing CVD without overfitting. The DOS-ALSTM methods training a) accuracy and b) loss are demonstrated in figure 4.

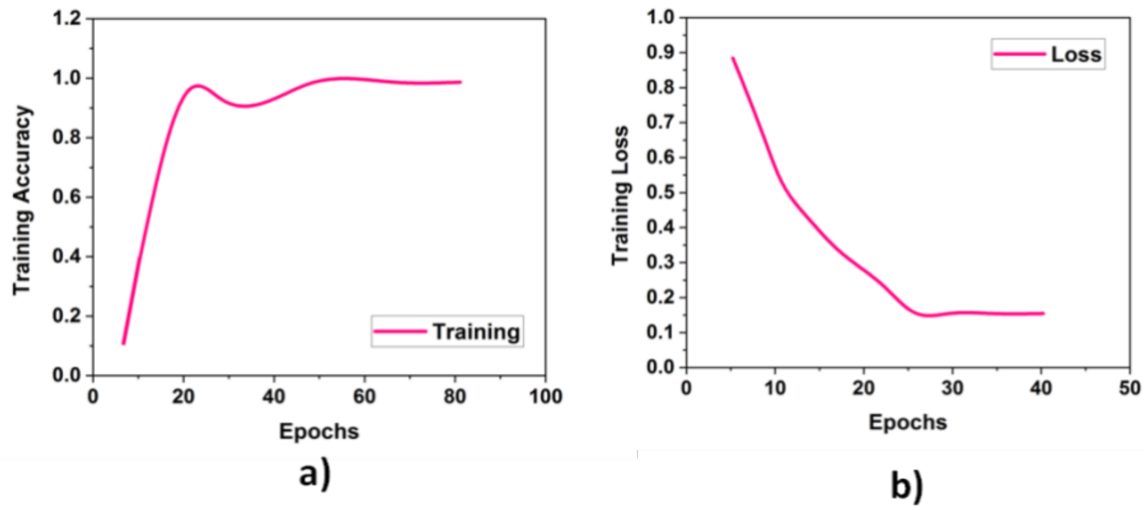

Figure 4. Training a) accuracy and b) loss

High cardiovascular risk prediction accuracy by the DOS-ALSTM model, demonstrating how accurately individuals are categorized based on their ECG readings. The model shows a low loss value during the training and validation process; therefore, it minimizes prediction errors, making its reliability in assessing cardiovascular risk better.

DISCUSSION

The goal of the present study is to help in reaching more insightful outcomes and making cardiovascular risk prediction as sharp as possible. CNN-XG-Boost poses clear disadvantages in the prediction of the cardiovascular risk, including overfitting, particularly when the data is limited or inconsistent in complex architectures.

Overfitting results in poor generalization; that is, when the model is used on new patient data, the model becomes ineffective. In addition, since the model highly relies on feature extraction from CNNs, it ignores some essential temporal patterns of ECG signals and as such lowers predictive accuracy. DNNs have notable limitations in the application of cardiovascular risk estimation primarily due to their inefficacy in capturing long-range dependencies in time-series data, such as electrocardiograms (ECGs). Such a limitation may result in suboptimal recall rates and hence erroneous model prediction. These deficiencies call for advanced techniques like DOS-ALSTM, which utilizes the Dynamic Owl Search algorithm to improve its model. Therefore, this is able to engross a strong dependency capture within sequential data like ECGs and provides for greater accuracy and overall performance in CVD risk assessment. The DOS-ALSTM model overcomes these limitations by integrating an adaptive mechanism that allows for active adjustments of its interior parameters based on changing input situations. This flexibility enhances the model's flexibility and effectiveness in series modeling tasks. Moreover, the integration of the DSO ensures a robust optimization practice that avoids early convergence, enabling the model to discover a larger search space efficiently. These findings specify that the suggested method enhances the predictive power of CVD assessment. This progression has crucial implications for healthcare, as it facilitates more accurate diagnosis and better-informed executives in medical environments.

CONCLUSIONS

CVD is the most important reason or mortality worldwide, necessitating timely and accurate risk assessment to enhance patient outcomes. Study aimed to enhance CVD risk forecast by developing a novel DOS-ALSTM, utilizing ECG data. The important outcome of there search is the superior performance of the DOS-ALSTM method, which achieved an F1-Score of 97,9 %, a Precision of 98,8 %, accuracy of 99 %, and recall of 98 %. These findings emphasized the latent of superior DL techniques in accurately assessing CVD risk, allowing for enhanced decision-making in medical environments. Study has constraints that can harm its generalisability to diverse demographics and remedial situations, even with its capable performance. Future research should focus on expanding the data to include a large diversity of health settings and demographics, as well as investigating combinations with further analytical instruments to offer a thorough assessment of cardiovascular health. In the end, getting better patient organization and defensive healthcare strategies can be significantly aided by expanding CVD estimation with advanced methods like DOS-ALSTM.

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