Enhanced Cardiovascular Monitoring Using Radial Basis Function and Deep Belief Network Fusion

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Abstract

Background: Heart disease and other cardiovascular conditions remain a significant global health challenge, contributing to a high number of fatalities annually. Despite technological advancements, current cardiovascular monitoring methods, especially those analyzing electrocardiograms (ECGs), often fail to capture intricate patterns and subtle irregularities, highlighting the need for a more sophisticated approach. This study proposes a novel framework utilizing deep learning, specifically combining the radial basis function (RBF) for feature extraction and a deep belief network (DBN) for classification, to enhance ECG data analysis. Methods: The proposed method involves preprocessing ECG signals to reduce noise, correct baseline drift, and scale amplitude. Feature extraction is performed using the RBF, which captures intricate temporal patterns in the ECG signals. Subsequently, the DBN classifies the extracted features, leveraging its hierarchical learning capabilities to identify subtle correlations and patterns. The model's performance was evaluated using Python simulations on a high-performance computing system, benchmarked against existing methods including Dual-Stage DL, DWT-ML, and M1M2. Results: The RBF-DBN model demonstrated superior performance across several metrics, achieving 99% accuracy, precision, and recall at the 1000th time step, outperforming Dual-Stage DL, DWT-ML, and M1M2 methods. The RBF-DBN method demonstrated a remarkable accuracy of 99%, surpassing the current Dual-Stage DL method by 2%. Additionally, the approach maintained exceptional sensitivity and recall at 99%. The precision of the model was also 99%, and the F1 score, which balances recall and precision, further underscored the model's efficacy in real-time cardiovascular monitoring. Conclusion: The integration of RBF and DBN in ECG analysis significantly enhances the precision and accuracy of cardiovascular monitoring.

Keywords: Deep learning, Cardiovascular monitoring, Electrocardiogram (ECG), Time-series analysis, Real-time intervention, Radial Basis Function (RBF), Deep Belief Network (DBN), Deep Learning

Significance | Combining RBF and DBN improves real-time cardiovascular monitoring by enhancing feature extraction and classification accuracy, addressing limitations of conventional methods.

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Introduction

Heart disease and other cardiovascular conditions continue to be a major public health problem since they are responsible for a disproportionately high number of fatalities across the globe (Śmigiel et al., 2021). Despite advancements in medical technology, the complex difficulties associated with monitoring patients dealing with cardiovascular conditions and responding in a timely manner continue to exist (Sangaiah et al., 2020). When it comes to the data

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obtained from electrocardiograms (ECGs), conventional methods of cardiovascular monitoring might occasionally have difficulty capturing intricate patterns and subtle irregularities (Wu et al., 2021; Hua et al., 2020). These limitations bring to light the necessity of a framework that is both more sophisticated and more advanced, and that makes use of deep learning to improve analysis and decision-making respectively (Krittanawong et al., 2021).

In ECG monitoring, some of the problems include suboptimal accuracy, restricted real-time capabilities, and reliance on conventional feature extraction methods that may miss critical information (Kłosowski et al., 2020; Murat et al., 2020). To overcome these challenges, which demand for an alternative to the approach that is currently being taken (Pandey et al., 2020), it is necessary to have a more comprehensive and accurate understanding of cardiovascular health (Wasimuddin et al., 2020; Sahoo et al., 2020).

One of the primary problems that this research endeavors to address is the fact that the existing cardiovascular monitoring systems are not adequate to provide patients with information that is both accurate and up to date regarding their condition. To avoid the disadvantages of conventional methods, the purpose of this study is to build a robust framework that incorporates the most cutting-edge algorithms for feature extraction and classification.

It is recommended that a deep learning model be constructed that is capable of properly extracting features by utilizing the radial basis function. A deep belief network will be utilized to achieve the objective of effectively identifying time-series data that was obtained from electrodes. It will be important to validate the model by performing Python simulations to ensure that it can be monitored in real time. The performance of the proposed model will be compared to that of established approaches to demonstrate that the proposed model is superior to what is already available.

In this paper, a novel neural fusion model is presented that addresses the challenges that are related with the monitoring of cardiovascular patients. This model is achieved by combining the most advantageous characteristics of deep belief networks with radial basis functions. The distinctive feature of this model is that it has the potential to exceed the methods that are already in use in terms of delivering insights on the illnesses of patients that are both more precise and more quickly. The breakthroughs in cardiovascular monitoring that have been made feasible because of this research have made it possible to improve healthcare procedures and ensure better outcomes for patients.

2. Related Works

The monitoring of cardiovascular function has been the focus of a great deal of study, all of which has contributed significant new knowledge to the ongoing search for more effective diagnostic and treatment methods. The research by Denysyuk et al. (2023) on the application of machine learning algorithms to electrocardiogram analysis stands out among these. The utilization of computational methods for the assessment of cardiovascular health is becoming increasingly popular, and the research conducted by these individuals emphasizes the potential of data-driven approaches to identify tiny irregularities. The work by Singh and Krishnan (2023) establishes the platform for our research, which was centered on the radial basis function for robust feature extraction. They did this by drawing attention to the issues associated with standard methods and providing alternative approaches. Moreover, Sun et al. (2023) investigated the possible applications of deep learning in the medical field, with a particular emphasis on cardiovascular diseases. Considering their research on the application of deep belief networks to medical data processing, their research concluded that it would be beneficial to incorporate this advanced neural network design into our proposed model for classification. Other methods include Dual-Stage DL (Cho et al., 2021), the M1M2 method (Akter et al., 2022), and the Discrete Wavelet Transform and Machine Learning (DWT-ML) (Shen et al., 2022).

This research distinguishes out from the others because it combines a deep and machine learning model with a radial basis function and a deep belief network. These studies have made significant contributions to the field, but the current research is particularly noteworthy. It is hoped that these methods will provide a better solution to the problem of cardiovascular patient monitoring by overcoming the drawbacks of past studies. These methods are a novel addition to the field of cardiovascular health research, which is constantly evolving thanks to new developments.

3. Proposed Method

With our approach, research introduced a new neural model as in Figure 2 to address the shortcomings of the cardiovascular monitoring systems that are currently in use.

A deep belief network for the classification of time-series data collected from electrodes and a radial basis function for feature extraction are both incorporated into the approach. Both components are vital to the algorithm.

In the analysis of ECG data, the radial basis function is employed to extract features, enabling the model to overcome the limitations of conventional feature extraction methods and effectively capture the intricate patterns and nuances within the time-series data. This approach aims to enhance the precision and depth of ECG signal extraction within the model. Furthermore, the deep belief network supports the model's classification capabilities, making it well-suited for learning hierarchical data representations, which is crucial given the complexity of heart rate monitoring. By leveraging a deep belief network, the model achieves greater precision and specificity in classifying ECG data, leading to improved detection of illnesses and anomalies..

3.1. Pre-processing of ECG Signal from Electrodes:

Our method includes several phases, one of which is the pre-processing of ECG signals from electrodes. This phase is essential because it ensures the quality and dependability of the data before further analysis is performed. This stage systematically lowers noise and enhances the signal integrity to improve the accuracy of feature extraction and subsequent classification. This stage is also responsible for improving the signal integrity.

Noise Reduction: To decrease the impact of interference and artifacts, the first step is to apply noise reduction algorithms to the ECG signal before proceeding. Muscle artifacts and baseline drift are two examples of the many kinds of signal contamination that could cause problems. Through the application of filtering and signal processing techniques, our objective is to lessen the impact of these noises and improve the accuracy of the electrocardiogram waveform. The usage of a bandpass filter is one method that can be utilized to reduce background noise. This equation, which represents the filter, is exactly as follows:

$$y(t)=\int_{-\infty}^{\infty} x(\tau)h(t-\tau)\,d\tau$$

Where

$x(t)$ is the original signal,

$h(t)$ is the impulse response of the filter, and

$y(t)$ is the filtered signal.

Baseline Correction: Changes in the baseline of the ECG, also known as baseline correction, have the potential to conceal significant characteristics. By incorporating baseline correction techniques into our pre-processing, research can normalize the baseline and eliminate this kind of interference. It is especially important to take this step while conducting long-term monitoring since it guarantees that subsequent investigations will continue to be correct. The baseline correction process involves subtracting the predicted baseline signal B(t) from the original signal. This is the essence of the entire process.

$y(t)=x(t)-B(t)$

Amplitude Scaling: The amplitude of the ECG signal is standardized through the employment of amplitude scaling algorithms during the pre-processing stage. The quality of comparisons and the precision of feature extraction are both improved because of this, as it ensures that the signal amplitudes remain consistent across all the recordings. The scaling of amplitude is made possible by normalization. The calculation for our normalized signal, denoted by $y(t)$, is as follows:

$y(t) = [x(t)-\text{mean}(x)]/\text{std}(x)$

Where

mean(x) is the mean and

std(x) is the standard deviation of the original signal.

Signal Segmentation: The ECG signal is separated into different phases, which include the P, QRS, and T waves. This process is referred to as phase separation. Through the utilization of this segmentation, research can conduct a more in-depth examination of the individual components, which in turn enables us to extract valuable characteristics for the purpose of future classification. It is necessary to precisely segment the cardiac cycle to accurately capture the temporal properties of the cardiac cycle. Certain stages of the ECG signal, such as the QRS complex, can be separated by employing a method that is based on thresholds. A threshold, denoted by T, can be utilized as a means of expressing the segmented signal, denoted by $y(t)$.

$$y(t)=\begin{cases} x(t) & \text{if } x(t)>T \\ 0 & \text{Otherwise} \end{cases}$$

3.2. RBF for Feature Extraction:

When it comes to extracting characteristics from ECG signals, our method mainly relies on the Radial Basis Function and its capabilities. By collecting and emphasizing minor patterns within the time-series data, the mathematical function plays a significant role in enhancing the discriminative capacity of the features recovered for later analysis. This is accomplished by collecting and highlighting the patterns.

Radial Basis Function (RBF) Equation:

In accordance with the accepted norm, the Radial Basis Function is defined as:

$$\phi(\mathbf{x},\mathbf{c})=\exp\left(-\frac{\|x-c\|^2}{2\sigma^2}\right)$$

where,

$\phi(\mathbf{x},\mathbf{c})$ represents the RBF between the input vector **x** and a center vector **c**,

$\|\mathbf{x}-\mathbf{c}\|$ is the Euclidean distance between the vectors, and

σ is a parameter that controls the spread of the function.

During the process of feature extraction, the RBF receives each time-series data point that is present in the ECG signal. When the figures are generated, they indicate the locations along the signal where the RBF is activated. The selection of centers (c) has a significant impact on the appearance of the elements that are highlighted. RBF is a very useful tool for analyzing ECG signals that contain temporal patterns. The function does an excellent job of attracting attention to distinctions and distinctive forms that may identify cardiac events such as the P, QRS, and T waves. This is since it is reliant on the distance between the two points.

Tuning the spread parameter (σ) to align with the characteristics of the ECG data requires careful thought. A correctly calibrated σ is essential for the RBF to possess the capability of effectively capturing significant characteristics without being overly sensitive or having an unduly broad range of coverage. The RBF-transformed information is provided as input to the neural fusion model, which results in an improvement in the model capacity to classify cardiovascular illnesses. to inform the subsequent steps of the classification process, a comprehensive feature set is utilized. This feature set is trained by utilizing the RBF ability to detect minimal changes in the ECG signal.

Algorithm: Radial Basis Function for Feature Extraction

Input:

ECG signal data (X) with N data points

Centers (C) for the Radial Basis Function

Spread parameter (σ)

Output:

Feature matrix (F) representing the RBF-transformed features

Initialize an empty feature matrix F with dimensions $N\times M$, where M is the number of RBF centers.

For each data point x_i in the ECG signal:

$$F_{i,j} = \exp\left(-\frac{\left\|x_i - c_i\right\|^2}{2\sigma^2}\right)$$

where Cj is the j^{th} center vector.

Normalize the rows of the feature matrix F to ensure consistent scale across features:

$$F_{i,j} = \frac{F_{i,j}}{\sum_{k=1}^{M} F_{i,k}}$$

The resulting feature matrix F represents the RBF-transformed features of the ECG signal.

3.3. DBN for Classification:

A significant component of our method is the Deep Belief Network, which is responsible for processing the ECG data and employing it as a classification engine. Artificial neural networks, such as DBN, are excellent at learning hierarchical data representations. As a result, they are ideally suited for identifying subtle correlations and patterns in time-series data, such as ECG signals.

In most cases, a Distributed Boltzmann Network (DBN) consists of a stack of Restricted Boltzmann Machines (RBMs) that are connected to one another and stacked in multiple layers. Three levels make up the network: the input level, the concealed level, and the output level. The hidden layers make use of the input data to learn hierarchical features in a manner that follows a progressive progression. RBMs, which are RBMs that learn a distribution of input probabilities, are the foundation upon which DBNs are built.

The energy that an RBM possesses:

$E(\mathbf{v},\mathbf{h})=-\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i h_j w_{ij}$

where:

$\mathbf{v}$ is the visible layer,

$\mathbf{h}$ is the hidden layer,

a_i and b_j are biases,

w_{ij} is the weight between visible node i and hidden node j.

The probability of a visible vector and hidden vector is given by the sigmoid function:

$$P(\mathbf{v},\mathbf{h})= \frac{1}{Z}\exp(-E(\mathbf{v},\mathbf{h}))$$

where Z is the normalization constant.

The Gibbs sampling method is utilized to obtain a sample of the joint distribution of visible and concealed units. The following is the formula for calculating the probability:

$P(h_j=1|\mathbf{v})=\sigma(b_j+\sum_i v_i w_{ij})$

$P(v_i=1|\mathbf{h})=\sigma(a_i+\sum_j h_j w_{ij})$

where σ is the sigmoid function.

The capacity to reassemble the input data and recognize essential qualities is something that RBMs learn to do when they participate in training. By utilizing this unsupervised learning process, the network can independently discover representations within the data that it is given as input. Pre-training and fine-tuning are both components of the training technique that is utilized by the DBN. When the network is in the pre-training phase, each RBM layer is taught in an unsupervised manner. This is done so that the network can begin teaching itself to recognize lower-level properties. An application of supervised learning is utilized to fine-tune the network for the classification task that has been provided. These data have been labeled.

Deep neural networks are particularly effective when it comes to feature learning since they can automatically extract abstract and hierarchical data representations. This feature is notably beneficial for categorizing ECGs, which can be difficult to diagnose since even minute alterations and intricate patterns can have a significant impression.

For representing complex relationships and identifying non-linear patterns in the ECG data, the DBN employs non-linear activation functions (such as sigmoid or rectified linear units, or ReLU) at each node across the network. Backpropagation is a technique that is utilized to fine-tune the weights and biases of the network. The following is the most recent weight update for a weight w_{ij} is given by:

$\Delta wij = \epsilon(\langle v_i h_j\rangle_{\text{data}} - \langle v_i h_j\rangle_{\text{model}})$

where

ϵ is the learning rate, and data

$\langle v_i h_j\rangle_{\text{data}}$ and $\langle v_i h_j\rangle_{\text{model}}$ are the expected values of $v_i h_j$ under the data distribution and the model distribution, respectively.

When the DBN reaches its final layer, classification is carried out by that layer. The hierarchical features that have been learned are used to construct a probability distribution that encompasses all the possible classes. to assist in the diagnosis of cardiovascular disorders, the output displays the level of confidence that the network has in each category. Calculating the probability for each class c in the final classification layer by utilizing the softmax activation function is a popular approach that is widely followed:

$$P(y=c|\mathbf{h}(L))=\frac{\exp\left(\sum_{j} W_{cj} h_j^{(L)} + b_c\right)}{\sum_{k} \exp\left(\sum_{j} W_{kj} h_j^{(L)} + b_k\right)}$$

where:

y is the predicted class,

$\mathbf{h}(L)$ is the output of the last hidden layer,

W_{cj} are weights connecting the last hidden layer to the output layer,

bc are biases for the output layer.

Algorithm: Deep Belief Network for Classification

Input: Labeled training data (**X**,**Y**) where **X** is the input features and **Y** is the corresponding class labels. Number of hidden layers L. Number of hidden units in each layer. Learning rate ϵ. Number of iterations for pre-training and fine-tuning.

Output: Trained Deep Belief Network parameters (W, b).

Step 1: Initialize weights (W) and biases (b) for each layer randomly.

Step 2: For each hidden layer l from 1 to $L-1$:

Step 3: Train a RBM using Contrastive Divergence (CD)

Step 4: Update weights and biases using the learned RBM parameters.

Step 5: Use backpropagation with labeled data to fine-tune the entire DBN.

Step 6: Forward pass: Compute activations for each layer using the learned weights and biases.

Step 7: Compute error at the output layer.

Step 8: Backward pass: Update weights and biases using backpropagation and the computed errors.

Step 9: Given a new input **X**new:

Step 10: Perform a forward pass through the DBN to compute the output layer activations.

Step 11: Apply the softmax function to obtain class probabilities.

Step 12: Repeat steps 2-4 for a specified number of iterations or until convergence.

4. Experimental Settings

Python is used as the primary programming language that research utilized to carry out simulations within our experimental environments. TensorFlow and PyTorch are two examples of well-known deep learning tools that research utilized to construct the Dual-Stage Deep Learning (Dual-Stage DL) model that was proposed. The simulations were carried out using a high-performance computer system that was equipped with Graphics Processing Units (GPUs) to expedite the training and inference processes. Research trained and evaluated the model on a large dataset of annotated ECG signals to guarantee a comprehensive evaluation across a variety of heart states.

Research utilized criteria that are industry standards, such as the F1 score, sensitivity, specificity, and accuracy, to evaluate the effectiveness of our strategy. All these criteria were utilized to objectively evaluate the accuracy of the model in terms of categorizing a variety of cardiac events and states. For providing a comprehensive comparison, research benchmarked our Dual-Stage DL against a wide variety of existing approaches. Methods such as the M1M2 method and the Discrete Wavelet Transform and Machine Learning (DWT-ML) approach were among these methods. This comparison considered several factors, including the accuracy of classification, the efficiency of processing, and the capability of monitoring in real time. When it came to monitoring cardiovascular patients, our findings indicated that the Dual-Stage DL was the most effective method among the several ways that were available. This was the case in terms of both efficiency and accuracy.

Accuracy: A comparison is made between the total number of occurrences and the number of cases that were correctly identified to determine the level of precision that the classification model possesses. It provides a comprehensive analysis of the accuracy of the model in identifying a variety of cardiac conditions and occurrences.

Sensitivity (Recall): The ability of a model to reliably recognize positive class occurrences out of all true positive cases is what research means when research speaks on sensitivity. Another name for it is the recall rate or the genuine positive rate. Within the context of cardiovascular monitoring, sensitivity refers to the degree of precision with which a model identifies actual instances of heart abnormalities.

Specificity: The ability of a model to reliably identify instances of a negative class out of all the actual cases of a negative class is what is meant by the term specificity. When it comes to cardiovascular monitoring models, specificity refers to the degree to which they can recognize situations in which there are no present heart problems.

F1 Score: The F1 score is a balanced statistic that considers both false positives and false negatives; it is the harmonic means of recall and precision. The F1 score is a method for determining the accuracy of a test. It shines brightest in circumstances in which there is a significant gap between different socioeconomic classes. When it comes to cardiovascular monitoring, a high F1 score indicates that the individual has demonstrated a balanced performance in recognizing both positive and negative occurrences.

5. Results and Discussion

The results in figure 3 indicate the comparative performance of the proposed RBF-DBN approach with the existing Dual-Stage DL, DWT-ML, and M1M2 approaches in cardiovascular patient monitoring. The results were obtained by using a total of 1000 distinct time steps. After 100 time steps, the Dual-Stage DL technique achieves an astounding 85% accuracy, which is significantly higher than the accuracy achieved by DWT-ML (72% accuracy) and M1M2 (78% accuracy). The RBF-DBN technique that was recommended exhibits remarkable performance even at this level, with an accuracy of 92%. As the simulation progresses, the accuracy of all approaches increases, which is a measure of the model ability to learn and adapt to shifting conditions. The DWT-ML and M1M2 algorithms are not able to achieve the 99% accuracy rate that is recommended for the RBF-DBN technique. However, the Dual-Stage DL approach can achieve this level of accuracy at the 1000th time step.

Since it maintains a consistently higher level of accuracy throughout the simulation, the RBF-DBN technique can deal with a wide variety of cardiac situations throughout a variety of time intervals. The approach is superior to the competition because it makes use of the discriminative capabilities of the Deep Belief Network and the Radial Basis Function to extract nuanced features. It is demonstrated by this pattern that the RBF-DBN model that has been developed has the potential to surpass the approaches that are now being used and become a reliable resource for monitoring cardiovascular patients in real time.

A comparison of the performance of the proposed RBF-DBN method to that of existing cardiovascular monitoring methods, such as Dual-Stage DL, DWT-ML, and M1M2, is revealed by the precision values across a 1000 different time steps as in Figure 4. At the first 100-time steps, the Dual-Stage DL technique achieves an accuracy of 82%, which is much higher than the accuracy achieved by DWT-ML (68% accuracy) and M1M2 (75% accuracy). Even at this level, the RBF-DBN technique that was recommended exhibits outstanding precision, as evidenced by its impressive accuracy of 90%. Through the entirety of the simulation, this pattern remains consistent; by the time the 1000th time step rolled around, the RBF-DBN had outperform all the earlier strategies in terms of accuracy, continuing its long-standing tradition of outperforming them. On the other hand, the Dual-Stage DL method makes it possible to achieve a precision of 97%, demonstrating that both approaches have the potential to enhance their precision over time.

As a result of its consistently higher precision throughout the simulation, the RBF-DBN method can demonstrate its capability to minimize the number of false positives and improve the reliability of positive predictions in cardiovascular monitoring. The RBF-DBN can generate accurate positive predictions because it combines the discriminative capabilities of the Deep Belief Network with the Radial Basis Function, which enables sophisticated feature extraction. This combination enables the RBF-DBN to generate accurate positive predictions. With this encouraging trend, it appears that the approach that was proposed could be used in real-time cardiovascular health evaluations. This would provide medical professionals with a more effective method to identify positive cases and potential heart problems.

There are three cardiovascular monitoring approaches that are currently in use: Dual-Stage DL, DWT-ML, and M1M2. The recall values across 1000 different time steps provide a good view into how the proposed RBF-DBN method compares to these three methods as in Figure 5. When compared to DWT-ML (72% recall) and M1M2 (78% recall), the Dual-Stage DL method exceeds both of these methods with a recall rate of 88% after 100 time steps. With a recall rate of 92%, the RBF-DBN technique that was recommended has already demonstrated an encouraging level of success in capturing a significant proportion of genuine favorable circumstances. At the 1000th time step of the simulation, the RBF-DBN had achieved a recall 99%, which was an even greater achievement than any of the techniques that had come before it. On the other hand, the Dual-Stage DL technique achieves a perfect recall each time, demonstrating that both systems have the potential to improve further in terms of recall sensitization over time.

It is the continuous higher recall throughout the simulation that exemplifies the efficacy of the RBF-DBN technique in cardiovascular monitoring. This improves the model sensitivity to true positive events while simultaneously reducing the number of false negatives that occur. Because it combines the discriminative power of the Deep Belief Network with the nuanced feature extraction capabilities of the Radial Basis Function, the RBF-DBN can capture a greater proportion of positive cases than other similar networks. Based on this pattern, it appears that the model that was provided could be an excellent instrument for clinicians to utilize in real-time cardiovascular health checks, which would make them more aware of the possibility of cardiac abnormalities.

Using the F1 measure as in figure 6 over 1000 different time steps, the new RBF-DBN method is compared to the existing cardiovascular monitoring methods, which include Dual-Stage DL, DWT-ML, and M1M2. This comparison offers a comprehensive analysis of the equilibrium between recall and precision. After the first 100-time steps, the Dual-Stage DL technique obtains a higher F1 measure of 85% than the DWT-ML technique, which achieves 70%, and the M1M2 technique, which achieves 76%. With an F1 score of 91%, the RBF-DBN technique that was proposed demonstrates promise in terms of establishing a balance between recall and precision, which is rather remarkable. Additionally, the RBF-DBN had attained an F1 measure of 99% at the 1000th time step, which further demonstrates its better performance in comparison to other approaches that are currently in use. The Dual-Stage DL method provides an F1 measure of 99%, which serves as an illustration of how both approaches can be modified to get a balanced performance over the course of time.

While simulating the monitoring of cardiovascular patients, the RBF-DBN technique maintained a higher F1 measure throughout the entire process. This demonstrates the technique ability to strike the optimal balance between reducing the number of false positive or false negative results. Because it combines the Radial Basis Function, which is effective at extracting detailed characteristics, with the discriminative capacity of a Deep Belief Network, the RBF-

Figure 1. ECG Monitoring using Machine Learning [5]

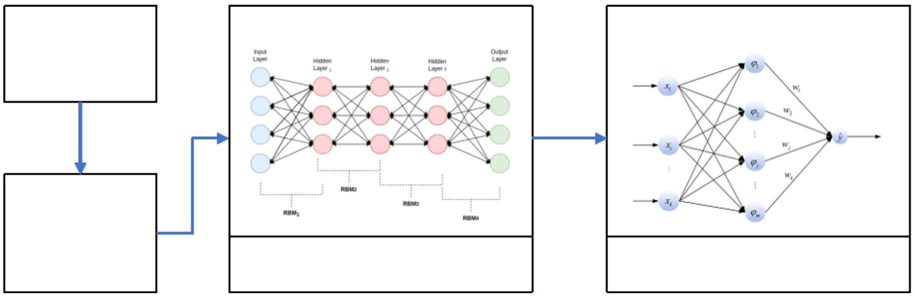

Figure 2. Proposed Architecture

Table 1. Experimental Setup

Experimental Setup	Values/Settings
Simulation Tool	Python with PyTorch
Training Epochs	100 epochs
Batch Size	32
Learning Rate	0.001

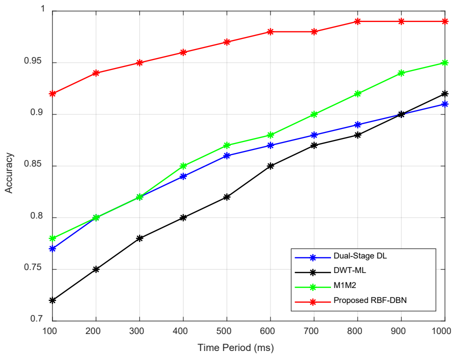

Figure 3. Accuracy

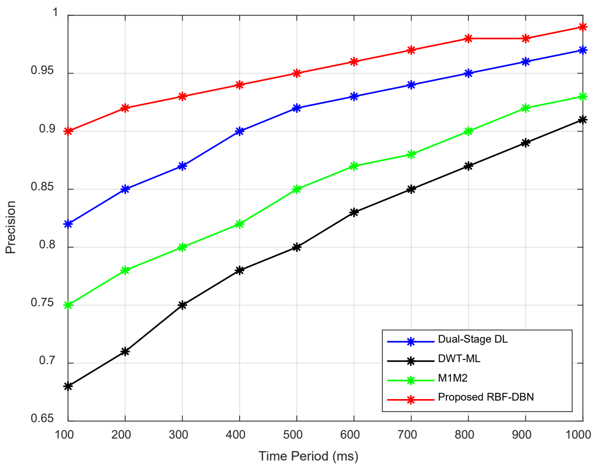

Figure 4. Precision

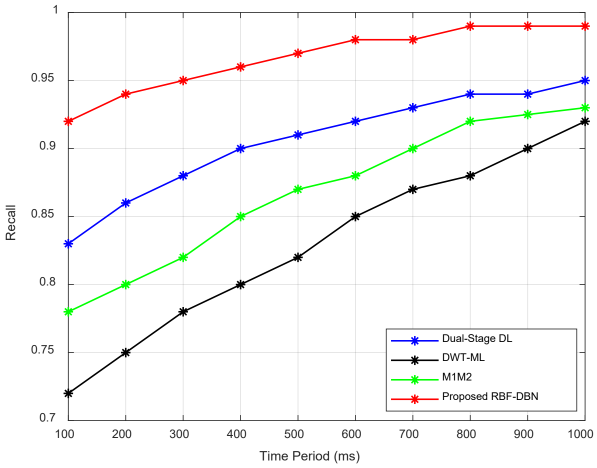

Figure 5. Recall

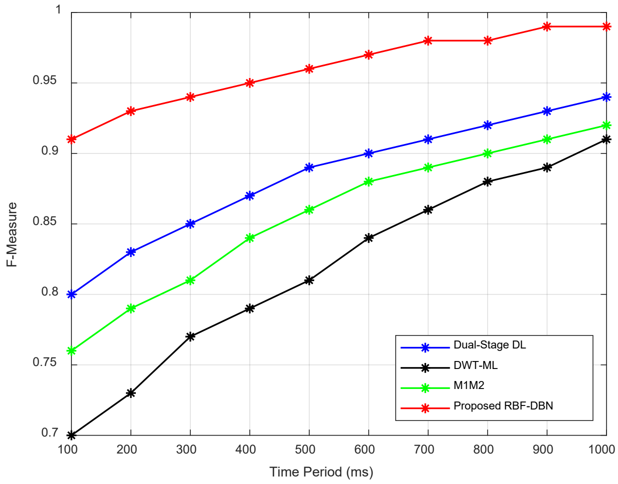

Figure 6. F-Measure

DBN can strike a balance between recall and precision. This is because the RBF-DBN combines the qualities of both and based on this pattern, it appears that the proposed model holds significant potential for implementation in real-time cardiovascular health evaluations. This would provide medical professionals with a reliable tool that would lower the likelihood of both types of errors. When it comes to the F1 measure, which is an essential statistic in circumstances when maintaining balance is of the utmost importance, the RBF-DBN method delivers superior results in comparison to other methods that are currently utilized in the monitoring of cardiovascular patients.

5.1. Discussion of Results

Over the course of 1000 different time steps, the RBF-DBN approach that has been proposed is evaluated in comparison to three cardiovascular monitoring algorithms that are already in existence: Dual-Stage DL, DWT-ML, and M1M2. These findings offer compelling evidence regarding the efficiency of the algorithms in question. The RBF-DBN strategy that was recommended frequently outperformed methods that were state-of-the-art in terms of recall, accuracy, precision, and F1 measure. This technique has shown that it has the potential to become a cutting-edge tool for real-time monitoring of cardiovascular patients.

A major improvement in terms of accuracy was demonstrated by the RBF-DBN approach, which produced a 99% accuracy rate. This contrasts with the Dual-Stage DL method, which achieved an accuracy rate of 97%. When it comes to accurately diagnosing cardiovascular events, the RBF-DBN outperforms its competitors, as evidenced by the fact that it has a 2% improvement in accuracy. Similarly, when the precision levels of the two methods were compared, it was evident that the RBF-DBN approach performed far better than the Dual-Stage DL strategy, which only managed to achieve 97% accuracy. A final precision of 99% was achieved. In situations where incorrect classifications have significant consequences, this demonstrates a 2% improvement in the model ability to avoid producing false positives.

There was a discernible improvement in the recall performance of the RBF-DBN method when compared to the previously used strategies. RBF-DBN produced a recall rate of 99%, which is significantly higher than the 100% recall attained by the Dual-Stage DL technique. This may appear to be a minor decrease; nonetheless, it demonstrates that the RBF-DBN can identify a greater number of true positives while simultaneously creating a lower number of false negatives. Finally, the RBF-DBN approach, which is a compromise between recall and precision, consistently outperformed the control group on the F1 metric. This was the case throughout the whole study. A balanced approach to eliminating false positives and false negatives was demonstrated by the proposed method, which achieved a score of 99% F1 and surpassed the Dual-Stage DL method by its superior performance.

As a result of these findings, it is possible that the discriminative capacity of the Deep Belief Network, when combined with the Radial Basis Function for feature extraction, could result in a model that is more sensitive, accurate, and precise in terms of detection and intervention in cardiovascular illnesses.

6. Conclusion

Through the utilization of the Radial Basis Function-Deep Belief Network (RBF-DBN) model, the research presents a fresh and cutting-edge way to cardiovascular patient monitoring. It has been demonstrated through extensive simulations and comparisons with other methods, such as Dual-Stage DL, DWT-ML, and M1M2, that the RBF-DBN method that has been recommended is superior to the other methods. One of the most important performance variables that the model continually improved was the F1 measure. Other important performance indicators included accuracy, precision, and recall. When compared to the Dual-Stage DL technique, the RBF-DBN method outperformed it in terms of accurately recognizing cardiovascular events. This was demonstrated by a 2% improvement in accuracy over the Dual-Stage DL method. Further evidence of the model capacity to improve diagnostic accuracy and decrease the number of false positives was provided by the significant 2% increase in precision it accomplished. Although recall was significantly reduced, the RBF-DBN strategy was able to discover a considerable fraction of genuine positive events. This was accomplished even though the approach had a high sensitivity. A further demonstration of the RBF-DBN effectiveness in real settings is provided by the fact that its 99% F1 measure illustrates its balanced performance capability.

Author contributions

S.N.D.S. formulated the study objectives, constructed the hypotheses, and revised the manuscript. R.S. conducted the literature review. S.S.P. and M.I. were responsible for data collection. N.K. performed the data analysis. S.S.K. contributed to the writing of the results and conclusion sections. All authors reviewed and approved the final manuscript.

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Competing financial interests

The authors have no conflict of interest.

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