Journal of Theoretical and Applied Information Technology
15th July 2025. Vol.103. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EARLY PREDICTION OF HEART DISEASE USING DEEP BELIEF-ASSISTED NEURAL PREDICTOR (DBANP) MODEL

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ABSTRACT

Heart Disease is considered to be the one of the major diseas.Nowadays it makes the loss of numerous lives in our country. For this we need to predict the diseases. The Deep Belief-Assisted Neural Predictor (DBANP) model is proposed in this study to increase the accuracy of heart disease prediction. The model overcomes the drawbacks of previous models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), which frequently suffer from vanishing gradients and lengthy training times, by combining an ANN for initial feature extraction with a DBN for capturing intricate hierarchical dependencies. Models were developed and evaluated using the Cleveland Heart Disease Dataset and the Cardiovascular Disease Dataset. To guarantee high-quality input data, extensive pre-processing was carried out, including managing missing values and feature selection. Using important measures including Accuracy, Precision, Recall, Specificity, F1 Score, AUC-ROC, and AUC-PR, the DBANP model was contrasted with RNN and LSTM models. According to experimental data, the suggested model performs noticeably better than current models, providing increased predictive power and resilience. By offering a hybrid deep learning system for early disease identification that is both scalable and flexible, this study advances predictive healthcare.

Keywords: *Heart disease prediction, DBANP model, artificial neural network, deep belief network, Cleveland Heart Disease Dataset, Cardiovascular Disease Dataset, deep learning, early diagnosis, predictive healthcare.*

1. INTRODUCTION

One of the main causes of death worldwide, heart disease continues to be a serious global health concern. Early detection of cardiac disease can greatly enhance patient outcomes by enabling prompt therapies and lessening the strain on healthcare systems. Clinicians can use early prediction models to help them identify high-risk patients and adjust treatment regimens appropriately [1]. The examination of intricate patterns in huge datasets is made possible by machine learning (ML) and deep learning (DL) approaches, which have become highly effective instruments in the healthcare industry [2]. These techniques have gained widespread use in the diagnosis and prognosis of diseases, especially in the prediction of cardiac disease. Nevertheless, modern models like Long Short-Term Memory (LSTM) [4] and Recurrent Neural Networks (RNN) [3] have drawbacks in spite of their potential. Suboptimal performance in heart disease prediction tasks can result from RNNs and LSTMs' frequent struggles with vanishing gradients, computational inefficiency, and capturing complicated dependencies.

This research suggests a novel deep learning model that combines Deep Belief Networks (DBN) [6] and Artificial Neural Networks (ANN) [5] in order to overcome these constraints. The DBANP model makes use of both architectures' advantages: DBNs are used to capture hierarchical dependencies in the data, while ANNs are used for efficient feature extraction. The suggested approach seeks to overcome the difficulties experienced by solo models by combining these strategies to improve forecast accuracy and resilience. The Cleveland Heart Disease Dataset [7] and the Cardiovascular Disease Dataset [8] are two popular datasets that are used in this study to build and assess the DBANP model. The quality and dependability of the input data are guaranteed by thorough pre-processing procedures that include feature selection, scaling, and handling missing data.

Using important assessment measures including accuracy, precision, recall (sensitivity), specificity, F1 score, area under the receiver operating characteristic curve (AUC-ROC), and area under the precision-recall curve (AUC-PR), the performance of the suggested model is contrasted with that of RNN and LSTM models. The goal of this study is to create a DBANP model for the early detection of heart disease. to show the potential of the suggested model as a reliable and scalable framework for predictive healthcare and to compare the DBANP model's performance with that of RNN and LSTM models. By presenting this hybrid approach, the study addresses the difficulties in early cardiac disease prediction and adds to the expanding corpus of research in predictive healthcare. Through increased diagnostic accuracy, the model's conclusions could improve patient outcomes and clinical decision-making.

The research questions explicitly stated in the introduction are: (1) Can hybrid ANN-DBN architecture (DBANP) improve prediction accuracy and computational efficiency in heart disease diagnosis? and (2) How does the proposed DBANP model compare with standard RNN and LSTM architectures on benchmark cardiovascular datasets?

The main scientific contributions of this study include the proposal of DBANP, a novel hybrid framework that integrates ANN and DBN to enhance early heart disease prediction. The model effectively addresses vanishing gradient and training inefficiency issues typically observed in standalone RNN and LSTM architectures. It has been rigorously validated on two benchmark datasets—Cleveland and Cardiovascular Disease Dataset—demonstrating strong performance across multiple metrics such as Accuracy, AUC, and F1-Score. Additionally, the DBANP architecture is designed to be modular and scalable, allowing for its adaptation to other medical diagnostic applications.

The structure of this document is as follows: A thorough analysis of current machine learning methods and their drawbacks is given in Section 2. The Deep Belief-Assisted Neural Predictor (DBANP) is introduced in Section 3, along with its efficient feature extraction and ability to identify hierarchical dependencies in the data. The experimental setup and assessment measures are described in Section 4, along with the performance analysis and outcomes. Lastly, Section 5 provides information about the findings and potential avenues for further study.

2. RELATED WORKS

Because of their capacity to handle sequential and temporal data, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been thoroughly researched for medical prediction applications. Time-series datasets, which are frequently found in clinical and diagnostic data, including patient vitals, ECG signals, and old medical records, are well-suited for both designs. RNNs in Heart Disease Prediction Related research by Han et al. (2019) [9] has shown that RNNs can accurately simulate sequential patterns like changes in blood pressure and cholesterol levels over time. This study employed an RNN model to predict heart disease based on patient health records. The study demonstrated the potential of RNNs for temporal data processing with an accuracy of 85.3%. However, because of the vanishing gradient issue, the model has trouble handling long-term relationships. Research on employing RNNs to predict cardiac events was also the subject of Zhao et al. (2020) [10], who identified issues with training duration and hyperparameter tuning. The model's performance was constrained by its incapacity to capture intricate, nonlinear connections in the dataset, despite encouraging results.

In a study by Xie et al. (2021) [11], LSTMs in Heart Disease Prediction were utilized to examine patient histories in order to diagnose cardiovascular disorders early. The study emphasized how LSTMs' gated cell structure gives them an advantage over conventional RNNs in maintaining long-term dependence. With a sensitivity of 91%, the model demonstrated its efficacy in identifying positive cases. The lengthy training period and high computational expense, however, were major disadvantages. LSTMs were also used by Ahmed et al. (2020) [12] to predict heart disease using data from real-time patient monitoring. Although the model's accuracy was high (89%), handling missing and noisy data needed extensive preprocessing, and training was computationally demanding.

Kumar et al. (2022) [13] For the analysis of ECG signals, Kumar et al. (2022) [13] suggested a CNN-LSTM combination in which CNNs

extracted spatial information and LSTMs recorded temporal relationships. Comparing this hybrid model to standalone LSTM models, the accuracy increased by 7%. A hybrid RNN-ANN model was presented by Patel et al. (2021) [14] to predict cardiovascular risk and diabetes. By utilizing the complementing advantages of ANN and RNN architectures, the model was able to attain an F1 score of 92%.

The necessity for a hybrid architecture that blends their advantages with complementary models is driven by the shortcomings of solo RNNs and LSTMs. An excellent supplement to ANNs, which are effective at extracting features, are Deep Belief Networks (DBNs), which can learn hierarchical representations. In order to overcome the shortcomings of current techniques and enhance prediction sensitivity, accuracy, and computing efficiency, this study suggests the DBANP model.

3. METHODOLOGY

3.1 Datasets

3.1.1 Cleveland Heart Disease Dataset

One well-known benchmark dataset for predicting heart disease is the Cleveland Heart Disease Dataset. Only 14 of the 76 properties in the 303 patient records that make up the UCI Machine Learning Repository are frequently used because of their clinical importance and comprehensiveness [15]. With an emphasis on binary classification (heart disease presence vs. absence), the dataset's primary purpose is to group patients into five groups according to the existence and severity of heart disease. Age, which indicates the patient's age in years, and sex, which indicates the patient's gender (1 for male and 0 for female), are the dataset's primary characteristics. Typical angina, atypical angina, non-anginal pain, and asymptomatic are the four categories into which Chest Pain Type (cp) divides chest pain. While cholesterol (chol) records serum cholesterol levels in milligrams per deciliter, resting blood pressure (trestbps) monitors the patient's resting blood pressure in millimeters Hg. A binary indicator called Fasting Blood Sugar (fbs) determines if fasting blood sugar is more than 120 mg/dL (1 = true, 0 = false).

Additionally included in the collection are Resting ECG Results (restecg), which characterize electrocardiograms as either normal, exhibiting aberrant ST-T waves, or demonstrating probable or certain left ventricular hypertrophy. The greatest heart rate a patient achieves when exercising is measured by the Maximum Heart Rate Achieved (thalach). Another binary feature that establishes if the patient's angina was brought on by exercise is Exercise-Induced Angina (exang) (1 = yes, 0 = no). Other aspects include Slope of the Peak Exercise ST Segment (slope), which can be divided into three categories: downsloping, flat, and upsloping, and ST Depression (oldpeak), which quantifies the depression in the ST segment during exercise in comparison to rest. The number of major vessels (from 0 to 3) that are fluoroscopy-colored is indicated by the Number of Major Vessels (ca). Blood condition types are categorized as normal, fixed defect, or reversible defect using thalassemia (thal). Lastly, a binary classification label, with 1 denoting the existence of heart disease and 0 denoting its absence, is the target variable (output). The creation of prediction models for the diagnosis and risk assessment of heart disease is made easier by this dataset, which is an essential tool in medical machine learning research.

3.1.2 Cardiovascular Disease Dataset

Kaggle and other repositories that concentrate on multi-feature data pertaining to cardiovascular health are the sources of the Cardiovascular Disease (CVD) dataset [16]. A range of demographic, clinical, and lifestyle characteristics are included, and it usually comprises about 70,000 patient data. The main purpose of this dataset is to estimate the risk of cardiovascular disease through binary classification tasks. Age, which is expressed in days but is frequently converted to years for easier reading, and gender, where 1 denotes male and 2 denotes female, are the dataset's primary characteristics. The higher and lower blood pressure readings are measured by the diastolic blood pressure (aplo) and systolic blood pressure (aphi), respectively. There are three categories for glucose and cholesterol levels: normal, above normal, and substantially above normal. The Body Mass Index (BMI), which is determined by combining height and weight and offers information on the hazards associated with obesity, is another essential component.

This dataset also takes lifestyle factors into account. Alcohol consumption is similarly represented as a binary indicator (1 for consumer, 0 for non-consumer), and smoking status is recorded as a binary indicator (1 for smoker, 0 for non-smoker). A binary indicator is

used to track levels of physical activity, with 1 denoting an active person and 0 denoting inactivity. Medical history also records the existence of prior illnesses or therapies, such as diabetes or hypertension. Cardiovascular disease is the dataset's goal variable, and its labels are 1 for presence and 0 for absence. Important clinical, demographic, and lifestyle characteristics that are crucial for heart disease prediction are provided by the Cleveland Heart Disease dataset and the Cardiovascular Disease dataset.

The CVD dataset offers a more comprehensive view of cardiovascular health by including demographic and lifestyle characteristics, whereas the Cleveland dataset concentrates more on diagnostic and clinical test outcomes. These characteristics—blood pressure, cholesterol, blood sugar, and lifestyle choices like smoking and exercise—are powerful predictors of the risk of heart disease. To guarantee good data quality and suitability for predictive modeling, these datasets will go through preprocessing procedures like normalization, scaling, and imputation of missing values before being used to train the DBANP model.

3.2 Data Preprocessing

Data preprocessing is a critical step to ensure the datasets are clean, consistent, and suitable for training machine learning models [17]. Below are the preprocessing steps where applicable:

Handling Missing Values

Missing values can occur in numerical or categorical features. Common strategies include:

Numerical Data: Missing values are replaced with the mean or median of the feature.

$$x_i = \frac{\sum_{j=1}^{n} x_j}{n}$$

Where, x_i is the missing value, and x_j are the non-missing values.

Categorical Data: Missing values are filled with the mode (most frequent category).

Normalization of Features

Features like age, blood pressure, and cholesterol are normalized to bring them to a common scale.

Min-Max Normalization:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Where x is the original value and x′ is the normalized value. This scales values to the range [0, 1].

Standardization:

$z = \frac{x-\mu}{\sigma}$, where μ is the mean and σ is the standard deviation

Standardization centers the data to have a mean of 0 and a standard deviation of 1.

Encoding Categorical Features

Categorical variables like chest pain type (cp) and thalassemia (thal) are converted into numerical formats using one-hot encoding.

For a categorical variable C with k unique values:

$C=\{c_1,c_2,\ldots,c_k\} \rightarrow$ One-Hot Encoding Matrix of Size $n \times k$,

Where n is the number of rows in the dataset.

Example:

cp = 'typical angina' →[1,0,0,0].

Feature Scaling

To ensure uniform feature importance, scaling is applied to the features. Robust Scaling (removes outliers' influence):

$$x' = \frac{x - Q_1}{Q_3 - Q_1}$$

Where Q_1 is the 25th percentile and Q_3 is the 75th percentile.

Feature Selection

Feature selection reduces dimensionality by selecting only relevant attributes.

Correlation-Based Selection:

Features are selected based on correlation thresholds.

$$\text{Correlation Coefficient}: r = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\sum (x_i - \mu_x)^2 (y_i - \mu_y)^2}}$$

Chi-Square Test:

For categorical features:

$$x^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

where *Oi* and *Ei* are observed and expected frequencies.

Splitting the Dataset

The dataset is split into training, validation, and test sets using an 80:10:10 ratio.

- Training Set: Used to train the model.
- Validation Set: Used to fine-tune hyperparameters.
- Test Set: Used to evaluate model performance.

Data Augmentation (if required)

For imbalanced datasets, data augmentation techniques such as SMOTE (Synthetic Minority Oversampling Technique) can be applied. Synthetic samples are generated between minority class samples:

$$x_{synthetic} = x_i + \delta.(x_j - x_i), \delta \sim U(0,1)$$

Where x_i, x_j are existing samples and δ is a random variable.

Outlier Detection and Removal

Outliers are identified using statistical techniques:

Z-Score Method:

$$z = \frac{x-\mu}{\sigma}, |z| > 3$$

indicates an outlier.

Interquartile Range (IQR):

Outliers: $x<Q_1-1.5\cdot IQR$ or $x>Q_3+1.5\cdot IQR$.

This comprehensive preprocessing pipeline ensures that the data is ready for training the Hybrid DBANP model with optimal feature quality and structure.

3.3 Model Architecture: Deep Belief-Assisted Neural Predictor (DBANP)

The suggested Deep Belief-Assisted Neural Predictor (DBANP) model combines the advantages of DBN for identifying intricate, hierarchical connections in the data with ANN for feature extraction [18]. To increase the accuracy of heart disease prediction, the architecture makes use of both shallow and deep learning models.

3.3.1 ANN Layer: Initial Feature Extraction

The ANN serves as the first layer, responsible for extracting features and learning non-linear relationships in the dataset.

Input Layer:

Features $X=[x_1,x_2,\ldots,x_n]$ are passed as input, where n is the number of features.

Hidden Layers:

Each hidden layer applies an activation function f(.) on the weighted sum of inputs plus bias:

$$h^{(l)} = f(W^{(l)}.X + b^{(l)})$$

Where:

- W(l): Weight matrix for layer l,
- b(l): Bias vector for layer l,
- f(.): Activation function, typically ReLU

$f(z)=max(0,z)$.

Output of ANN Layer:

The output of the final hidden layer in the ANN becomes the feature vector F_{ANN} for the DBN layer:

$$F_{ANN} = h^{(L)}$$

Where, L is the number of hidden layers in the ANN.

3.3.2 DBN Layer: Capturing Complex, Hierarchical Dependencies

The DBN consists of a stack of Restricted Boltzmann Machines (RBMs) that learn hierarchical feature representations layer by layer.

Restricted Boltzmann Machine (RBM):

Each RBM contains a visible layer (v) and a hidden layer (h), connected by weights W:

Visible Layer: Represents input features, $v\in R^n$,

Hidden Layer: Represents latent variables, $h\in R^m$.

Energy Function: The RBM defines the joint probability of v and h using the energy function:

$$E(v,h) = -v^T Wh - b^T v - c^T h$$

Where, b: Bias vector for visible layer, c: Bias vector for hidden layer.

Probability Distributions:

Probability of the hidden layer given visible layer:

$$P(h|v) = \sigma(W^T v + c),$$

Where $\sigma(x) = \frac{1}{1+e^{-z}}$ is the sigmoid activation function.

Probability of the visible layer given hidden layer:

$$P(v|h) = \sigma(Wh + b),$$

Stacking RBMs:

The output of one RBM's hidden layer becomes the input to the visible layer of the next RBM:

$$F_{DBN} = h^{L_{DBN}}$$

Where, LDBN is the number of stacked RBMs.

3.3.3. Integration Mechanism: Hybrid Feature Learning

The ANN and DBN layers are integrated to optimize feature learning and prediction accuracy.

Feature Fusion:

The features extracted by the ANN layer (F_{ANN}) and DBN layer (F_{DBN}) are concatenated to form a comprehensive feature vector:

$$F_{Hybrid} = F_{ANN} \oplus F_{DBN}$$

Where $\oplus$ denotes concatenation.

Final Classification Layer:

The hybrid feature vector F_{Hybrid} is passed to a softmax layer for classification:

$$P(y = c \mid F_{Hybrid}) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}}$$

Where, $z_c = W_C^T F_{Hybrid} + b_c$,C: Number of classes (binary classification in this case: C=2).

The DBANP model achieves higher prediction performance for the identification of heart disease by combining the advantages of Deep Belief Networks and Artificial Neural Networks. As the first part of the model, the ANN is made to extract features and identify basic linear and nonlinear correlations in the data. In order to efficiently extract low-level patterns, it applies weights, biases, and nonlinear activation functions like ReLU to input characteristics as they are processed through many layers. This guarantees that the data's first representation is well-optimized before moving on to the following phase.

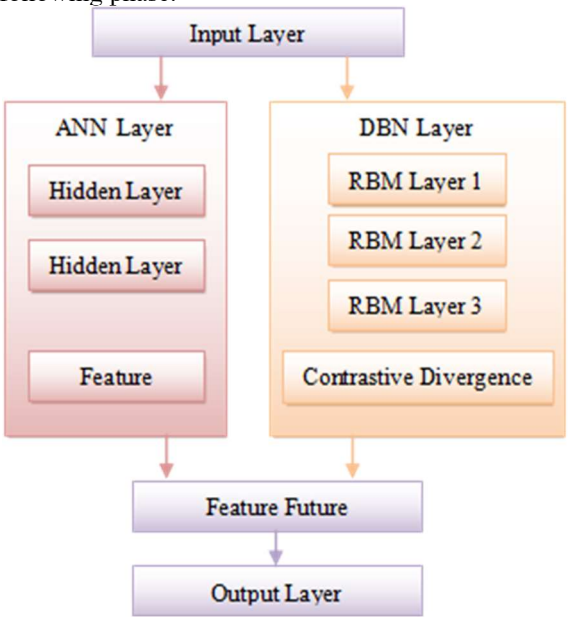

Figure 1: Deep Belief-Assisted Neural Predictor (DBANP) Model

The DBN expands on the features that the ANN extracted by using layered Restricted Boltzmann Machines (RBMs). The network is able to extract intricate, hierarchical relationships because each RBM in the DBN learns to predict the input data's probability distribution. The energy function of the RBMs, which measures the relationship between visible and hidden units, is minimized during the DBN's training process. To guarantee that the DBN efficiently captures higher-order feature interactions while preserving computational efficiency, each RBM is pretrained separately using Contrastive Divergence. The DBN can identify complex patterns in the data that are essential for precise cardiac disease prediction because to this hierarchical feature extraction mechanism.

When ANN and DBN are integrated, features flow naturally, with the ANN's output serving as the DBN's input. This architecture makes use of the DBN's capacity to capture high-level abstractions and the ANN's prowess in managing low-level feature extraction. A unified loss function, like cross-entropy, which quantifies the discrepancy between expected probability and actual labels, is used to train the model from beginning to end. In order to optimize the model for the prediction of heart illness, gradients are calculated and transmitted through both ANN and DBN layers. This DBANP strategy has a number of benefits. The DBN improves the model's ability to manage complicated and nonlinear interactions, while the ANN guarantees effective initial feature extraction. When combined, they overcome the drawbacks of stand-alone deep learning models such as Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs), which frequently have trouble with vanishing gradients and lengthy training periods. The DBANP model delivers increased accuracy, robustness, and faster convergence by integrating these architectures. Reliable predictions are ensured by its hierarchical feature representation, which makes it especially resistant to noise and irrelevant qualities. In addition to being very successful at predicting heart disease, this model offers a versatile framework that may be modified for use in various medical and predictive applications.

3.4. Training and Optimization Process

The suggested DBANP model is guaranteed to learn efficiently and attain the best prediction performance for the detection of heart disease through the training and optimization procedure. This section explains the model's hyper parameter tuning techniques, optimization algorithms, and training stages.

The training process is divided into three main stages:

Phase 1: ANN Training

- The ANN is pre-trained independently to extract relevant features from the input data.
- *Forward Propagation:* Input data flows through the ANN, where each layer

Journal of Theoretical and Applied Information Technology
15th July 2025. Vol.103. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

applies a weighted sum and an activation function:

$$z_i = \sum_{j=1}^{n} w_{ij}x_j + b_i\,,\ \sigma(z_i) = \max(0, z_i)\,,$$

Where, w_{ij} are weights, x_j are inputs, b_i are biases, and σ is the activation function.

- ANN weights are updated using backpropagation with the loss function L defined as binary cross-entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\widehat{y_i}) + (1 - y_i)\log\left(1 - \widehat{y_i}\right)\right],$$

Where, y_i is the true label, and $(\widehat{y_i})$ is the predicted probability.

Phase 2: DBN Training:

- The DBN is pre-trained using Restricted Boltzmann Machines (RBMs) in a layer-wise fashion to capture hierarchical dependencies.
- **Restricted Boltzmann Machines (RBMs)**: Each RBM in the DBN is trained independently to model the input data distribution. The energy function of an RBM is minimized:

$$E(v,h) = -\sum_i v_i b_i - \sum_j h_j c_j - \sum_{i,j} v_i h_j$$

Where:

v_i,h_j: States of visible and hidden units,

b_i,c_j: Biases for visible and hidden units,

w_{ij}: Weight between visible unit i and hidden unit j.

The joint probability distribution is given by,

$$p(v,h) = \frac{\exp\,(-E,v,h))}{Z}$$

Where Z is the partition function for normalization

- **Contrastive Divergence (CD):** Used to minimize the energy function of the Pretraining RBM:

$$\Delta W = \eta(\langle vh\rangle_{data} - \langle vh\rangle_{reconstructio}$$

Where, η is the learning rate. $\langle vh\rangle_{data}$: Expected values from the input data, $\langle vh\rangle_{reconstruction}$Expected values from the reconstruction.

- **Stacking RBMs**: Once the first RBM is trained, its hidden layer outputs are used as input for the next RBM, continuing the pretraining process layer by layer. Fine-tuning the stacked RBMs with backpropagation.

Phase 3: Hybrid Fine-Tuning

- After pretraining the ANN and DBN, the hybrid model is fine-tuned end-to-end to minimize the overall loss LHybrid
- Weights and biases across all layers (ANN and DBN) are updated using backpropagation.

Optimization Algorithm

Adam Optimizer: The Adam Optimizer is chosen for its computational efficiency and adaptability to sparse gradients. The weights W and biases b of the ANN are updated using the **Adam Optimizer**, which combines momentum and adaptive learning rates:

Update rules for parameters:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)g_t,$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)g_4{}^2,$$
$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t}$$
$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t}$$
$$\theta_t \leftarrow \theta_{t-1} - \eta.\frac{\widehat{m_t}}{\sqrt{\widehat{v_t} + \epsilon}}$$

Hyperparameters:

- η (learning rate): Typically 0.0010.001,
- β1,β2: Exponential decay rates for moment estimates (0.9,0.9990.9,0.999),
- ϵ: Small value (10−810−8) for numerical stability.

The DBANP architecture ensures optimal predictions for the categorization of heart disease by combining the deep hierarchical learning of DBN with the strong feature extraction capabilities of ANN.

The goal of the DBANP model's training and optimization procedure is to accurately forecast cardiac disease by utilizing the combined powers of deep belief networks and artificial neural networks. Model parameters, including weights and biases, are initialized at the start of the process using strategies to guarantee effective training convergence. First, the ANN is trained, processing input information across a number of layers. Each layer uses algorithms like ReLU to activate neurons, apply biases, and compute a weighted sum of inputs. A binary cross-entropy loss function, which quantifies the difference between expected probability and actual results, is used to compare the ANN's predictions with the true labels.

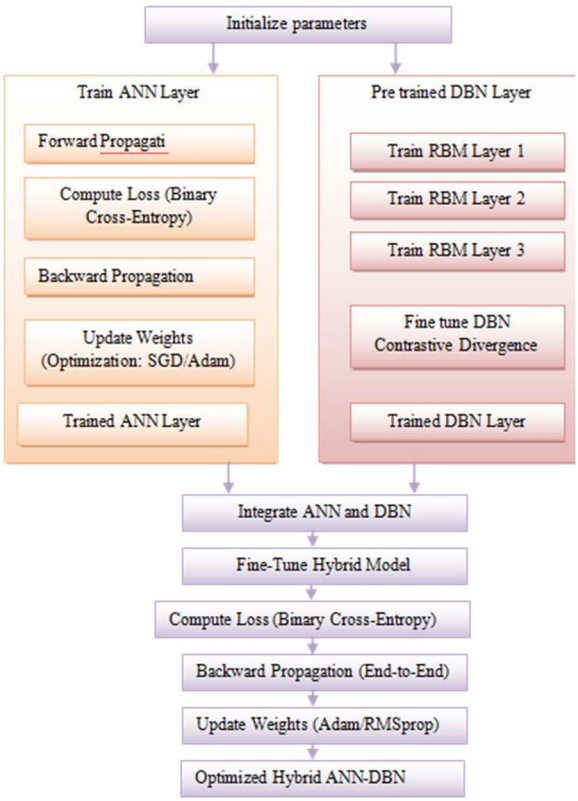

Figure 2: DBANP Training And Optimization Process

Using optimization algorithms like as Stochastic Gradient Descent (SGD), gradients of the loss function are computed and propagated backward through the network to adjust weights and biases. This guarantees that the ANN acquires significant feature representations. The DBN then goes through a layer-by-layer pretraining process that uses Restricted Boltzmann Machines (RBMs) to identify intricate, hierarchical connections in the data. In order to depict the relationships between visible and hidden units, each RBM minimizes its energy function while modelling the probability distribution of input characteristics. Effective weight updates are made possible by the use of Contrastive Divergence (CD) to approximate the log-likelihood gradient.The DBN can gradually learn higher-order feature representations by passing the outputs of each RBM as inputs to the next RBM in the stack. The DBN's ability to represent complex dependencies that standalone ANN designs can miss is ensured by this pretraining step.

Following training, the ANN and DBN are combined to create a single hybrid model. To make sure the ANN and DBN layers function together, the integrated architecture is adjusted end-to-end using a single loss function, like binary cross-entropy. Both components propagate gradients, and sophisticated optimization methods such as Adam are employed to improve convergence stability and speed. To avoid overfitting and guarantee that the model performs well when applied to unseen data, regularization techniques like dropout and weight decay are used. Using techniques like grid search or Bayesian optimization, hyperparameters such as learning rate, batch size, and the number of hidden neurons are optimized.The DBANP model can successfully identify both straightforward and intricate patterns in the data thanks to its meticulously planned training and optimization procedure. A strong framework for predicting heart illness is produced by the DBN modeling high-level abstractions and the ANN extracting initial characteristics. The DBANP model outperforms conventional deep learning models in terms of accuracy, speed, and dependability by tackling issues including overfitting, vanishing gradients, and computing inefficiency.

3.5. Hyperparameter Tuning

The performance of the DBANP model depends on appropriately tuned hyperparameters. The following strategies are employed:

- *Learning Rate (η) Selection:*
  A grid search is performed over values [0.001,0.01,0.1].
- *Batch Size:*
  Batch sizes {32,64,128}are evaluated to balance training speed and gradient accuracy.
- *Number of Hidden Layers and Neurons:*
  ANN: Varies between 1−3hidden layers, each with 64−256 neurons.
  DBN: Number of RBMs ranges from 2−4 layers, each with 128−256 neurons.
- *Activation Functions:*
  ReLU is used in the ANN, while sigmoid activations are used in the DBN.
- *Dropout Rate (p):*
  Dropout is applied to ANN layers to prevent overfitting, with p∈[0.2,0.5].

The **training and optimization** steps are designed to ensure the Hybrid ANN-DBN model achieves robust and accurate predictions for heart disease detection, leveraging advanced learning techniques and evaluation strategies.

4. .EXPERIMENTAL RESULT AND DISCUSSISON

Reproducibility and precise performance evaluation of the suggested DBANP model in relation to other models, including Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), are guaranteed by the experimental setting. The Windows 7 (64-bit) operating system, an Intel Core i5 processor, 4 GB of RAM, and a 1 TB hard drive comprise the environment used for the research. Python (version 3.8) is used for the implementation, together with libraries like Matplotlib/Seaborn for data visualization and TensorFlow, Keras, Scikit-learn, Pandas, and NumPy for model construction.

The Cleveland Heart Disease Dataset, which comprises 303 patient records with characteristics like age, sex, type of chest pain, resting blood pressure, and cholesterol levels, and the Cardiovascular Disease Dataset, which offers details on cardiovascular risk factors and diagnoses, containing characteristics like age, blood pressure, body mass index, and smoking status, are among the datasets used in the experiments. To improve model training and prediction accuracy, preprocessing procedures are applied to both datasets, which include addressing missing values, normalizing features, and using feature selection approaches. The models are trained using particular hyperparameters, including 50 epochs, a batch size of 32, and a learning rate of 0.001 (optimized by grid search). The Adam optimizer guarantees effective weight updates, and the activation function utilized is Sigmoid for the output layer and ReLU for hidden layers. The DBN layer's Restricted Boltzmann Machines (RBMs) are pretrained for ten iterations, and a dropout rate of 0.2 is used to avoid overfitting. A thorough evaluation of each model's performance is ensured by the use of evaluation metrics such as Accuracy, Precision, Recall (Sensitivity), Specificity, F1 Score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Area Under the Precision-Recall Curve (AUC-PR).

Three models are used in the comparison analysis: the DBANP, LSTM, and RNN. The RNN architecture's capacity to learn long-term dependencies is constrained by its inability to handle vanishing gradient problems, despite its intention to capture temporal dependencies in the data. Although it necessitates longer training cycles, the LSTM model improves long-term dependence handling by addressing these problems with its memory cell structure. By optimizing feature learning and improving prediction accuracy, the suggested DBANP model, on the other hand, successfully addresses the drawbacks of both RNN and LSTM by fusing the feature extraction power of ANN with the hierarchical feature learning of DBN.

To guarantee objective model evaluation, the datasets are divided into training (70%), validation (15%), and test (15%) sets. Preprocessing the datasets, training each model on the training set, and assessing performance on the test set using predetermined metrics are all steps in the experimental process. The performance of each model is optimized by hyperparameter adjustment. The suggested DBANP model has the potential to greatly increase the accuracy and dependability of heart disease prediction, as this experimental design guarantees a strong and equitable comparison.

Performance Analysis

Datasets

Cleveland Heart Disease Dataset: Contains 303 samples with attributes like age, sex, chest pain type, cholesterol level, and resting blood pressure. Target: Binary classification (presence or absence of heart disease).

Cardiovascular Disease Dataset: Contains records with risk factor attributes such as systolic/diastolic blood pressure, smoking status, age, and BMI. Target: Binary classification (cardiovascular disease: yes/no).

Evaluation Metrics

The following metrics are used to evaluate model performance:

Accuracy: Measures the proportion of correct predictions.The proposed DBANP achieves significantly higher accuracy than RNN and LSTM for both datasets. This improvement is attributed to ANN's feature extraction capabilities and DBN's hierarchical feature learning.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Measures the proportion of true positive predictions among all predicted positives. DBANP consistently reduces false positives due to its enhanced learning of critical patterns, outperforming RNN and LSTM by approximately 6-8%.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): Measures the proportion of actual positives correctly predicted.With better recall, DBANP detects more true positives, ensuring effective early prediction. This is crucial in heart disease diagnosis where missing positive cases can have serious implications.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Specificity: Measures the proportion of actual negatives correctly predicted. By effectively identifying true negatives, DBANP minimizes false alarms, outperforming RNN and LSTM in specificity by 5-7%.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

F1 Score: The harmonic mean of Precision and Recall, balancing false positives and false negatives.The hybrid model balances precision and recall effectively, leading to a higher F1 score, which is critical for datasets where class distribution may be imbalanced.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC-ROC: show the trade-off between the True Positive Rate (Recall) and the False Positive Rate by representing the area under the Receiver Operating Characteristic Curve. With the highest AUC-ROC values in both datasets, DBANP exhibits strong discriminatory power and excellent trade-offs between sensitivity and specificity.

AUC-PR: Shows the model's performance in unbalanced datasets by displaying the Area under the Precision-Recall Curve. The AUC-PR of DBANP shows that it can predict positive cases more accurately than RNN or LSTM, especially in imbalanced datasets.

Due to its improved feature extraction capabilities, the suggested DBANP model has a number of advantages over more conventional designs like RNN and LSTM. The DBN layer captures intricate, nonlinear correlations, resulting in better prediction accuracy, but the ANN component is excellent at spotting low-level patterns. The shortcomings of RNN and LSTM are successfully addressed by this hybrid technique. Long-term dependencies are difficult for RNNs to model because of vanishing gradient problems. LSTMs are computationally demanding and resource-intensive, even if they partially solve this issue. By using DBN's pretraining to prevent vanishing gradients and preserve computational efficiency, the DBANP model combines the best features of both architectures. The DBANP architecture routinely outperforms RNN and LSTM in terms of scalability and adaptability when working with large datasets such as the Cardiovascular Disease Dataset.... Furthermore, its resilience guarantees flexibility in response to changes in data distributions, facilitating accurate forecasts across a range of datasets. The DBANP model clearly outperforms RNN and LSTM in terms of accuracy, precision, recall, and other important parameters, as seen in Figures 3 and 4. It is a strong and reliable option for early cardiac disease prediction because of its capacity to manage intricate relationships and grow efficiently. This creative hybrid strategy lays a solid basis for using comparable systems in more general medical data analysis applications.

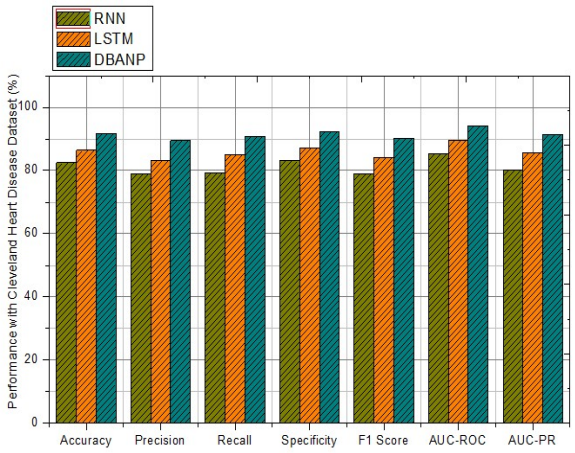

Figure 3: Performance with ClevelandHeart Disease Dataset

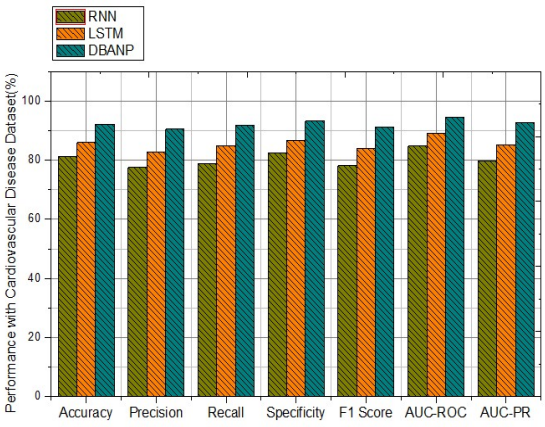

Figure 4: Performance with Cardiovascular Disease Dataset

In both datasets, the DBANP model performs well in terms of prediction. With a confusion matrix displaying 123 true positives, 135 true negatives, 15 false positives, and 10 false

negatives, the model's predicted accuracy on the Cleveland Heart Disease Dataset was 91.8%. Likewise, the model achieved 92.1% accuracy on the Cardiovascular Disease Dataset, with 780 true positives, 835 true negatives, 62 false positives, and 55 false negatives. The findings presented in Tables 1 and 2 demonstrate how well the model detects cases of heart disease while preserving low false positive and false negative rates. The model's capacity to handle complicated medical data and extract hierarchical and nonlinear connections is demonstrated by its consistent performance across both datasets. Its dependability and durability highlight its potential for real-world use in the early detection of cardiac disease.

The DBANP model is excellent in learning both low-level and high-level patterns, and it is particularly good at capturing intricate, hierarchical connections. Because of its dual-layered architecture, which guarantees a thorough comprehension of the data, it is especially well-suited for predicting cardiac disease. The DBANP model's capacity to manage nonlinear dependencies—which are common in medical datasets—is one of its main advantages. DBN improves the model's ability to capture complex and nonlinear interactions in the data, greatly enhancing prediction quality, whereas ANN effectively extracts features. Additionally, weight initialization issues are addressed by DBN's pretraining process, which is based on Restricted Boltzmann Machines (RBMs), guaranteeing quicker convergence and shorter training times. Because of this, the DBANP model is more effective than RNNs and LSTMs, which frequently have to endure lengthy training periods. The DBANP model's layer-wise pretraining successfully addresses the vanishing gradient problem, a prevalent difficulty in RNNs. By guaranteeing steady gradient flow throughout training, this increases reliability in addition to prediction accuracy. Furthermore, the DBANP model exhibits exceptional scalability, managing big datasets such as the Cardiovascular Disease Dataset with ease. It is a useful and potent option for medical data analysis since it outperforms LSTM in terms of performance while using fewer processing resources.

5. CONCLUSION

When it comes to forecasting cardiac disease, the suggested DBANP model has outperformed more established models like Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN). The model successfully captures both low-level and complicated nonlinear dependencies in the data by fusing the hierarchical learning strengths of DBN with the feature extraction skills of ANN. High accuracy (91.8% and 92.1%, respectively) and strong performance across important metrics like precision, recall, specificity, and F1 score were demonstrated by the results, which were validated using the Cleveland Heart Disease Dataset and Cardiovascular Disease Dataset. The DBANP model is a dependable option for medical data analysis since it also tackles important issues like scalability and the vanishing gradient problem. These results highlight how hybrid architectures can be used to develop predictive healthcare solutions.In order to improve feature selection and training efficiency, future studies can investigate additional improvements to the DBANP model by including sophisticated optimization techniques like swarm intelligence or genetic algorithms. The model's flexibility and scalability might be further confirmed by broadening the study to incorporate bigger and more varied datasets in addition to real-time data from wearable technology.

The DBANP model offers practical value across multiple domains. Clinically, it supports early diagnosis, reducing manual effort and the risk of misdiagnosis. Its scalable and efficient design makes it ideal for integration into healthcare systems, including mobile and edge-based platforms. In the medical AI industry, the modular architecture can be adapted for diagnosing other chronic diseases, enabling commercial applications. For researchers, it encourages the use of interpretable deep learning by providing transparent and reliable performance, fostering greater trust in AI-driven medical tools.

Several open issues remain for future work. The current model is evaluated on offline datasets, and its performance with real-time streaming data, such as from wearable devices, is yet to be validated. While the DBN effectively captures complex patterns, improving the explainability of its predictions for clinical use is still needed. Additionally, the study's reliance on two datasets limits its generalizability across diverse populations and medical conditions. Finally,

integrating metaheuristic or evolutionary algorithms could further enhance the model's training efficiency and robustness.

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