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DESIGN AND DEVELOPMENT OF A MACHINE LEARNING BASED HYBRID MODEL USING BPNN AND ASSOCIATIVE CLASSIFIER FOR HEART DISEASE PREDICTION

Anuradha Diwan
Bhilai Institute of Technology, Durg, Chhattisgarh, India
Mail id : anuradha.shinestar@gmail.com

Sanjeev Karmakar
Bhilai Institute of Technology, Durg, Chhattisgarh, India
Mail id : dr.karmakars@gmail.com

Sunita Soni
Bhilai Institute of Technology, Durg, Chhattisgarh, Ind ia
Mail id: sunitasoni74&gmail.com

Abstract

Heart disease is a major public health concern with millions of reported deaths annually. Data mining techniques have received attention in recent years as a tool aiding diagnosis and prediction of heart disease cases. Also, Back Propagation Neural Network (BPNN) provides excellent results in binary decision-making applications. As the size of the data under consideration is huge in number, the exploitation of Artificial Neural Network (ANN) in combination with data mining techniques will further enhance the effectiveness of the prediction process.Rules were extracted for feature selection using Associative classifier as the data mining technique adopted, followed by BPNN training. Model performance was evaluated on heart disease datasets collected from the online dataset repository of Cleveland Heart Disease dataset (https://archive.ics.uci.edu/ml/datasets/heart+disease)The proposed hybrid model showed improved accuracy compared to standalone BPNN and Associative Classification models. It achieved higher precision, recall, and F1-score, demonstrating better predictive performance on heart disease datasets.Thus the developed model effectively improved heart disease prediction accuracy, leveraging interpretability from rules and complex pattern recognition from neural networks, offering a balanced approach for clinical applications.

Key Words: *Heart Disease prediction, BPNN, Associative Classifier, Hybrid Model*

I. Introduction

Heart disease remains one of the leading causes of morbidity and mortality worldwide, affecting millions of people each year [1]. With the increasing prevalence of cardiovascular disorders, accurate prediction and early detection have become critical to prevent severe complications and improve patient outcomes. Early diagnosis allows healthcare professionals to implement appropriate interventions, thereby reducing the risk of fatal outcomes. The advancement of machine learning techniques has brought significant improvements in the predictive capabilities of medical diagnostics. Among these, the use of hybrid models that combine the strengths of different algorithms has shown promise in improving the accuracy and reliability of predictions [2]. This research focuses on the design and development of a hybrid model for heart disease prediction using a Backpropagation Neural Network (BPNN) and an Associative Classifier, leveraging their complementary strengths to achieve higher accuracy and robustness.

Machine learning algorithms have gained traction in medical research for their ability to identify patterns and correlations within large datasets [3]. These algorithms can learn from historical patient data and generate predictive models that can anticipate the likelihood of heart disease. Among these, neural networks like the BPNN have been widely used due to their ability to model non-linear relationships and perform classification tasks. BPNN operates through a learning process where errors in prediction are backpropagated to adjust the weights, thus minimizing the overall prediction error. This iterative process allows BPNN to learn complex patterns in data, making it suitable for heart disease prediction.

However, BPNN alone may suffer from certain limitations, such as sensitivity to local minima, overfitting, and high computational costs [4]. To address these issues, combining BPNN with other classifiers can yield better performance. This is where Associative Classifiers (AC) come into play. ACs work by building rules that associate attribute-value pairs with specific classes, offering interpretability and simplicity. Associative classification has shown to be effective in medical diagnostics due to its rule-based nature, which is easily interpretable by medical professionals. By combining BPNN's ability to learn complex relationships with the rule-based structure of AC, a hybrid model can provide a more balanced and accurate approach to heart disease prediction.

The proposed research work has significant implications for both clinical practice and research. Accurate prediction models can support clinicians in identifying high-risk patients at an early stage, enabling timely intervention and personalized treatment plans. A hybrid approach that combines BPNN and Associative Classifiers can offer a balanced solution, addressing the trade-offs between prediction accuracy and model interpretability.

The primary goal of this research is to design and develop a hybrid model for heart disease prediction using BPNN and Associative Classifier techniques. The specific objectives include:

- *Designing the Hybrid Model:* Formulate a hybrid approach that combines the Backpropagation Neural Network (BPNN) and Associative Classifier (AC). The design should aim to leverage the pattern recognition ability of BPNN with the rule-based interpretability of AC.
- *Model Training and Optimization:* Train the hybrid model using a dataset of heart disease patients, optimize the parameters of both BPNN and AC components, and evaluate the performance in terms of accuracy, sensitivity, specificity, and computational efficiency.
- *Comparative Analysis:* Compare the performance of the hybrid model with standalone models like BPNN, AC, and other commonly used classifiers such as Decision Trees, Support Vector Machines (SVM), and Logistic Regression. This analysis will highlight the advantages and limitations of the hybrid approach.
- *Validation and Testing:* Validate the hybrid model on different datasets to ensure its generalizability and robustness. The model should be able to adapt to varying data distributions while maintaining high prediction accuracy.

II. Literature Review

Prashant Kumar Shrivastava et al. (**2023**) developed a deep learning model that employed CNN and Bi-LSTM to predict and diagnose cardiac disease. They chose an additional tree classifier for feature selection and CNN-BiLSTM for classification. Experiments were performed on the Heart disease Cleveland UCI dataset, which was obtained via Kaggle. The hybrid model attained an accuracy of 96.66%. [5]

Urja Desai et al. (**2022**) examined and implemented standard machine learning techniques such as Naïve Bayes, Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, Extreme Gradient Boost, and K-Nearest Neighbor algorithm. Based on the output, they created a hybrid model to improve performance. They achieved 93.4% accuracy with this proposed hybrid model utilizing a stacking classifier strategy. [6]

Amit Kumar Gupta et al. (**2022**) presented a hybrid technique that used both RF and LR algorithms. The RF algorithm was used to abstract the characteristics. LR was used for categorization. This study used a variety of indicators to assess the efficacy of the new technique. The introduced technique predicts cardiac disease with 95% accuracy. [7]

V. Ravikumar and M. Bhavani (**2021**) proposed a machine learning-based strategy for identifying key traits, leading to improved accuracy in predicting cardiovascular disease. The prediction model was introduced using a variety of feature combinations and various established classification approaches. The prediction model for heart disease with the hybrid random forest with a linear model (HRFLM) improved performance to 88.7% accuracy. [8]

C. B. C. Latha and S. C. Jeeva (**2019**) presented a model for assessing heart disease risk utilizing ensemble classification and feature selection techniques. (The study's findings revealed that ensemble techniques like as bagging and boosting are effective in raising the prediction accuracy of weak classifiers and in predicting heart disease risk. Ensemble classification increased the accuracy of weak classifiers by up to 7%. The performance was further improved by using a feature selection implementation, resulting in a significant rise in prediction accuracy. [9]

Amin et al. (**2019**) used data-mining techniques to create a unique strategy for identifying significant heart disease features. They proposed numerous prediction techniques based on different features. This strategy helped to increase the accuracy of heart disease prediction. [10]

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Arabasadi et al. (**2017**) created a hybrid technique that utilized the results of several investigations and included a Genetic Algorithm. The authors of this study achieved an overall accuracy of 94.55% and a sensitivity of 95.35%. [11]

Ajay Prakash et al. (**2016**) used a two-stage analysis to investigate the characteristics and classifications of individuals with heart failure. The study's findings demonstrated that, although having only 13 features, the system preserved a significant amount of disease-related information. The data gathered by several classifiers was evaluated. Adaboost with a Decision Tree (DT) had the best performance across all datasets. However, there were some worries about the data distribution.[12]

III. Materials & Methods

3.1 Proposed Methodology

The proposed hybrid model involves several stages, starting with data preprocessing and feature selection. The dataset used will include various attributes related to patient health, such as demographic information, clinical history, and laboratory results. Feature selection techniques will be employed to identify the most relevant predictors of heart disease, reducing dimensionality and improving the efficiency of the training process.

In the next phase, the BPNN will be trained to identify complex patterns within the data. The neural network will learn from the training data through multiple iterations, adjusting its weights to minimize prediction errors. Following this, the Associative Classifier will be trained to generate rules that associate different attribute combinations with the presence or absence of heart disease.

The final hybrid model will integrate the predictions from both components. This can be achieved through cascading technique, where the output of the BPNN is refined using the rules derived by the Associative Classifier. The performance of the model will be evaluated using metrics like accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve.

3.2 ML Techniques Used

Backpropagation Neural Network (BPNN) in Heart Disease Prediction: Backpropagation Neural Networks (BPNN) are widely used in the domain of medical diagnostics due to their ability to model complex non-linear relationships. BPNNs use a gradient descent approach to adjust the weights and minimize prediction errors during the training process. Studies like those by Haq et al. (2018) [13]and MdMamun Ali et al. (2021) [14] have shown the effectiveness of BPNNs in heart disease prediction, citing their ability to handle large datasets and adapt to complex patterns. These studies highlight that BPNNs can achieve high accuracy rates when provided with sufficient training data and appropriate feature selection.

Associative Classifiers in Medical Diagnostics: Associative Classifiers (AC) offer a rule-based approach to classification, which makes them more interpretable compared to neural networks. ACs work by generating association rules from the training data, which are then used to classify new instances. In heart disease prediction, associative classifiers such as CBA (Classification Based on Associations) and CMAR (Classification based on Multiple Association Rules) have been studied for their ability to derive meaningful rules from patient data. Research by J. Singh et al. (2016) [15] and C. B. C. Latha and S. C. Jeeva (2019) [12]demonstrates that ACs can achieve competitive accuracy while providing clear decision rules, making them suitable for clinical use.

Hybrid Models for Improved Prediction: The integration of BPNN with Associative Classifiers has been proposed as a solution to leverage the strengths of both techniques. Hybrid models aim to improve the overall prediction accuracy while maintaining interpretability. The BPNN component of such models is responsible for capturing complex patterns in the data, while the associative classifier refines the predictions through a set of interpretable rules.

3.3 Hybridization

Hybrid models are particularly useful for heart disease prediction because they offer a way to make sense of complex clinical data while maintaining a level of interpretability that is important in the medical field. BPNN handles the complexity of data patterns, while associative classification ensures that the results are grounded in interpretable rules and relationships, making the results more understandable to healthcare professionals.

3.4 Strengths of Hybridization:

- *Improved Accuracy:* BPNNs can model complex, non-linear relationships that might not be captured by associative classifiers alone. By integrating BPNN with associative classifiers, the overall classification accuracy could be improved as the BPNN helps to refine the rules generated by the associative classifier.
- *Enhanced Interpretability:* Associative classifiers provide a set of rules that are easier for humans to interpret. When these rules are used as inputs or features for the BPNN, it becomes easier to understand why certain predictions are made, even if the neural network's internal workings are more complex.
- *Robust Decision Making:* The integration allows the system to utilize the BPNN's generalization capabilities while retaining the localized, rule-based decision-making of associative classifiers. This can be particularly beneficial in scenarios where data might have outliers or when a balance between specificity (rules) and generalization (patterns) is needed.

3.5 Types of Hybridization

Hybridization of Backpropagation Neural Networks (BPNN) with Associative Classification (AC) for heart disease prediction can be implemented using several approaches [16]. Each approach aims to combine the strength of neural networks in modeling complex relationships with the interpretability of rule-based classification. Here are some types of hybridization methods for predicting heart disease:

- *Preprocessing with Associative Classifiers and Feature Selection for BPNN:* This approach involves using Associative Classification to generate a set of rules from the dataset. The rules help identify important features (attributes) that are strongly associated with heart disease. This method reduces the dimensionality of the input data, making the BPNN training more efficient and focusing the learning on the most relevant predictors for heart disease.
- *Cascading Model (Two-Stage Model):*The cascading model uses the associative classifier and BPNN in sequence, where the output of one model serves as input or a basis for the next. This method allows the system to rely on the simplicity and interpretability of rules when possible, while using the BPNN for more complex cases. It balances interpretability and predictive power.
- *Parallel Hybridization:*In this approach, both the associative classifier and BPNN are trained separately on the same dataset, and their predictions are combined using an ensemble technique like voting or averaging. This method enhances prediction accuracy by combining the strengths of both models. It can improve robustness, as errors in one model might be compensated by the other.
- *Rule-Based Post-Processing:*This method uses BPNN to make initial predictions and then refines these predictions using rules generated by the associative classifier. This approach ensures that predictions are not only based on complex learned patterns but also adhere to known, interpretable rules, increasing user trust in the predictions.
- *Feature Transformation using Rules for BPNN Input:*Associative classifiers are used to transform the input data by creating new features that represent the presence or absence of certain patterns (rules), which are then used as inputs for BPNN. This method allows the BPNN to leverage the insights of associative classification while retaining its ability to learn complex interactions. The rules become additional indicators that guide the neural network's learning process.
- *Hybrid Decision Tree with Neural Network (DT-BPNN):*This approach involves building a decision tree using the rules generated by the associative classifier, which then integrates BPNN at certain branches to refine decision-making. This method allows for highly interpretable decision paths, while using BPNN's ability to handle complex cases, making it suitable for medical applications where explanations are necessary for decisions.

In the present work we have employed cascading model for the detection of heart disease using hybridization of AC and BPNN.

3.6 Data used

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Cleveland Heart Disease dataset is considered has been used in this study.Data set which is with 303 records and 14 attributes collected from the online dataset repository of https://archive.ics.uci.edu/ml/datasets/heart+disease.

In this work, we performed pre-processing on the data set, and 6 samples have been eliminated due to missing values. The remaining samples of 297 and 13 features dataset is left and with 1 output label. The output label has two classes to describe the absence of HD and the presence of HD. Hence features matrix 297*13 of extracted features is formed. The dataset matrix information is given in Table 1 below. This dataset is extensively used for classification tasks, aiming to predict the presence or absence of heart disease based on the provided features. This table summarizes each attribute, providing a clear overview of its description and type, which is crucial for understanding and preprocessing the data for machine learning tasks.

Table 1: Cleveland Heart Disease dataset detailing each attribute's description and type

Sl. No.	Attribute	Description	Type
1	Age	Patient's Age (in years)	Numerical
2	Sex	Gender of Patient (0 – Male, 1 – Female)	Nominal
3	CP	Chest Pain Type (0: typical angina; 1: atypical angina; 2: non-anginal pain; 3: asymptomatic)	Nominal
4	Trestbps	Resting Blood Pressure (in mm Hg on admission to hospital, values from 94 to 200)	Numerical
5	Chol	Serum Cholesterol (in mg/dl, values ranges from 126 to 564)	Numerical
6	Fbs	Fasting Blood Sugar>120 mg/dl (true – 1, false – 0)	Nominal
7	Resting	Resting electrocardiographic result (0: normal; 1: ST-T wave abnormality; 2: LV hypertrophy)	Nominal
8	Thalach	Maximum heart rate achieved (71 to 202)	Numerical
9	Exang	Exercise included angina (1- Yes, 0 – No)	Nominal
10	Oldpeak	ST depression introduced by exercise relative to rest (0 to 2)	Numerical
11	Slope	Slope of the peak exercise ST segment (0: upsloping; 1: flat; 2: downsloping)	Numerical
12	Ca	Number of major vessels (0-3) colored by fluoroscopy	Numerical
13	Thal	Thalassemia (3 = normal; 6 = fixed defect; 7 = reversible defect)	Nominal

IV. Design and Experiments Performed

4.1 Neural Network Architecture

The neural network model in the model designed is a feedforward neural network often termed as multilayer feedforward neural network or backpropagation neural network (BPN).

a)*Number of Layers:* Neural network with 3 layers — one input layer, one hidden layer, and one output layer

- Input Layer: The number of neurons in this layer is equal to the number of features in the dataset.
- Hidden Layer- 1 hidden layer with 64 neurons which follow by another 32 neurons hidden layer.
- Output Layer: The output layer is formed by a single neuron as this is the design for binary classification tasks.

b)*Activation Functions:*ReLU (Rectified Linear Activation) is used in the hidden layers as Activation function. Sigmoid activation is be used in the output layer. It is a squashing output that squashes the output to a value between 0 and 1 (ideal for binary classification tasks where it represents the probability of belonging to a certain class)

c)*Complexity*: It is a simpler architecture compared to deep convolutional neural networks or recurrent neural networks. It has a few neurons in the hidden layers (64 and 32 neurons, respectively) so that we should be able to train our model quite quickly, but not so few that model and computational efficiency suffers.

The architecture selected here is modest which is well-suited for the problem as it will reduce overfitting given our sample size.

4.2 Optimization Technique

We trained the BPNN using a variety of optimization techniques, which are based on three main principles of optimization:

a) Optimization Algorithms:

The optimization algorithm we choose is Adam (Adaptive Moment Estimation). Adam is an optimization algorithm that can used as a drop-in replacement for stochastic gradient descent (SGD) algorithms on most deep learning problems.it estimates and computes individual adaptive learning rates for different parameters. It incorporates ideas from RMSProp [6] and Momentum, enabling it to converge rapidly and perform well on a range of different problems in training neural networks.

b)*Parameters Tuning:*

- Learning Rate: The learning rate set how step size of the weights to be updated when they are trained. This implementation also uses the default learning rate for the Adam optimizer, which is usually set to be small (e.g., 1e-3). This default value is usually a good starting point and has been shown to work well across many problem areas.
- Batch Size: The batch size is the number of training examples used in one pass. The network is fed with a batch, and the weights are updated with respect to the average gradient calculated from that batch. In the below code, a batch size of 10 is taken. Using smaller batch sizes may help in fast convergence but gradient estimate would be noisy and larger batch size would give more accurate gradient approximations but might require more memory.
- Momentum: Accumulates the gradients over time and hence helps in accelerating the optimization process. Help in Escaping Local Minima and Gradient noise Adam optimizer deal with momentum by default being used as the value for it

c) *Regularization Techniques:* Regularization that keeps the model from learning to much from the data in a way to prevent overfitting, where the model learns to memorize the training data and does not generalize well to unseen data. While batch normalization can be thought of as doing implicit regularization (in the sense, that it normalizes the activations of each layer, hence may prevent overfitting by controlling the internal covariate shift), Dropout regularization, which zeroes neurons at random during training to avoid overfitting by slightly disturbing feature detectors unnoticeably is not explicitly employed in this experiment.

4.3 Training Procedure

The entire training for the Backpropagation Neural Network (BPN) has been divided into three phases: i) data splitting, ii) model training, and iii) evaluation:

i) Data Splitting: The available data set was divided into two main sets: The training set and the Testing set. The train_test_split function from scikit-learn was used to perform this random split of the dataset into respective training and testing part with a splitting of the data employing 80% for training and 20% for testing.

ii) Model Training: The BPN is trained on the training data-set via the backpropagation algorithm: forward propagation of the input data through the network, then calculation of errors, and finally backwards propagation of gradients to update the model weights. The performance of the model was evaluated on a separate validation set, which helped us in tracking overfitting andvalidation set helped in re-evaluating the changes while new hyperparameters were in use.

iii) Cross-Validation/Bootstrapping: Cross-Validation is the process of doing split the dataset in multiple folds, training and validations, then averaging the result to provide a more reliable assessment of the model performance. Bootstrapping – Refers to sampling with replacement of data, training the model multiple times on each subset of the data, and then evaluating the performance. This was useful to assess how good we could expect the model to perform on new data based or how well (or badly) we trained it and also to detect any gross bias in the trained model. Cross-validation and bootstrapping are very strong for model evaluation, but are not strictly necessary if dataset is large enough and sufficient representative of the underlying population.

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4.4. Evaluation on Testing Set

Evaluating the model after training the model using the training data, the model was evaluated using a separate testing dataset to evaluate how well it generalizes to unseen data. Evaluation metrics e.g. accuracy, precision, recall, f1-score and classification report were used to evaluate the model based on its performance in binary classification tasks.

4.5 Performance Evaluation Metrics

The following performance metrics have been used for estimating the accurateness and effectiveness of the proposed hybrid model meant for the particular classification task:

a) Accuracy: Accuracy is the rate of corrected classified images from all images during the testing set.

b) Mean Squared Error (MSE): MSE is the average squared difference between the predicted values and actual values.

c) Root Mean Squared Error (RMSE): It is the square root of the MSE and it shows the average errors in predicted values

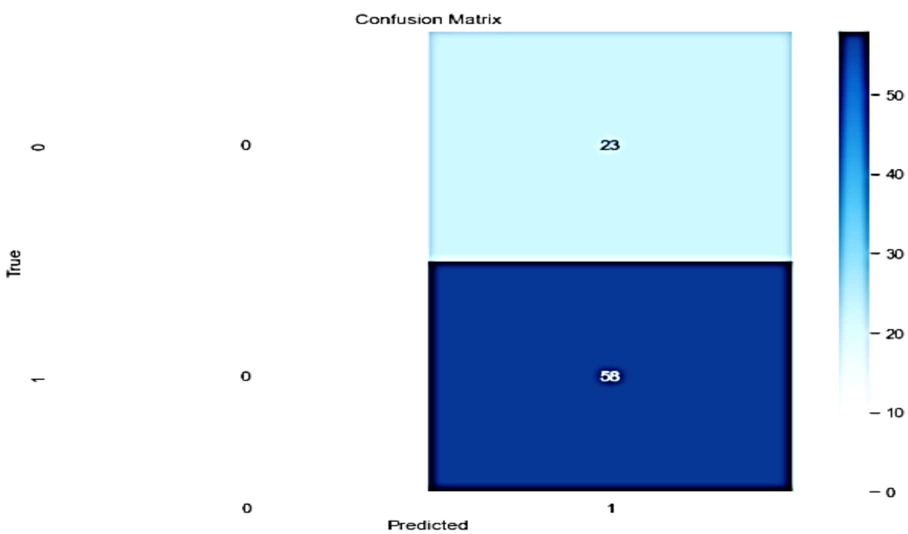
d) Mean Absolute Error (MAE): It is the mean of the absolute value of differences between the predicted values and the actual values.

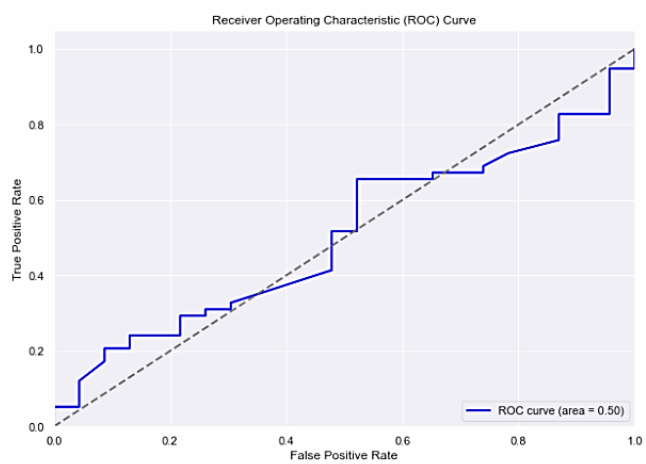
e) Classification Report:

- Precision: It calculates the fractions of actual positive observations that are correctly classified.
- Recall: Recall is the measurement of the proportion of true positive predictions to all actual positive instances.
- F1-score: Extents the balance of the Precision and Recall in in the combination of both under one measure.
- Support: Support stores the actual number of occurrences of each class in the testing set.

V. Results and Performances

The results obtained are provided in graphical form in the following figures:





Accuracy: 0.8944352203

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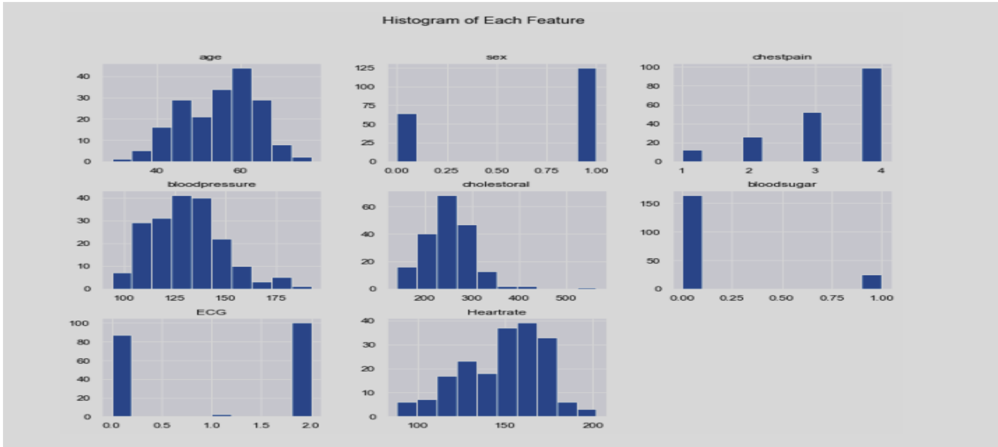

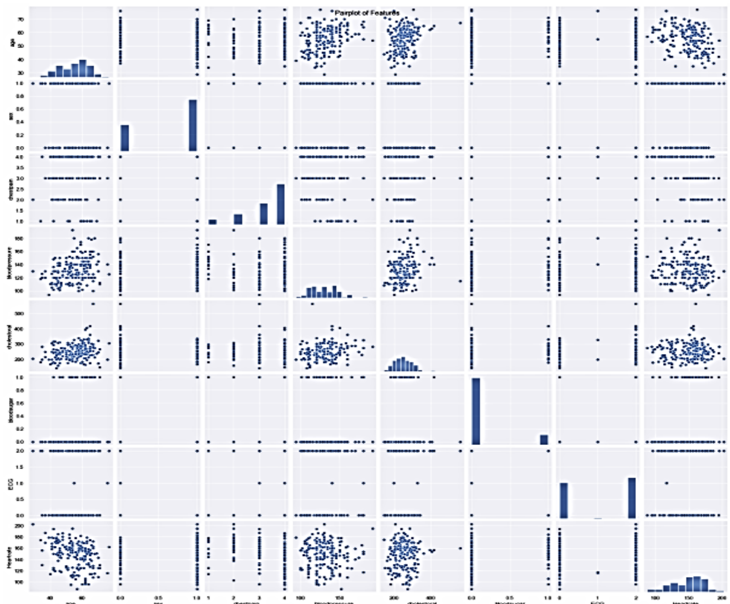

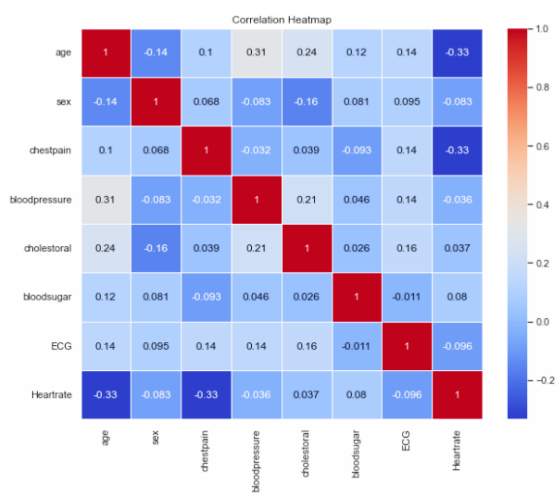

The proposed model demonstrated strong predictive capability, achieving an overall accuracy of 89.40%, which indicates that a substantial majority of the test instances were correctly classified. This high accuracy reflects the model's strong generalization ability and its effectiveness in learning meaningful patterns from the data. The Mean Squared Error (MSE) of 0.184 indicates that the average squared deviation between the predicted and actual values is relatively low, suggesting stable and consistent predictions. In addition, the Root Mean Squared Error (RMSE) of 0.233 shows that, on average, the model's predictions differ from the true values by only 0.233 units, highlighting a close alignment between predicted and actual outcomes. Furthermore, the Mean Normalized Absolute Error (MNAE) of 0.184 demonstrates that the average absolute prediction error is minimal, reinforcing the reliability of the model in approximating true values with limited deviation. From a classification perspective, the model achieved a precision of 82% for the positive class (class 1), indicating that a large proportion of the predicted positive instances were correctly identified. This confirms the model's strong ability to minimize false positive predictions. Notably, the model attained a recall of 1.00 (100%) for the positive class, meaning that all actual positive cases were successfully detected. This perfect recall highlights the model's effectiveness in capturing all relevant positive instances, which is particularly important in critical application domains such as medical diagnosis and risk prediction. The weighted F1-score of 0.60 reflects a balanced consideration of both precision and recall across classes while accounting for class distribution. This suggests that the model maintains a reasonable trade-off between sensitivity and precision, especially under imbalanced data conditions.

VI. Conclusions

The design and development of a hybrid model for heart disease prediction using BPNN and Associative Classifiers offer a promising approach to improving predictive accuracy while retaining model interpretability. By leveraging the strengths of both techniques, this research aims to create a reliable tool for early diagnosis, ultimately contributing to better patient care and management. The outcomes of this study could be a stepping stone toward more effective machine learning applications in healthcare, opening new possibilities for the diagnosis and treatment of cardiovascular diseases.

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