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DEVELOPMENT OF A CONGENITAL HEART DISEASE PREDICTION MODEL USING MACHINE LEARNING TECHNIQUE

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Abstract -This paper presents the design of a congenital heart disease prediction model using machine learning techniques. The aim is to reduce the mortality and morbidity rates among infants, foetuses, and pregnant women due to issues relating to Congenital Heart Disease (CHD). In realizing this goal, data that considered Peripartum Cardiomyopathy (PPCM), Patent Ductus Arteriosus (PDA), and Ventricular Sepal Defect (VSD) was collected and a new data model for CHD was developed.The data model was processed through imputation, feature selection, and transformation using the imputation method and Principal Component Analysis (PCA). After the data processing stage, a machine learning algorithm which is an Artificial Neural Network (ANN) was adopted and trained with the data to generate three models for the prediction of the CHD. Then, the ANN was trained and selected as a worthy prediction ML algorithm considering MSE, RMSE, MAE, and accuracy. ANN reported MSE of 0.22099, RMSE of 0.44009, accuracy of 0.98950, and MAE of 0.35801. The result, when applied with life data experiments, showed that the new model was capable of detecting the three considered CHD features with high reliability.

Keywords: Heart Disease; Congenital; Artificial Neural Network; Principal Component Analysis; Machine Learning

1. Introduction

Love is the tender melody that lulls the unborn child in the cradle of a mother's womb, the joyous celebration that welcomes a new life into the world, and the radiant glow that envelops a pregnant woman as she nurtures the miracle of existence (Odumegwu et al., 2020). It is the silent promise that parents make to their unborn child, the first heartbeat of a new baby's arrival, and the glowing embrace of a pregnant woman's dream. Sadly, this love and joyful feelings are turned to sorrow in many homes today, as every two minutes the World Health Organization (WHO) reports that a pregnant woman dies due to childbirth (WHO, 2023).

In the same vein, over 287,000 maternal deaths were recorded worldwide in 2020, while in the year 2021, the United Nations Children Fund (UNICEF) reported that over 1.9 million stillbirths were recorded globally (UNICEF, 2023). However, even in the middle of these dark storms, the love for those we have lost still shines brightly and remains eternally cherished in the garden of our hearts.

According to Tedros (2023), while pregnancy presents immense hope, positive experience, and expectation for women, the lack of good healthcare facilities exposes these women and their unborn babies to grave dangers and requires urgent attention in order to address the rising mortality rate among pregnant women and stillbirth (Jones et al., 2023). Kotit and Yacoub (2021) submitted that while there are many contributing factors to these challenges of stillbirth and mortality due to pregnancy, heart disease has continued to play a major role over the years. Today, heart diseases have consistently threatened the lives of expectant mothers and their unborn babies. In addition, Xu et al. (2022) posited that this challenge further affects newborn babies and their mothers even after birth, thus resulting in complications that not only jeopardize wellbeing but also pose a significant risk to survival.

Congenital Heart Disease (CHD) is a type of heart disease that occurs before and after childbirth among women and their unborn/newborn babies. According to the Center for Disease Control (CDC), CHD is responsible for 4.2% of all deaths in the first 27 days of life, making it a major threat to humanity (CDC, 2006). CHD is of diverse types, including Patent Ductus Artery (PDA), which is dominant among preterm infants aged 12–25 weeks after birth; Peripartum Cardiomyopathy (PPCM), which is characterized in pregnant women; and Ventricular Septal Defect (VSD), which is popular among foetuses aged within 12 weeks in the womb.

Today, the need for early detection of this CHD was revealed by Jones et al. (2022) as critical for effective management and diagnosis of patients. In this vein, artificial intelligence (AI), specifically Machine Learning Algorithms (MLA), which have dominated studies on prediction models, was proposed.

This paper proposes the modelling of a CHD prediction system focused on early prediction of heart diseases among diverse demographic groups, such as preterm infants, foetuses, and pregnant women. This will be achieved using machine-learning algorithm. The highlights of the research proposed a more holistic and robust dataset that incorporates the critical demographic aforementioned for the study; careful data processing techniques will be applied to prepare and transform the data to the best version of its feature vector before training with three multiple machine learning algorithms.

2. Research Methodology

The methodology used for this research combines experimental and observational methods, respectively. The observation method was used for the heart disease data collection, while the experimental method was used for the model implementation, evaluation, and validation.In the realization of the research design, data was collected on congestive heart disease, considering classes peculiar to pregnant women, infants, and foetuses, respectively. The data was integrated to develop a robust data model for the prediction of congenital heart diseases. To ensure the quality of data collection, data processing and analysis were applied to address issues of missing data, data complications, and issues of overfitting that may arise as a result of the utilization of a model for training. In addition, feature selection was applied to allow dimensionality reduction while maintaining data quality, and a feature transformation algorithm was also applied to convert the data into a compatible feature vector for machine learning algorithm identification. Machinelearning algorithm was used to train the data to generate the model for the prediction of CHD. Comparative analysis was applied among different techniques adopted for heart disease prediction to identify the best machine learning-based prediction model for the modelling of an intelligent cardiovascular heart disease prediction and diagnostic model. A simple prototype model was developed with the model and then tested and validated through practical experimentation.

2.1 Data Collection

The electrocardiogram (ECG) data on congenital heart diseases was collected from four different hospitals in the south-eastern part of Nigeria, considering three major classes: patent ductus artery (PDA), peripartum cardiomyopathy (PPCM), and ventricular septal defect (VSD). The demographics considered for the data collection are preterm infants, pregnant women, and foetuses over a population size of 70 subjects. Data for the PDA class was collected from the Nnamdi Azikiwe University Teaching Hospital, Nnewi, considering a population size of 10 infant subjects, aged 28–38 weeks, using an electrocardiogram machine and a respiratory rate monitor.

Data on Ventricular Sepal Defect (VSD) was collected from 15 foetus(subjects) aged 12–25 weeks from the St. Vincent Cardiac Clinic, Imo State, Owerri, using a foetal monitor instrument and ultrasound. Brave Heart Cardiac and Specialist Clinic, Umuahia, Abia

State, was considered for data collection for PPCM, with a sample size of 10 pregnant women aged 26–37 years using an electrocardiogram machine and a respiratory rate monitor.

Finally, the University of Nigeria Teaching Hospital (UNTH), Enugu State, provided data on the normal heartbeat of 10 preterm infants, 10 pregnant women, and 15 foetuses. In addition, more data on CHD, considering the three classes of pregnant women, preterm infants, and foetuses, was collected from the physiobank repository (Goldberger et al., 2003) and used to augment the dataset.

2.2 Data Imputation and Normalization

The data collected was first processed through the imputation technique. In this approach, missing data on the dataset was identified and replaced using the mean of the respective variables. This was performed in Excel software and then saved as a CSV file. Having achieved the imputation process successfully, the data normalization approach was applied using the Z-normalization technique. This is a standardization approach that ensures that the data has a mean of zero and a standard deviation of 1. The aim was to ensure that all the features in the dataset were in equal value ranges and also to address issues of classification bias during the training of the algorithm. The model for the standardization was posited in Equation1 (Pandit, 2023);

$$Z_{norm} = \frac{X-mu}{sigma} \qquad 1$$

Where Z is the original data point, mu is the mean of the dataset, sigma is the standard deviation of the dataset.

2.3 Feature selection

The feature selection algorithm used in this research is the chi-square technique. This approach computes the chi-square between the features of the datasets and identified the number of features with the best chi-square score using the model in Equation 2 (Meesad et al., 2020);

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

Where c is the degree of freedom, O is the observed feature score, E is the expected feature score and X is the feature selected.

2.4 Feature transformation

The technique used for the feature transformation approach is the Principal Component Analysis (PCA). To achieve this, the data was standardized with the equation 2; then the Covariance Matrix (C) computed with equation 3;

$$C = \frac{\Sigma\left((X-\mu)*(X-\mu)'\right)}{(N-1)} \qquad 3$$

Where X is the data matrix where each row represents an observation and each column represents a variable; μ (mu) is the mean vector of the variables; N is the number of data samples. The Eigenvalues $E_{vl}$and vectors E_v of the data points are computed with equation 4 and 5;

$$E_{vl} = det(C - \lambda I) \qquad 4$$

$$\boldsymbol{E_v} = C * v = \lambda * v \qquad 5$$

Where v represents the eigenvector; λ represents the eigen-value associated with that eigenvector; "det" stands for the determinant of the matrix; I is the identity matrix. The PCA algorithm is presented as; while the PCA life-cycle was reported in Figure1;

PCA: Algorithm 1

1. Start
2. Apply equation 2 for data standardize
3. Apply equation 3 for Covariance Matrix computation
4. Calculate Eigen-values and Eigenvectors with equation 4 and 5
5. Sort Eigen-values
6. Select Principal Components
7. Transform Data
8. End

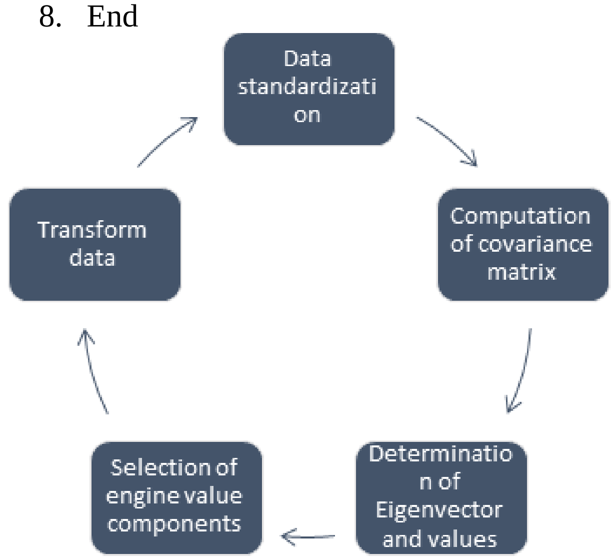

Figure 1: The PCA life-cycle

The PCA first standardizes the data points to ensure uniform scaling and then computes the covariance matrix for each feature point. The covariance matrix was then applied to the determination of the engine values and vector, which were later sorted to determine their principal components for transformation into a compact feature vector. Figure 2 presents the flow chart for the data processing.

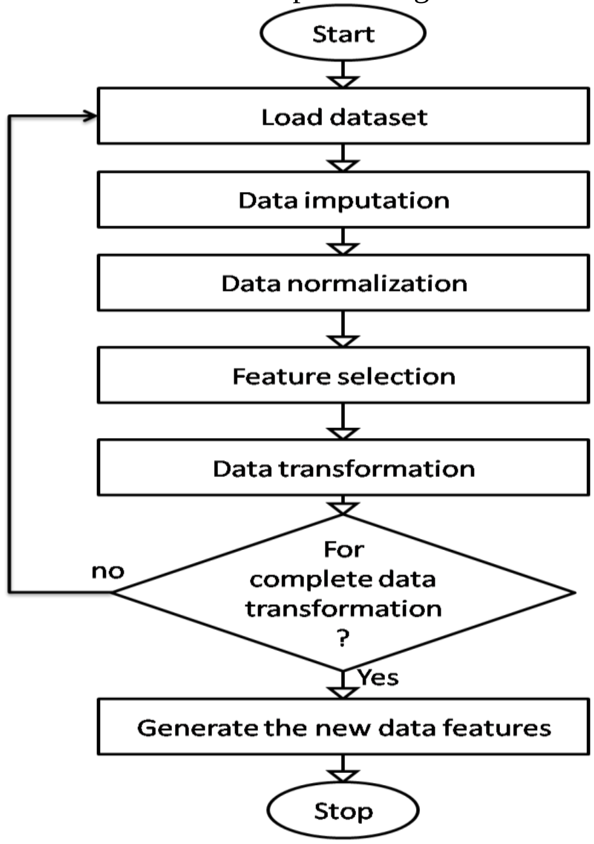

Figure 2: Flow chart for the data processing steps

Figure 2 presents the various steps used in dataset preparation for training. The data after importation was first processed by searching and replacing missing values using the mean imputation technique, then the Z-score standardization technique was applied for the normalization of the data to ensure uniformity in the scaling. Chi-square was then applied for the feature selection of the key attributes with the aim of dimensionality reduction while maintaining data integrity. The data was transformed using the PCA algorithm into a compact feature vector, ready to be applied for the training of machine learning algorithms.

2.5 The Artificial Neural Network Algorithm

The Artificial Neural Network (ANN) was utilized in this study as one of the machine learning algorithms selected for the development of the heart disease prediction model (Ebere et al., 2021). The ANN utilized is the feed-forward multi-layered neural network developed with the interconnection of neurons as depicted in the figure 3

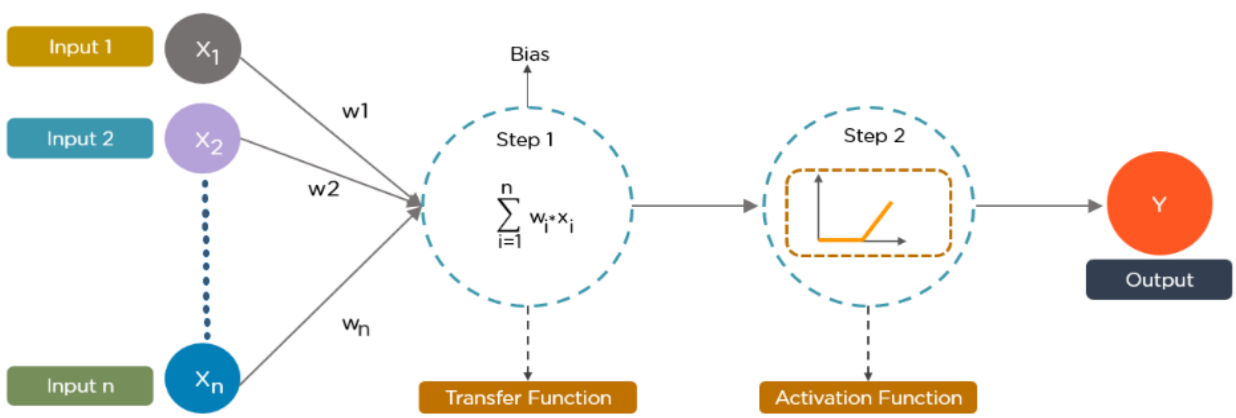

Figure 3: Neural network architecture

Where w is the weights, x is the data, b is the bias, Y is the output of the *i* input, where n is the number of inputs to the neurons. The activation function used is the hyperbolic tangent for the normalization of the feature values between 0 and 1.

The input layers were constituted with the features of 20 attributes of the CHD data collected considering the three demograph (infant, fetus and pregnant woman). The output on the other hand is a binary classification which predicts normal or abnormal CHD.

Algorithm 2: The Neural Network Algorithm

1. Start
2. Initialization of hyper-parameters
3. Define the network architecture
4. Receive input data as a feature vector.
5. For each neuron
6. Passes the input values forward
7. Compute the weighted sum of inputs for each neuron
8. Weighted Sum = $b + \sum_{i=1}^{n} w_i x_i$
9. Apply an activation function to the weighted sum as $(b + Tanh\ \sum_{i=1}^{n} w_i x_i)$
10. Pass the outputs from one layer as inputs to the next layer.
11. Repeat this process for each layer until the output layer is reached.
12. Get final Output
13. End

3. Model Training

The training of the ANN model was achieved utilizing the dataset and back-propagation algorithm (Al-Garadi, 2020) process, which adjusts the neurons hyper-parameters, while monitoring the loss function until the prediction model is generated. The training process was achieved as shown in the flow chart of figure 5 to generate the prediction model for heart disease.

Figure 5 presents the flow chart of the trained ANN algorithm for the generation of the Heart Disease Prediction (HDP). The processed data using imputation, the Z-normalization model in equation 1, and the PCA-based feature selection algorithm was imported into the neural network algorithm and then trained using the back-propagation process, which considers the gradient loss of the neurons and then adjusts the neuron hyper-parameters during the training process until neurons converge after testing and validation before generating the heart disease prediction model.

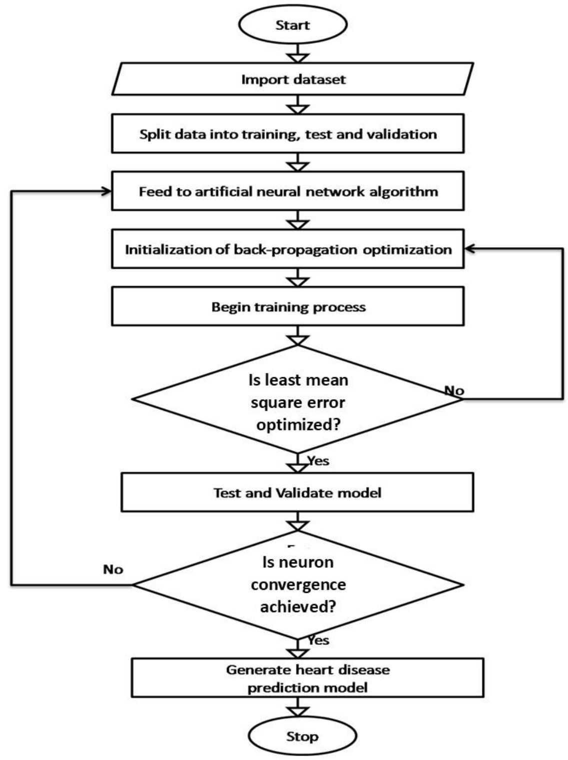

Figure 5: Flow chart of the ANN training process

3.1 The Machine Learning Based Heart Disease Prediction Model

The machine learning-based heart disease prediction model was developed using trained algorithms and a test dataset of normal and abnormal heart features. The data was imported into the data processing tool for feature selection, considering key features with the highest-ranking score as depicted in the chi-square feature selection model of equation 2. The PCA algorithm was then applied to convert these features into a compact feature vector for compatibility with the trained machine learning algorithms for heart disease prediction. The test features are identified and then compared with the trained algorithm features, whose outcomes are classified under the class of heart diseases and return heart disease predictions; however, when the features are classified as normal heartbeat, the outcome is returned as normal heart beat. The flow chart in Figure 6 was utilized in presenting the data flow of the HDP.

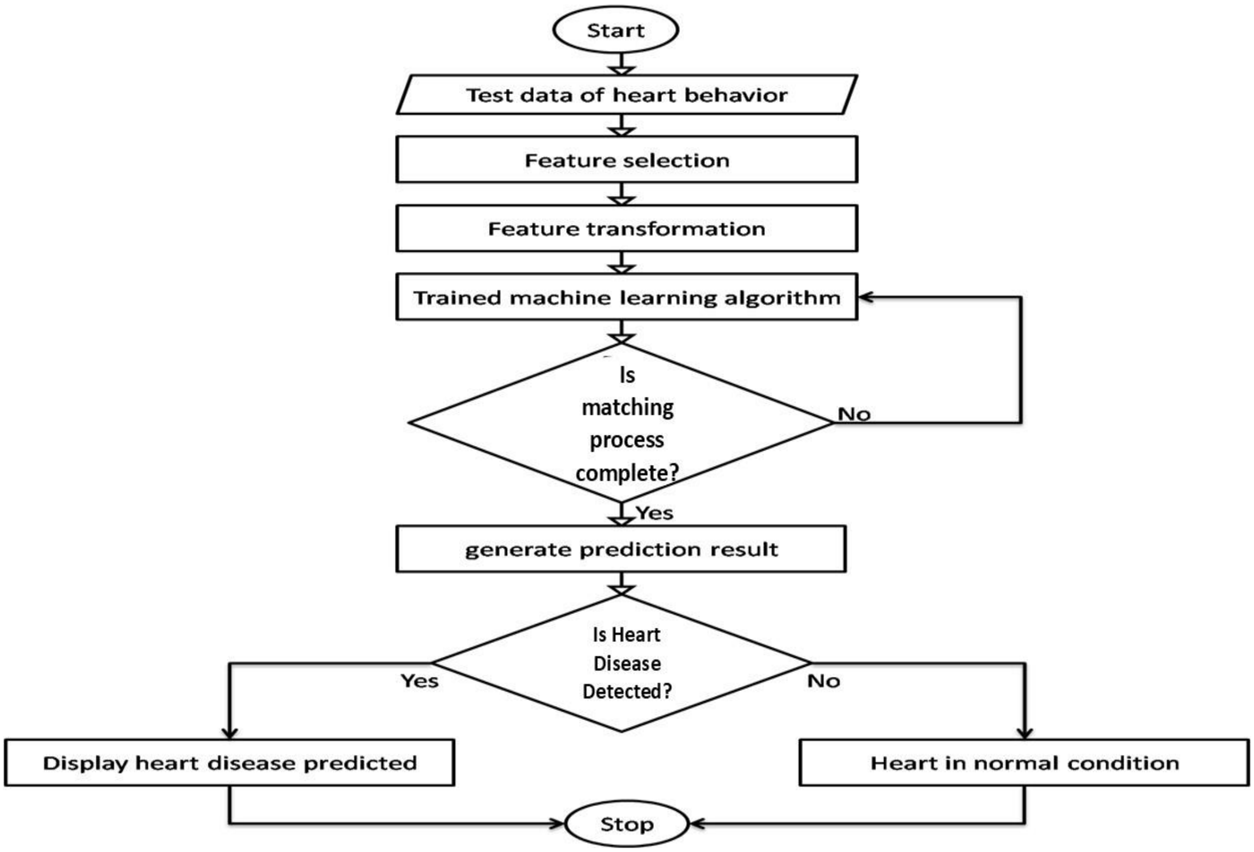

Figure 6: Flow chart of the heart disease prediction model

Figure 6 shows how the test data were imported for processing using the feature selection approach in the chi-square model of equation 2. The selected features are the key attributes that model the main behaviour of heart disease instances. These data are transformed using the PCA algorithm and then fed to machine learning for training and the generation of the prediction result. When the predicted result is heart disease, it returns an output to inform the examiner of the prediction outcome, while the outcome when heart disease is not predicted is also returned as a normal heartbeat condition.

4. Performance Evaluation

When evaluating the performance of an artificial neural network in heart disease detection, several key metrics are used. These include Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Accuracy. Each metric provides valuable insights into the model's effectiveness in identifying heart disease.

i. Root Mean Squared Error (RMSE)

RMSE measures the square root of the average of the squared differences between the predicted probabilities of heart disease and the actual outcomes. The RMSE formula is:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad 6$$

Where y_i represents the actual diagnosis (0 for no disease, 1 for disease), $\hat{y}$ denotes the predicted probability, and n is the number of samples.

ii. Mean Squared Error (MSE)

MSE calculates the average of the squared differences between the predicted probabilities of heart disease and the actual diagnoses. This metric indicates the average squared error in the model's predictions. The formula for MSE is:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad 7$$

In this equation 2, y_i is the actual diagnosis, $\hat{y}_i$ is the predicted probability, and n the number of samples.

iii. Mean Absolute Error (MAE)

MAE measures the average of the absolute differences between the predicted probabilities and the actual diagnoses. This metric provides a straightforward measure of how close the model's predictions are to the true diagnoses, without considering the direction of errors. The MAE formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad 8$$

Where y_i is the actual diagnosis, $\hat{y}_i$ is the predicted probability, and n is the number of samples.

iv. Accuracy

Accuracy measures the proportion of correctly predicted cases of heart disease out of the total number of cases. The Accuracy formula is:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \qquad 9$$

4.1. System Results

This section presents the results of the ML training and testing process, considering the ANN trained with the heart detection model. In the results of the ANN, it was observed that the residuals were distributed across variable targets within the model during the training process. This suggested that the model was able to capture complex patterns in the data and make errors that were not consistent. Overall, the result of the residual distribution revealed that the ANN was able to learn the complex feature intricacies of the feature vector for heart disease prediction and were able to make good predictions. In Figure 7, a scattered plot was applied to visualize the residual distribution of the three modes.

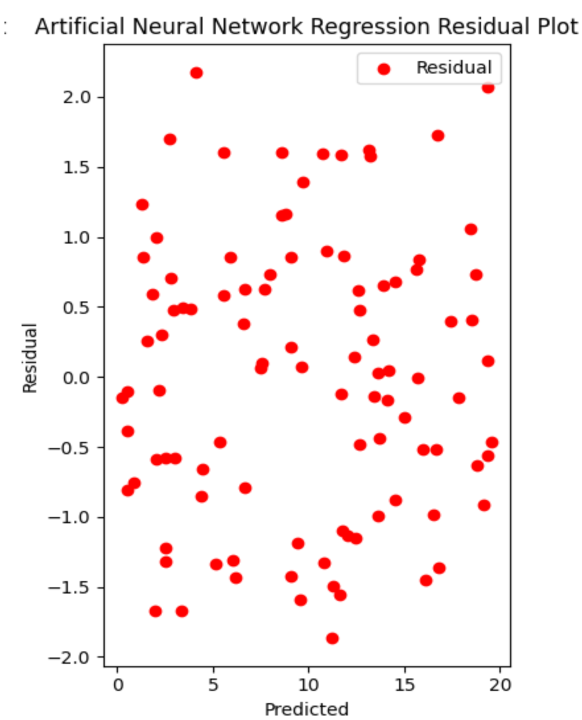

Figure 7: Residual plots for the ANN model

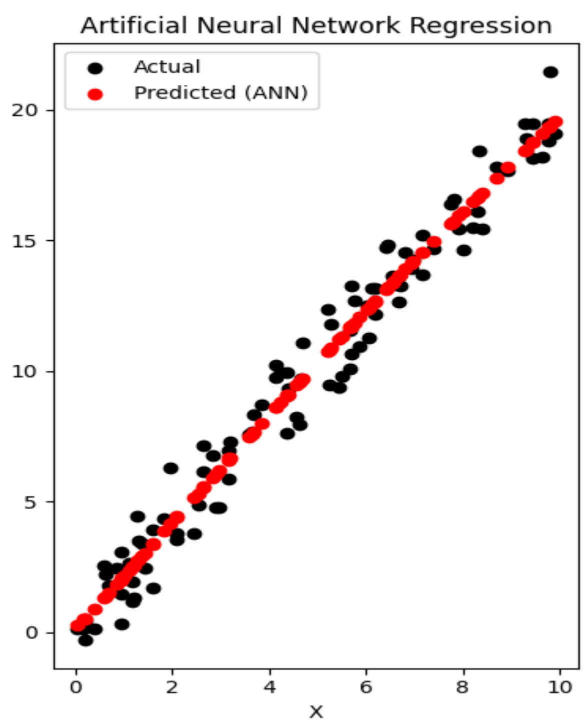

Figure 8: Regression result of the three models

Figure 7 showcases the residual plot for the three ML models trained for the prediction of heart disease. In the next graph, which presents the ANN model, it was observed that the residuals were distributed across the target variables. In addition, the number of neurons coupled with the optimization algorithm used for the neural network training was able to optimize the hyper-parameters of the neurons and allow for a generalized model, as evident in the residual distribution. To measure the regression performance for the ANN model, figure 8 was presented.

This model was used to measure the relationships between the actual data (y) and predicted data (x), as shown in figure 8. The aim is to achieve a perfect fit between the two variables, indicating that the predicted values perfectly match the actual values (residual). From the results, it was observed that the individual regression plots presented a very close fit and, in some instances, recorded a perfect fit between the actual and predicted values. What this result suggests is that the ANN model was able to correctly predict the heart disease features during the training process when tested at various instances. Table 1 presents the result of the ANN algorithm for heart disease prediction.

Table 1: Results of the ANN model for heart disease prediction

Iteration	MSE	RMSE	MAE	Accuracy
1	0.08514	0.2861	0.2436	0.9744
2	0.08564	0.2774	0.2563	0.9863
3	0.08763	0.2646	0.2640	0.9845
4	0.08654	0.2345	0.2535	0.9844
5	0.08532	0.2447	0.2644	0.9747
6	0.08323	0.2534	0.2535	0.9893
7	0.08644	0.2643	0.2645	0.9845
8	0.08567	0.2622	0.2533	0.9917
9	0.08646	0.2645	0.2567	0.9860
10	0.08656	0.2543	0.2035	0.9744
Average	0.08586	0.2606	0.25133	0.9895

Table 1 presents the results of the ANN validation considering the MSE, RMSE, MAE and Accuracy. From the results, it was observed that the average MSE is 0.085856, the RMSE is 0.2606, and the MAE and Accuracy is 0.25133 and 0.9895, respectively. These results implied that the ANN was able to achieve a limited error between the actual and predicted values. Overall, the performance of the artificial ANN in predicting the values was satisfactory, with relatively low MSE, RMSE, and MAE values. This indicates that the ANN model effectively captured the underlying patterns in the heart disease data and produced predictions that were close to the actual values.

4.2. Comparative Analysis

This section presents the comparative results of different heart disease prediction techniques to validate the results attained by our proposed neural network technique on a much bigger scale. The comparison is presented in table 2 as follows.

Table 2: Comparative Analysis of the various techniques for the prediction of heart diseases

Author	Technique	Performance Accuracy (%)
Adewole et al. (2016)	Naïve Bayes (NB)	85.30
Adetiba et al. (2018)	Support Vector Machines (SVM)	73.30
Adewole and Adebiyi (2013)	Random Forest (RF)	84.00
Manrique et al. (2019)	K-Nearest Neighbour	76.70
Kodati and Vivekanandam (2018)	Decision Table	84.81
Gomath and Shanmugapriyaa (2016)	Naïve Bayes	79.90
Rani and Masood (2020)	NB	97.60
Srinivasan et. al. (2023)	Radial Basis	90.78
Proposed Model	ANN	98.95

Table 2 presents a detailed comparison of various machine learning techniques utilized for predicting heart diseases based on performance accuracy. Naïve Bayes (NB) appears to be a commontechnique among researchers, with Adewole et al. (2016) and Gomath and Shanmugapriyaa (2016) achieving accuracies of 85.30% and 79.90%, respectively. Rani and Masood (2020) reported a significantly higher accuracy of 97.60% using the same technique, which suggests substantial improvements or variations in implementation. Support Vector Machines (SVM) as applied by Adetiba et al. (2018) yielded a relatively lower accuracy of 73.30%, indicating that while effective, SVM might not be as robust in this application as other methods.

Random Forest (RF) and Decision Table techniques also show competitive performance, with accuracies of 84.00% by Adewole and Adebiyi (2013) and 84.81% by Kodati and Vivekanandam (2018), respectively. K-Nearest Neighbour (KNN) implemented by Manrique et al. (2019) achieved a modest accuracy of 76.70%, which is better than SVM but not as high as NB, RF, or Decision Table methods. The Radial Basis technique reported by Srinivasan et al. (2023) shows a high accuracy of 90.78%, showcasing its effectiveness. Notably, the proposed model employing Artificial Neural Networks (ANN) stands out with the highest accuracy of 98.95%, highlighting the potential of ANN in improving predictive accuracy for heart disease detection compared to traditional methods.

5. Conclusion

Over the years, congenital heart disease (CHD) prediction has continued to witness a consistent increase in research attention. CHD diseases are vast and also span across diverse demographics, without sparing pregnant women, unborn babies, or newly born babies. While several studies have been presented considering other demographs, these three aforementioned demographs have received very little attention despite the high mortality rate and rising issues of heart disease among the categories of persons.This study presents the development of a congenital heart disease prediction and diagnostic model using machine learning techniques. The aim is to reduce the mortality and morbidity rates among infants, fetuses, and pregnant women due to issues relating to CHD. In realizing this goal, data that considered PPCM, PDA, and VDD was collected and a new data model for CHD was developed.The data model was processed through imputation, feature selection, and transformation using the imputation method and PCA. After the data processing stage, ML algorithm which is ANN was adopted and trained with the data to generate three models for the prediction of the CHD.

Secondly, ANN was trained and selected as a worthy prediction ML algorithm considering MSE, RMSE, MAE, and accuracy. ANN reported MSE of 0.22099, RMSE of 0.44009, accuracy of 0.98950, and MAE of 0.35801. The ANN model was integrated with a decision-based model for the prediction and diagnosis of CHD using Python and Java programming. The result, when treated with life data experiments, showed that the new model was capable of detecting the three considered CHD features with high reliability.

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