



Volume 5, Issue III, March, 2026; No. 83, pp. 1058-1068

Submitted 2/1/2026; Final peer review 27/3/2026

Online Publication 2/4/2026

Available Online at <http://www.ijortacs.com>

DEVELOPMENT OF A MACHINE LEARNING-BASED HEART DISEASE DETECTION SYSTEM FOR EARLY DIAGNOSIS AND CLINICAL DECISION-MAKING IN RESOURCE-CONSTRAINED RURAL SETTINGS

¹Agboeze Onyinyechi C., ²Ugwu Edith A.

^{1,2}Department of Computer Science, Enugu State University of Science and Technology, Agbani, Enugu, Nigeria

¹onyinyeagboeze@gmail.com, ²edith.ugwu@esut.edu.ng

Abstract

Heart disease remains a major cause of morbidity and mortality worldwide and is an emerging public health challenge in rural Nigerian communities, where access to diagnostic facilities and specialized healthcare services is limited. Therefore, this study presents the development of a machine learning-based heart disease detection system aimed at improving early diagnosis and clinical decision-making in resource-constrained rural settings. In the study, an Artificial Neural Network (ANN) model was designed and implemented using the Extreme Programming (XP) methodology to ensure flexibility, rapid iteration and continuous system validation. The model was trained on a hybrid dataset comprising primary health records collected from rural health centres in Enugu State, Nigeria and a secondary publicly available heart disease dataset from Kaggle, yielding a total of 20,428 samples. Comprehensive data pre-processing techniques including imputation, normalization, feature selection, feature transformation, and class balancing using SMOTE were applied to enhance model performance. The ANN architecture employed multiple hidden layers with ReLU activation, dropout regularization and a sigmoid-based output layer for binary classification. Experimental results from the study implementation demonstrated a training accuracy of 90.50% and a test accuracy of 89.10%, with strong precision, recall, and F1-score values, indicating reliable generalization and effective heart disease prediction. Comparative analysis with existing state-of-the-art techniques further validated the robustness of the proposed approach. The developed system provides a scalable and practical decision-support tool capable of assisting healthcare workers in early heart disease detection, thereby improving patient outcomes and reducing mortality in underserved rural communities.

Keywords: Heart Disease Detection; Artificial Neural Network (ANN); Machine Learning; Rural Healthcare; Clinical Decision Support System.

1. INTRODUCTION

Heart disease, a leading cause of death globally, is becoming an increasingly serious public health issue in Nigeria, particularly in rural communities. Traditionally, Nigeria's healthcare challenges were dominated by infectious diseases; however, the rising burden of non-communicable diseases (NCDs) like cardiovascular diseases (CVDs) has drawn significant concern. In rural areas, where healthcare infrastructure is often inadequate and access to healthcare is limited, the impact of heart disease is growing rapidly. The lack of awareness about

heart disease, combined with poor access to diagnostic and treatment facilities, has left many cases undetected and untreated, leading to high morbidity and mortality rates (Bozyelet *et al.*, 2024).

Several factors contribute to the rising prevalence of heart disease in Nigeria's rural areas. Poverty, poor nutrition, and lack of access to quality healthcare are significant contributors. Diets high in carbohydrates and unhealthy fats, combined with sedentary lifestyles, increase the risk of hypertension, diabetes, and other conditions linked to heart disease. Additionally, inadequate healthcare infrastructure makes it difficult for individuals in rural areas to receive early diagnoses or manage existing health conditions effectively (Penso *et al.*, 2022). Environmental factors such as lack of clean water and exposure to pollutants further exacerbate the health challenges faced by these communities. One of the main challenges in addressing heart disease in Nigerian rural communities is the scarcity of healthcare resources, including trained healthcare personnel, diagnostic equipment, and health education programs. Many rural healthcare centres lack the necessary technology and expertise to perform basic diagnostic tests for heart conditions, such as electrocardiograms (ECGs) and blood pressure monitoring. This leads to late diagnosis, when the disease is often in an advanced stage. Furthermore, the awareness of risk factors like hypertension, obesity, and smoking remains low, with many rural dwellers unaware of the links between these factors and heart disease (Javeed *et al.*, 2023).

Machine Learning (ML) offers a powerful tool to bridge the gap in healthcare access and management for heart disease in rural Nigeria. ML algorithms can analyze large datasets, identify risk factors, and predict the likelihood of heart disease, enabling early diagnosis even in resource-constrained settings (Nashifet *et al.*, 2018). These models can use data from wearable devices, community health records, and patient surveys to provide real-time monitoring and analysis. By integrating ML-based solutions into healthcare, non-specialist healthcare workers in rural areas can be equipped with tools to assess heart disease risk and provide timely interventions, thus reducing the disease burden (Ahmed, 2023).

Exploring machine learning-based solutions tailored to the specific needs of Nigerian rural populations presents an opportunity to transform cardiovascular care. Predictive models can be designed to account for the unique demographic, environmental, and lifestyle factors prevalent in these communities (Almazroiet *et al.*, 2023). A machine learning system could be implemented through mobile health (mHealth) platforms, allowing rural healthcare workers to diagnose and monitor patients using real-time data. The automation and scalability of such systems could drastically improve early detection and management of heart disease, reducing fatalities and improving overall public health outcomes in rural Nigeria.

The methodology adopted for the implementation of the study was the Extreme Programming (XP) methodology. The XP is an improved agile approach which supports rapid improvement and real-time validation, leading to an overall enhanced effective tool for early detection and prevention of heart disease. The choice of XP for the development of the study is based on its flexibility and adaptability, which makes the system highly adaptive to changing requirements which is essential for real-world healthcare challenges in rural communities. Then, XP's rapid and continuous development which ensures rapid iterations that allows the incremental improvements in diagnosis accuracy and system performance. The methodology equally promotes frequent releases making sure essential features are developed and tested in early development stage of the system. By adopting XP, the study ensures that the heart disease

detection model and clinical diagnosis software are continuously improved, validated, and tailored to the needs of rural communities.

2. DATA COLLECTION

For the development of the system, both primary and secondary data was used. The primary data was collected from Nsukka Medical Clinic in the rural areas of Enugu State, Nigeria. The data collected in this health centres are health records of heart disease infected patients between the ages of 26-70 years due to their high susceptibility to various forms and stages of heart diseases in different intensity levels. The age grades were equally considered due to their various exposure to the environmental stress and activities. The data collected was made up of 35 patient's health volunteer records with 1,540 samples. Then, the secondary data used was the heart disease prediction dataset acquired from Kaggle (<https://www.kaggle.com/datasets/mfarhaannazirkhan/heart-dataset>) widely used for cardiovascular risk modelling and machine learning classification tasks..

This dataset contains 18,888 records merged from five publicly available heart disease datasets from tertiary institution-based hospital. It includes 14 features that are crucial for predicting heart attack and stroke risks, covering both medical and demographic factors and the major features include age and sex, capturing basic patient demographics; chest pain type, resting blood pressure, serum cholesterol, and fasting blood sugar, which provide measures of cardiovascular health and metabolic risk; resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, ST depression (oldpeak) and ST-segment slope, which reflect functional and stress-test indicators of cardiac performance. These features collectively represent a mix of numerical and categorical data, enabling machine learning models to detect patterns associated with heart disease. By integrating both static factors (age, sex, cholesterol) and dynamic response indicators from exercise tests, the dataset provides a comprehensive snapshot of patient cardiovascular status, making it suitable for predictive modelling, although its cross-sectional nature limits longitudinal analysis of disease progression. Therefore, the total sample size used for the purpose of this study was 20,428 samples.

2.1 Data Processing

Data processing is a very important stage for preparing the data of the heart disease detection dataset for machine learning usage. The data processing step ensures adequate data quality, removal of inconsistencies and enhancement of model performances. All these are done through data cleaning, handling of missing values and fixing inconsistencies, feature encoding and feature scaling.

2.2 Imputation, Normalization, Feature selection, feature transformation, data splitting

This stage of the processing involves the use of filter methods approach for feature selection and SHapley Additive exPlanations (SHAP) and Min-Max scaling for feature engineering, where the most relevant features are identified and created for predictive analysis through encoding of categorical variables and normalization of numerical features. Log transformation has been applied in the study for feature transformation to reshape the data for better model learning. Synthetic Minority Oversampling Technique (SMOTE) is applied for data balancing by recovering cases and randomly remove samples from the majority cases. Then finally, train-test split is used for splitting the data into training, testing and validation sets. This splitting is done on a ratio of 70:20:10 as training, testing and validation respectively.

2.3 The Design of the ANN

The training process of the Artificial Neural Network (ANN) for early heart disease detection begins with data pre-processing, which involves handling missing values, encoding categorical features, and normalizing numerical data to ensure uniformity across different scales. The dataset, comprising both primary data from rural health centres in Enugu State and secondary data from Kaggle, was split into training (70%), testing (20%) and validation (10%) sets to enable model evaluation. The ANN architecture consisted of an input layer, two hidden layers with ReLU activation, and an output layer with a sigmoid activation function for binary classification. Dropout layers are included to prevent overfitting, and the Adam optimizer is used for efficient weight updates. The input layer accepts a feature vector representing patient data, where each neuron corresponds to one medical attribute such as age, cholesterol level, blood pressure, and heart rate. This layer is followed by three fully connected hidden layers, each comprising 64, 32 and 16 neurons, respectively, and using the Rectified Linear Unit (ReLU) activation function to introduce non-linearity, enabling the model to learn complex relationships within the data. Then the output layer has a single fully connected neuron with Sigmoid function which processes the classification of the model. The model is compiled using binary cross-entropy loss, as the task involves distinguishing between heart disease presence and absence. To enhance generalization and prevent overfitting, dropout layers with a dropout rate of 30% are applied after each hidden layer, randomly deactivating some neurons during training. The output layer consists of a single neuron with a sigmoid activation function, which produces a probability score between 0 and 1, determining the likelihood of heart disease presence. The model is trained using the Adam optimizer for efficient weight updates, and binary cross-entropy is used as the loss function due to the binary nature of the classification task. This structured architecture ensures that the ANN can effectively learn from both local and global heart disease datasets, making it a reliable tool for early diagnosis in clinical settings. Figure 1 illustrates the training of the ANN model.

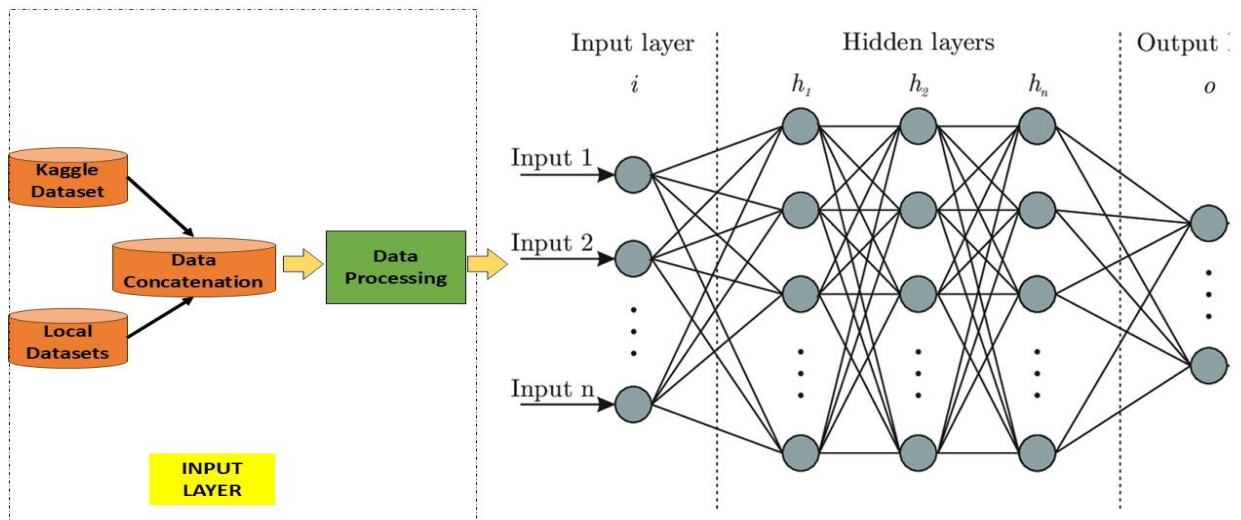


Figure 1: Training of the ANN Model

During training, the ANN presented in Figure 1 learns by adjusting weights using back propagation and gradient descent. The model went through 50 epochs of training with a batch size of 32, where it iteratively minimized the loss function based on training data feedback. Throughout training, performance metrics such as accuracy and validation loss are monitored to

prevent overfitting or under fitting. The trained model was then evaluated using the test dataset, where it predicts outcomes for unseen patient records. Performance assessment is conducted using accuracy, classification reports, and confusion matrices, ensuring the model generalizes well to new data. Once validated, the final model was saved for deployment in a clinical decision-support system to assist healthcare professionals in early heart disease diagnosis.

2.4 The design of the heart disease detection system

The heart disease detection model shown in Figure 2 is an Artificial Neural Network (ANN) trained on a combination of primary and secondary heart disease datasets. The model takes patient health records as input, processes them through multiple layers, and predicts the likelihood of heart disease. The input layer consists of medical attributes such as age, cholesterol levels, blood pressure, heart rate, and other relevant features. These inputs are passed through two fully connected hidden layers with ReLU activation functions, which help the model learn complex relationships between the features. To prevent overfitting, dropout layers are included to randomly deactivate neurons during training. The output layer has a single neuron with a sigmoid activation function, which produces a probability score between 0 and 1, determining the likelihood of heart disease in a patient.

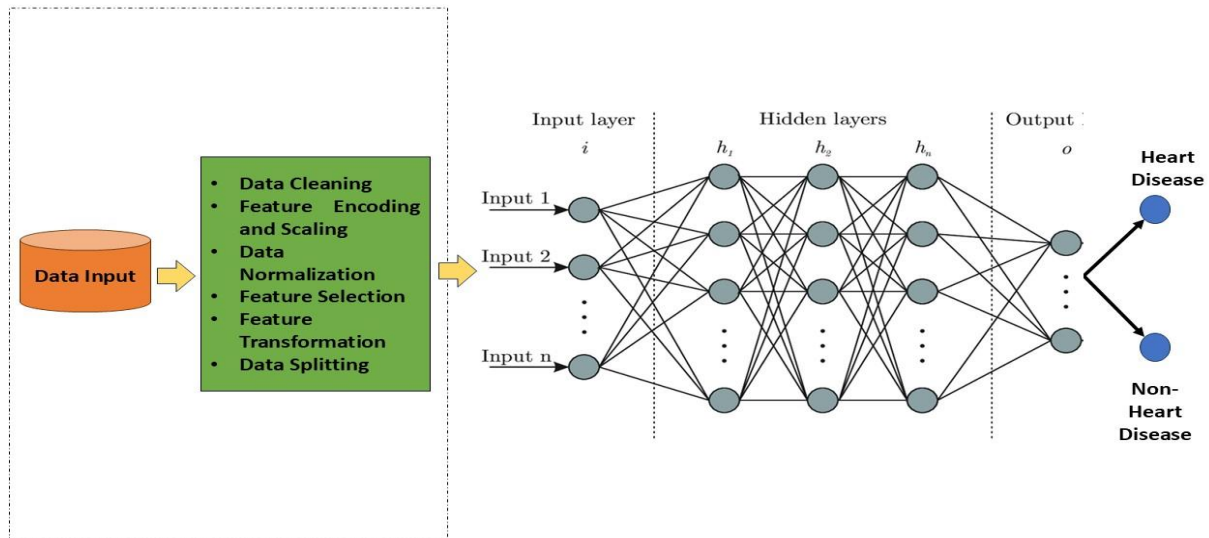


Figure 2: Heart Disease Detection Model

The model is trained using the Adam optimizer and binary cross-entropy loss function, ensuring efficient weight updates for accurate classification. Once trained, the model is used to predict heart disease presence based on new patient data. Before making predictions, new data undergoes the same pre-processing steps as the training data, including feature scaling and encoding. The trained ANN model can analyze individual patient records and output a diagnosis, where a probability score above 0.5 indicates heart disease presence and below 0.5 suggests no heart disease. This detection model provides a reliable and efficient clinical decision-support tool, helping healthcare professionals in early diagnosis, risk assessment, and timely medical intervention for patients in rural and urban communities.

2.5 System flow chart

The flowchart of the ANN based heart disease detection system which represents the flow of data and processes within the system is presented in Figure 3 and 4, the flowchart shows the movements involved from data collection to the diagnosis level of the detective system. Figure 3

presents the flowchart for training the ANN model for heart disease detection capability while Figure 4 presents the flowchart for the heart disease diagnostic system.

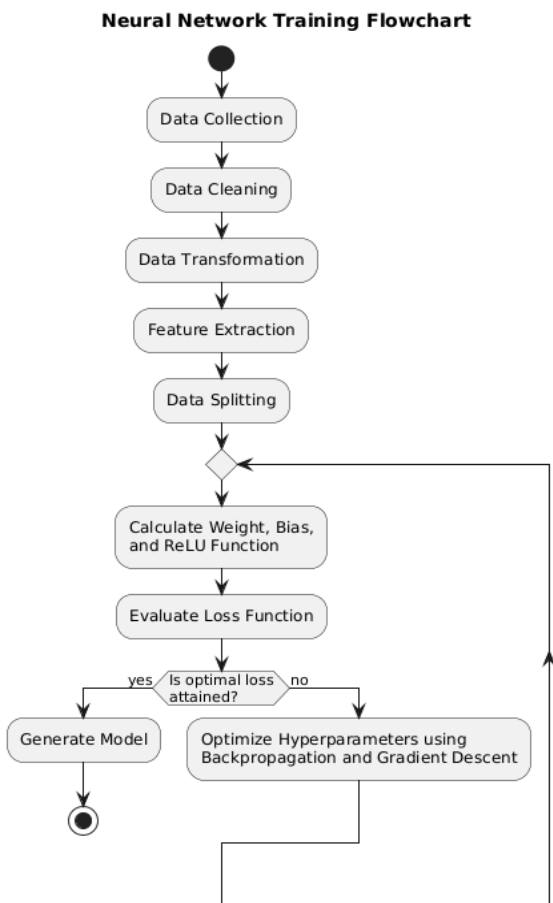


Figure 3: Flowchart of the ANN Model

Heart Disease Detection using ANN

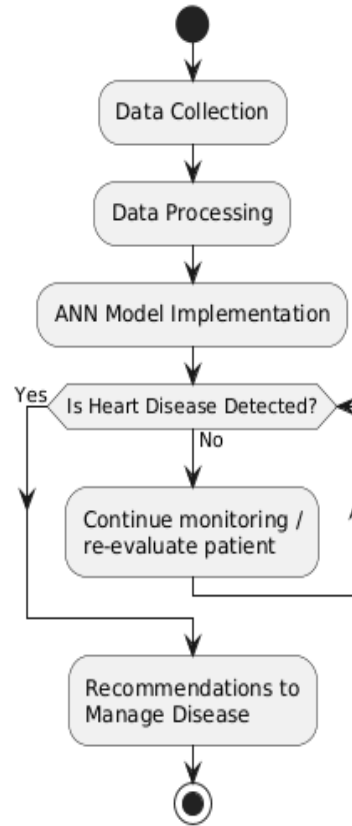


Figure 4: Flowchart of the Heart Disease Detection System based on ANN Model

The flowchart in Figure 4 presents the heart disease detection system which integrates the ANN model trained in Figure 3 for early diagnosis of heart diseases.

2.7 System Implementation

The implementation of the heart disease detection system using an ANN in Python through Google Colab follows a structured approach, starting from data pre-processing to model training and deployment. The dataset, which consists of primary health records collected from rural health centres in Enugu State, Nigeria, and a secondary dataset from Kaggle, undergoes cleaning, normalization, and encoding to prepare it for training. The dataset features key heart disease indicators, including blood pressure, cholesterol levels, heart rate, and other medical parameters. After pre-processing, the data is split into training (70%), testing (20%) and validation (10%) sets, ensuring a balanced model evaluation. The ANN model is structured with multiple dense layers: an input layer for processing features, hidden layers with ReLU activation functions for learning complex patterns, and an output layer with a sigmoid activation function for binary classification (presence or absence of heart disease). The model is compiled using the Adam optimizer and trained using binary cross-entropy loss, ensuring optimal weight adjustments to improve prediction accuracy.

Once trained, the model is evaluated on the test dataset, achieving high accuracy through metrics like precision, recall, F1-score, and confusion matrix analysis. The trained ANN model is then saved in HDF5 format for future use, allowing it to be integrated into a real-time clinical diagnosis system. The system implementation also includes Python-based software where doctors can input patient health parameters, and the model predicts the likelihood of heart disease, providing instant results. The trained model can be deployed using Flask or Tensor Flow Serving, enabling seamless integration into desktop applications, web apps, or mobile health platforms. This implementation provides a robust and scalable solution for early detection and risk prediction of heart disease, improving diagnostic efficiency in rural healthcare settings.

3. RESULTS AND DISCUSSIONS

The parameters utilized for the model assessment are positive predictive value, false discovery rate, accuracy, true positive rate and area under curve.

3.1 Result of the ANN training

The ANN model for heart disease detection achieved a training accuracy of 90.50% and a test accuracy of 89.02% as shown in Figure 5, indicating strong generalization without significant overfitting. The confusion matrix shows high recall (91%) for heart disease cases, meaning the model effectively identifies most patients with heart disease, which is crucial in a clinical setting. The precision of 89% ensures that false positives remain relatively low, reducing unnecessary medical interventions. However, 17 false positives and 12 false negatives suggest room for improvement through better data balancing and feature optimization. Overall, the model demonstrates high reliability for early heart disease detection, with potential refinements to further enhance accuracy.

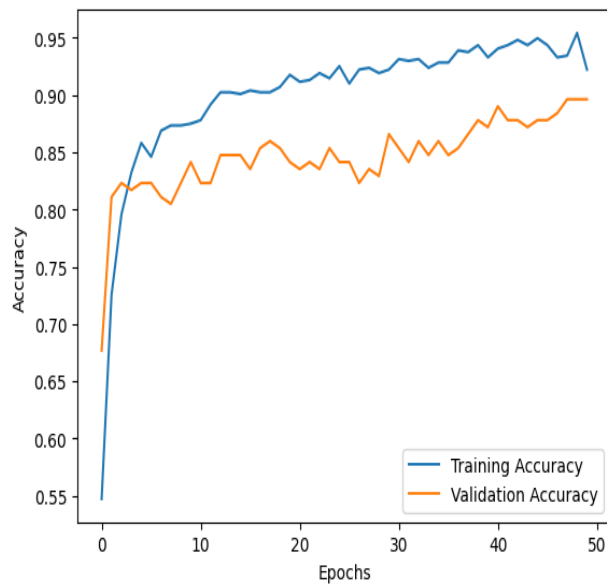


Figure 5: Performance accuracy of the ANN Model

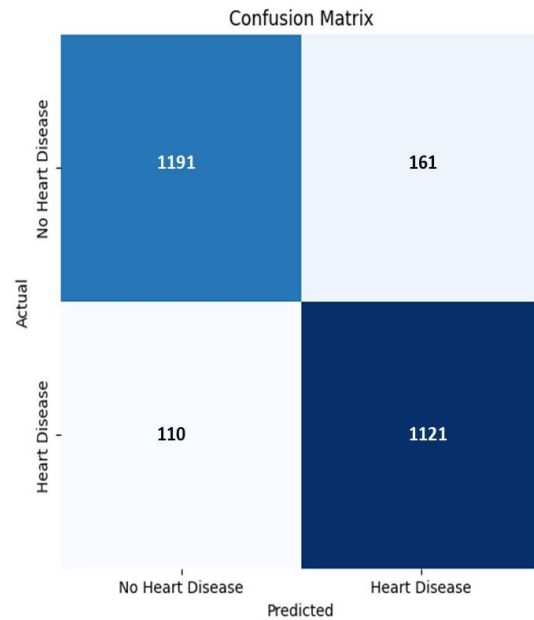


Figure 6: Confusion Matrix

The chart in Figure 5 demonstrates the performance accuracy of the ANN model implementation during the 50-epoch execution of the model on the training environment. Figure 6 presents the confusion matrix illustration of the model during the training of the model.

The confusion matrix shown in Figure 6 indicates that the ANN model correctly classified 1191 non-disease cases (True Negatives) and 1121 heart disease cases (True Positives), demonstrating

strong predictive performance. However, 161 false positives (healthy individuals misclassified as having heart disease) and 110 false negatives (actual heart disease cases missed) suggest that while the model performs well, it is not perfect. The recall for heart disease cases is 92%, meaning the model successfully identifies most individuals with heart disease, reducing the risk of undiagnosed conditions. However, the 85% recall for non-disease cases suggests that some healthy individuals may receive unnecessary medical attention due to misclassification.

The classification report further highlights the model's reliability, with an overall accuracy of 89.10%, ensuring that predictions are generally correct. The precision for non-disease cases (90%) means that when the model predicts a person is healthy, it is correct 90% of the time, reducing false alarms. Meanwhile, the precision for heart disease cases (88%) ensures that most diagnosed cases are indeed affected individuals. The F1-scores of 88% (non-disease) and 90% (disease) as shown in Table 1 confirm a strong balance between precision and recall. While the model effectively detects heart disease, fine-tuning hyper-parameters, incorporating additional features, or adjusting the decision threshold could further minimize false classifications, making the system even more reliable for early detection.

Table 1: Classification Results of the ANN Model

Metric	Class 0 (No Heart Disease)	Class 1(Heart Disease)	Overall (%)
Accuracy	-	-	89.10
Precision	90%	88%	89.00 (Weighted Avg)
Recall	85%	92%	89.02 (Macro Avg)
F1-Score	88%	90%	89.01 (Weighted Avg)

This Table 1 concisely presents the classification performance of the ANN model for heart disease detection.

3.2 Comparative analysis of ANN with other works in literature

For the validation of the system, the result attained from this study presents the comparative analysis of the results attained with other state-of-the-art models, in order to ascertain the capacity and strength of the model adopted for heart disease detection. This is equally performed to justify the technique adopted and identify the advantage of adopting it for further integration into the health system. The comparative results of the techniques are presented in Table 2 which considers the accuracy of the other techniques and the proposed technique.

Table 2: Comparative Analysis

Author	Technique	Accuracy (%)
Nkereuwemet al., (2024)	Ensemble Model	99.13
Zabeeullaet al., (2023)	Random Forest and Extra-tree Classifiers	98.8
Khan et al., (2024)	Hybrid Machine Learning (SVM, Naïve Bayes (NB) and ANN)	99.30
Uddin et al., (2023)	Decision Tree (DT)	99.16
Nia and Hesar (2024)	Sequential Forward Feature Selection (SFFS) and Particle Swarm Optimisation (PSO)	98.03
Omotehinwaet al., (2024)	Light-GBM	98.82
Shrestha and Chatterjee (2019)	DT and NB	88.00
Baghdadi et al., (2023)	Catboost	90.94
Rani et al., (2023)	Regularised Deep Neural Network model (Reg-DNN)	94.79

Ozcan and Peker (2023)	Classification and Regression Tree (CART)	87.00
Hossain et al., (2023)	Random Forest	90.00
Ahmed (2022)	Random Forest	89.40
Rani et al., (2021)	Recursive Feature Elimination and Genetic Algorithm (GA)	86.60
Kektar and Gawade (2022)	SVM	80.00
The Proposed System	ANN	89.10

In Table 2, the comparative results of the proposed system are tabulated alongside other conventional technique which was adopted for heart disease detection. The comparative result presented in Table 2 illustrates a chart that represents the performances attained by the various techniques applied. From the results presented, the Ensemble mode, Hybrid ML, DT and LightGBM technique showed exceptional performance accuracies, topping the charts with performance accuracies above 90%. The performance of the proposed ANN technique was shown to not have the best performance accuracy; however, the performance of the technique showed that it still performed better than other techniques.

Despite the proposed ANN technique adopted in this study not giving the best performance, it is still recommended that it is the most reliable technique to be applied for the detection of heart disease in rural area. This is because the training of the ANN model used multiple datasets that considers both primary (local) and secondary (global) datasets. This increases the model's generalizability of the system to capture the features of the global dataset and the features of the local datasets. This is shown to be very effective for easy detection of heart diseases considering local and global settings.

4. CONCLUSION

This study successfully developed a machine learning-based system for the early detection of heart disease, with a focus on rural communities in Enugu State, Nigeria. By combining primary and secondary datasets, an Artificial Neural Network (ANN) model was trained to identify heart disease with high accuracy. The system was implemented using Python for model training and web application for clinical software integration, ensuring usability in real-world healthcare settings. Performance evaluation using accuracy, precision, recall, and F1-score confirmed the reliability of the proposed system, while comparative analysis was used to validate the result of the study, this demonstrated its stability across different data splits.

The results indicate that machine learning can significantly enhance early diagnosis and risk prediction of heart disease, particularly in resource-limited environments. The developed system provides a scalable, automated diagnostic tool that aids healthcare professionals in making timely and informed decisions. Despite its success, future research can focus on expanding the dataset, incorporating additional medical features, and improving real-time usability. Overall, this study contributes to improving heart disease diagnosis and management, ultimately reducing mortality rates and enhancing healthcare delivery in underserved communities.

5. REFERENCES

- Ahmed, I. (2022). A study of heart disease diagnosis using machine learning and data mining (Publication No. 1591) [Electronic Theses, Projects, and Dissertations]. California State University, San Bernardino ScholarWorks. <https://scholarworks.lib.csusb.edu/etd/1591>
- Ahmed, R. (2023). Decision support system for early diagnosis of heart diseases. VFAST Transactions on Software Engineering, 124–130.

- Almazroi, A., Aldahri, E., Bashir, S., & Ashfaq, S. (2023). A clinical decision support system for heart disease prediction using deep learning. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2023.3285247>
- Baghdadi, N., Abdelaliem, M., Malki, A., Gad, I., Ewis, A., & Atlam, E. (2023). Advanced machine learning techniques for cardiovascular disease early detection and diagnosis. *Journal of Big Data*, 10, Article 144. <https://doi.org/10.1186/s40537-023-00817-1>
- Bozyel, S., Şimşek, E., Koçyiğit, D., Guler, A., Korkmaz, Y., Seker, M., Erturk, M., & Keser, N. (2023). Artificial intelligence-based clinical decision support systems in cardiovascular diseases. *Anatolian Journal of Cardiology*, 28(2), 74–86. <https://doi.org/10.14744/AnatolJCardiol.2023.3685>
- Hossain, I., Maruf, M., Khan, A., Prity, F., Fatema, S., Ejaz, S., & Khan, A. (2023). Heart disease prediction using distinct artificial intelligence techniques: Performance analysis and comparison. *Iran Journal of Computer Science*, 6, 397–417. <https://doi.org/10.1007/s42044-023-00148-7>
- Javeed, A., Saleem, M. A., Dallora, A. L., Ali, L., Berglund, J. S., & Anderberg, P. (2023). Decision support system for predicting mortality in cardiac patients based on machine learning. *Applied Sciences*, 13, Article 5188. <https://doi.org/10.3390/app13085188>
- Ketkar, Y., & Gawade, S. (2022). A decision support system for selecting the most suitable machine learning in healthcare using user parameters and requirements. *Healthcare Analytics*, 2, Article 100117. <https://doi.org/10.1016/j.health.2022.100117>
- Khan, S., Azade, S., Sawane, D., & Pathan, S. (2024). An effective heart disease detection and classification using machine learning. *Journal of Electrical Systems*, 20(3s), 869–879.
- Nashif, S., Raihan, R., Islam, R., & Imam, M. H. (2018). Heart disease detection by using machine learning algorithms and a real-time cardiovascular health monitoring system. *World Journal of Engineering and Technology*, 6, 854–873. <https://doi.org/10.4236/wjet.2018.64057>
- Nia, P., & Hesar, H. (2024). Abnormal heart sound detection using time-frequency analysis and machine learning techniques. *Biomedical Signal Processing and Control*, 90, Article 105899. <https://doi.org/10.1016/j.bspc.2023.105899>
- Nkereuwem, E., Ansa, G., Umoh, U., Essien, U., Nkereuwem, E., & Asuquo, M. (2024). Machine learning based system for early heart disease detection and classification using audio signal processing approach. *Global Journal of Engineering and Technology Advances*, 21(1), 87–104. <https://doi.org/10.30574/gjeta.2024.21.1.0178>
- Omotehinwa, T., Oyewola, D., & Moug, E. (2024). Optimizing the light gradient-boosting machine algorithm for an efficient early detection of coronary heart disease. *Informatics and Health*, 1, 70–81. <https://doi.org/10.1016/j.infoh.2024.06.001>
- Ozcan, M., & Peker, S. (2023). A classification and regression tree algorithm for heart disease modeling and prediction. *Healthcare Analytics*, 3, Article 100130. <https://doi.org/10.1016/j.health.2022.100130>
- Penso, M., Solbiati, S., Moccia, S., & Calani, E. (2022). Decision support systems in HF based on deep learning technologies. *Current Heart Failure Reports*, 19, 38–51. <https://doi.org/10.1007/s11897-022-00540-7>
- Rani, P., Kumar, R., & Jain, A. (2023). An intelligent system for heart disease diagnosis using regularized deep neural network. *Journal of Applied Research and Technology*, 21, 87–97.

- Rani, P., Kumar, R., Ahmed, N., & Jain, A. (2021). A decision support system for heart disease prediction based upon machine learning. *Journal of Reliable Intelligent Environments*. <https://doi.org/10.1007/s40860-021-00133-6>
- Shrestha, R., & Chatterjee, J. (2019). Heart disease prediction system using machine learning. *LBEF Research Journal of Science, Technology and Management*. ISSN: 2705-4683; e-ISSN: 2705-4748.
- Uddin, K., Ripa, R., Yeasmin, N., Biswas, N., & Dey, S. (2023). Machine learning-based approach to the diagnosis of cardiovascular vascular disease using a combined dataset. *Intelligence-Based Medicine*, 7, Article 100100. <https://doi.org/10.1016/j.ibmed.2023.100100>
- Zabeeulla, M., Sharma, C., & Anand, A. (2023). Early detection of heart disease using machine learning approach. *Cardiometry*, 26, 342–347. <https://doi.org/10.18137/cardiometry.2023.26.342347>