



Artificial Neural Network Prediction Model for Maternal Health Services Quality in Nigeria

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ABSTRACT

This study presents an innovative approach in predicting the quality of maternal health services in Nigeria using artificial neural networks (ANNs). It focuses on a binary classification task in categorizing maternal health services facilities into "High_Quality" and "Low_Quality" classes. Dataset was collected from diverse healthcare facilities in Nigeria through a WHO Health Resources and Services Availability Monitoring System (HeRAMS) cross sectional-survey report. The collected data was preprocessed; the ANN architecture was developed and trained using back-propagation method. The network was modeled using feed-forward modeling approach with 16 variables at the input layer, 2 hidden layers of 65 and 55 neurons each, and an output of 2 neurons. Hence, 87.17% accuracy with only 2.48% deviation at the 50 epoch was achieved. The model's performance was evaluated using standard metrics of accuracy (87%), precision (88%), recall (89%), and F1-score (88%) to assess its ability to accurately classify maternal health services facilities. The findings of the study can have significant implications to policymakers, healthcare providers, and maternal health advocates to optimize healthcare resources and achieve better maternal health outcomes in Nigeria. Data availability, potential biases in the data, and the subjective nature of some quality-related indicators were acknowledged as limitations. However, despite these challenges, the ANN classification model remains a valuable tool for supporting decision-making in maternal healthcare facility delivery service in Nigeria.

1. Introduction

Maternal health is a critical aspect of healthcare, directly impacting the well-being of expectant mothers and their newborns. In the global world, pregnancy ranks among the most pressing reproductive health problems and statistics has shown that an annual estimate of 600,000 women aged 15 – 49 died of pregnancy-related causes, with 99 per cent coming from the developing countries (Oladejo and Olajide, 2020), and Nigeria alone accounting for maternal deaths of 556 women for every 100,000 live births, accounting for one of sub-Saharan Africa's highest maternal mortality rates (WHO, 2020). It is pertinent that the high rate of maternal and neonatal mortality in Nigeria is linked to insufficient quality of care during pregnancy and labor, skilled health care attendants and modern health care facilities. Therefore, a timely access to quality maternal health services is essential for ensuring safe pregnancies and positive birth outcomes. The introduction of digital healthcare technology has led to reductions in maternal and neonatal mortality, low birth weight (LBW), and preterm birth (PTB) rates, which are indicators of the progress gained in maternal and infant health over the past few decades. Such technologies include: mobile applications, websites and short-message service (SMS)-based technologies and decision support system for antenatal and maternal, neonatal and child health (MNCH) care. Despite introducing these technologies, the country failed to meet the Millennium Development Goals for maternal and child mortality, and is poised to fail to meet the Sustainable Development Goals (SDGs) for the same health outcomes of getting the priority of health interventions (United Nations, 2020).

As a result, efforts to reduce mother and child mortality to acceptable levels by digital interventions have not been successful. Therefore, the rise of emerging digital healthcare technologies calls for a revolution from mere

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electronic health to data-driven healthcare, especially given the importance of data in computerized decision-making (Nico *et al.*, 2022). A well-performing healthcare system needs to utilize all the data at its disposal to improve service provision and provide evidence-based healthcare to make the necessary changes to improve the quality, access and efficiency of the healthcare system (Batani and Maharaj, 2022). Machine learning, deep learning, automation, neural networks, big data analytics, and other algorithms are some of the advancements driving the creation of new data that can be helpful for data-driven antenatal care. The application of data-centric design is critical for developing a data-centered artificial intelligence (AI)-guided predictive model in maternal health services. In recent years, artificial intelligence (AI) has emerged as a powerful tool in healthcare, with artificial neural networks (ANNs) offering promising capabilities in predicting complex healthcare scenarios (Bundi, *et al.*, 2021). The emergence of artificial intelligence (AI) has changed the entire health care services and the ways providers deliver care provisions to patients. Numerous AI researches have been applied to the prediction of a wide range of health-related problems, specifically pregnancy related disorders among many others (Oprescu *et al.*, 2020). Various predictive models have been developed to forecast maternal health service needs (Raza, *et al.*, 2022). Such prediction studies and models have been used in different domains to solve diverse problems, with the aim to identify what contribute to the prediction of an outcome, in which the development, validation or improvement of prediction are proposed to be used for forecasting complex scenarios into precise and accurate decisions (Oprescu *et al.*, 2022).

Traditional statistical approaches, such as linear regression and logistic regression, have been widely used in forecasting maternal health needs (Espinosa, *et al.*, 2021; Fredriksson *et al.*, 2022). To date, few published papers have used Artificial Neural Network techniques to predict maternal health service as it relates to facility needs in Nigeria (Togunwa *et al.*, 2023). However, they often lack accuracy, flexibility, and fail to capture the dynamic nature of maternal health needs. This presents a significant challenge for healthcare providers in efficiently allocating resources and providing personalized care to expectant mothers.

Artificial Neural Networks (ANN) offers a more sophisticated approach that can learn from vast amounts of data and adapt to changing patterns, leading to improved predictions. Hence, reduce the burden of administrative processes that create work-related stress (Al-Badi *et al.*, 2021). The multi-class classification and prediction task will enable healthcare providers in Nigeria to proactively allocate resources and provide targeted maternal health services, contributing to the reduction of maternal mortality rates and overall improvement in maternal and infant outcomes (Bala *et al.*, 2023).

By leveraging the power of artificial neural networks for this binary-class classification task, the study aims to enhance maternal healthcare decision-making and contribute to the advancement of AI-driven healthcare solutions in resource-constrained settings.

The primary Question that needs an answer is: How can artificial neural networks be leveraged to accurately predict maternal health service quality, considering various facility and service indicators that account for factors to optimizing resource allocation and improve maternal outcomes? This study is significant in that AI applications can improve operational efficiency and organizational effectiveness through automation of the workforce, enhancing predictive intelligence of the decision-makers, and creating better competitive advantages (Patil *et al.*, 2021). It is pertinent that AI-based health care services have great potential to enhance the existing health care systems in developing countries specifically Nigeria.

2. Literature Review

2.1 AI and Artificial Neural Network (ANN) in Maternal Health Services Prediction

AI is a field of science that simulates human intelligence and behavior to perform a specific task (Ramakrishnan *et al.*, 2021). It can facilitate decision-making and enhance medical treatment. AI can be utilized in the healthcare industry for monitoring, diagnostics, early detection, and prediction modeling. It stimulates human intelligence in healthcare by improving diagnostic effectiveness, enabling predictive analytics, aiding in drug discovery and enhancing the efficiency of administrative activities (Ramakrishnan *et al.*, 2021). Machine learning models like artificial neural network is a sub-division of AI. Machine learning could be broadly categorized as supervised, semi-supervised, unsupervised, or reinforced, uses computer models and algorithms to do certain tasks. ML can be used to infer conclusions from new data and learn from old data. Supervised learning uses label data to train machine learning models, while unsupervised learning uses unlabelled data to find patterns and relationships in the data (Togunwa *et al.*, 2023). The semi supervised learning is a hybrid type of learning while reinforcement learning involves training a machine learning model to make decisions based on reward and punishment.

The artificial neural network (ANN) is a biological working structure capable of delivering the best results transformed by inputs without affecting the output operation. It is a class of algorithms with an essential ability to deal

with a complicated design data set and can forecast model problems similar to how the human brain can (Togunwa *et al.*, 2023). The artificial neural network (ANN) is a member of a class of algorithms known as multi layer perceptron (MLP) that accepts numerical and structured data to be built on many layers or neurons, such as input, hidden, and output. However, the input layer serves as the point of entry for the independent variables into the network system, followed by hidden (intermediate) neurons, which help to connect the computation between the input and the output, while the output layer serves as the final neuron to produce the results (Hammoud *et al.*, 2022). The artificial neural network (ANN) is a function based on the principles of neurons, which serve as processing components assembled in an organized pattern in which each separately connects. As a result, the input is united with the weight and the bias of the network in every single neuron, and the structure levels then act as the primary route for the data to pass through the activation function (Bala *et al.*, 2023).

2.2 Binary Classification in Neural Network Modeling

Binary Classification is one out of many machine learning Techniques that has many applications. It is a supervised learning algorithm that categorizes new observations into one of two classes (Togunwa, et al., 2023). The two classes are typically labeled as 0, and 1 or positive and Negative, with the aim of predicting which class a new observation belongs to. The most popular algorithms used by binary classification includes logistic regression, decision tree and support vector machines.

2.3 Related Studies: Maternal Health Services Prediction using Machine Learning

The importance of maternal health led many researchers to devise models and approaches for the timely prediction of health care services and associated issues using both traditional and machine learning techniques. The study of Fredriksson, et al., (2022) developed a Machine learning prediction model that accurately predicts whether a newly enrolled pregnant woman will deliver in a health facility using four machine learning methods: logistic regression, LASSO regularized logistic regression, random forest and an artificial neural network and three sampling techniques to address the imbalanced data. Togunwa *et al.*, (2023), employed a deep hybrid model for maternal health risk classification in pregnancy, which utilizes the strengths of artificial neural networks (ANN) and random forest (RF) algorithms. An artificial neural network-based system for predicting maternal health risks using health data records was developed where a novel deep neural network architecture, DT-BiLTCN, which uses decision trees, a bidirectional long short-term memory network, and a temporal convolutional network, was proposed (Raza *et al.*, 2022). Bala *et al.*, (2023), employed artificial neural networks (ANNs), adaptive Neuro-fuzzy inference systems (ANFISs) and support vector machines (SVMs) and a classical linear regression model of multiple linear regressions (MLR) to predict and visualize the progress of Antiretroviral therapy (ART) Hospital Unit of Federal Teaching Hospital in Gombe. Raja *et al.* (2021) presented a machine learning model as risk prediction conceptual model for the prediction of Preterm birth (PTB) and implemented using three different classifiers, namely, decision tree (DT), logistic regression (LR), and support vector machine (SVM) for the prediction. Bolanle and Oladejo (2020) explored a machine learning-based decision support system for maternal health care where a multi-class Support Vector Machine (SVM) was developed a Web-based Decision Support System for Maternity Health Care (DSSMC to facilitate automatic diagnosis of patient and to solve the problem of human error and bias. Meanwhile Shrivastava *et al.* (2023) proposed an AI-guided citizen-centric tool that was designed, developed, implemented, and evaluated using principles of human-centered design that help to predict early at-risk pregnancy outcomes.

Furthermore, Hammoud *et al.* (2022), built, trained and tested five machine learning models: Support Vector Machine (SVM), Random Forest (RF), XGBoost, CatBoost and Artificial Neural Network (ANN) for classification and regression identifying the salient features contributing to maternal and newborn healthcare providers' perception of safety in the workplace. Conversely, the envision of artificial intelligence for prenatal prediction and classification in health care research and the development of methods for explaining the decision-making processes of artificial intelligence models for prenatal health indicators (Ramakrishnan *et al.*, 2021). Odion *et al.* (2021) collected data from Nigerian Demographic and health Survey and nine risk factors were used to predict neonatal mortality risk by applying Support Vector Machine algorithm to build a predictive model, it uses KMeansSMOTE to solve the problem of class imbalance in the dataset, while model hyper-parameter tuning was applied to the model to get a better prediction. Ope (2020), in a study highlights the need to understand and address the perception and experiences of maternal services particularly at point of delivery, as this is imperative towards increasing the utilization of maternal health facilities in a multicultural setting like Nigeria. On the same vein, Bundi *et al.* (2021) explore the Role of Artificial Intelligence and Machine Learning in Maternal Health.

The analysis of the studies mentioned above suggests that additional research is needed in a number of areas. First, with the exception of a few single and ensemble models, the majority of the studies have used Personal

Computing Environment as opposed to this study. Second, most researches frequently ignore the calibre of maternal health care facilities in favor of patient-centric classification and risk variables. Third, research on deep learning models is scarce, particularly in Nigeria and the delivery of maternal healthcare services.

This study employs Binary-class classification model using an artificial neural network (ANN) to predict maternal health service facility needs in Nigeria. The task involves categorizing maternal health services into two classes: "High_Quality" and "Low_Quality," based on the level of care and services received by expectant mothers during pregnancy and delivery. High_Quality refers to healthcare facilities that provide services that increase the likelihood of desired maternal health outcomes While Low_Quality refers to healthcare facilities that hold back the progress of improving maternal health outcomes.

3. Materials and Methods

The focus of this work is to provide the health care providers a support system which will aid in making timely decision as a reference baseline for Maternal Health care facility: primary and secondary. The following sections analyses the technique and approach used in the development of the artificial neural network (ANN) prediction model for maternity health care needs.

3.1 Study Area and Method of data Collection

The study was conducted in Adamawa State, Nigeria, based on the report of Health Resources and Services Availability Monitoring System (HeRAMS) Assessment Nov 2017 that cut across various healthcare facilities: primary and secondary. The study utilized ssecondary ddata collected from the HeRAMS. It is an electronic system for monitoring medical resources for standardizing and assessing the availability of medical services, and has been implemented for cross sectional- survey. The Health Resources Availability and Monitoring System 2017 dataset were used because it was the latest survey available conducted by Adamawa State Ministry of Health with the support of WHO. The dataset represents the collection of raw statistics used in the study.

A total of 539 labeled dataset with 16 input (539, 16) features were collected and used for learning. The data file was saved in the comma separated value (CSV) format, and this facilitated easy reading into the python script.

3.2 Data Preprocessing

Before feeding the data into the artificial neural network, a thorough data pre-processing step was carried out. This involves data cleaning, deleting duplicate values, handling missing values, normalizing numerical variables, and encoding categorical variables (grouping by classification).

Data cleaning involves removing or modifying data that is incorrect, incomplete, irrelevant, or improperly formatted in order to ensure accuracy and reliability of the models prediction.

Deleting duplicate values simplify the model by preventing bias, improves data quality and the model accuracy.

Handling missing values is the process of detecting and removing missing values from the dataset to ensure the model is trained on complete data.

Normalizing is the scaling of the data to a standard range typically between 0 and 1, to ensure that all features contribute equally to the model's prediction.

Encoding categorical variables refers to the classification of data into a numerical value as a binary vector in training neural networks because the model requires numerical input data.

3.3 Model Approach

The study uses a feed-forward modeling approach, where the INPUT data is fed forward through a series of hidden layers to produce an OUTPUT. The connections to the neurons are unidirectional, and the OUTPUT of one neuron is used as the INPUT for the next neuron. The Study used two activation functions, the Relu and Sigmoid Activation, at the input and output layers respectively. An inbuilt open-source neural network library in Python that support multilayer perceptron, Keras sequential model and Scikit-Learn library were used to formulate the maternal health services prediction artificial neural network (ANN) model. The model was trained using back-propagation to minimize the binary cross-entropy loss and improve the accuracy of predictions.

3.4 Modeling Tools

A Cloud based development platform "Google Colab" is utilized for proposed model building and performance evaluations. It is provided with 'Platform As A Service' to run Jupiter Notebook for Machine Learning development

in the Cloud, powered by Google. It embeds all the required Infrastructures, Platforms, and Applications required for Machine Learning experiments. Its advantage includes: Supporting vast libraries like TensorFlow, PyTorch, and Scikit-learn. It integrates seamlessly with Google drive to store and share notebooks easily; it provides access to powerful computing resources like GPU's and TPU's which significantly speed up model training and lastly it allows multiple users to work on the same notebook simultaneously.

3.5 Evaluation/Performance Metrics

To evaluate the artificial neural network (ANN)'s performance, the study employed various metrics such as accuracy, precision, recall, F1-score and Support to assess its ability to correctly classify maternal health services into "High_Quality" and "Low_Quality" categories. However, the performance of the model was enhanced using cross validation and confusion Matrix.

Cross validation is a technique used in evaluating the performance of the model on unseen data. It helps in selecting an appropriate model and prevent over fitting.

A confusion matrix is a table that shows how well an artificial neural network (ANN) classifies data into different categories. It can be a valuable tool for understanding how well the model is classifying data by comparing the actual labels with the predicted labels and counts the number of true positives, true negatives, and false positive, false negatives.

Accuracy is the ratio of correct predictions to total predictions useful for binary or multi class classification problems where there is need to know how well the model can distinguish between different classes.

Precision measures the proportion of correctly predicted positive observations to the total number of positive observations predicted, and is used to consider other evaluation metrics, such as recall and FI-score.

Recall is also known as sensitivity, it measures the proportion of correctly predicted positive observations to the total numbers of actual positive observations. However it is essential to consider other evaluation metrics to get more comprehensive understanding of the model's performance when dealing with imbalanced data set.

F1-score is a harmonic mean of precision and recall, combining both metrics into a single value, providing a balanced assessment of the models predictive capability.

The performance metrics are summarized as formulas below in table 1, and table 2 depicts the confusion matrix categories.

TABLE 1 PERFORMANCE METRICS FOR MACHINE LEARNING CLASSIFIERS

<i>Metrics</i>	<i>Formula</i>
Precision	$TP/(TP + FP)$
Recall	$TP/(TN + FN)$
F1 score	$2 * TP/(2 * TP + FP + FN)$
Accuracy	$TP+TN/TP + FP + TN +FN$ $= 2 * Precision * Recall/ Precision +Recall$

TABLE 2 CONFUSION MATRIX

	<i>Predictive positive</i>	<i>Predictive negative</i>
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

4. Results

4.1 Data Presentation and Visualization

The research used 539 labelled datasets with 16 input (539, 16) features: The Data set were collected and

annotated to create domain specific machine learning model that can be used to predict any maternal health delivery services facility inventory. The dataset contains the following header components; emergency_transport, skilled_birth_attendant, phcn_electricity, c_section_yn, child_health_measles_immun_calc, improved_water_supply, improved_sanitation, vaccines_fridge_freezer, antenatal_care_yn, family_planning_yn, malaria_treatment_artemisinin, num_chews_fulltime, num_nurses_fulltime, num_nursemidwives_fulltime, num_doctors_fulltime, maternal_health_delivery_services. Figure 1 depicts the sample of datasets used in the study.

Figure 1. Sample Research Dataset

num_chews_fulltime	num_nurses_fulltime	num_nursemidwives_fulltime	num_doctors_fulltime	maternal_health_delivery_services
1	0	0	0	High_quality
4	1	1	1	High_quality
2	4	11	2	High_quality
2	0	0	0	High_quality
0	0	0	0	High_quality

After deleting duplicate values, the dataset becomes 468 rows, and 16 (468, 16) columns. The Data pre-processing is crucial to ensure the accuracy and reliability of the artificial neural network (ANN) model. The dataset is divided into training and testing sets, with 346 (70%) of the data used for training and (122) 30% used for testing. The major pre-processing step carried out was coding the target (categorical) variables into numerical variables to facilitate computation. Low-Quality and high-Quality classes were coded as 0 and 1 respectively. The output is binary in nature, a facility is High Quality when the number of input features variable sum above 50% of the whole features and Low Quality is when the number of input features variable sum below 50%.

4.2 Model Development /Model Architecture

An artificial neural network (ANN) with feed-forward architecture was designed, comprising appropriate input, hidden, and output layers. An input layer with sixteen (16) neurons, two (2) hidden layers with fifty-five (55) and sixty-five (65) neurons, and an output layer with two (2) neurons made up of the artificial neural network (ANN) architecture used in this work. Rectified Linear Unit (ReLU) activation was employed in the input layer, hidden layers, and output layer, while a softmax activation function was used in the hidden layers. A modified version of the stochastic gradient algorithm called the "Adam Optimizer" was used to change the connection weights between the neurons (an adaptive learning rate optimization algorithm). Binary cross-entropy was the loss function used for parameter estimation during model training (measures the performance of a classification model whose output is a probability value between 0 and 1). The number of neurons at the hidden layer was varied for different performance of the network until the performance was optimized with 55 neurons in the first hidden layer and 65 neurons in the second hidden layer. The Keras model was used in formulating the neural network architecture framework for the prediction.

The learning process was configured via the `compile()` method in Keras model, which has three arguments: an optimizer, a loss function and a list of metrics. The study used optimizer because it combines the best properties of optimizers that handles gradient on noisy problems, computational efficiency, little memory requirement, and invariance to diagonal rescale of the gradients. Binary cross entropy was used because the research is a classification prediction model, which is binary in nature. The research also used accuracy as the metric in the Keras Compile model. The compile model is:

```
Model.compile(loss='binary_crossentropy', optimizer = 'adam', metrics=['accuracy'])
```

The training algorithm on the data is part of the learning process of the model designed and the training was done for a fixed number of epochs or iterations on a dataset in order to make predictions. An epoch is a complete pass through the entire training dataset. The parameters needed to fit to a model are: the trained data, the labels, number of epochs and the batch size. Figure 2 provides a sample of accuracy and loss metrics during training across multiple epochs.

Figure 4 depicts the output of the classification report and the confusion matrix respectively. This shows the performance variables used for the training and prediction of the Model. It presents the precision, recall, F1-score, and support averages, hence the overall accuracy for both classes.

	precision	recall	f1-score	support
class 0(High_Quality)	0.90	0.96	0.93	110
class 1(Low_Quality)	0.83	0.61	0.70	31
avg / total	0.88	0.89	0.88	141

[[106	4]
[12	19]]

Figure 4: Prediction output of classification and confusion matrix.

In Figure 4, the confusion matrix shows that for class_1 (High-quality) samples, out of 110 samples, 106 was correctly predicted, while 4 was incorrect. On the other hand, for class_2 (Low-quality) samples, out of 31 samples, 19 was correct while 12 was incorrect.

5. Discussion

Simple binary class was set up in the artificial neural network (ANN) design, which is a subset of the supervised machine learning. The experimental simulations of the artificial neural network (ANN) model showed an optimal performance at 55, 65 neurons in the middle layer with the predictive accuracy of 87.17% and standard deviation of 2.48%. This denotes that the model is expected to predict correctly at most 87% of the time with little variation of 2.48% in real-world practice, which was achieved at the 50 epochs. Figure 5a and 5b provides a snapshot of how the model's performance changes over the course of training. Figure 5a depicts the model accuracy and Figure 5b depicts the model loss where the accuracy increases and the loss decreases as the number of epochs progresses, which is generally a positive sign.



Figure 5a: Model Accuracy

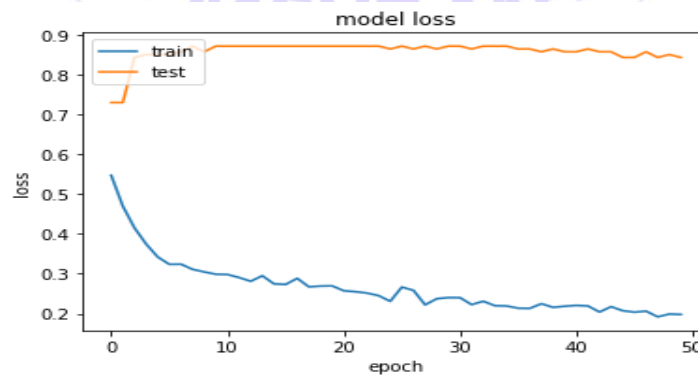


Figure 5b: Model Loss

The Figure 5a and 5b shows that the model has started learning predictions at epoch 50 and the learning phase takes a bit longer time so as to make correct predictions. It also shows that the model learns faster in order to be able to make prediction for maternal health delivery services. In model loss, it shows downward slant from the upper left to the right thereby showing reduction of incorrect predictions until it reaches 50 epochs. It used gradient descent which learns patterns in datasets by reducing loss function of the binary cross entropy. Dropout was used in the ANN model to regularize the model for generalization of unseen data which is a way to solve the problem of over-fitting or under-fitting of the artificial neural network (ANN) model. The Class imbalance is resolved using the synthetic minority oversampling technique of batch-5 size.

The overall Performance is evaluated using various metrics, such as accuracy, precision, recall, and F1 score. Results showed that the proposed model achieves 88% accuracy, 88% precision, 89% recall, and an F1 score of 88% on the testing dataset. Furthermore, the Model provides a feature set to obtain high accuracy results which in this case are provided by 87.17% accuracy. Maternal health services facility data analysis reveals that the health facility needs are the strongest indications of maternal health delivery services.

6. Conclusion

In conclusion, this study has demonstrated the potential of using artificial neural network (ANN) binary classification to predict the quality of maternal health services in Nigeria. By employing a comprehensive methodology and leveraging the power of artificial neural network (ANN)'s, the study aimed to address the challenge of accurately assessing maternal health service quality, which is crucial for improving maternal outcomes and ensuring positive birth experiences. The binary classification model developed through this study showed promising results in accurately categorizing maternal health services into "High_Quality" and "Low_Quality" classes. The artificial neural network (ANN)'s ability to analyze complex patterns within vast datasets allowed it to make data-driven predictions, assisting healthcare providers in identifying areas that require improvement and optimizing resource allocation for expectant mothers. The findings of this research can have significant implications for policymakers, healthcare providers, and maternal health advocates, guiding efforts to optimize healthcare resources and achieve better maternal health outcomes, in Adamawa and Nigeria at large. The study acknowledges certain limitations, including potential biases in the data, data availability, and the subjective nature of some quality-related indicators. However, despite these challenges, the binary classification model remains a valuable tool for supporting decision-making in maternal healthcare facility delivery service. Conclusively, the study emphasizes the importance of leveraging data-driven approaches to enhance maternal healthcare services, ultimately striving towards reducing maternal mortality rates and fostering a healthier and safer environment for expectant mothers and their newborns in Nigeria.

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