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LONG SHORT TERM MEMORY (LSTM)-BASED DEEP LEARNING MODEL FOR DETECTING RESPIRATORY DISEASES IN NEONATES

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ABSTRACT

Neonatal death remains a major health concern in the world. 45% of under-five deaths are those of neonates, and 40% of neonates' deaths occur within the first 24 hours. The most deadly of these diseases are those associated with breath. Previous research findings have shown that decrease in world neonatal mortality rate is slower than infant and under five mortality rates, especially in the sub-Saharan African countries because of lack of the state of the art technology for neonatal health care. There is a need to explore the potential of artificial intelligence techniques such as deep learning in this field. This research focused on the development of classification model to predict respiratory diseases in newborns. Data was collected from 1800 hospital records of previously treated neonates in two major hospital in south west Nigeria: Federal Teaching Hospital Ido Ekiti, Ekiti State and Ladoke Akintola University Teaching Hospital Ogbomosho, Oyo Sate Nigeria. The data was preprocessed and use in training two deep learning models; ANN and LSTM. The model was evaluated on precision, recall, F1-score and accuracy. Comparing the performances of the two models during the training and evaluation, LSTM learned well on the training data and gave the best performance on the evaluation metrics with a precision of 83%, a recall of 82%, F1-Score of 80% and an overall system accuracy of 83%. This study shows that LSTM model that gave the best performance is an efficient model and is therefore recommended for detecting respiratory diseases in neonates.

Keywords: Diseases, Deep learning, Data, Model**,** Neonates, Mortality

INTRODUCTION

Neonates are newborn babies within the first 28 days of life. The neonatal period is a time of rapid changes in a baby's life in that it is the time of establishment of feeding and sleeping patterns and adaptation to the outside womb life (Khan, 2023). This period is a critical time in human life when a newborn baby has to adapt to a new environment and complete several physiological adjustments that are essential for life. These make the neonates to be at risk of infections and abnormalities that sometimes lead to their death (Kareem, 2023; Mujahid *et al.*, 2024). Neonatal mortality is a significant contributor to under-five death. According to estimates for 2018, more than 2.4 million children died before their second month of life. The neonatal mortality rate shows differences between regions and nations. One-third of the world's neonatal deaths are from sub-Saharan Africa, with about 34 deaths per 1000 live births (Statistical, 2022; WHO, 2023).

Neonatal health is a critical aspect of healthcare that focuses on the well-being of newborn babies during the first 28 days of life. Understanding the significance of neonatal health and the effects of neonatal diseases is essential for effective newborn health management (Mujahid *et al*., 2024). Common neonatal diseases are jaundice, birth asphyxia, sepsis, congenital heart defects and the most deadly breathe related issues such as respiratory distress syndrome and pneumonia. Respiratory related neonatal diseases pose significant challenges to newborn health and require prompt diagnosis and treatment to prevent complications and deaths (Khan, 2023; Shen, 2024; Arslan *et al.*, 2025). Newborns' respiratory systems are immature and undergoing developments which make them susceptible to breathing challenges (Effah *et al*., 2022; Arslan *et al.*, 2025). Therefore, any breath associated disease is life threatening, prompt and accurate diagnoses of neonatal respiratory diseases are necessary for newborns' survival. Most newborn deaths are as a result of error in diagnosis, especially when medical personnel are able to arrive at a specific conclusion concerning the diagnosis on time mostly because of similarities in disease symptoms (Arslan *et al.*, 2025). Although, there are many neonatal ailments that may have some effect on the babies' breathing pattern, the major respiratory disorder in neonates are the neonatal pneumonia and respiratory distress syndrome (RDS).

RDS usually occur when newborns' lungs do not have sufficient surfactant; a liquid produced in the lungs within 26 weeks of pregnancy. The surfactant covers the air sacs of the lungs, thus preventing them from collapsing but keeps them open for oxygen exchange. The surfactants normally increase with the growth of the fetus, but when their growths are not proportional to that of the fetus, it may result in RDS once the baby is born. This is a condition characterized by fast breathing with respiratory rate > 60/minute in a quiet resting baby, inspiratory recessions, expiratory grunting, flaring of nostrils with or without cyanosis (Khan, 2023). The required laboratory tests for respiratory distress syndrome are; blood gas analysis (low oxygen and excess acid in the body fluids confirm RDS). Radiological scans such as X-Ray are also used for the diagnosis of RDS (Ervural and Ceylan, 2021). The second respiratory diseases that commonly affects neonates is pneumonia, it is an infection of the small air sacs (alveoli) of the lung in a neonate that usually occur within hours of birth. Pneumonia is causes by bacteria, virus or fungi infection in newborns' lungs (Hackett *et al*., 2021). The signs of neonatal pneumonia begin with breathing distress, cough and fever to shock or death. The laboratory test is the blood test (bacteria culture test), to look for the presence of bacteria in the blood and or low oxygen level in the blood. Radiological scan; X-ray is sometimes also employed for confirming the presence of pneumonia (Ten, 2021).

The conventional method involving human observations of neonate patients for diagnosis is subject to errors which

usually occur as a result of fatigues and stress associated with medical profession, as well as the fact that the neonates cannot express themselves. Therefore, the potentials of the artificial intelligence tools such as machine and deep learning models should be explored for timely and accurate diagnosis of neonatal respiratory diseases. Deep learning which is a subset of machine learning is capable of analyzing very complex and large multi-class datasets and establishes very important patterns which might not be easy to observe by humans. Therefore, it has several advantages that could favor early detection of respiratory diseases in newborns.

Available publications reveal several studies employing artificial intelligence (AI) and deep learning to manage the health of neonates. Without any doubt, these studies made important contributions but none of them specifically focus on developing a technique that could detect these two major respiratory diseases in a single system. The study by Gojak *et al*. (2022) discusses the use of artificial intelligence in diagnosing neonatal sepsis. The researchers used a database of 1,000 data to develop an artificial neural network, with 200 healthy and 800 sick. The results showed an accuracy of 98.33%. This indicates the importance of artificial intelligence in predicting sepsis, but not respiratory related ailments in newborns.

Jone *et. al.,* (2022) noted that artificial intelligence is being underutilized in clinical diagnosis, prognosis and management of congenital heart disease patients. A review was then carried out to highlight the current state of AI in congenital heart disease, opportunities, challenges and priority areas for AI-based intervention in congenital heart diseases management. This review, which is not an experimental study focused on congenital heart disease and not respiratory diseases.

Effah *et. al.,* (2022) developed machine learning to predict pneumonia in neonates. Data from 535 patients were preprocessed for data normalization, feature selection and extraction. Eight machine learning models were compared to evaluate their effectiveness in predicting pneumonia. C-reactive protein and procalcitonin were most outstanding in classification. The highest performance was achieved through Ensemble machine learning; random forest. This is actually advancement in the application of machine learning to neonatal health care but this research focused only on neonatal pneumonia which is not the only respiratory disease.

Yildrim and Canayaz (2023) developed a hybrid model C+EffxNet to predict pneumonia in neonates. Data were sourced from X-ray images of patients in the Neonatal Intensive Care Unit. The trained model and perform quite well in the classification of pneumonia, but pneumonia is not the only respiratory diseases of neonates. NDL-Net hybrid deep learning model was developed to predict neonatal respiratory distress using X-rays images. Evaluation shows a good accuracy but this research was carried out on RDS in neonates only (Arslan *et al.,* 2025). These are of course important researches but their efficiency could not be trusted in that they were trained with datasets made up of the symptoms or X-ray results only. It was also observed that published researches on neonatal respiratory disorders have been developing different models to detect different respiratory ailments. Respiratory related diseases require timely detection to save the newborns, testing different models on sick neonates would result in delay in diagnosis which is very dangerous (Yildirim and Canayaz, 2023).

There is therefore a need for a single model capable of detecting multiple diseases. The sensitivity of lives involved necessitates that the model be trained on a multiclass dataset to enhance efficiency. This observed gap is what this study is focusing on. This research employed a dataset obtained from two teaching hospitals to train two deep learning models; the dataset consists of symptoms, age, radiological scan results and laboratory test results.

MATERIALS AND METHODS

The methods and procedures employed in the study are presented in this section. This includes data collection, data preprocessing, model training, validation and model evaluation. The developed system is based on the framework illustrated in the architecture in figure 1. Data collected from the sick neonates is preprocessed, then used in training deep learning model and the final results are evaluated.

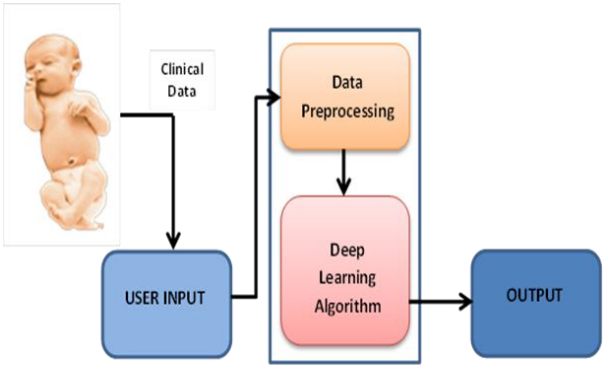

Figure 1: The System Architecture

Data Collection

The study employed quantitative data extracted from the medical records of previously treated neonates at the Federal Teaching Hospital Ido Ekiti, Ekiti State and Ladoke Akintola University of Technology Teaching Hospital Ogbomosho, Oyo State. The medical information were collected after securing the ethical clearance certificates from the ethical and research units of both institutions. Information relating to neonatal respiratory diseases was copied out of the files, excluding the patients' names, parents' identities, addresses, file numbers and other personal information to ensure confidentiality and data privacy. The dataset contained neonatal clinical information of 1800 previously treated patients. Since the information was unstructured, it contains other information other than those required, it was copied out and tabulated according to the required features using Microsoft Excel for easy analysis.

Data Preprocessing

The collected data was preprocessed to ensure that the dataset is in the format that the algorithm can accept, that is punctuation, conjunctions and stop words were removed, then

it was converted to discrete data. Therefore, preprocessing undertaken involved the process of preparing the raw data to make it suitable for the model. It involved data balancing, data integration; bringing datasets with similar attributes together, data cleaning. Natural Language processing (NLP) techniques were employed in this research because the dataset is textual. As shown in figure 4, the data undergo preprocessing like removal of stop words and punctuation, lemmatization, stemming, vectorization and; word and sentence tokenization. All these preprocessing helped the performance of the system for improved accuracy and accurate prediction of neonatal diseases.

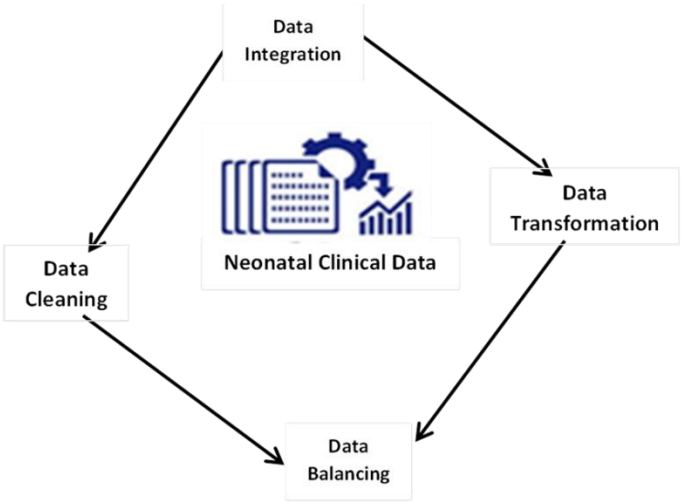

Figure 2: Illustration of Data Preprocessing

Data preprocessing tools that were used for this study are the needed libraries and dependencies such as NumPy, Pandas, Nltk and spaCy, these were imported from python. Features extraction and selection was done by identifying and extracting specific and measurable information from the patients' medical records, thus transforming the raw data to structured data suitable for data processing. The basic symptoms, essential laboratory tests and the relevant radiological scans of each disease were selected with the neonatal age (≤ 28 days). These features were selected due to their strong association with neonatal disease and because they provided a manageable number of features for model training.

Model Development

The model development began with algorithm selection to data splitting, hyper parameter tuning, model training and evaluation. The basic machine learning algorithms would have been enough for developing the classification model for this task, but available publications on related research show the need for deep learning algorithms because of the complexity of the clinical datasets (Pachiyannan *et al.*, 2024). Thus, the Long Short-Term Memory networks (LSTM) which is a variant of Recurrent Neural Networks (RNN) and the Artificial Neural Network (ANN) that has the advantage of being simple to implement, train and faster processing because of its parallel computation were employed in this study (Fashid *et al.*, 2023).

Training of the ANN Model

This research employed the Feed forward Neural Network (FNN) approach for the training of the ANN model. ANN is made up of several layers of interconnected artificial neurons enabled by the activation functions that turn them ON and OFF (Golak *et al.*, 2022). As shown in the architecture of ANN in Figure 5, each neuron receives a multiplied version of inputs and random weights, which is then added with a static bias value (unique to each neuron layer); this is then passed to the sigmoid activation function which decides the final value to be given out of the neuron. There are various activation functions available as per the nature of input values. The classification was made by the model based on the weight assigned to the symptoms fed into the model through the input.

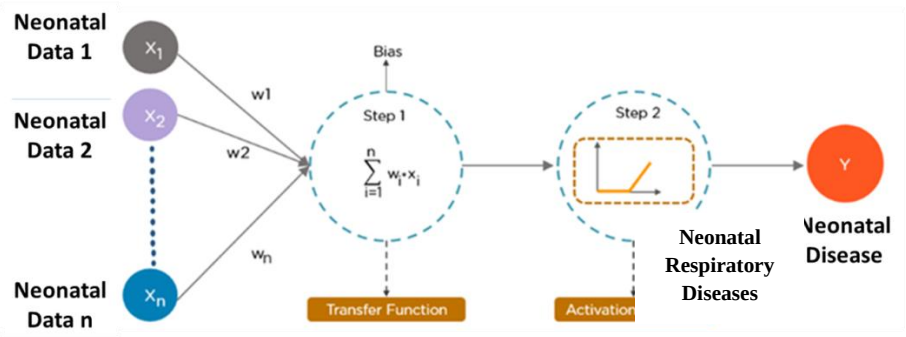

Figure 3: The Architecture of ANN

The Input layer (i/p) receives the features as data formats. A computation of the weighted sum of the inputs and a bias was carried out based on equation (1).

$$\sum_{i=1}^{n} Wi * Xi + b \quad (1)$$

Where:
Xi = input
Wi = input weight
b = bias
(Hashim *et al*., 2021; Singh *et al*., 2024)

The Hidden layer operates like a set of filters, each extracting some important input patterns and passing them to the next layer for detection. A set of weighted inputs were used to produce output through an activation function. Using the sigmoid activation expressed in equation 2, it has two important functions:

i. It represents the non-linear relationship between the inputs
ii. It helps to transform the input into a more useful output.

It is expressed mathematically thus:

$$O1 = \frac{1}{1+e^{-F}} \quad (2)$$

From Equation 1, the weighted inputs received at various layers of the input
Layer is as expressed in equation 3.

$$F = W1X1 + W2X2 + W3X3 \quad (3)$$

The Output layer (o/p) represents the output of the neural network. The hidden layer then led to the final prediction at the output layer as expressed in equation 4 thus:

$$O2 = \frac{1}{1+e^{-F1}} \quad (4)$$

Where:

$$F1 = W1H1 + W1H2 \quad (5)$$

Where H = hidden layer
(Helguera-Repetto, *et al*., 2020)
O2 which is the final output value range from 0 to 1. That is, the closest value to 1 is predicted.

Training of the LSTM model

The LSTM shown in the architecture in Figure 6 was selected for this research due to its capability for processing sequential data such as text data used in this study.

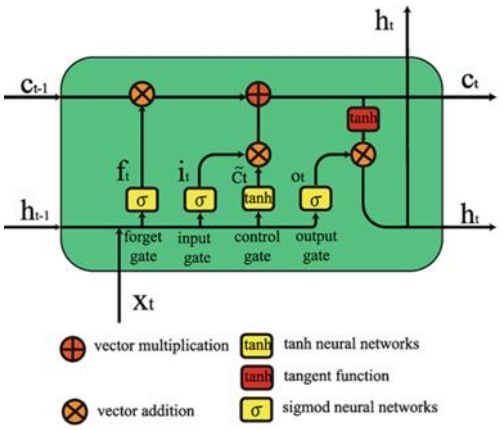

Figure 4: The Architecture of the LSTM

The training of the LSTM model involved the use of Keras library since it supports fast deep learning model prototyping and can run on different frameworks and platforms. The model was initialized and LSTM layers added, more dense layers were included and compiled. Training data file (containing the 70% of the dataset) was imported and used to train the model, back propagated and trained for 50 epochs. The default sigmoid function of the gated mechanism helps to output between 0 and 1. The step-by-step description of the operation of LSTM cell is as represented in equations (6) – (11) (Kizito, *et al.*, 2021).

Equation (6) represents the input gate,
Equation (7) represents the candid memory cell value,
Equation (8) defines forget-gate activation,
Equation (9) calculates the new memory cell value, and
Equations (10) and (11) define the final output gate value.

$$i_t = \sigma(W_i [x_t , h_{t-1}] + b_i), \quad (6)$$

$$\tilde{C}_t = \tanh(W_c[x_t , h_{t-1}] + b_c), \quad (7)$$

$$f_t = \sigma(W_f [x_t , h_{t-1}] + b_f), \quad (8)$$

$$C_t = i_t * \tilde{C}t + f_t C_{t-1}, \quad (9)$$

$$o_t = \sigma(W_o[x_t , h_{t-1}] + b_o), \quad (10)$$

$$h_t = o_t \tanh(C_t), \quad (11)$$

Each ***b*** represents a bias vector, each ***W*** represents a weight matrix, and $\boldsymbol{x}_t$ represents input to the memory cell at time ***t***. Furthermore, ***i, c, f, o*** indices refer to input, cell memory, forget and output gates respectively (Shen *et al.*, 2024).
The system flow chat is as represented in Figure 6. The model was developed using Python 3.9v in Google Collab environment for easier and faster computation.

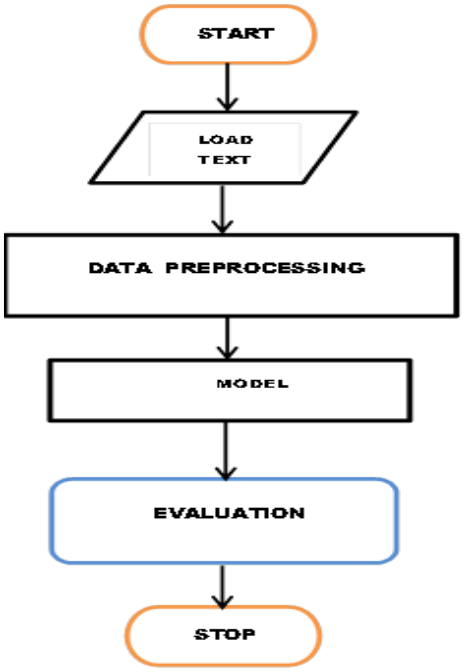

Figure 5: The Flowchat of the System

Model Evaluation

This research being a classification task was evaluated using the best set of evaluation metrics for deep learning algorithms; accuracy based on equation (12), precision shown in equation (13), recall as shown in equation (14) and F1 score represented in equation (15). These were employed as the evaluation metrics as they take into consideration the true positive, true negative, false positive and false negative values during evaluation. These serve as good performance metrics for this study due to its proven application and results.

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

$$F1-Score = \frac{2}{\frac{1}{Recall}+\frac{1}{Precision}} \quad (15)$$

Where TP – True Positive; TN – True Negative; FP – False Positive and FN – False Negative (Rainio *et al*., 2024).

RESULT AND DISCUSSION

This section presents the results of the experimental studies in a systematic order, the models' training, validation and evaluation of the performances on unseen data. The research findings were also discussed to highlight how they meet the stated objectives.

Results of ANN Model

As shown in Figure 7, the training and validation loss was plotted per epoch, after several hyper-parameters tuning the graph showed a decrease in values from around 163% to less than 65% loss for the training and from 161% to 67% for the validation. This plot of loss values show that the model could be seen to have over-fitted during training. However, the difference could be catered for due to different start points of the two graphs and the difference that exist between them at the starting point is enough to cater for the obvious difference showing towards the end of the training. The training and validation accuracies were also plotted in Figure 7 and the same obvious difference in the training and validation curves implying that over fitting was also noticed in the accuracy curves. Similarly, the training accuracy started at a lower value compared to the validation accuracy as the difference between them was almost 4% which is a good margin between these two metrics and curves. These two curves were noticed to have started increasing significantly after the 20th epoch and the training accuracy was seen to have been higher than the validations' which might have been the reason for the obvious less than 5% difference between them as they both approach the 100th epoch. The model recorded 76% and 79% training and validation accuracies respectively. These plots help in understanding the varying loss and accuracy values this model went through during the training and highlight the lowest and highest possible values attained by the models.

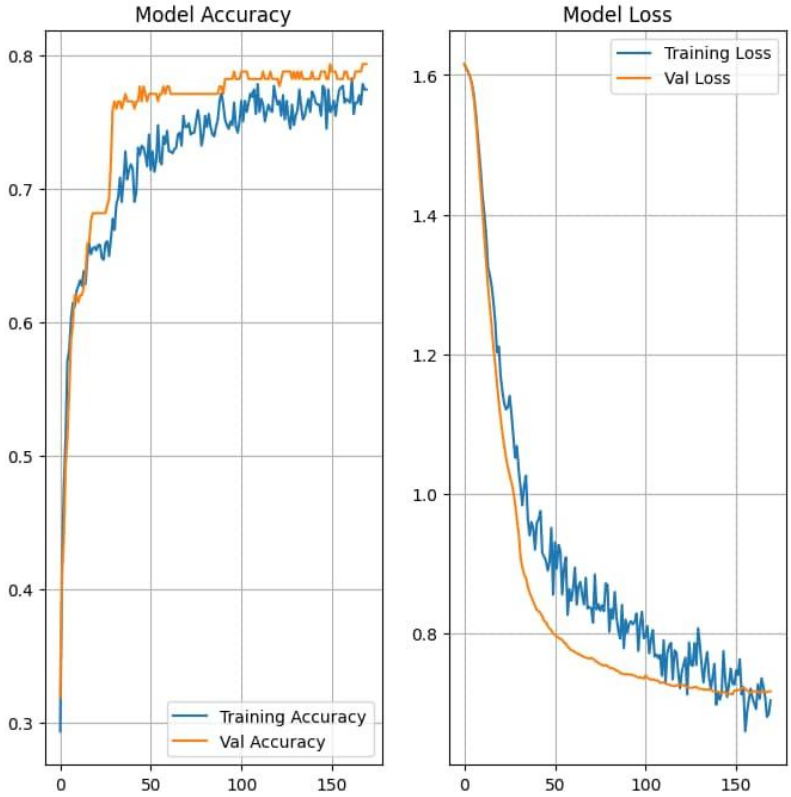

Figure 6: Training and Validation Accuracy and Loss Plots for ANN

Based on the experimental setup and hyper parameter tuning, the ANN model was trained on the neonatal respiratory diseases classification dataset and evaluated on accuracy, precision, recall and F1-score. Classification report was employed to show the experimentation result obtained from evaluating this model using the aforementioned metrics. This result is presented in Table 1 for easier representation

Table 1: Evaluation Report of ANN Model Classification of Neonatal Respiratory Diseases

Respiratory Related diseases	Precision	Recall	F1-Score	Support
Respiratory Distress Syndrome (RDS)	0.86	0.84	0.80	19
Pneumonia	0.82	0.80	0.79	29
Accuracy			0.81	48
Macro avg.	0.84	0.82	0.80	48
Weighted avg.	0.84	0.81	0.79	48

As presented in Table 1, the evaluation of the two major neonatal respiratory diseases shows that RDS recorded the best Precision, recall and F1-score of 86%, 84% and 80% respectively. These could be attributed to the fact that it has good number of cases and the attributes are more. The macro average is 84%, 82% and 80% respectively and the overall accuracy of the model is 81%.

Results of LSTM Model

The performance of the LSTM model during training is as presented in Figure 8, the training and validation loss was plotted per epoch after hyper parameter tunings. The graph showed a decrease in these values from 159% to 41% loss for the training and 140% to 78% for the validation curves. The relationship shown by these two curves is better than that of ANN in Figure 7, the training and validation loss curves of the LSTM model did not over fit. This shows that the LSTM model was able to perfectly learn through the learning stage more than the ANN model. The training and validation accuracies was also plotted in Figure 8 and the same observation was noticed as the training and validation accuracy were noticed to have increased significantly after the 50^{th} epoch and they both maintain their uniform increase in values till the last epoch. These values were closely plotted as the model does not show any sign of over fitting as shown by the ANN model earlier presented. The close flow of the two curves shows that LSTM was able to learn through the training and validation dataset perfectly and nothing like over-fitting or under-fitting was experienced. The model recorded 86% and 82% training and validation accuracies respectively.

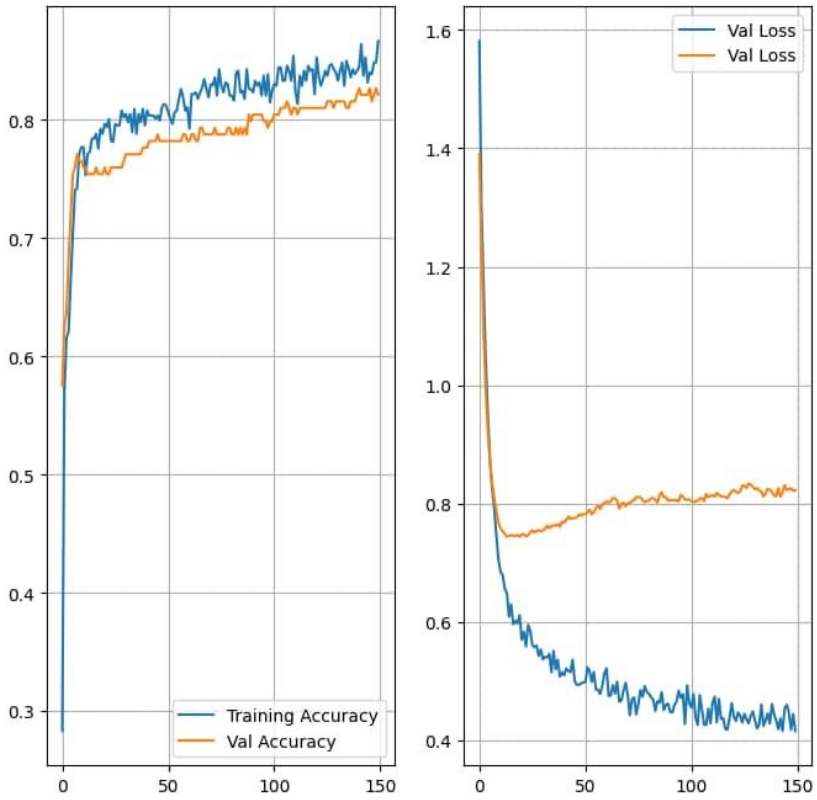

Figure 7: Training and Validation Accuracy and Loss Plots for LSTM

Following the experimental setup and hyper parameter tuning, the LSTM model was trained on the neonatal respiratory diseases classification dataset and evaluated on accuracy, precision, recall and F1-score. Classification report was employed to show the experimentation result obtained from evaluating this model using the aforementioned metrics. This result is presented in Table 2 for easier representation

Table 2: Evaluation Report of LSTM Model Classification of Neonatal Respiratory Diseases

Respiratory Related diseases	Precision	Recall	F1-Score	Support
Respiratory Distress Syndrome (RDS)	0.85	0.86	0.80	19
Pneumonia	0.80	0.81	0.80	29
Accuracy			0.83	48
Macro avg.	0.83	0.84	0.80	48
Weighted avg.	0.82	0.83	0.80	48

As presented in Table 2, the evaluation of the two major neonatal respiratory diseases shows that RDS recorded the best Precision, recall and F1-score of 85%, 86% and 80% respectively. These could be attributed to the fact that it has good number of cases and the attributes are more. The macro average is 83%, 84% and 80% respectively and the overall accuracy of the model is 83%.

As presented on the training and validation plots in Figures 7 and 8; and the on the evaluation reports in tables 1 and 2, LSTM was found to have had better performance than ANN on the dataset. As observed, LSTM outperformed ANN in terms of recall by 2%. The overall accuracy of LSTM was observed to be higher than that of ANN by 2%. The models performances during training also show that LSTM learn the underlying patterns of the neonatal respiratory diseases dataset well without any sign of over fitting. Therefore, LSTM was found to be the best-performing model in this study.

CONCLUSION

The potential of deep learning in reducing infant mortality has been demonstrated in its capability for detection of neonatal respiratory diseases. This study employed a multiclass dataset obtained from the medical records of 1800 previously treated neonates at the Federal Teaching Hospital Ido Ekiti, Ekiti State and Ladoke Akintola University of Technology, Ogbomosho Oyo State; two major tertiary hospitals in the south west Nigeria to train two deep learning models: ANN and LSTM. The evaluation of the two models shows that LSTM which had the most efficient performance during training also outperformed the ANN model on the evaluation metrics employed. LSTM model is therefore the best performing model in this study. Employing a multiclass dataset to develop the LSTM classification model for detecting neonatal respiratory diseases has therefore been found to be a cheap and efficient technique of detecting respiratory diseases in newborns. This study could be deployed in a web or mobile application as neonatal clinical decision support system for timely diagnosis, this has a

potential to help in reducing infant mortality. Future research should focus on employing data from other African countries to validate the findings in this study.

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