Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 10
October 2024

Application of a Feed Forward Neural Network for the Prediction of Differential Anemia

[1]Mohammed A. A. Elmaleeh

[1]Computer Engineering Department, Faculty of Computer and Information Technology, University of Tabuk, Tabuk, Saudi Arabia

Abstract:

Anemia is one of the most prevalent ailments afflicting the least developed nations. It refers to the deficiency of Red Blood Cells (RBC) count in the blood. A comprehensive blood test is conducted in clinical laboratories, employing manual approaches to analyze patient samples. The methodology involves initial data processing, ANN design, and Final output processing. This study evaluates the pathological findings from 250 individuals, focusing on Complete Blood Count (CBC). As detailed in the following subsection, the sample is divided into two sets: one for training the ANN model and another for testing its performance. Learning data provides an accuracy of 88.0%, and validation and test datasets provide 87.5% and 86.5% accuracy respectively. The Feedforward Neural Network was observed to effectively detect cases of anemia, suggesting increased accuracy in the diagnosis.

Keywords: Red Blood Cells, Anemia, Complete Blood Count, Neural Network, Artificial Intelligence

1. Introduction

Anemia is one of the most common disorders of the blood. The World Health Organization [WHO] claims that anemia is the deficiency of red blood cells (RBC) which leads to the inadequacy of the oxygen necessary for the physiological requirements of the body [1]. The types of anemia are based on the two classification systems. According to Wintrobe’s observations, the first classification is based on the size of the anemia, such as microcytic anemia, macrocytic anemia, or normocytic anemia. Microcytic anemia results in the mean corpuscular volume (MCV) less than normal (<80fl). Macrocytic anemia results from either a defect in the red cell membrane or DNA synthesis. The membrane fault in the RBC results in liver illness or hypothyroidism. RBC in the macrocytic anemia is round-shaped when observed in the peripheral smear [2].

In contrast, any fault in the making of DNA that results in megaloblastic anemia or chemotherapy reveals an oval macrocytosis [3]. The prevalence of anemia in elderly patients of more than 65 years of age is 17%. Anemia can also be classified into nutritional deficiency anemia, anemia due to bleeding disorders, anemia resulting from chronic inflammation, and clonal anemias [4].

The diagnosis of anemia is performed by testing the complete blood count [CBC], which offers the proper data set. The data includes the RBC's quantity and size, hemoglobin level, and hematocrit. The anemia is confirmed by decreased hemoglobin in the blood [5]. The usual size of the RBC and the anemia types are typically recognized by determining the mean corpuscular volume [MCV] and by microscopically peripheral blood smear consent examination. Additionally, the serum iron, vitamin B12 evaluation and folate level can contribute to the diagnosis of anemia [6].

According to a study by Tuba et al., a system was made based on four Artificial Intelligence [AI] techniques. The methods involved Artificial Neural Networks (ANN) and support Vector Machines. Naïve Bayes and Ensemble Decision Tree methods. The results illustrated the greatest success rate of 86.4% in diagnosing iron deficiency anemia and the lowest rate of 64.0% in diagnosing hemolytic anemia [7]. An ANN refers to an interrelated set of nodes that energizes the widespread network of neurons in the brain and has been part of the medical field since the 1980s. An artificial neuron is a computing device that acts as a biotic neuron and accepts the signal from the input link from the ANN. The neuron's weight and transfer ability impact the function of ANN as shown in Figure1[8].

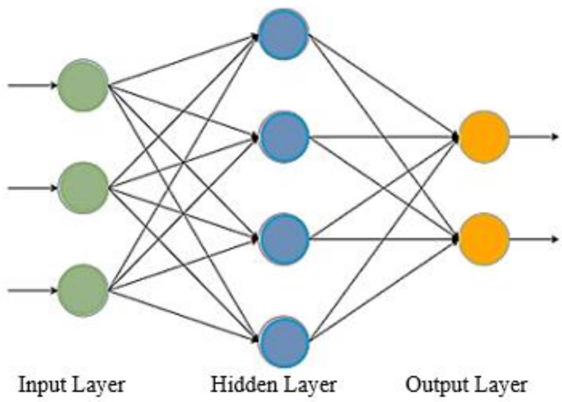

Figure 1: Basic structure of Artificial Neural Network [ANN]

Computer learning approaches such as SVM, Random Forest, and ANN have been useful in diagnosing several medical problems, including diabetes Mellitus [DM] [9]. Multiple sclerosis [MS] [10], Appendicitis [11], and anemia in children are now in progress [12]. The approaches involving AI require the efficiency of computers to activate human mind processes. It is essential to highlight that designing the computer learning, its function and a subtype of AI (deep learning)algorithms need the application of special hardware and software [13].

Algorithms can offer computerized models to execute specialized work. Another neural network is a feedforward neural network, which can determine complicated non-linear mappings with the help of the available input data. One of the recognized feedforward neural networks is the single hidden layer feedforward neural network, or SLFN, which has been a part of theoretical and practical studies [14, 15]. The extreme learning machine [ELM] is a proficient training approach to enhance the function of SLFNs [16].

Feedforward Neural Network [FFNN] comprises serial data flow from the input layer through the hidden layer to the output layer without any feedback paths. The message transports in a single path so that each pattern of neuron processes the input and contributes to the output. The neuron or node in a pattern utilizes a function of activation and connection to recognize the complicated data. The FFNN is known for several implications, including speech, AI, and pattern identification [17]. The simplest type of FFN is a single-layer perception [SLP], as illustrated in figure 2 [18]. It is composed of one coat of input neurons and an output neuron. The function of SLP is to tackle easy binary classified tasks by utilizing input characteristics, weights, and an activation perception for decision-making. It has the solution of linearly separable issues. By designing several layers of perception, the network can solve more complicated and non-linear patterns [19].

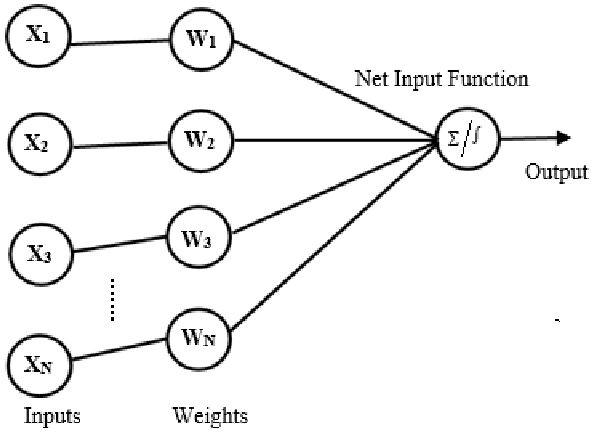

Figure 2: Single Layer Perception

Journal of Harbin Engineering University
ISSN: 1006-7043
Vol 45 No. 10
October 2024

Another type of ANN is the Multi-Layer Perception [MLP], as shown in figure 3 which consists of layers: an input layer receiving raw dataset including values of the pixel, hidden layers processing the data through weighted connection and function of activation like sigmoid or ReLU, and an output layer responsible or final decisions. The MLP is accountable for image recognition and language processing by analyzing the patterns in data. Training MLP involves two phases: forward propagation, where data moves through the network to make predictions, and backpropagation, adjusting weights based on prediction errors to improve accuracy. MLPs are versatile due to their ability to handle complicated functions and relationships, though they face challenges such as overfitting and high computational needs. Techniques like regularization and dropout help manage these issues, making MLPs vital in modern AI and machine learning applications. Figure 3 shows an example of MLP feed forward networks [20].

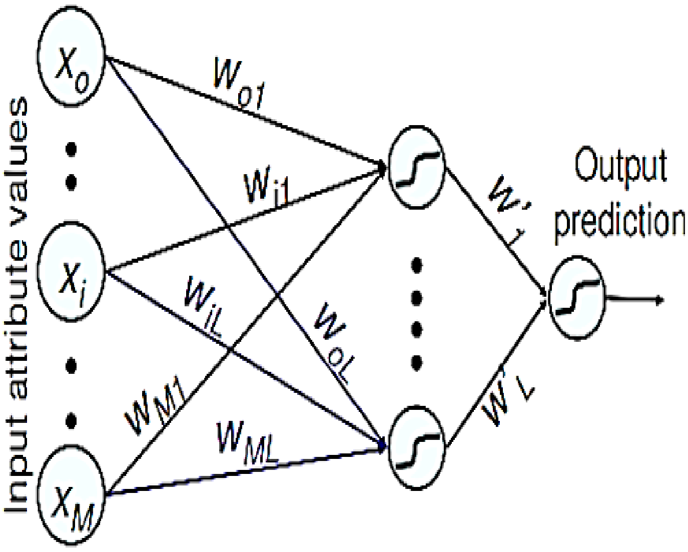

Figure 3: Multi-layer Perceptron Feedforward Networks

This paper aims to detect and categorize anemia by implementing an advanced method that relies on an Artificial Neural Network (ANN) based on FFNN.

2. Methodology

This method is divided into three main parts: Initial data processing, ANN design and the Final output processing.

- ***Initial Data Processing***

This part emphasizes the preliminary processing of input data. It is exactly concerned with the results obtained from the CBC examination. The initial processing steps include cleaning, standardizing, and arranging the information to confirm it is appropriate for input into the neural network. This step is essential to improve the correctness and efficiency of the succeeding investigation.

- ***ANN Design***

This section explores the design and architecture of the FFNN model, detailing the implementation, training, and testing processes. The design phase is divided into two sub-modules: Diagnosis Sub-Module; which is responsible for the initial detection of anemia. It utilizes the preprocessed CBC data to identify whether the patient is anemic by learning from labeled training data. Another sub-module is the Categorization Sub-Module, which further classifies the type or severity of anemia after the detection of anemia. The categorization is based on distinct patterns and features in the CBC data, enabling more precise and personalized medical recommendations.

- ***Final Output Processing***

The last part of the technique includes processing the outputs generated by ANN. It comprises the results interpretation, diagnostic reports generation, and providing the medical practitioners with valued information that can be used to enhance patient care, make diagnoses, develop treatment strategies, or improve the complete medical results. The final output processing guarantees that the output is user-friendly and can be easily combined into the step-by-step processes of healthcare providers delivering patient care. Figure 4 in the paper demonstrates the flowchart of the proposed technique, providing a visual illustration of the steps involved in the discovery and classification process of anemia.

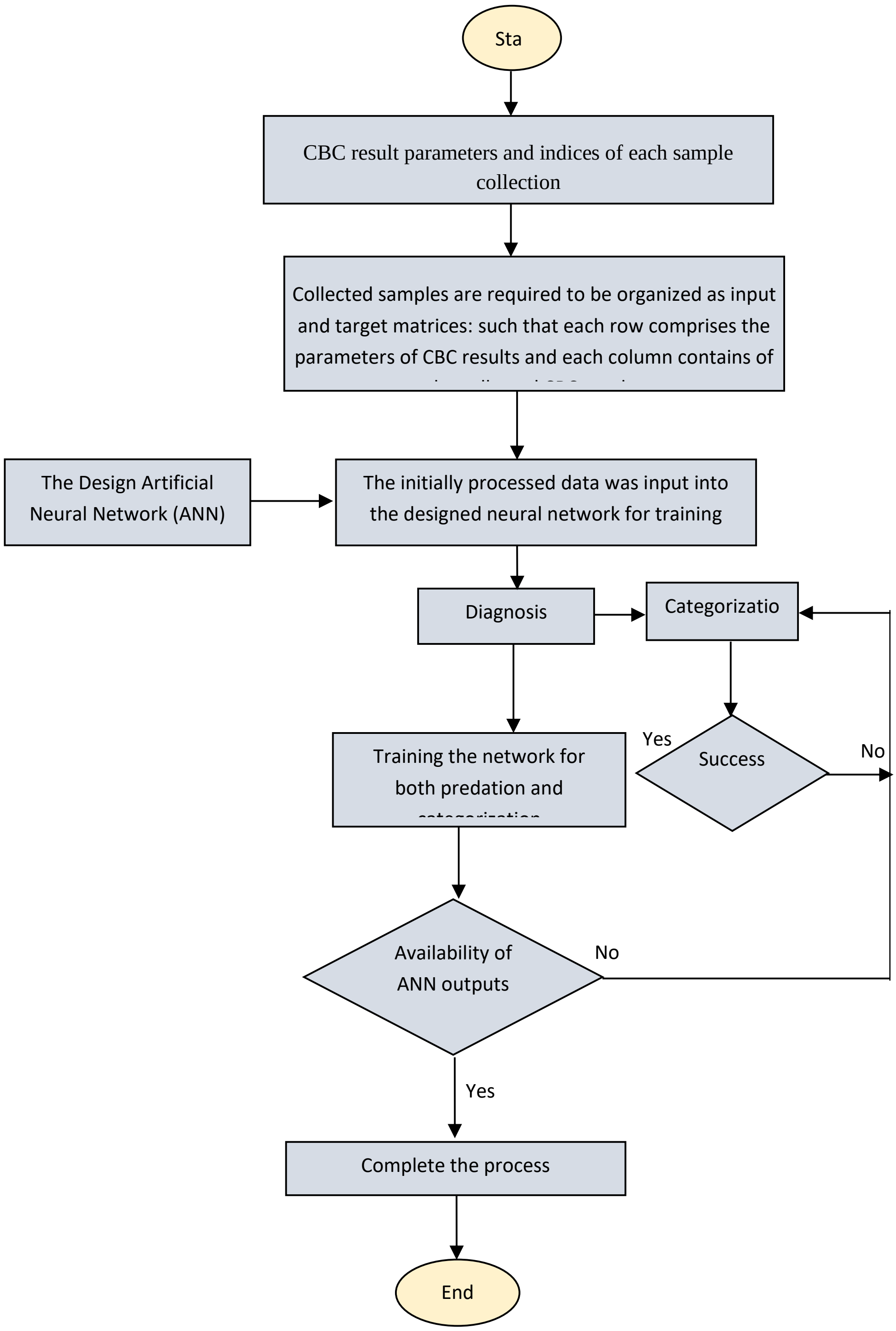

Figure 4: The Flowchart of the Proposed Method for Detecting and Categorizing Anemia using ANN

This study evaluates the pathological findings from 250 individuals, focusing on CBC. As detailed in the following subsection, the sample is divided into two sets: one for training the ANN model and another for testing its performance. The split of the samples confirms that the model is trained on a subset of the data and tested on independent samples to assess its generalization capability and accuracy in predicting and categorizing pathological conditions based on CBC results. This approach helps validate the effectiveness of the ANN in clinical diagnostics and underscores the importance of robust training and testing methodologies in medical research.

- ***Procedure and Analysis***

For the study, 250 datasets were gathered from the Omdurman Teaching Hospital in Sudan. The dataset was divided into input variables and target outcomes. The selection of input variables depends on the relevance and was used in an MLP, including the FFNN algorithm. The patients were classified into healthy and frail patients. The variables needed for the neural network models were defined, affirming that input and targets were combined into the proposed structure of the model.

The initial processing of the input data includes arranging and cleaning the data before using it as input to the proposed model for starting the processing. This stage is essential since it confirms that the information (data) is prepared in an appropriate arrangement and preeminence for the next step of analysis and modeling.

- ***Adjusting Initial Weight***

The algorithm offers adjustments on every connection in the network with the specific aim of minimizing the error function. This is done through several training cycles in which the error is reduced until it reaches the acceptable state. While the weights in the network are being worked on, the error ultimately levels off and utilizing the current model is the best to categorize and find patterns and correlations within the data. This optimization process helps enhance the network's capability in predictions and classifications. The term convergence is that the model has incorporated the training data and can utilize the knowledge of the new data; this enhances the model's rating, accuracy, and ability. This state is attained to make the modality relevant to the targeted real-world applications.

- ***Training and testing the network***

The initial process of training the intended network aims to create the estimation and validation samples. This suggests that one can do pilot training several times, which yields different results since they have distinct beginnings and samples. As for the training dataset to be used, it will comprise 70 percent of cases; those of anemia patients are also included; therefore, identification encompasses both. If the validation criteria are met, the network undergoes retraining until optimal performance parameters are achieved. The test set, comprising 15% of the samples, is used similarly to the training set, but only inputs are fed into the neural network for evaluation. This systematic approach ensures that the model undergoes thorough testing and refinement to handle new data, thereby enhancing its reliability effectively. The Neural Network Toolbox interface for training and testing is depicted in Figure 5.

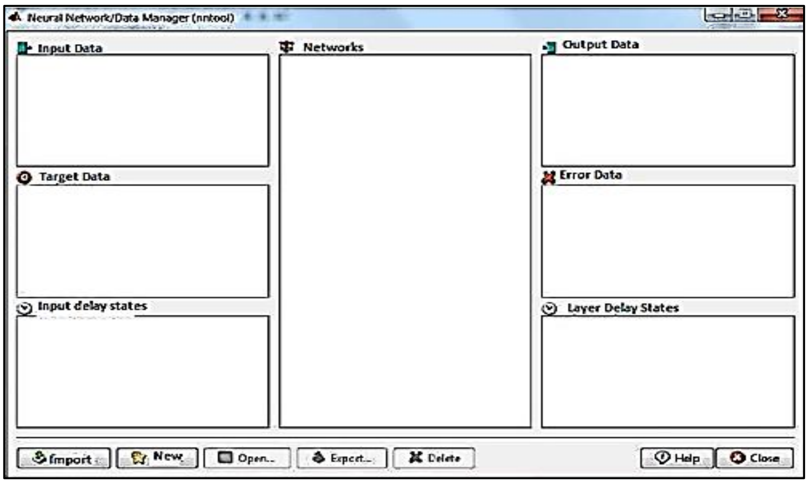

Figure 5: ANN Toolbox Interface

The output obtained from the trained data functions as the target data, which is utilized to generate the network. The "Create Network or Data" interface simplifies the network formation method, as shown in Figure 6. This interface simplifies setting up and configuring the neural network structure concerning the task's requirements.

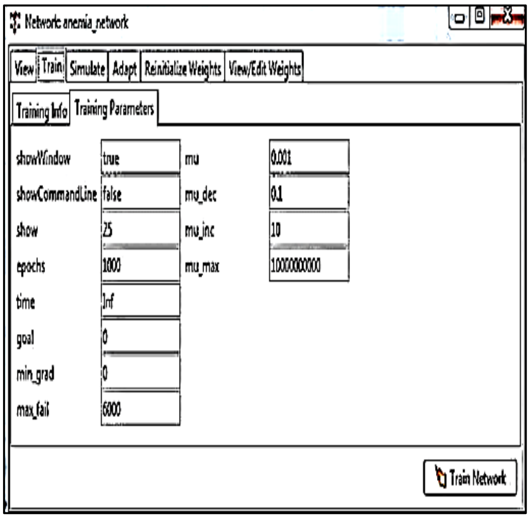

Figure 6: Create a Network or Data Interface

The next stage after creating the network is the training stage. In this stage, the parameters used to train the network are shown in Figure 7. They determine the network optimization and adjustment requirements to enhance the performance of a specific task.

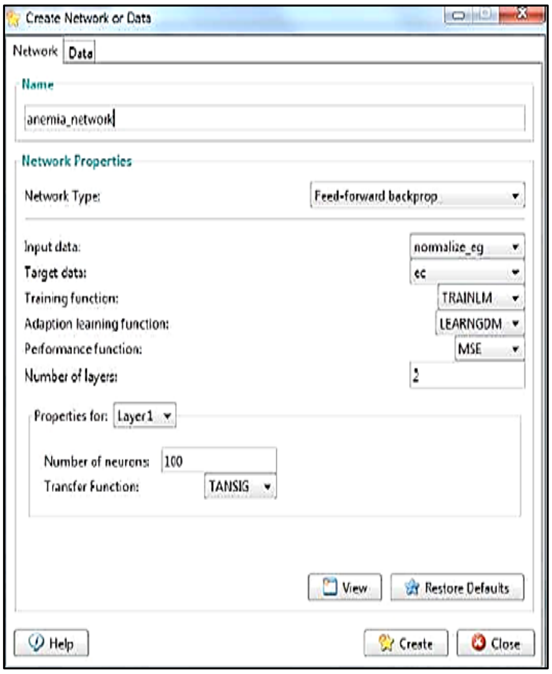

Figure 7: The Network Training

➢ ***Diagnosis of ANN Processes***

Based on gender, age and, RBCs, HGB, and HCT values, the processed data is input into the ANN for diagnosis. A special focus is on the structure of the RBC, which offers unique diagnostic insights in a small percentage of anemia cases. If the diagnosis indicates anemia, the data are passed to the next sub-module.

➢ ***Categorization***

Anemia is divided into three groups: anemia due to deficiency of vitamin B12, which is called Macrocytic anemia; anemia, which is categorized by a small number of red blood cells named Microcytic anemia; and finally, normal-sized anemia red blood cells, which is called Normocytic anemia.

➢ ***Final Processing***

The study explained how the test and validation groups' data input into the network, the network efficiency measures, and the validation process. The following are the factors: the design of the network, its structure, and the techniques used. To compare how accurately the network could classify different, other tests such as the confusion matrix and the receiver operating characteristic (ROC) test were also used in the assessment. It was thought that these metrics could provide a better view of how the network had performed in classifying and predicting the outcomes from the input data and a valid check on the strengths of classification.

3. Results and Discussion

The programming environment of ANN was employed for training and testing the models for the classification of anemia. The input parameters are a wide range of physiological measures, including; gender, MCHC, MCH, MCV, HCT, HB, RBC, WBC, calcium, and electrolytes, RDW-CV. To achieve its effectiveness in evaluation, the training dataset was further partitioned into test and validation datasets to complete the assessment of the model [21]. A Retrospective study was conducted to differentiate the several types of anemia by developing an automated model utilizing the Extreme Learning Machine [ELM] algorithm. The model was observed to show an increased accuracy of 99.21% and was capable of effectively differentiating anemia [16].

In this study, a Perception Neural Network is applied, which has used FFNN algorithms capable of handling complicated patterns and accomplishing accuracy in the prediction activity [22]. Another study focused on the learning processes, architecture, and application in solving complex issues. The ANNs were proven to perform tasks like pattern identification and abstract reasoning [23].

A study was conducted to suggest a new approach that substitutes the fully connected layers in neural networks with the sparse ones, thereby decreasing the parameters without affecting the accuracy. The approach successfully reduces the size of the neural network while maintaining accuracy, enabling them to tackle more complicated tasks [24].

The neural networks are composed of microcytic, macrocytic, and normocytic individuals. They were divided into learning datasets, validation datasets, and test datasets. In ethnographical research, self-reported notes as a source of information are debated among scholars. The diagnostic outcomes were evaluated through the confusion matrix and the receiver operating characteristic [ROC]. The FFNN achieved an 88% level of classification accuracy for the learning dataset, 87.5% when considering both the validation and test dataset, and the accuracy of an overall network is 86.5%, as illustrated in Figure 8. These indicators show how effectively the network can classify one form of anemia with another depending on the number of physiological parameters. These objectives give an understanding of the details of the network's performance to differentiate various types of anemia concerning some crucial physiological characteristics.

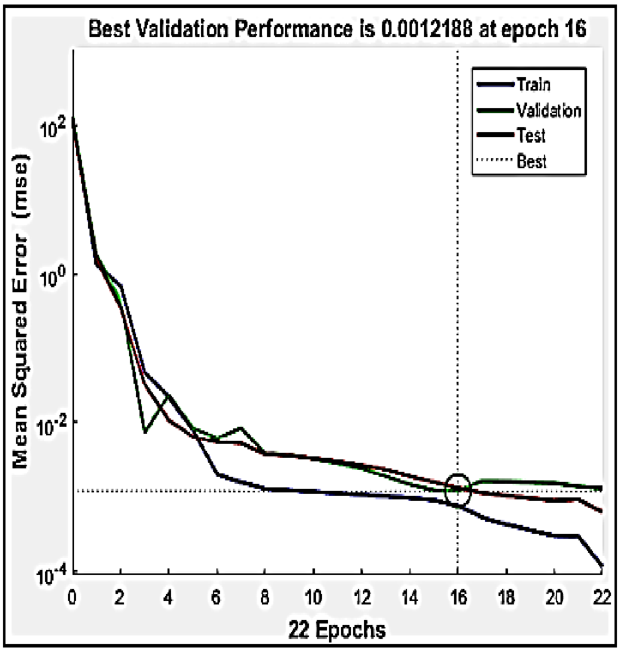

Figure8: Learning Performance of the Network

In the regression plots illustrated in Figure 9, the network outputs were observed to be aligned with the targets at a 45-degree line. The accuracy indicates that the prediction of the network values coincides with the expected values. Overall, the performance across all the datasets for the problem does not impose restrictions on the type of dataset to be used for this problem, has the correlation coefficients (R values) are equal to 0. 86 or greater. These outcomes confirm that the predicted outcomes of the network are compatible with targets, suggesting the validity of the network.

According to the systematic reviews and meta-analysis conducted to compare ANN and Logistic Regression [LR] in the prediction activity. The results concluded that the ANN performed better than LR in the prediction activity to predict the terminal outcomes of the individuals in the Area under the curve [AUC] and accuracy rate [25].

Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 10
October 2024

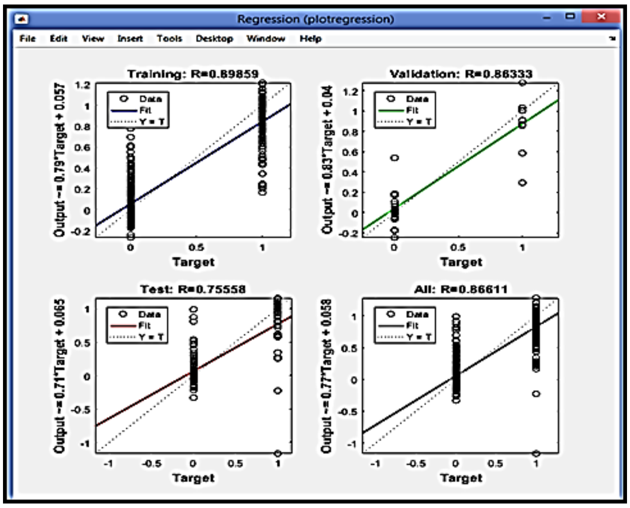

Figure 9: Network Outputs Regressions Plots

Figure 10 shows how the gradient coefficient alters at the end of each epoch in the training session. For epoch 22, the gradient coefficient is stable at 0.057135, near zero. A small gradient coefficient indicates that during training and testing the networks, the amount of errors being corrected and the fine-tuning of the model parameters are in the right direction. This trend depicts that the network is getting to a good position for the subsequent tasks when making accurate and precise predictions.

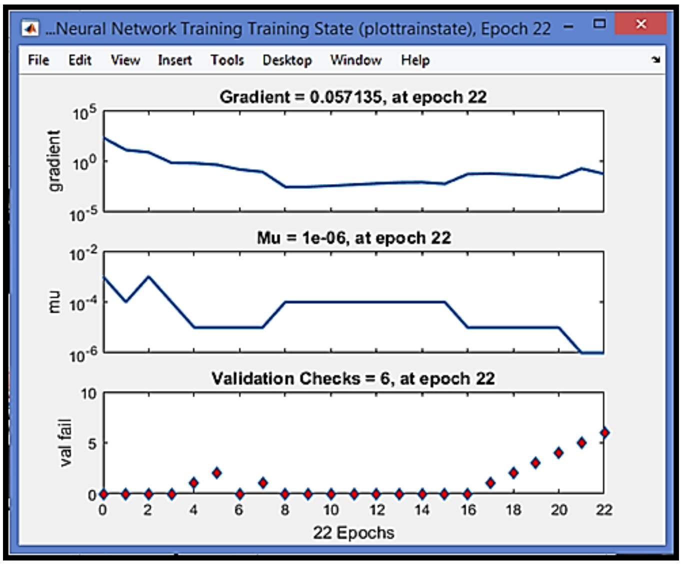

Figure 10: Training State Results

Figure 11 is an error histogram, another network performance check. The histogram is divided into three sets: The blue bar, which shows the errors for the training data; the Green bars, which show the errors for the validation data; and the Red bar for the testing data. This figure shows that most mistakes are concentrated within the range of -5 to 5, suggesting that the prediction for all the datasets is reasonably accurate. However, the training data point has an error of 17 validation data points of error 12 and 13. These observations indicate cases where the network outputs deviate from the real values by a fairly good margin. Other information from the error histogram helps describe the network's stability and define the potential further needed for the improvements and models' modifications. This analysis increases overall confidence in the networks and, in turn, increases areas where we know the predictive accuracy needs more work

.

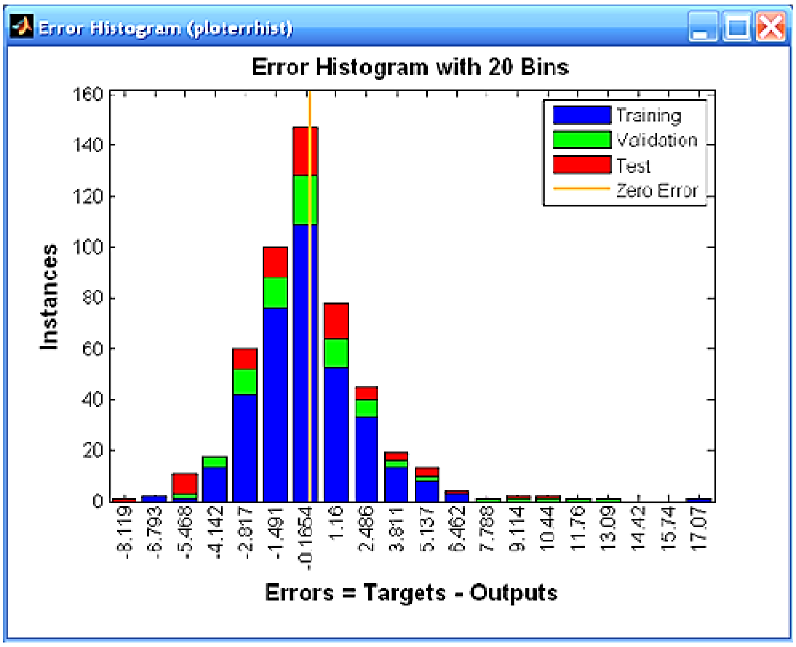

Figure11: Error Histogram of the Network

4. Conclusion

This study presents an artificial neural network that can be used for prediction and differentiation between anemia. The findings showed that the network achieved 92 percent accuracy in 230 of the 83 samples wherein the doctors' diagnosis aligned with the company's network. The training phase gave a high accuracy of 87% indicating that the network is trained and capable of propelling anemia using the dataset. As suggested, complex network architecture has the potential to be effectively implemented in actual medical practice based on anemia diagnosis results which can help the medical staff members in taking better decisions.

5. Acknowledgments

The author thanks the staff and technicians of the Hematology Unit at Omdurman Teaching Hospital, Sudan, for offering the different samples of anemia.

References

1. Organization, W.H., *Haemoglobin concentrations for the diagnosis of anaemia and assessment of severity*. 2011, World Health Organization.
2. Koury, M.J. and D.J. Hausrath, *Macrocytic anemias.* Current Opinion in Hematology, 2024. **31**(3): p. 82-88.
3. Cascio, M.J. and T.G. DeLoughery, *Anemia: evaluation and diagnostic tests.* Medical Clinics, 2017. **101**(2): p. 263-284.
4. Stauder, R., P. Valent, and I. Theurl, *Anemia at older age: etiologies, clinical implications, and management.* Blood, The Journal of the American Society of Hematology, 2018. **131**(5): p. 505-514.
5. Yenilmez, E.D. and A. Tuli, *Laboratory approach to anemia.* Current topics in anemia, 2017: p. 235-256.
6. Farrukh, S., et al., *Comparison of classification of anemia based on mean corpuscular volume by hematology analyzer and peripheral smear examination.* Pakistan Journal of Pathology, 2024. **35**(2): p. 81-86.
7. Yıldız, T.K., N. Yurtay, and B. Öneç, *Classifying anemia types using artificial learning methods.* Engineering Science and Technology, an International Journal, 2021. **24**(1): p. 50-70.
8. Yu, C.-H., et al., *Anemic Status Prediction using Multilayer Perceptron Neural Network Model.* GCAI, 2017. **50**: p. 213-220.
9. Meng, X.-H., et al., *Comparison of three data mining models for predicting diabetes or prediabetes by risk factors.* The Kaohsiung journal of medical sciences, 2013. **29**(2): p. 93-99.
10. Zhao, Y., et al., *Exploration of machine learning techniques in predicting multiple sclerosis*

disease course. PloS one, 2017. **12**(4): p. e0174866.

11. Hsieh, C.-H., et al., *Novel solutions for an old disease: diagnosis of acute appendicitis with random forest, support vector machines, and artificial neural networks.* Surgery, 2011. **149**(1): p. 87-93.
12. Abdullah, M. and S. Al-Asmari, *Anemia types prediction based on data mining classification algorithms*, in *Communication, management and information technology*. 2016, CRC Press. p. 629-636.
13. Dimiduk, D.M., E.A. Holm, and S.R. Niezgoda, *Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering.* Integrating Materials and Manufacturing Innovation, 2018. **7**: p. 157-172.
14. Li, S., X. Huang, and D. Wang, *Stochastic configuration networks for multi-dimensional integral evaluation.* Information Sciences, 2022. **601**: p. 323-339.
15. Qin, Q., et al., *Hodrick–Prescott filter-based hybrid ARIMA–SLFNs model with residual decomposition scheme for carbon price forecasting.* Applied Soft Computing, 2022. **119**: p. 108560.
16. Saputra, D.C.E., K. Sunat, and T. Ratnaningsih. *A new artificial intelligence approach using extreme learning machine as the potentially effective model to predict and analyze the diagnosis of anemia*. in *Healthcare*. 2023. MDPI.
17. Abiodun, O.I., et al., *Comprehensive review of artificial neural network applications to pattern recognition.* IEEE access, 2019. **7**: p. 158820-158846.
18. Gurney, K., *An introduction to neural networks*. 2018: CRC press.
19. Baruah, S.M.B., et al., *Primate vision: a single layer perception.* Neural Computing and Applications, 2021. **33**: p. 11765-11775.
20. Vang-Mata, R., *Multilayer perceptrons: theory and applications*. 2020: Nova Science Publishers.
21. Alzubaidi, L., et al. *Classification of red blood cells in sickle cell anemia using deep convolutional neural network*. in *Intelligent Systems Design and Applications: 18th International Conference on Intelligent Systems Design and Applications (ISDA 2018) held in Vellore, India, December 6-8, 2018, Volume 1*. 2020. Springer.
22. Kleyko, D., et al., *Perceptron theory can predict the accuracy of neural networks.* IEEE transactions on neural networks and learning systems, 2023.
23. Islam, M., G. Chen, and S. Jin, *An overview of neural network.* American Journal of Neural Networks and Applications, 2019. **5**(1): p. 7-11.
24. Mocanu, D.C., et al., *Scalable training of artificial neural networks with adaptive sparse connectivity inspired by network science.* Nature communications, 2018. **9**(1): p. 2383.
25. Hassanipour, S., et al., *Comparison of artificial neural network and logistic regression models for prediction of outcomes in trauma patients: A systematic review and meta-analysis.* Injury, 2019. **50**(2): p. 244-250.