Enhancing ABG Data Prediction: A Comprehensive Comparative Study of Neural Network Architectures

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Abstract

Arterial Blood Gas (ABG) analysis plays a pivotal role in diagnosing respiratory and metabolic imbalances in critically ill patients. Traditional manual interpretation methods are inherently time- consuming and susceptible to human error, thereby motivating the development of automated computational approaches to streamline diagnostics. The advent of machine learning, particularly neural networks, offers promising solutions for enhancing diagnostic accuracy and reliability. This study investigates the comparative efficacy of two neural network architectures: a Simple Neural Network (Simple NN) with homogeneous activation functions and an Augmented Neural Network (Augmented NN) that integrates heterogeneous activation functions and dropout regularization to mitigate overfitting. The framework leverages ABG datasets comprising key physiological parameters such as pH, $PaCO_2$, and HCO_3 were collected in real-time at Balaji Hospital. Training protocols utilized categorical cross-entropy loss with ReLU activation for the Simple NN, while the Augmented NN incorporated a combination of ReLU, tanh, sigmoid, and softmax activations across its layers. Dropout layers were strategically integrated into the Augmented NN to improve generalization. Results demonstrate that the Augmented NN achieves superior performance, with a validation accuracy of 94%, underscoring its robustness and predictive reliability. This study contributes a critical evaluation of neural network configurations for medical diagnostics, advancing the application of machine learning in healthcare and paving the way for future research in automated diagnostic tools.

Keywords: ABG Analysis, Neural Networks, Machine Learning, Respiratory Imbalance, Dropout Regularization, Medical Diagnostics

1 Introduction

Arterial Blood Gas (ABG) analysis is a cornerstone diagnostic tool in assessing and managing respiratory and metabolic disorders, particularly in critically ill patients. The conventional approach, reliant on manual interpretation by clinicians, poses significant challenges such as inter-observer variability, inefficiency, and the potentialfor error. These limitations necessitate the exploration of computational methodologies to enhance the accuracy, consistency, and efficiency of ABG analysis [1,7]. Machine learning, particularly deep learning, offers transformative potential in automating data interpretation, minimizing human error, and optimizing diagnostic processes. This study centers on evaluating two neural network architectures with distinct configurations: The Simple Neural Network (Simple NN) employs a homogeneous activation strategy for straightforward implementation, while theAugmented Neural Network (Augmented NN) integrates diverse activation functions coupled with dropout regularization to enhance generalization and robustness [12]. By leveraging ABG datasets are collected in real time for varying physiological conditions, this research elucidates the impact of architectural differences on performance metrics, ultimately contributing to the development of reliable diagnostic systems and advancing machinelearning applications in critical care [8,9,13].

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2 Literature Survey

Srivastava et al. (2014)[1] Introduced Dropout, a regularization technique that prevents overfitting by randomly deactivating neurons during training, significantly improving model generalization. This method has been widely adopted in deep learning architectures for enhancing robustness. LeCun et al. (1998) [2] Pioneered CNNs for document recognition, laying the foundation for modern deep learning techniques and influencing a wide range of computer vision applications. Their work demonstrated the efficiency of hierarchical feature extraction in image processing. Chollet (2017) [3] Proposed Xception, an architecture utilizing depthwise separable convolutions to enhance computational efficiency and performance over traditional CNNs. This approach led to improvements in deep network performance while reducing computational complexity.

Kingma and Ba (2014) [4] Developed Adam, an adaptive optimization algorithm combining momentum-based techniques with per-parameter learning rates, making it widely adopted in deep learning. The algorithm has become a standard for training neural networks due to its efficiency and adaptability. Paviglianiti et al. (2022)[5] Compared multiple deep learning techniques for arterial blood pressure prediction, showcasing the effectiveness of AI in physiological monitoring. Their study highlighted the potential of machine learning models in real-time health assessments. Shayan et al. (2020)[6] Applied neural networks to predict arterial blood gas (ABG) values in trauma victims, demonstrating AI's potential in emergency medical care. Their research emphasized the role of AI in improving early diagnosis and intervention.

3 Materials and Methods

This research utilized ABG datasets featuring key parameters such as pH, PaCO2, and HCO3, categorized into four imbalance types: respiratory acidosis, metabolic acidosis, respiratory alkalosis, and metabolic alkalosis. Data preprocessing involved meticulous feature normalization using Standard Scaler and label encodingvia one-hot encoding [12]. The datasets were split into training, validation, and testing subsets, ensuring unbiased evaluation. Both models were evaluated based on accuracy, loss metrics, and statistical significance using pairedt-tests, facilitating a rigorous comparison of the architectures under consideration [10,11].

4 Framework Proposed

The proposed framework comprises two distinct neural network architectures. The Simple NN relies exclusivelyon homogeneous ReLU activation across all layers, optimized with categorical cross-entropy loss and the Adam optimizer. In contrast, the Augmented NN employs heterogeneous activation functions strategically: ReLU for input layers to capture basic interactions, tanh for intermediate layers to model complex nonlinearities, sigmoid for feature interactions, and softmax for output classification. Dropout layers are integrated after each dense layer to mitigate overfitting and enhance generalization. Early stopping is implemented to prevent overtraining once validation loss stagnates, ensuring computational efficiency while maintaining optimal performance.

Pseudocode for Augmented Neural Network:
Input: ABG dataset with features (pH, PaCO2, HCO3) and labels (Imbalance types)
Output: Trained Augmented Neural Network Model

1. Preprocess data:
   a. Normalize features using StandardScaler.
   b. One-hot encode imbalance types.
2. Split dataset into training, validation, and test subsets.
3. Define the Augmented Neural Network architecture:
   a. Input layer with ReLU activation.
   b. Intermediate layers with tanh and sigmoid activations.
   c. Dropout layers to prevent overfitting.
   d. Output layer with softmax activation.
4. Compile model with Adam optimizer and categorical cross-entropy loss.
5. Train model with early stopping based on validation loss.
6. Evaluate model on test set and calculate performance metrics.
7. Save trained model for deployment.

Summary: The pseudocode outlines a step-by-step process for implementing the Augmented Neural Network, detailing data preprocessing, model architecture, training protocols, and evaluation methods to ensure robust predictive performance.

5 Experimental Setup

The experiments were conducted using ABG datasets on a GPU-enabled system to ensure computationalefficiency. Key steps included:

Data Preparation: The ABG dataset was preprocessed by normalizing features (pH, PaCO2, and HCO3) and encoding imbalance types using one-hot encoding. The dataset was then split into training (80%), validation(10%), and test (10%) subsets.

Model Training: Both architectures, Simple NN and Augmented NN, were trained using Tensor Flow and Keras. The training incorporated categorical cross-entropy loss and the Adam optimizer. Early stopping was used to halt training upon stagnation of validation loss.

Evaluation Metrics: The performance of the models was assessed based on accuracy and loss. Paired t- tests were performed to evaluate the statistical significance of differences in performance metrics between the two architectures.

The code implementation followed a structured workflow to ensure reproducibility. Hyper parameter tuning was carried out for optimal performance.

6 Results and Discussion

As shown in Figure 1, the training and validation accuracy demonstrate a steady improvement over the epochs, indicating effective learning and generalization of the Augmented Neural Network. The trend lines reveal a significant enhancement in validation accuracy compared to the Simple Neural Network architecture.

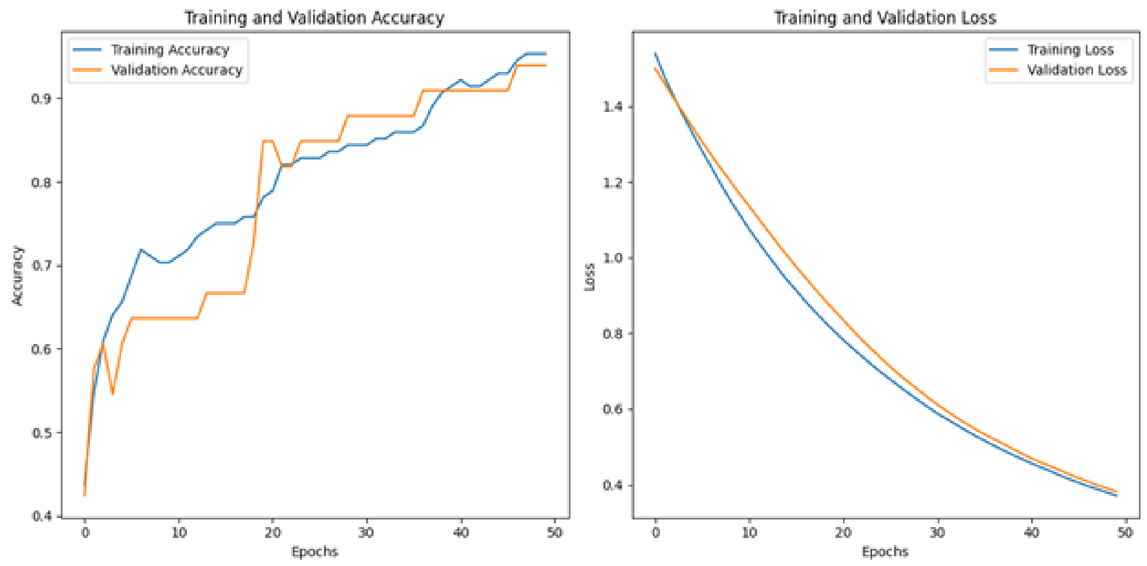

Figure 1: Training and Validation Accuracy (Left) and Loss (Right) Over Epochs for the Augmented NN.

Similarly, the training and validation loss, depicted in Figure 2, show a consistent decrease over time, signifying reduced errors in predictions. This trend highlights the effectiveness of heterogeneous activation functions and dropout regularization in the Augmented Neural Network.

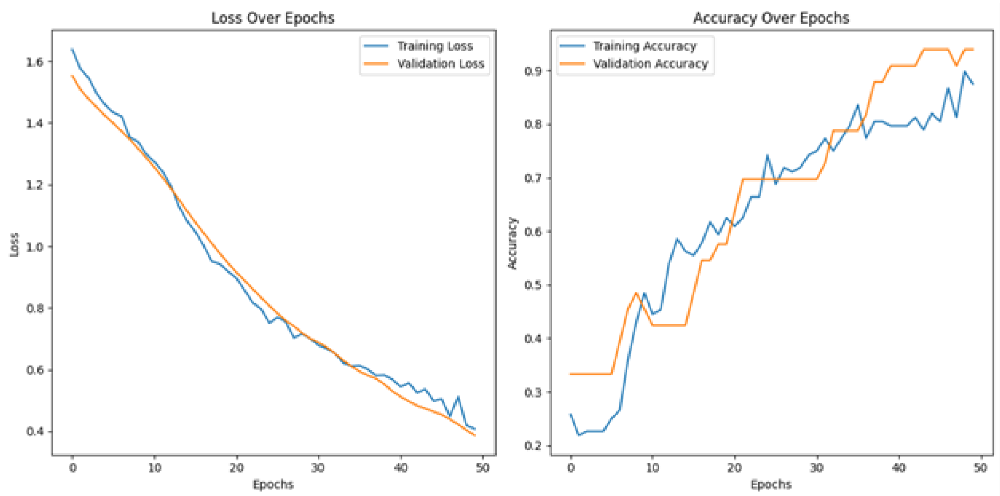

Figure 2: Loss Over Epochs (Left) and Accuracy Over Epochs (Right) for the Simple NN.

Metric	**t-statistic**	**p-value**
Training Accuracy	11.4289	0
Validation Accuracy	9.7919	0
Training Loss	-19.5883	0
Validation Loss	-17.3651	0

Statistical analyses reveal substantial performance improvements following the activation configuration modifications. Key observations include that the t-statistic of 11.4289 (p = 0.0000) confirms significant improvements due to heterogeneous activations. Similarly, a t-statistic of 9.7919 (p = 0.0000) underscores enhanced generalization capabilities. The negative t-statistic (-19.5883, p = 0.0000) indicates effective error minimization, while a t-statistic of -17.3651 (p = 0.0000) affirms better model generalization.

7 References

1. N. Srivastava et al., "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," Journal of Machine Learning Research, vol. 15, pp. 1929-1958, 2014.
2. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, Nov. 1998, doi: 10.1109/5.726791.
3. F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 1800-1807, doi: 10.1109/CVPR.2017.195.
4. D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," arXiv, Jan. 2014, doi: 10.48550/arxiv.1412.6980.
5. Paviglianiti, V. Randazzo, S. Villata, G. Cirrincione, and E. Pasero, "A Comparison of Deep Learning Techniques for Arterial Blood Pressure Prediction," Cognitive Computation, vol. 14, no. 5, pp. 1689-1710, 2022, doi: 10.1007/s12559-021-09910-0.
6. M. Shayan, M. Sabouri, L. Shayan, and S. Paydar, "Use of artificial intelligence and neural network algorithms to predict arterial blood gas items in trauma victims," medRxiv, Mar. 2020, doi: 10.1101/2020.03.14.20035584.
7. B. Shi et al., "An evolutionary machine learning for pulmonary hypertension animal model from arterial blood gas analysis," Computers in Biology and Medicine, vol. 146, p. 105529, Apr. 2022, doi: 10.1016/j.compbiomed.2022.105529.
8. S. Kajanan, B. T. G. S. Kumara, K. Banujan, S. Prasanth, and K. Manitheepan, "Classify the Outcome of Arterial Blood Gas Test to Detect the Respiratory Failure Using Machine Learning," 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 2022, pp. 1139-1143, doi: 10.1109/DASA54658.2022.9765012.
9. W. J. Ventriglia, "Arterial Blood Gases," Journal of Emergency Medicine Clinics of North America, vol. 4, no. 2, pp. 235-251, 1986.
10. S. Rodríguez-Villar et al., "Automatic Real-time Analysis and Interpretation of Arterial Blood Gas Sample for Point-of-care Testing: Clinical Validation," PloS One Journal, vol. 16, no. 3, p. e0248264, 2021.
11. Y.-C. Chu, C.-Z. Chen, C.-H. Lee, C.-W. Chen, H.-Y. Chang, and T.-R. Hsiue, "Prediction of Arterial Blood Gas Values From Venous Blood Gas Values in Patients With Acute Respiratory Failure Receiving Mechanical Ventilation," Journal of the Formosan Medical Association, vol. 102, no. 8, pp. 539-543, 2003.
12. K. Prabhu, M R K. Rao, "Evaluating Decision Tree and Rule-Based Models in Arterial Blood Analysis", Knowledge Transactions on Applied Machine Learning, Vol. 02, Issue. 01, pp. 09–16, Jan. 2024. DOI: https://doi.org/10.59567/ktAML.V2.01.02
13. T. Boulain, D. Garot, P. Vignon, J.-B. Lascarrou, D. Benzekri-Lefevre, and P.-F. Dequin, "Predicting Arterial Blood Gas and Lactate From Central Venous Blood Analysis in Critically Ill Patients: a Multicentre Prospective Diagnostic Accuracy Study," BJA: British Journal of Anaesthesia, vol. 117, no. 3, pp. 341-349, 2016.