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Enhanced Security for a Patient Healthcare Delivery Realtime Vital Signs Monitoring and Alert Ensemble

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ABSTRACT

Remote health monitor systems have enormous potential of becoming an integral part of medical system. Their outstanding roles are seen in treatment and monitor of patients with critical healthcare issues to reduce unnecessary visits to hospitals and unneeded pressure of healthcare experts. Health care monitors generate enormous data that must be analyzed to aid improved care delivery. We thus, advance a deep learning deep-learning techniques to detect reliability and accuracy of data obtained via an IoT-based remote health monitor. With dataset retrieved from Kaggle, we seek minimum training error that will also result in the best fit, selecting the number of hidden layers (a neuron for each layer) was established via a trail-and-error method, and examining the results. The best possible number of layers was found via tests on single layer with 1-to-20 neurons, and shows that our best F1-score with the least amount of train-loss time is with the configuration of 9-neurons and F1 of 93% and train time loss of 1.140. The accuracy comparison is performed between strongly correlated features and weakly correlated features. Finally, accuracy comparison between two approaches is performed to check which method is performing better for detecting erroneous data for the given dataset.

1. INTRODUCTION

Healthcare today, is ever-changing with the birth of wireless sensors and Internet of Things (M. I. Akazue, Edje, et al., 2024; Hurt, 2019; Ifioko et al., 2024), and has continued to leverage on as well as integrate these IoTs on medical equipment to help remote patient monitor and alert system (Ibor et al., 2023). The many merits of IoTs in healthcare sector includes its increased monitor care delivery, better patient engagement, ease access of patient records, and improved patient safety (Allenotor et al., 2015; Allenotor & Ojugo, 2017; Omede et al., 2024). The provision of healthcare facilities to ambient assisted living is mostly linked with smart e-healthcare in nations like as Germany, United Kingdom, United States, and Australia (Atuduhor et al., 2024; Ojugo & Oyemade, 2020; Setiadi et al., 2024). Patients can access healthcare services nearest to them, use telemedicine to manage their medical crises electronically (in some

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cases) (Afifah et al., 2022; Ojugo, Eboka, Okonta, et al., 2015; Ojugo & Otakore, 2018b; Smith et al., 2020), and also proffer greater assistance via the use of smart healthcare (Al-Nbhany et al., 2024). Studies have shown that smart healthcare delivery paradigm can also attract drawbacks such as interoperability in adoption (Ojugo et al., 2024), tech adoption (Binitie et al., 2021; Ojugo, Ejeh, Odiakaose, Eboka, et al., 2023), privacy and security (M. Akazue et al., 2023; Obasuyi et al., 2024; Ojugo, Ejeh, Akazue, Ashioba, et al., 2023).

Vital signs shows evidence of the current functioning of a patient's body (Atuduhor et al., 2024). They provide critical information, vital for life – which are addressed as vital signs. Thus, in emergencies, a patient's heart rate is the first of vital sign checked. Today, various fitness and medical devices available in the market, that monitor and provide different vital and medical parameters such as calories burnt, step count, oxygen saturation level, blood pressure, heart rate variation, and respiration rate. These devices use Bluetooth Low Energy (BLE) to connect other devices like smartphones. Its major drawback is that data flow occurs in one way although some companies such as Fitbit and Garmin provide the functionality of making their phone apps to receive data with limited features.

Various fitness devices are available on the market to monitor/alert different medical (vitals) features like calories spent, step count, oxygen saturation level (SPO_2), heart rate, blood pressure, and respiration rate. These use Bluetooth Low Energy to interact with others like smartphones; Though, companies like Fitbit and Garmin aim at providing apps that receive limited feats functionality data. Real-time monitoring delivers on continuous updates about observed events and data for analysis with low latency and minimal delay. Thus, the need for a model that can analyse collected data for accuracy, consistency, and viability for medical purpose. Thus, when a feat is above a threshold value, an alert is sent to the medical expert – to observe more and provision advance warning/advice to patients. This can play an essential role in providing remote health monitoring to patients and most notably be useful for the elderly, women, and infants (Gaye & Wulamu, 2019; Maya Gopal P S & Bhargavi R, 2019; Nartey et al., 2021; Oyewola et al., 2021).

Healthcare records yields useful insight to improve EMR performance and strategies implementation to guide better monetization policies and portfolios for such organization. Information has also become both an integral foundation and fundamental requirement cum basis for today's complex culture (Al-Mhiqani et al., 2021; Shanmuga Sundari & Subaji, 2020). This ease of integration can be attributed to its ubiquitous nature, low-cost, ease of use, mobility, portability and user-trust (Muslikh et al., 2023; Ojugo et al., 2012; Safriandono et al., 2024) – all of which does continue to advance the popularity, adoption ease of ICTs. This growth has also attracted intrusion activities from adversaries (M. I. Akazue et al., 2022; Yoro, Aghware, Akazue, et al., 2023; Yoro, Aghware, Malasowe, et al., 2023) whom for their personal gains, seek to exploit device of unsuspecting users. They do achieve these feats via socially-engineered phishing techniques; And its rise today, has become a great concern to both businesses and individuals (Evans, 2019; Haryani et al., 2023; Oyemade et al., 2016; Oyetunde et al., 2019; Srivastava et al., 2020).

1.1 Secure Electronic Medical Records

Patients especially on emergencies today, are not limited to receive care at specific hospitals (Nahavandi et al., 2022). Exchange of patient record is a panacea for improved healthcare, and tracking such record history is crucial and mandatory in provisioning quality healthcare. The unavailability of such records to care professional – especially off facilities where these records is/were created (Castro & Liskov, 2002) will continue to pose a range of complications, which may include: (a) healthcare coordination, (b) non-adoption of telemedicine with patient access (Ojugo & Ekurume, 2021b), (c) records corruption via tamper, mishandle and stealing (Okpor et al., 2024), and (d) data exchange without patients' consent with unauthorized persons (Aghware et al., 2023b; Aghware, Ojugo, et al., 2024; Ojugo, Akazue, Ejeh, Odiakaose, et al., 2023). With EMRs – there are inherent issues like platform interoperability, data confidentiality, and security must be addressed urgently.

Blockchain is aimed at resolving security challenges with immutability, which prevents records alteration (Amalraj & Lourdusamy, 2022; Ileberi et al., 2022; Sasikala et al., 2022). Blockchain in healthcare will improve user-trust and effective use of healthcare data (Christidis & Devetsikiotis, 2016; Ojugo et al., 2021b). Blockchain feats include tamper proof, improved authentication, smart contract, consensus verification, and others – unique to record sharing abilities (Damoska & Erceg, 2022; Eboka & Ojugo, 2020). As an emerging tech, blockchains can be fused with other technologies (Ojugo & Otakore, 2020b; Ojugo & Oyemade, 2021) to harness its many features, and resolve issues of interoperability. Lack of standards for developing care-based blockchain apps must be addressed to guide practitioners toward a transformative scheme (Akazue, Debekeme, et al., 2023; Fan et al., 2020; Ojugo, Aghware, Yoro, et al., 2015b).

Akazue et al. (2023) Blockchain is an tamper-proof, distributed database that is maintained cum validated over a network of interconnected users (Habib et al., 2022; Ojugo, Oyemade, Allenotor, et al., 2015). Its tamper-proof allows adoption in many platforms to quickly resolve security issues using conventional databases (M. I. Akazue, Yoro, et al., 2023). It timestamps data to avoid tamper (Dourado & Brito, 2014) using any of 4-modes: private, public, hybrid and consortium – each of which yields its ideal uses, benefits, and drawbacks (Tingfei et al., 2020). Oladele et al. (2024) used the blockchain EMR for improved services that authenticates records as transaction to ensure user-data confidentiality, to yield greater interoperability as well as comply with the HIPAA regulations and standards in Nigeria (Ako et al., 2024; Oladele et al., 2024).

1.2 Machine Learning Detections

With healthcare delivery today – securing EMRs to ease patient and professionals access even from healthcare facilities outside of those where these records are created, have become the new quest for healthcare experts (Ojugo & Eboka, 2018c). This will help reduce records corruptions of various forms vis-à-vis reduce theft risk; And in turn, results in a great amount of monetary losses for both healthcare facilities and patients alike (Ojugo, Aghware, Yoro, et al., 2015a). The rise in trend of adversaries continue to raise concerns of urgency if both patients and medical centres are to remain productive (Malasowe, Okpako, et al., 2024; Odiakaose, Emordi, Ejeh, Ashioba, Odeh, Attoh, et al., 2024; Sahmoud & Mikki, 2022). Adopting machine learning (ML) as low-cost alternatives mode now continues to yield successfully trained heuristics that effectively recognize normal activities as profiled patterns (Ileberi et al., 2022). ML models learns these patterns via features of interest, which helps them identify these patterns as signature classification that deviates from a norm in behaviour, or its quick detection as an unusual activity for a pattern indicative of an anomaly (Okobah & Ojugo, 2018).

MLs have yielded successful adaption in vital sign detection. E.g. Logistic Regression (Lakshimi & Kavila, 2018; Li et al., 2021; Ojugo, Odiakaose, Emordi, Ejeh, et al., 2023), Deep Learning (Benchaji et al., 2021; Ojugo, Eboka, Yoro, et al., 2015), Bayes (Emordi et al., 2024; Mukhanov, 2008; Ojugo, Odiakaose, Emordi, Ako, et al., 2023), SVM (Altman, 2019), Random Forest (Ojugo, Yoro, Oyemade, et al., 2013; Xuan et al., 2018), KNN (Marazqah Btoush et al., 2023; Ojugo & Eboka, 2018a), and others (Abakarim et al., 2018; Ojugo, Yoro, Yerokun, et al., 2013; Zareapoor & Shamsolmoali, 2015). ML's performance, flexibility and robust adoption is often degraded with the choice in their adopted feature selection and pre-processing scheme (Malasowe et al., 2023; Malasowe, Ojie, et al., 2024; Ojugo et al., 2014).

1.3 Study Motivation

Our study motivations include (Meghana et al., 2023; Ojugo & Eboka, 2018b; Ojugo & Yoro, 2013; Sharmila et al., 2019; Supriya & Akki, 2021):

1. Appropriate format dataset is crucial to machine learning task as it aids faster training and yield good generalization and performance evaluation (Okonta et al., 2014). Some tasks lend to imbalanced datasets. Thus, studies must explore intricate sampling techniques, and harness the robust power of ensemble(s) tailored explicitly to mitigating the issues of imbalanced dataset (Ojugo & Eboka, 2021; Ojugo & Otakore, 2021).
2. Previous studies use hill-climb schemes, which are often struck at local maxima and yield non-optimal feature selection in the quest for ground truth, heuristic construction, and training. These, can lead to both poor generalization and poor test dataset classifying for the proposed model.
3. Fusion learning with feature engineering, sparse anomalies learning, and association rules have since also become issues with deep learning networks (DLNN). To resolve anomaly optimization(s) and outlier detection in vital signs monitor devices from collected data, we seek to detect outlier in the normal behavior of the system to aid remote monitor/alert with accurate classifying of measures via well-established interactions. Smart devices let us use sensor-collected data and interact with other devices. To provide proof of concept, sensor devices with open APIs are selected to demonstrate this challenge and can be overcome and data can be collected and processed in a cloud system.
4. The second challenge that needs to be addressed arises in the data processing and usage phase (source). In the data processing phase, it must be ensured that the collected data is reliable.
5. Regression tasks are often continuous due to insufficient test dataset, feature selection among other factors required to help validate such heuristics' performance. This can lead to degraded performance, poor generalization, model overfit and overtrain; And thus, hampers adoption.

To overcome these, we adopt deep learning ensemble for Kaggle dataset. Our choice is due to its ability to greatly reduce overfitting, to address imbalanced datasets, and yield a vigorous prediction accuracy.

2. MATERIALS AND METHODS

2.1 Data Gathering

System design involves a prototype for data collection via IoTs; And implementation involves various DL algorithms. Functional block diagram as implemented is seen as in Figure 1. User data is retrieved via graphic-user-interface, and sent for analysis. Data is collected via two devices, and transmitted via Bluetooth to the intermediate devices as transmission medium. This data is stored via intermediate device and transmitted to the cloud via Wi-Fi as the transmission medium. This data from the cloud is further extracted to the remote server for analysis. In our work, data analysis involves erroneous detection with processed data stored in remote server.

The first phase senses (retrieves) data as collected. The task of data collection is performed in two steps. The first step in data collection involves a device to be used for data collection. In our work, we are making use of IOT devices, namely spire stone and iHealth Sense. The second phase includes the communication phase. This phase has 3-steps: (a) first, establishes communication between devices and BLE-medium to control the device, (b) it then establishes communication to transmit the data from the WiFi interface, and (c) lastly, we send data from the cloud to server via open APIs or a file transfer protocol. Lastly, the third phase includes the data processing phase, which deals with data analysis. The primary purpose of data analysis for our work is to detect anomalies in the collected data. Outlier detection depends on the type of information being collected. There are three main types of outliers, such as global outliers (point outlier), collective outliers, and contextual outliers. These outlier detection methodologies will be done by using DL. The last step of the proposed method includes the processed data storage in the Excel Spreadsheet.

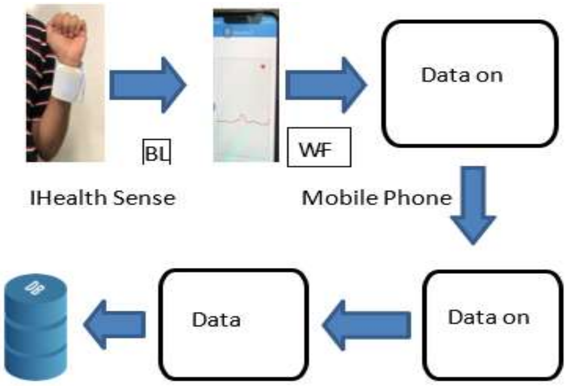

Figure 1. Heart pressure rate monitor design

2.2 Experimental Deep Learning Model

DNN uses deep learning to adapt useful selected feat of interest, to carefully construct a multi-layer network from vast amount of data. Its deep architecture uses the hidden layer to transform non-linearly from previous layers and improves prediction accuracy to the next (Aghware et al., 2023a). Hinto et al. (2021) proposed DNN trained via 2-phases using an unsupervised auto-encoder, which is a multi-layered network with a decoder and encoder. The encoder transforms inputs from high-to-low dimension via its function f_{encoder}; while, a decoder reconstruct the function via f_{decoder} to reverse the encoder task (Ojugo & Ekurume, 2021a) in (Mohebbi et al., 2017) for detailed encoder/decoder algorithms.

At pre-training, *N* autoencoders are stacked to N-hidden-layer for input. With input accepted, the input (first hidden) layer acts as auto-encoder, and is trained to minimize reconstruction error. Training parameter(s) of the encoder is used to initialize this hidden layer. Our 1st and 2nd hidden layers are selected as encoder(s) for training. Process continues till the *N*th auto-encoder is trained and initializes the final hidden layer. With all hidden layers stacked in the auto-encoder at each training *N*-times, they are regarded as pre-trained. This feat yields better result than random initialization. It achieves better generalization (Charan et al., 2020; Dong et al., 2024; Lu & Rakovski, 2022; Ojugo & Yoro, 2021b)

Fine-tuning is a supervised phase that seeks to optimize a DNN's performance by retraining the network labeled training data. It computes the errors as a difference in real versus predicted values via back-propagated stochastic gradient descent (SGD), which randomly selects data, and iteratively updates gradient direction with the weight parameters. A merit of the SGD is that it converges faster and does not require the entire dataset. This makes it suitable for complex neural networks as given in Equation 1 with E as loss function, *y* is label and *t* is output of the network (Ojugo & Eboka, 2020a; Ojugo & Otakore, 2020a; Yoro & Ojugo, 2019a):

$$E=\frac{1}{2}\sum_{j=1}^{M}(y_i-t_i)^2 \quad (1)$$

The gradient of the weight *w* is obtained as a derivative of the error equation – so that an updated SGD is given by Equation 2 with ŋ is step-size, *h* is number of hidden layers (Odiakaose et al., 2023; Odiakaose, Emordi, Ejeh, Ashioba, Odeh, Obiageli, et al., 2024):

$$W_{ij}^{new}=W_{ij}^{old}-\eta.\left(y_j-t_j\right).y_j\left(1-y_i\right).h_i \quad (2)$$

This process is optimized by the weights and threshold based on correctly labelled data. Thus, a DNN can learn accurately at its final output and direct task all network parameters to perform correct classifications (Malasowe, Aghware, et al., 2024; Malasowe, Edim, et al., 2024).

2.3 Training Phase

The DLNN solves tasks by: (a) dividing train dataset and compute cluster center from each cluster point, (b) each cluster is trained so that each DNN learns the various attributes of each subset, (c) test data applies previous cluster centers to detect outlier(s) by the pre-trained DNNs, and (d) output of each DNN is aggregated as final output. Solution is divided into 3-steps (Ojugo & Eboka, 2019, 2020b; Okonta et al., 2014; Wemembu et al., 2014):

1. **Step 1** divides the dataset into train/test partitions. DNN stores computed cluster centers, used as initialization center(s) to generate test datasets. Dataset is formatted as data-points for selected parameters, and the data-points in the training dataset are aligned into same class. For its improved performance, it revises cluster numbers (to between 2 to 6) and sigma values (i.e. 0.1 to 1.0). The minimum distance from a data point to each cluster center is measured, and a data-point's nearness to a cluster, assigns it to that cluster-class. Training sets generated by clusters are taken up as input to DNNs. For training, the number of DNNs should equal the number of clusters. DNN architecture consists of five layers: an input, two hidden, a softmax and an output layer respectively. The hidden layers learn feats from each training subset, and the top layer is a five-dimensional output vector. Each training subset generated from the *k*th cluster center is regarded as input data to feed into *k*th DNN respectively. Trained sub-DNN models are marked sub-DNN 1 to *k*.
2. **Step 2** uses test dataset to generate *k*-datasets with the previous cluster center obtained from clusters in Step 1. Test sub-dataset is denoted as Test 1 through Test k.
3. **Step 3**: The *k*-test data subsets are fed into k sub-DNNs, which were completed by the k training data subsets in Step 1. Output of each sub-DNN is integrated as final output and used to analyses positive detection rates. Our confusion matrix performance of generated rules yields the algorithm thus (Ojugo et al., 2021a):

Algorithm 1: Listing of the Vital Signs Deep Learning Neural Network Algorithm

```
Input: dataset, cluster number, number of hidden-layer nodes HLN, number of hidden layers HL.
divide dataset into train and testing dataset   /*get the largest matrix eigenvectors and train datasets*/
function obtain (cluster train dataset, center and result
if (input_dataset_cluster = = train_dataset) then
  | select & set all parameters as learn_rate, denoise, sparse learning, weight and bias functions
  | compute sparsity_cost, update weights and bias afterwards
  | return true
  | else endif
End
function fine_tune (DNN for Vital_Signs)
use backpropagation with momentum leaning to train
obtain final structure of each trained sub-DNN
divide each test data-subset with cluster epi-center distance value using parameters from the train cluster
measure distance as cluster center between train and test data-subset
For each sub-DNN Result ←function DNN_integrate (parameter_quantity) then
  | integrate as final output
  | return output → (result == final output): else
end if: END
```

3. RESULTS AND DISCUSSION

3.1. Parameters Tuning

Our deep network uses 5-neurons at its input (a neuron for each feat), and 4-neuron for its output layer (a neuron for each possible class of low, normal, moderate and high). Our DL features are learning rate, activation function, hidden layer topology and number of epochs. We used Rectified Linear Unit (ReLU) activation Function with 500-epochs (with values of 100-to-500 epochs to account for training time and performance accuracy. With no rule in selecting number of hidden layer(s) and neuron(s), such flexibility helps improves the heuristics capability to evaluate complex function as in Table 1, which agrees with (Ojugo & Nwankwo, 2021a; Ojugo & Otakore, 2020c; Okonta et al., 2013; Omoruwou et al., 2024; Otorokpo et al., 2024; Oyemade & Ojugo, 2021).

Table 1. Performance Evaluation and Results

Hidden Layer	Preci-sion	Accu-racy	F1	Iteration	Train Loss	Epoch
1	0.84	0.92	0.88	44	0.294	500
2	0.84	0.92	0.87	24	0.278	500
3	0.84	0.92	0.88	26	0.293	500
4	0.84	0.92	0.88	9	0.501	500
5	0.89	0.55	0.64	19	1.496	500
6	0.94	0.94	0.92	18	1.400	500
7	0.86	0.53	0.63	4	2.230	500
8	0.90	0.84	0.86	16	2.071	500
9	**0.94**	**0.95**	**0.93**	**18**	**1.140**	**500**
10	0.92	0.92	0.90	16	1.779	500
11	0.88	0.91	0.89	7	2.134	500
12	0.91	0.92	0.89	8	2.320	500
13	0.87	0.87	0.87	13	2.006	500
14	0.92	0.92	0.90	8	1.970	500
15	0.92	0.92	0.90	5	1.730	500
16	0.85	0.85	0.85	10	1.540	500
17	0.90	0.84	0.86	15	2.320	500
18	0.91	0.92	0.90	8	1.440	500
19	0.92	0.93	0.90	14	2.160	500
20	0.91	0.91	0.91	5	1.772	500

We seek minimum training error that will also result in the best fit, selecting the number of hidden layers (and neurons for each layer) was established via a trail-and-error method, and examining the results. The best number of layers was found via single layer with 1-to-20 neurons, which shows that our best F1-score with the least amount of train-loss time as in Table 1, is with the configuration of 9-neurons and f-score of 93% at 18^{th}-iteration with train loss of 1.140 (**in bold**).

3.2. Discussion of Findings

Pre-processed dataset as obtained from the server, was employed for further analysis. In this work, the information is first collected from the IoT devices and then it is sent to the intermediate device (Fitbit app is paired to interact with the smartphone). Afterward, it is being stored in the cloud using Wi-fi and gets transferred to the server on a remote computer. The pre-processed data considers different features like systolic blood pressure, diastolic blood pressure, heart and respiration rate(s). With data samples as shown in Table 2, which agrees with (Armstrong & Vickers, 2020; Ihama et al., 2023; Ojugo, Ugboh, Onochie, et al., 2013).

Table 2. Processed Dataset from Test Dataset

Respiration Rate	SYS	DIA	PULSE
18.0	142.0	76.0	86.0
15.0	125.0	76.0	83.0
17.0	125.0	78.0	85.0
17.0	124.0	80.0	85.0
14.0	123.0	89.0	81.0
19.0	120.0	92.0	87.0
15.0	123.0	75.0	83.0
15.0	132.0	99.0	83.0
15.0	127.0	86.0	83.0
14.0	127.0	94.0	81.0
16.0	139.0	99.0	85.0
15.0	128.0	94.0	82.0
15.0	124.0	86.0	85.0
14.0	122.0	81.0	80.0
14.0	116.0	89.0	81.0
12.0	116.0	86.0	81.0
14.0	119.0	90.0	80.0
16.0	117.0	84.0	82.0
14.0	117.0	84.0	82.0
13.0	117.0	84.0	82.0
22.0	145.0	95.0	105.0
20.0	145.0	95.0	105.0

The visualized labels obtained from the autoencoder (AE) is performed using t-SNE display. (t-SNE) yields a device's non-linear dimensionality reduction algorithm used to exploring high dimensional data, and it also maps multi-dimensional data to two or more dimensions. A major merit of using t-SNE is that it focuses on preserving the distances between widely-separate data points; Rather than distances between the nearby locations. t-SNE shows inliers in green, and outliers in red as in Figure 2, and agrees with (Brizimor et al., 2024; Hamad et al., 2021; Ojugo & Nwankwo, 2021b; Ojugo & Otakore, 2018a).

The ground truth obtained is used by the DL models for computing accuracy. Once the labelling is provided by AE then the data is further divided into two parts (training set and test set) (Ejeh et al., 2024; Ojugo & Yoro, 2020, 2021a). The training set consists of 70-percent of samples; while, the remainder 30-percent were kept for test set. Train dataset is used to train the models, as was also validated by applying it on test dataset. The 70/30 rule is applied for dividing the samples into test set and training set. Afterward, these ML are compared based on accuracy achieved (Aghware, Adigwe, et al., 2024; Akpoyibo et al., 2022; Ukadike et al., 2023).

Figure 2. The Autoencoder visual output for our proposed DNN (Ojugo & Eboka, 2014, 2018a, 2018c)

4. CONCLUSION

Models are useful to represent reality as their primary value is to serve as educational tools for insight to help us better understand and reflect upon reality (Ojugo, Allenotor, Oyemade, et al., 2015; Oyemade & Ojugo, 2020). The chaotic nature of medical vitals as rippled with noisy dataset in its many features, will continue to yield studies that explore deep learning ensemble as suitable to address it (M. I. Akazue, Okofu, et al., 2024). The variance and bias in ML tasks also makes possible, the optimization of training sample if greater performance is to be achieved (Ejeh et al., 2024; Ojugo & Yoro, 2020, 2021a). Thus, our DNN solution yield 56-rules, and top rules had a classification accuracy of [0.8, 0.96]. This, implies that over 80% of its rules can adequately classify test-cases to achieve optimality (Ojugo, Akazue, Ejeh, Ashioba, et al., 2023; Shoeibi et al., 2022; Yao et al., 2022; Yoro & Ojugo, 2019b).

Conflict of Interest

The authors declare that there is no conflict of interest.

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