www.ijecs.in
International Journal of Engineering and Computer Science
Volume 14 Issue 01 January 2025, Page No. 26793-26802
ISSN: 2319-7242 DOI: 10.18535/ijecs/v14i01.4970

An Internet of Medical Things (Iomt)-Based Model for Predicting Optimal Temperatures and Heart Rates on Hyperthemia Patients

IGWE, S. E.[1], Anireh, V. I. E. [2], Emmah, V. T. [3]

Abstract

With the rising use of computer devices and the increasing application of Internet-of-Things, many domains have incorporated it to make life easy. One of such is in the medical field where wearable devices are used to check heart beats, perform medical procedure and so on. This research proposed an Internet of Medical Things (IoMT) model based on the Continual Neural Machine Learning Artificial Neural Network (CNML-ANN). The model was adapted for the prediction of Hyperthemia condition of a patient based on the detection of temperature and heart-rate signals. The results of simulations showed the optimal temperatures of between 36oC and 42oC for the Temperature Block (TB) and between 30pulses and 120pulses for the Heart Rate Block (HRB) for a total of 200 training data points have been synthesized. In addition, the numbers of false positives are higher for temperature predictions and zero for heart rate using proposed approach. When compared to the Long Short-Term Memory Artificial Neural Network (LSTM-ANN), the classifications for the temperature symptoms is much better with a mean CA of 86% and 68.6% for CNML-ANN and LSTM-ANN respectively. Also, the classifications for the heart rate symptoms is much better with an estimated mean CA of 98% and 82.5% CNML-ANN and LSTM-ANN respectively. Thus, based on the performance of the developed continual learning predictive classifier system, it holds a promising potential as a candidate IoMT machine learning model for real-time diagnosis of Hyperthemia patients.

Keywords: *Machine Learning, Internet of Medical Things, LSTM, Hypertemia*

1. Introduction

Internet of Medical Things (IoMTs) is an emerging paradigm in the field of medicine and remote healthcare that seamlessly enable physicians and other medical professionals to serve their patients via internet-enabled medical sensors. In particular, the concept is actively developed by a vast number of researchers due to its significance in solving/eliminating the Geographical Barrier Diagnosis and Treatment (GB-D&T) problem. In an IoMTs context, medical sensing devices (medical sensors) are typically attached to human beings at specific parts of the body or by other proxy-methods to continually detect and remotely send patients' physiological data to medical experts for subsequent diagnosis and medical recommendations (Si-Ahmed et al., 2023). This has the important benefits of early diagnosis prior to a severe medical condition with huge medical cost savings to the patients. As an application area, the benefits of the IoMT concept can be exploited for the early treatment or diagnosis different diseases such as hyperthermia – a medical condition or disease that temperature and heart-beat symptomatic. In this regard, remote monitoring temperature and heart-rate sensors can be deployed on patients with histories of such condition in order to effectively mitigate against future occurrences. In an Io MTs platform, patients can seamlessly get useful feedback on their state of health and doctors can perform diagnostic functions in a timely and more efficient manner. This is possible because the GB-D&T challenge is circumvented using modern approaches that revolve around real-time sensing, remote internet-enabled communications and Machine Learning Systems (MLSs). In particular, the large proliferation of Machine Learning (ML) techniques and corresponding diversity in medical data due to the variety of diseases to detect and classify have made the choice of selecting a particular ML technique a daunting one. Notwithstanding the active research as accounted for in the aforementioned surveys/reviews, there still remains a gap to be filled in the area of small (limited) data analysis and Continual Machine Learning (CML) methods for Io MTs systems.

This paper provides a novel solution to the GB-D&T problem with a Continual Machine Learning (CML) model. The primary idea is to exploit the benefits of a distributed pool of medical expert recommendations to properly diagnose and treat a patient. Indeed, arriving at a base decision is a matter that requires an agreeable set of recommendations achieved notably by the CML. Thus, this paper will equally seek to validate the CML considering several mixtures of experts in a decision-making context.

2. RELATED LITERATURES

Extensive surveys have been carried out by several researchers to serve this important requirement of ML technique selection in various contexts. For instance, in the context of Intrusion Detection Systems (IDS) for IoMTs (Si-Ahmed et al., 2023), IoMTs with extensive reviews on the hypertensive disease called preeclampsia (Hadiyanto et al., 2023) and in the context of IoMTs ML applications (Aminizadeh et al., 2023).

Ding et al (2020) proposed a Decryption/Encryption approach based on Deep Learning (DL) and IoMTs (DeepEDN-IoMTs) for securing medical images from X-rays. The DL approach was based on the Cycle Generative Adversarial Network (cGAN) with back-propagation. Their results showed better frames per second (fps) when compared to other competing techniques and considering 2 image resolution size formats.

Hosseinzadeh et al (2020) proposed an IoMTs capable solution based on a set of Multi-Layered Perceptron ANNs (MLP-ANNs) with adaptive learning algorithm (ALA) for thyroid disease detection. The ALA counters the slow-convergence and local optimality (minima) problem that affects back-propagation error driven MLPs. When compared with the standard back-propagation training (learning) algorithm, it was found that the set of MLP-ANNs is able to improve accuracy by a factor 4.6%. The need to guarantee global minima of error during convergence was equally identified.

Ning et al (2020) used a hybrid DL IoMTs-capable approach based on the Convolutional Neural Network (CNN) and a Recursive Neural Network (RNN) for the detection of congestive heart failure condition. Their approach was specifically used to classify remote data on the Normal Sinus Heart Rate (NSHR) signals and the Congestive Heart Failure (CHF) using the Electro-Cardio-Graphs (ECG). Their results showed improvements on other studies with accuracy, specificity, and sensitivity of 99.93%, 99.85% and 100% respectively.

Raj et al (2020) used an IoMTs-capable DL solution with optimal feature selection for remote classification of medical image data. The Opportunistic based Crow Search (OCS) approach was adopted for the enhancement of DL classifier. They reported an accuracy, specificity, and sensitivity of 95.22%, 100% and 86.45% respectively.

Wang et al (2020) proposed a 6-G enabled IoMT solution including a DL approach comprising of a fusion of CNN and a Residual Network (ResNet) for detecting lung nodule features obtained from Computed Tomography (CT) data (based on ELCAP database) and a Long Short-Term Memory (LSTM) for the prediction of future risk of cancer. They reported improved performances when compared with that of other similarly used algorithms with accuracy, specificity, and sensitivity of 91.70%, 91.17% and 92.23% respectively.

Xuan & You (2020) proposed a DL based Hierarchical CNN (DL-HCNN) based IoMTs ML solution for the detection and diagnosis of pancreatic tumor in image scans of humans. The DL-HCNN introduced Recurrent nets (RNN) for pancreatic segmentation in Magnetic Resonance Imaging (MRI) and CT scans. The results in comparison with other similar algorithms showed that the DL-HCNN is able to attain better dice index specificity and sensitivity ratios in addition to better precision ratio. In general, the best dice-performance ratio of 98.7% was attained by the proposed solution.

Kishor & Chakraborty (2021) proposed the use of 7 Machine Learning (ML) approaches including the Decision Tree (DT) Support Vector Machine (SVM), Naïve Bayes (NB), Adaptive Boosting (AdaBoost), the Random Forest (RF), Artificial Neural Network (ANN), and the K-nearest neighbor (k-NN) for the prediction of 9 fatal diseases in a Medical IoT context. Data module supports the local collection of patient data from available health centers and using IoT capable medical sensors. Their results show that the RF classifier will do best with a maximum accuracy, sensitivity, specificity, and Area Under Curve (AUC) of 97.62%, 99.67%, 97.81%, and 99.32% respectively.

Su et al (2021) proposed an IoMTs-capable Valvular Heart-Disease Screening System (VHDSS) using an STM-32 IoT controller board for compression/pressure, heartbeat and temperature measurements and a Deep Learning (DL) model classifier. They reported temperature curve variations results from acquired remote data on 18 subjects with a specific subject presenting significant variation from others indicating a high likelihood of the valvular disease. Considering the critical subject, a blood-block and release cycle effectively showed a decrease in temperature when compared to other subjects indicating the capability of proposed DL model classifier.

El-shafeiy et al (2021) proposed Swarm Intelligence based on IoMTs (SIoMTs) for network optimization. They employed the Bee Colony Optimization Approach (BCOA) exploiting a so-called probability of abandonment model to identify similarity of the nodes with medical attributes transmitted by a set of participating nodes. Using the Ward2ICU dataset, the proposed approach was able to give better classification results (precision, silhouette coefficient, recall, F-1) and reduced CPU time when compared to other ML approaches such as Fuzzy C-Means (FCM), k-Means, and k-NN. Vankdothu et al (2022) proposed a Support Value based DL or Deep Neural Network (SDNN) IoMTs approach for remote classification of cancerous cells in brain images. The proposed SDNN was used to distinguish between a normal and an abnormal brain image with a best classification accuracy of about 94.30% when compared to other similar/hybridized DL techniques based on CNN.

3. Proposed Methodology

The proposed model shown in figure 1 employs an adaptive neural based Machine Learning (ML) approach which can act in unsupervised manner. In addition, it employs the Continual Machine Learning (CML) classifier to ensure that the learning can continue and not fixed as is the case in many neural ML approaches. In fact, the activation functions operate in a continual manner rather being fixated apriori.

Finally, the cloud server focuses on the medical data reporting while the medical sensor part handles such low-level computational details. This is made possible with the advancement in embedded IoT based microprocessor technology with high computational power and speed in addition to high power long duration portable batteries.

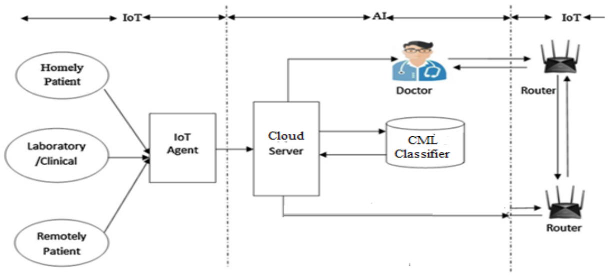

Figure 1: Architecture of the Proposed System Neural Topology

The model is categorized into three modules namely,

1) First IoT stage – This comprise the capturing of patient data from home (locally), from a laboratory/clinic and remotely using an IoT system made up of medical sensor(s) and the IoT controller/communication device. These data are either automatically captured by the medical sensor then fed to IoT smart module (IoT Agent), or it is manually fed to the IoT Agent.
2) AI stage – this stage comprises of the server processors (cloud server), the ML classifiers and the medical expert (doctor in this case) who uses the platform. Cloud-server is a visible server for primarily storing, retrieving and visualizing the results received from fog-server computations. The CML classifier is adapted for this research.
3) Last IoT stage – this stage primarily defines router employed in the transmission of medical sensor data. Typically, this has to be done via a communication gateway provided by relevant internet service providers.

The proposed system is adapted from the works of Kishor & Chakraborty (2021) With the following changes made;

a) The inclusion of a Continual Machine Learning Classifier. This enables the system to continually predict medical events or parameters rather than waiting on a fixed dataset as is the case with the existing approach. In addition, the system uses an improved activation function that does not restrict the magnitudes of the hidden activations but learn sparse set of hidden truths. This is particularly very useful in situations where the pattern can change continually over time such as in the case of the real-time IoMTs applications.
b) The elimination of fog server saves computational layer processing and reduces the potential latency drifts. In this case, all processing will be continually handled in cloud server which guarantees the savings in time.

The proposed system has the following operational details in addition to that already described in the existing system.

4. Experimental Setup

As with every computing application, this research primarily requires the use of software and hardware in-system simulators. The software part is primarily needed to implement the program logic or algorithm and to actualize important but abstract ideas or concepts

The software part includes the user interface models, system simulators and programming language. The hardware part includes the embedded smart controller bed, network controller

Table 1 gives the tentative software-hardware products including the functional purposes as used in the proposed IoMT ML model.

Table 1. Software-Hardware Materials for IoMT ML Modelling

s/n	Software		Hardware	
	Component	Function/Purpose	Component	Function/Purpose
1	Arduino-IDE	Embedded coding	Arduino®	Microprocessor/controller
2	MATLAB	Data Analysis/ ML Model Development/ Programming	Quectel® GSM/Internet Module (Optional)	Communication Module including SMS/Internet functionality
3	SIMULINK	Embedded Systems Simulator	Thermistor	Temperature sensor
4	PHP	Web server computing/ programming	Force sensor	Heart-beat/pulse monitor

a. Heart Beat Detector

Typically, the heartbeat detector is an electronic circuit that includes two primary sensors, a Light Emitting Diode (LED) and a photo transistor or Light Dependent Resistor (LDR). The primary purpose of this circuit is to detect and then amplify the heart beat signal before it is fed into an embedded microprocessor such as the Arduino. The schematic of a typical circuit including other associated components such as resistors and transistors is as shown in Figure 2a while the operational concept is as depicted in Figure 2b.

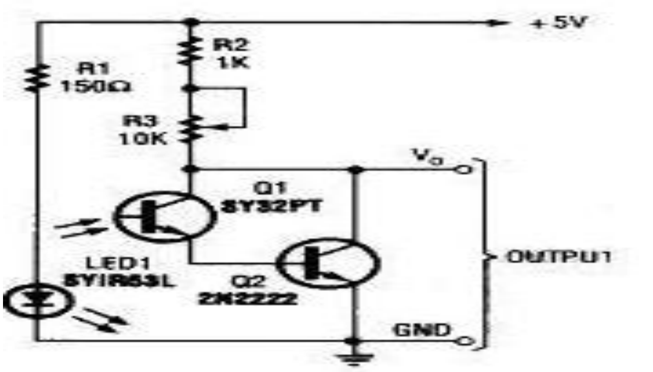

Figure 2a: Heart beat detector: (https://circuitwiring.com)

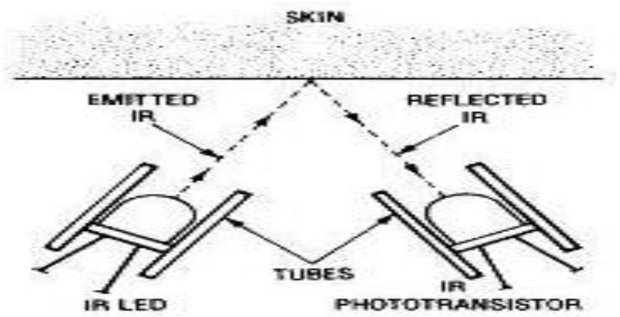

Figure 2b: Heart beat detector: (https://circuitwiring.com)

Q1 and Q2 formed a cascaded amplifier stage made of P-N-P Bipolar Junction Transistors (BJTs). The resistors R2 and R3 form the bias circuit configuration for the first stage amplifier (Q1) while resistor R1 is the limit resistor for the LED (LED1). It is important to emphasize here that the BJT Q1 is a photo transistor which changes in signal state in response to change in LED1 state. Thus, for each heartbeat, the LED1 sensor is triggered which further triggers the BJT Q1 and the signal is amplified by Q2 to generate an output signal at Vo. If a trigger is initiated Vo is high enough to initiate a logical state 1 and this activates an up-counter circuit.

b. Temperature Sensors

These sensors change in resistance in response to variations in ambient or localized heat waves. A popular used temperature sensing device is the LM35 temperature sensor which ships in an integrated circuit. Another important type of temperature sensor is the Negative Temperature Coefficient (NTC) Thermistor that comes as a physical device. As the NTC device is more versatile with wider temperature range, it is frequently used. A typical reduced circuit employing NTC type temperature device monitoring is as shown in of Figure 3.

Figure 3: A circuit configuration for the NTC-Thermistor type temperature sensor (Evans, 2007)

The NTC thermistor acts on the principle of variable resistance with respect to the temperature of a body. In essence, the resistance varies inversely in response to the temperature. The circuitry is described as a variable resistor with an arrow crossing down on a resistor component. The research also includes a dynamic system model Graphical User Interface (GUI) that captures the process of real-time signaling with respect to the detection as well as prediction of the temperature and heart-rate conditions for diagnosing hyperthemic diseases. The IoMT systems model is an interactive Graphical User Interface (GUI) developed in the MATLAB/SIMULINK Interactive and Integrative Development Environment (IIDE) tool as shown in Figure 4.

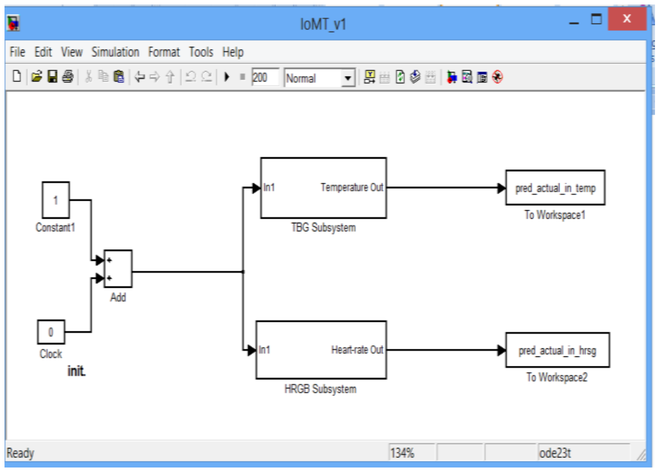

Figure 4: IoMT Systems Dynamic Model GUI

As can be seen, there are two core subsystems - the Temperature Block Generator (TBG) and the Heart Rate Block Generator (HRBG) subsystems as shown in Figures 5 and 6 respectively. These subsystems enable the dynamic capture of both temperature and heart-rate signals which are subsequently fed to their respective embedded MATLAB function blocks to handle the neural and internet communication processing functions.

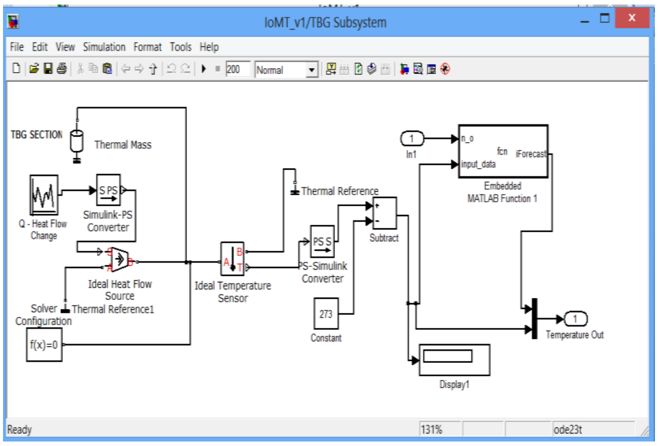

Figure 5: TBG Sub-Systems Model

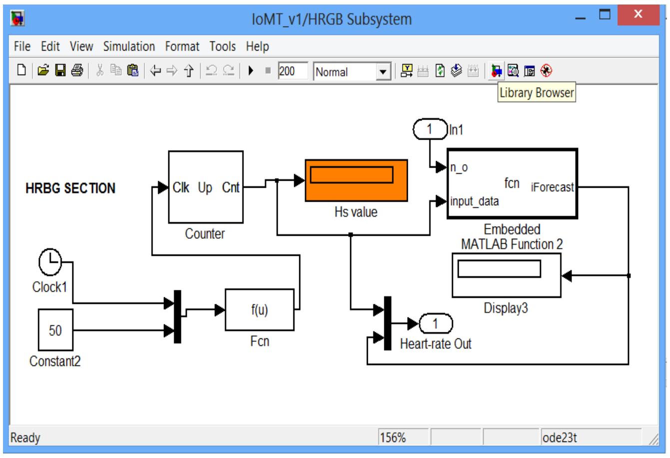

Figure 6: HRBG Sub-Systems Model

In particular, the subsystems temperature signal output of the TBG is based on the MATLAB standard thermal template obtained from the simscape library (MATHWORKS, 2007) while the heart rate signal output is simulated based on typical ranges using a counter model.

5. Results and Discussion

After testing the system, we deployed them in the various areas where the application is supposed to be executed. The stand-alone system needs to be executed on a PC and can be run from MATLAB. An Embedded Coder or Data Acquisition (DAQ) block may be integrated into the system model when real-time embedded solutions are needed.

Simulation results have been tabulated in Table 2 and Table 3 using specifically the TSG and HRSG blocks module sections respectively and based on the specified network parameters of the Continual Neural Machine Learning (CNML) approach.

These results were obtained from the dynamic simulations model and for a maximum input training data of 200 samples. A typical instance of the results captured by the system can be seen from the model interface as shown in Figure 7 while the instance shown in Figures 8 capture the results for temperature and heart-rate signals respectively after the first simulation. The temperature data can be obtained by varying thermal mass body initial temperature parameter while the heart rates by varying a counter switch frequency.

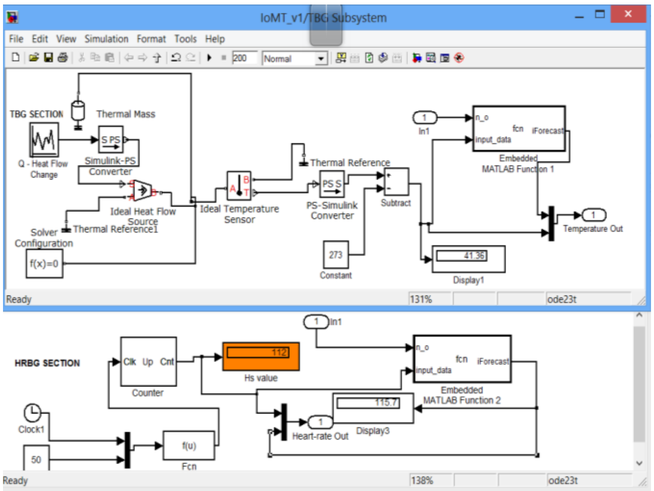

Figure 7: An Instance of Simulation Data as capture from the Model GUI

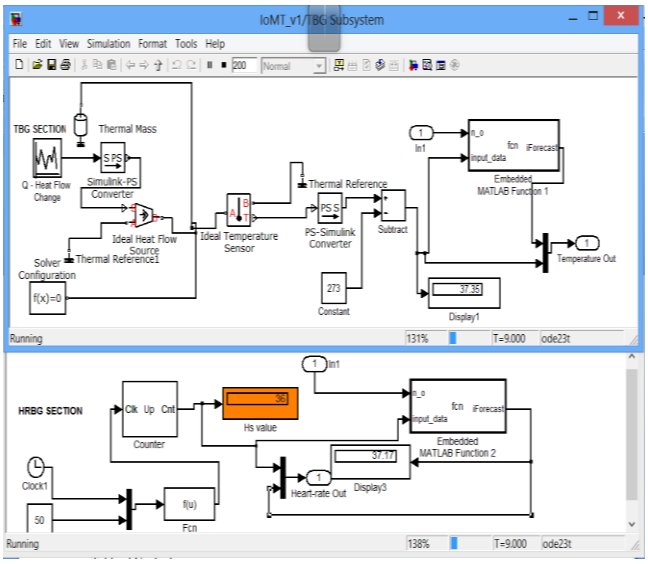

Figure 8: Screenshot of First Simulation Results for temperature and heart-rate from the Model GUI

Table 2: Simulation results of Temperature response (first twenty samples)

s/n	Initial Temperature (°C)	Predicted Optimal Temperature (°C)
1	38.01	37.35
2	37.81	36.63
3	37.81	36.63
4	37.91	36.72
5	38.14	36.94
6	37.94	36.74
7	38.08	36.88
8	38.04	36.85
9	38.26	37.06
10	38.45	37.24
11	38.52	37.31
12	38.46	37.25
13	38.43	37.22
14	38.44	37.23
15	38.51	37.30
16	38.56	37.35
17	38.43	37.23
18	38.41	37.20
19	38.51	37.30
20	38.32	37.12

Table 3: Simulation results of Heart Rate response (first twenty samples)

s/n	Initial Heart rate (°C)	Predicted Optimal Heart rate (°C)
1	31.00	32.00
2	31.00	32.00
3	32.00	33.03
4	33.00	34.07
5	34.00	35.10
6	34.00	35.10
7	34.00	35.10
8	35.00	36.13
9	36.00	37.17
10	36.00	37.17
11	36.00	37.17
12	36.00	37.17
13	37.00	38.20
14	38.00	39.23
15	38.00	39.23
16	39.00	40.27
17	39.00	40.27
18	40.00	41.30
19	40.00	41.30
20	40.00	41.30

The results in Tables 2 and 3 show predicted temperature and heart rate values respectively after several aforementioned parameters changes (parameter tuning) at 30% training data and setting the population of neurons to 50.

The classification metric based on the confusion matrix at this percent training data are as reported in Tables 4 and 5 for temperature and heart rate values respectively. Further results detailing the classification accuracies (CA) for different percentage training data are as shown in Table 6. In Figure 9, the Simulation graph of Predicted Optimal Temperature Values at 30% Training Data is presented while Figure 10 represents the Simulation graph of Predicted Optimal Heart Rate Values at 30% Training Data.

Table 4: Simulation results of Temperature response at 30% Training Data

	P	N
P	TP = 49	FP = 28
N	FN = 0	TN = 123

Table 5: Simulation results of Heart Rate response at 30% Training Data

	P	N
P	TP = 68	FP = 0
N	FN = 4	TN = 128

Table 6: Classification results

Percent Training	CA_{temp} (%)	CA_{heart_rate} (%)
30	86	98
40	86	98
50	86	98
60	86	98
70	86	98
Mean	86	98

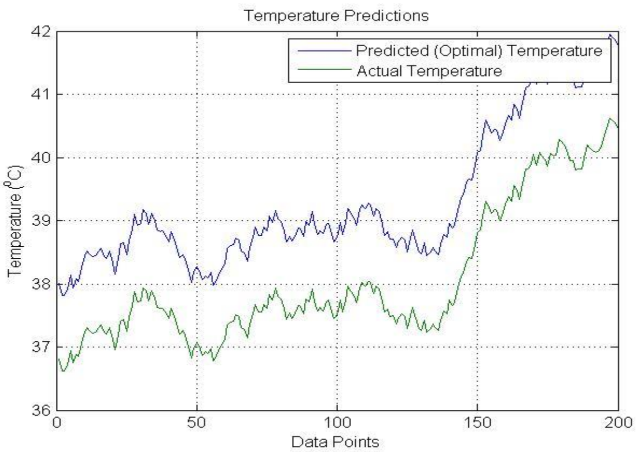

Figure 9: Simulation graph of Predicted Optimal Temperature Values at 30% Training Data

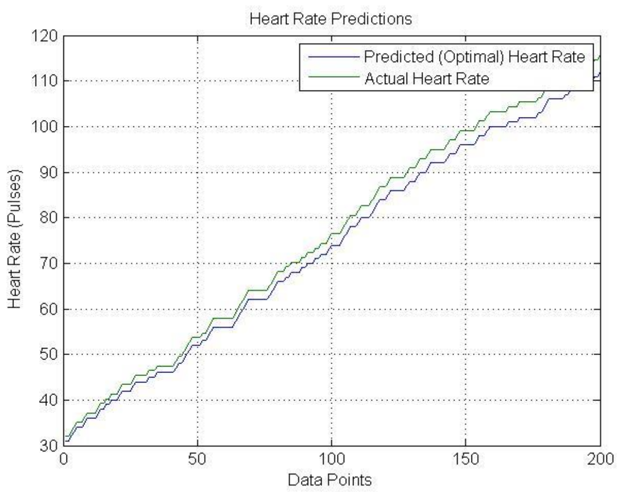

Figure 10: Simulation graph of Predicted Optimal Heart Rate Values at 30% Training Data

a. Comparative Results and Discussions

Results of the proposed Continual Learning Neural Machine ANN (CLNM) IoMT approach for hyperthermia disease prediction is compared with an existing state-of-the-art ANN approach called the Long-Term Short-Term Memory (LSTM). The results based on the classification accuracies are as shown in Tables 7 and 8 for the temperature and heart-rate symptom signals respectively.

Table 7: Comparative Classification results for Temperature Symptoms

Percent Training	CLNM CA_{temp}(%)	LSTM CA_{temp}(%)
30	86	60.0
40	86	65.0
50	86	70.0
60	86	74.0
70	86	74.0
Mean	**86**	**68.6**

Table 8: Comparative Classification results for Heart-Rate Symptoms

Percent Training	CLNM CA_{heart} (%)	LSTM CA $_{heart}$ (%)
30	98	82.0
40	98	82.0
50	98	82.0
60	98	82.0
70	98	84.5
Mean	**98**	82.5

The comparisons between proposed Continual Learning Neural Machine ANN (CLNM) IoMT approach and the existing state-of-the-art ANN approach called the Long-Term Short-Term Memory (LSTM) showed it should be considered as a better IoMT strategy for hyperthermia disease prediction.

As can be clearly seen, the classifications for the temperature symptoms is much better in the proposed CLNM ANN when compared to the LSTM ANN with a mean CA of 86% and 68.6% respectively. In the case of the heart rate, CLNM ANN still gave a better result even though the LSTM ANN CA improved greatly. For this case, the estimated mean CA is 98% and 82.5% respectively.

The implications of the results showed that it will be more efficient to employ the continual learning-based methods in medical diagnosis due to its real-time processing capability. This can be simulating the heart rate and temperature signal outputs and processing using a dynamical processing systems environment while considering typical ranges using the systems model.

6. Conclusion

In this study, we developed a Machine Learning (ML) based Internet of Medical Things (IoMT) approach for predicting the optimal temperatures and heart rates for potential patients that may suffer from such hypethermia related conditions such as Lassa Fever and Thyroid Storms. The system has been implemented in MATLAB-SIMULINK. Specifically, the study has focused on the principle of continual learning and dynamic systems modeling for realization of these heart rate and temperature predictions. The model-based software development approach using the SIMULINK dynamic programming language reduces the time taken to software development and in particular allows for real-time simulations and effective scenario modeling to be performed. It equally offers support for remote patient health monitoring via the Internet of Things (IoT) Framework to enable predicted signals to be communicated remotely to medical experts.

The contributions made in this paper include the development of a dynamic and adaptive ML systems model solution for IoMT applications and the integration of continual learning and sparsity concepts in a neural based ML IoMT solution. These facilitated the results of the simulations obtained in this paper.

7. Future Work

Further research may be needed to enhance the accuracy considering that the LSTM ANN gave some promising results. A typical direction is to enhance the LSTM design to accommodate continual learning.

References

1. Si-Ahmed, A., Al-Garadi, M. A., & Boustia, N. (2023). Survey of Machine Learning based intrusion detection methods for Internet of Medical Things. Applied Soft Computing, 110227.
2. Hadiyanto, H., Sukamto, S., Suryono, S., & Kurnianingsih, K. (2023). A Review on Internet of Medical Things (IoMT): A Case Study for Preeclampsia. In E3S Web of Conferences (Vol. 448, p. 02058). EDP Sciences.
3. Aminizadeh, S., Heidari, A., Toumaj, S., Darbandi, M., Navimipour, N. J., Rezaei, M., ... & Unal, M. (2023). The applications of machine learning techniques in medical data processing based on distributed computing and the Internet of Things. Computer methods and programs in biomedicine, 107745.
4. Ding, Y., Wu, G., Chen, D., Zhang, N., Gong, L., Cao, M., & Qin, Z. (2020). DeepEDN: A deep-learning-based image encryption and decryption network for internet of medical things. IEEE Internet of Things Journal, 8(3), 1504-1518.
5. Hosseinzadeh, M., Ahmed, O. H., Ghafour, M. Y., Safara, F., Hama, H. K., Ali, S., ... & Chiang, H. S. (2021). A multiple multilayer perceptron neural network with an adaptive learning algorithm for thyroid disease diagnosis in the internet of medical things. The Journal of Supercomputing, 77, 3616-3637.
6. Ning, W., Li, S., Wei, D., Guo, L. Z., & Chen, H. (2020). Automatic detection of congestive heart failure based on a hybrid deep learning algorithm in the internet of medical things. IEEE Internet of Things Journal, 8(16), 12550-12558.
7. Raj, R. J. S., Shobana, S. J., Pustokhina, I. V., Pustokhin, D. A., Gupta, D., & Shankar, K. J. I. A. (2020). Optimal feature selection-based medical image

classification using deep learning model in internet of medical things. IEEE Access, 8, 58006-58017.
8. Wang, W., Liu, F., Zhi, X., Zhang, T., & Huang, C. (2020). An integrated deep learning algorithm for detecting lung nodules with low-dose CT and its application in 6G-enabled internet of medical things. IEEE Internet of Things Journal, 8(7), 5274-5284.
9. Xuan, W., & You, G. (2020). Detection and diagnosis of pancreatic tumor using deep learning-based hierarchical convolutional neural network on the internet of medical things platform. Future Generation Computer Systems, 111, 132-142.
10. Kishor, A., & Chakraborty, C. (2022). Artificial intelligence and internet of things-based healthcare 4.0 monitoring system. Wireless personal communications, 127(2), 1615-1631.
11. Su, Y. S., Ding, T. J., & Chen, M. Y. (2021). Deep learning methods in internet of medical things for valvular heart disease screening system. IEEE Internet of Things Journal, 8(23), 16921-16932.
12. El-shafeiy, E., Sallam, K. M., Chakrabortty, R. K., & Abohany, A. A. (2021). A clustering-based Swarm Intelligence optimization technique for the Internet of Medical Things. Expert Systems with Applications, 173, 114648.
13. Vankdothu, R., Hameed, M. A., Ameen, A., & Unnisa, R. (2022). Brain image identification and classification on internet of medical things in healthcare system using support value based deep neural network. Computers and Electrical Engineering, 102, 108196. https://circuitwiring.com