Multibiosensor Data Sampling and Transmission Reduction with Decision-making for Remote Patient Monitoring in IoMT Networks

Ali Kadhum Idrees, Sara Kadhum Idrees, Tara Ali-Yahiya, and Raphaël Couturier

***Abstract*— The rise in chronic diseases and the aging of the population led to an increase in the demand for remote healthcare systems that employ biosensors to monitor people's health status. The increasing need for these automated systems has led to the emergence of the Internet of Medical Things (IoMT) networks. In the IoMT networks, the biosensor devices collect vital signs and transmit them to the gateway for further analysis and fusion. In light of the limited biosensor device resources (power, storage, and computation) and the periodical transmission of a large amount of data, it is necessary to optimize the transmission of data in order to conserve power while maintaining data quality at the gateway. Also, it became important to have a decision-making-based machine learning model at the gateway to evaluate a patient's health and make a quick, accurate decision in case of an emergency. This paper proposes Multibiosensor Data Sampling and Transmission Reduction with Decision-making (MuDaSaTReD) for Remote Patient Monitoring in the IoMTs Networks. The MuDaSaTReD achieves this goal on two levels: biosensors and a fog gateway. It uses an Energy-saving Lightweight Data Transmission (ELiDaT) algorithm to get rid of the repeated data and then adapts the sampling rate of each biosensor using an Adaptive Data Sampling (ADaS) algorithm. The MuDaFuDeC implements the machine learning model at the fog gateway to learn and decide the situation of the patient according to the received data from the biosensors. The performance evaluation shows that the MuDaFuDeC outperforms other approaches in terms of the data reduction percentage and energy consumption. It keeps a good representation of all the scores at the fog gateway and makes automated, fast, and accurate decisions based on the patient's condition.**

***Index Terms*— Internet of Medical Things (IoMTs), Patient Health Monitoring, Machine Learning, Decision Making, Sampling rate adaptation, Emergency Detection.**

I. Introduction

Recent advances in the Internet of Things (IoT) technologies have increased the number of interconnected devices [1]. As the number of devices increases, it will be necessary to enhance network infrastructure in order to enable effective communication or connectivity between geographically dispersed devices [2]. These changes should make it easier to do things in real-time with less delay and better performance. To achieve these objectives successfully, an appropriate communication platform is needed. 5G and beyond is a promising next-generation network that allows a variety of expanded features, including ultra-low latency, high dependability, seamless connectivity, and user mobility [3]. In recent years, the number of diseases and illnesses has increased globally. In addition, wars and human-animal interactions led to the emergence and distribution of new viruses and diseases, including COVID-19. Therefore, it will be very hard for medical staff to do their jobs. The governments had to pay a lot of money to provide different health and application services [4]. The IoMTs have emerged as a result of the rapid development of IoT technology, medical sensing devices, and big data methodologies. The automated remote patient monitoring systems represent one of the important services that will be managed by the ZTN. These systems allow medical staff to remotely access patient data and provide convenient and economical options for patient surveillance anytime, anywhere [5]. These systems are based on biosensor devices, which are either spread on the patient's body or implanted inside the patient's body [6]. Since remote patient monitoring is continuous and in real-time, these biosensors will send large amounts of data to the fog gateway, which causes a loss of power to these biosensors, utilizes more bandwidth, and will slow down the response time in IoMTs network, which can lead to risk to the patient's life. Biosensor battery drain is a critical challenge. Because vital physiological changes can be missed and data fusion can be disturbed if one or more biosensor nodes die, the energy required by biosensor nodes for detecting and transmitting is a challenge. Each piece of health data has health importance. Because essential signals are redundant and temporally correlated, ignoring or eliminating them could lead to wrong decisions. The remote automated patient monitoring system must conserve biosensor

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power so that the patient's monitoring can continue for a longer time. In addition, the fused vital signs of the patients at the fog gateway should be trained with an efficient machine learning method to accelerate the decision-making system to evaluate the patient 's health condition and recommend him or her to the right healthcare professional. This paper introduces the following contributions.

i) We propose Multibiosensor Data Sampling and Transmission Reduction with Decision-making (MuDaSaTReD) for Remote Patient Monitoring in the IoMTs Networks. The MuDaSaTReD is implemented on two levels: biosensors and a fog gateway in the IoMTs network. This will reduce the transmitting data after removing the redundant ones, improve the energy consumption, decrease the bandwidth usage, and introduce fast and accurate decisions according to the patient situation.
ii) The MuDaSaTReD executes an Energy-saving Lightweight Data Transmission (ELiDaT) algorithm based on lightweight prediction model inside the biosensor device to remove the repetitive data and save the power of the biosensors.
iii) An adaptive sampling rate adaptation algorithm is proposed. It changes the rate at which data is sampled inside the biosensor based on the patient situation.
iv) The MuDaSaTReD implements a decision-making algorithm at the fog gateway using machine learning algorithm to decide the situation of the patient after receiving the fused data from the biosensors.
v) To assess the proposed MuDaSaTReD, numerous experiments are conducted using a Python-based custom simulator. PhysioNet datasets MIMIC I and MIMIC II (Multiple Intelligent Monitoring in Intensive Care) that contain actual medical data are used [7]. Each experiment's simulation time is roughly two hours (70 periods). To demonstrate the usefulness of the suggested approach, the performance of the MuDaSaTReD approach is compared to two close related works: dynamic risk, static risk r = 0.4, and static risk r = 0.9 [8] and the Modified LED* [9]. This method was chosen for comparison because it is the most similar to the proposed work among recent related works.

The remaining sections of this article are structured as follows. The related works are described in the next section. Section 3 describes the proposed MuDaSaTReD approach. The performance assessment of the proposed work is presented in Section 4. In Section 5, the conclusion and the forthcoming work are addressed.

II. Related works

Currently, the growing number of patients associated with the appearance of new illnesses makes health evaluation and monitoring a challenging duty for medical personnel and institutions. In fact, the processing of large and heterogeneous data acquired by biomedical sensors and the necessity for patient categorization and diagnosis of diseases, as well as providing automatic remote patient monitoring, have become hurdles for a number of health-based sensing applications based on IoMTs networks. Therefore, several research papers are proposed to deal with these challenges.

In the presented work of [8], the authors present real-time local adaptation of the sampling rate of a sensor node in response to changes in the recorded vital sign and its hazard. They offer a real-time, dynamic evaluation of the hazard of any vital sign, based on the degree of the patient's health status and the harshness of the vital sign itself. They evaluated their suggested method by applying it to actual health datasets.

In [9], the authors present a framework for biosensor data management, from data collection to decision-making. Initially, they suggest an adaptive data gathering strategy at the level of the biosensor node. This method employs an early warning score system to decrease the amount of sent data and predict the sensing frequency in real-time. Then, they describe a coordinator-level data fusion model based on a decision matrix and fuzzy set theory.

The authors of [10] presented a BigReduce as a cloud-based, networked healthcare approach. BigReduce's purpose is to decrease the cost of data processing at the base station based on two schemes used locally by IoT Sensor devices: reduction and decision strategies. In [11], the authors introduce an energy-saving approach for stress assessment and detection. A wireless body sensor network (WBSN) implanted in the patient's body accumulates sensory stress-related digital signals. The skin conductance is initially assessed. Then, if any stress indicators are found, the level of stress is computed using the Fuzzy Inference System based on the following vital signs: respiration rate, heart rate, and systolic blood pressure. The results show that the stress assessment was in line with the many stages of experimentation that the person being looked at has been through. In [12], the authors offer an energy-efficient technique for WBSN data transfer. The suggested technique accepts as input numerous network factors, such as the bandwidth, the available power of the sensing devices, and the number of hops to the coordinator, and chooses the next hop device depending on the weights of each parameter and the data's priority. In [13], The authors present a technique for the recognition and assessment of emergency cases that uses WBSN infrastructure and is capable of distinguishing true emergency cases from other situations by incorporating an risk assessment process from each sensed data. Experimental results have shown that the presented technique is capable of achieving an average accuracy rate of 93%, a detection rate of 87.2 %, and an energy usage profile suitable for WBSN situations. Hospital and medical staff can benefit from sensor-based predictive analytics for real-time patient evaluation and monitoring. The suggested technique consists of three stages emergency recognition, sensing frequency adaptation, and real-time patient scenario forecasting. Through simulations using actual health data, they demonstrate the superiority of their approach to other recent methods [4].

SHORTCOMINGS. Despite demonstrating several methods for data fusion, data collection with reduction, and patient monitoring, the majority of the related works did not take energy-saving in biosensors into account. They presented methods with some limitations, such as high processing complexity, low redundant data reduction, and low data accuracy in biosensor devices. Moreover, most of these approaches were unable to recognize the urgent situation at the level of biosensor nodes. They detect the risk at the sink after getting information from the biosensor nodes. In addition, the related studies [8]–[13] did not take into account either the reduction in response time or the automation of their systems to cope with the concept of IoMTs networks. Furthermore, fast, smart, automated, and accurate decisions are not considered in most of the presented methods. As a result, the proposed solutions are highly specialized, rely on complex methodologies, necessitate extensive computations, and cannot be used in IoMTs networks.

OUR APPROACH. We proposed Multibiosensor Data Sampling and Transmission Reduction with Decision-making (MuDaSaTReD) for Remote Patient Monitoring in the IoMTs Networks. The proposed MuDaSaTReD is implemented at two levels: biosensor devices and a fog gateway. In the former, the MuDaSaTReD applies the data reduction-based local emergency detection algorithm to eliminate redundant data and save energy on the biosensor device. Moreover, the sampling rate of the biosensor will be adjusted based on the situation of the patient. In the latter, the MuDaSaTReD applied the machine learning algorithm at the fog gateway to provide fast decisions related to the status of the patient based on the fused data from the biosensor devices on the body of the patient. The fog gateway transmits the report of the decision to the hospital staff center, which then takes the required action on the patient remotely using the provided decision. With the MuDaSaTReD approach, a remote automated patient monitoring system that can handle the idea of IoMTs networks is made possible.

III. THE MUDASATRED APPROACH

This section introduces the proposed Multibiosensor Data Sampling and Transmission Reduction with Decision-making (MuDaSaTReD) for Remote Patient Monitoring in IoMTs networks in more detail. Figure 1 refers to the MuDaFuDeC approach. This is the architecture of the proposed automated remote patient monitoring system that will be based on the IoMTs networks.

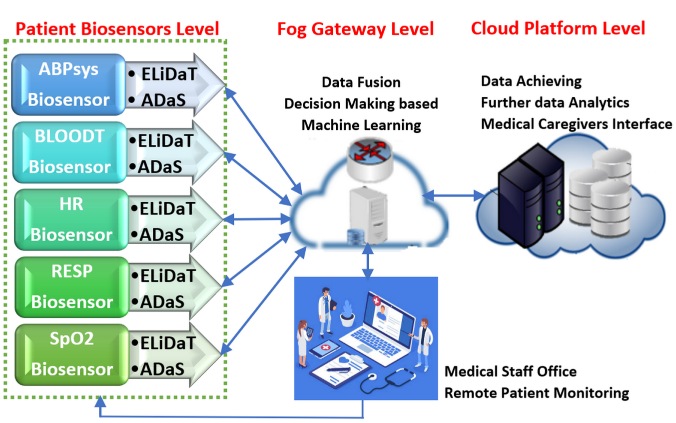


Fig. 1. The MuDaSaTReD approach.

The MuDaSaTReD approach works in real time by gathering the patient's data, removing redundancy at the biosensor node, and updating its sampling rate periodically according to the situation of the patient. Then, the trained machine learning algorithm gives a fast and accurate decision about the status of the patient. It works on two levels in the IoMTs networks: biosensor devices and fog gateway levels. The MuDaSaTReD will apply the Energy-saving Lightweight Data Transmission (ELiDaT) algorithm in each biosensor device to the collected vital signs before sending them to the fog gateway. The ELiDaT executes the naive prediction model, which is very light and simple and works in real-time on the patient's captured vital signs. The ELiDaT aims to reduce the number of transmitted vital signs on the biosensor by removing redundant ones. The ELiDaT is executed for each sensed vital sign to decide whether to send it to the fog gateway if the difference between the predicted score and current score is not equal to ϵ; otherwise, it will remove it. The ELiDaT is designed to work with continuous remote patient monitoring and to deal with the continuously captured data by biosensor devices. Furthermore, the MuDaSaTReD will implement the proposed Adaptive Data Sampling (ADaS) algorithm at each biosensor device at the end of each period. It adapts the sampling rate of the biosensor device based on the patient's situation. It is based on a scoring approach to predicting the illness of the patient. When the patient's situation is bad, the algorithm adjusts the sampling rate to the maximum, while in normal conditions, the sampling rate can be adjusted to the minimum. This will decrease the volume of captured and transmitted vital signs, especially in a normal patient. The MuDaSaTReD approach analyzes, updates, and aggregates the received vital signs from biosensors at the fog gateway at each slot time in the period and then uses the trained machine-learning technique to provide the appropriate decision according to the situation of the patient. Table I shows the symbols description used in this paper.

TABLE I
SYMBOLS DESCRIPTION.

Parameter	Meaning
VS	set of vital signs
SC	set of scores
ϵ	threshold%
vs^B, vs^R, vs^H, vs^S, and vs^A	the vital signs of BLOODT, RESP, HR, SpO2, and ABPsysm, respectively
sc^B, sc^R, sc^H, sc^S, and sc^A	the scores of vs^B, vs^R, vs^H, vs^S, and vs^A, respectively
RE	remaining energy
samMax	maximum sampling rate
samMin	minimum sampling rate
Wgt_j	weights of scores (j= 0, 1, 2, and 3)
r0Min, r0Max, r1Min, r1Max, r2Min, r2Max, r2Min, r2Max	score ranges of weights
$\nu 1$, $\nu 2$	application-specific parameters
samRate	the new sampling rate
ξ^k	the updated score for the biosensor k
Λ	the aggregated score
I_e	initial energy
ρ	total number of vital signs in the period

A. Biosensor level

In this section, we will explain the two main algorithms that will be applied by the MuDaSaTReD approach. It can be seen from the Figure 1 that there are five bisensor devices that will be deployed on the patient's body to collect its vital signs continuously and then transmit them to the fog gateway. These biosensor devices are the oxygen saturation (SpO2), heart (HR), systolic blood pressure (ABPsys), respiration (RESP), and blood temperature(BLOODT). Each biosensor device is in charge of collecting data and regularly forwarding it to the fog gateway. Since these biosensors continue to transmit important data for patient monitoring to the fog gateway, this will put a big burden on the IoMTs network. Therefore, it is necessary to propose an energy-efficient lightweight data transmission algorithm to carry out the mission of transmitting captured data at the biosensor devices, removing the data redundancy and saving energy while maintaining the quality of data reflecting variation in the patient's condition, especially in emergency situations at the fog gateway. The hospital's health team uses a physiological scoring system called the National Early Warning Score (NEWS) to assess patients' conditions and give relevant treatment attention and care for those who are at high risk. There are six physiological measures in NEWS: awareness level, systolic blood pressure, temperature, respiration rate, pulse rate, and oxygen saturation. NEWS reflects a method for scoring. NEWS' key characteristic is its ease of use in estimating the patient's risk level by utilising appropriate ratings for each type of biosensor. The NEWS can identify the patient's state by rating the detected values of various biosensors [16]. Figure 2 refers to the NEWS Chart.

National Early Warning Score (NEWS)

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Consciousness Level				A			V, P, or U

NHS Training for Innovation

Fig. 2. The NEWS Chart.

The six physiological measurements' values are calculated according to the National Early Warning Score (NEWS) that is used by the National Health Service (NHS) in the UK. The Royal College of Physicians recommends it for adult clinical examinations. UK hospitals utilize NEWS to assess emergency cases. NEWS is a weight-based chart that assigns scores to physiological signals obtained during routine examinations (whether in-person or in hospitals). In this article, the scoring method is based on five physiological parameters (vital signs) that represent the base of the scoring system: BLOODT, RESP, HR, SpO2, and ABPsys. Each vital sign is given a score of 0 if it is in the normal range. It is scored 1, 2, or 3 based on its divergence from the normal range, with 3 being the most critical. Suppose that the vital signs of BLOODT, RESP, HR, SpO2, and ABPsys are vs^B, vs^R, vs^H, vs^S, and vs^A, respectively. Hence, the score for each of these vital signs can be calculated using the NEWS chart (see Figure 2) as follows.

$$sc^B = \begin{cases} 3 & if \quad vs^B \leqslant 35.0 \\ 2 & if \quad vs^B \geq 39.1 \\ 1 & if \quad vs^B \in (35.1 - 36.0) \; or \; vs^B \in (38.1 - 39.0) \\ 0 & if \quad vs^B \in (36.1 - 38.0) \end{cases} \tag{1}$$

$$sc^R = \begin{cases} 3 & if \quad vs^R \leq 8 \; or \; vs^R \geq 25 \\ 2 & if \quad vs^R \in (21 - 24) \\ 1 & if \quad vs^R \in (9 - 11) \\ 0 & if \quad vs^R \in (12 - 20) \end{cases} \tag{2}$$

$$sc^H = \begin{cases} 3 & if \quad vs^H \leq 40 \; or \; vs^H \geq 131 \\ 2 & if \quad vs^H \in (111 - 130) \\ 1 & if \quad vs^H \in (41 - 50) \; or \; vs^H \in (91 - 110) \\ 0 & if \quad vs^H \in (51 - 90) \end{cases} \tag{3}$$

$$sc^S = \begin{cases} 3 & if \quad vs^S \leq 91 \\ 2 & if \quad vs^S \in (92 - 93) \\ 1 & if \quad vs^S \in (94 - 95) \\ 0 & if \quad vs^S \geqslant 96 \end{cases} \tag{4}$$

$$sc^A = \begin{cases} 3 & if \quad vs^A \leq 90 \; or \; vs^A \geq 220 \\ 2 & if \quad vs^A \in (91 - 100) \\ 1 & if \quad vs^A \in (101 - 110) \\ 0 & if \quad vs^A \in (111 - 219) \end{cases} \tag{5}$$

1) ELiDaT algorithm: Each biosensor device will apply the following Energy-saving Lightweight Data Transmission (ELiDaT) algorithm on the collected data before sending them to fog gateway. Suppose the set of vital signs of the patient during one period k is VS = $\{vs_1, vs_2, ..., vs_\rho\}$ and the corresponding score values set after applying the NEWS is SC = $\{sc_1, sc_2, ..., sc_\rho\}$. Each biosensor device initialized with 4000 units of energy, therefore the initial value of RE will be 4000 units.. Algorithm 1 refers to the ELiDaT algorithm.

The ELiDaT algorithm is implemented in each biosensor and operates in real-time on the patient's vital signs. The main goal of this algorithm is to reduce the number of transmitted data on the biosensor by removing the redundant ones. In Algorithm 1, step 1 refers to the condition of executing the algorithm when the remaining energy of the biosensor is greater than 0. Steps 1–2 are responsible for sending the first vital sign and updating the remaining energy in the biosensor. In step 4, the function NEWS() returns the score value of the vital sign vs_1 using one of the equations (1, 2, ...,5) that are based on the NEWS chart and according to the type of the biosensor. Steps 5-13 focus on the next set of vital signs. The function NEWS() is used to compute the score value of the vital sign vs_i. Since these medical biosensors have very limited resources, it would be better to use lightweight and energy-efficient techniques in order to get rid of redundant

Algorithm 1: *ELiDaT Algorithm*

Require: vs_i: *vital sign i*
Ensure: vs_i *and* sc_i *i⩾1*
1: **if** $RE > 0$ **then**
2: Transmit first vital sign vs_1 ;
3: Update RE of Biosensor device ;
4: PreviousScore $\leftarrow NEWS(vs_1)$;
5: **for each** sensed vital sign $vs_i \in VS$ and i$>$ 1 **do**
6: $sc_i \leftarrow$ NEWS(vs_i)
7: Predicted $\leftarrow$ Naive model($PreviousScore$);
8: **if** $Predicted$ - $sc_i \neq \epsilon$ **then**
9: Send vs_i to fog gateway ;
10: Update RE of Biosensor device ;
11: PreviousScore $\leftarrow sc_i$;
12: **end if**
13: **end for**
14: **end if**
15: return sc_i;

data, preserve their medical value, and reduce energy costs. The ELiDaT algorithm employs a very light prediction model to predict the next value and then decides whether to send it or not. It employed the Naive model to forecast the future vital signs [17]. The following prediction will be made if the score of given vital signs add up to sc_t:

$$sc_{t+1} \leftarrow sc_t \tag{6}$$

This means that the forecast for future score of vital signs is sc_t, where sc_t is the most recently score of observed vital sign value. In step 8, the Naive Prediction Model is used to predict the score of the next vital sign of the patient using Eq.6. The difference between the predicted scores and the current ones is calculated next, and if this difference does not equal ϵ, the vital sign is transmitted to the fog gateway and the biosensor's remaining energy is updated. The parameter ϵ is set to 0. It is given a zero value to avoid sending the vital sign with the same score as the previous vital sign.

2) Adaptive Data Sampling (ADaS) algorithm: This part explains the proposed adaptive sampling algorithm that is executed at each biosensor device at the end of each period. Algorithm 2 refrs to the adaptive sampling algorithm implemented on the biosensor device.

The novelty of the algorithm 2 lies in proposing a new sampling approach that adapts the sampling rate of the biosensor device based on the patient's situation. Most of the sampling algorithms depend on measures of similarity between the time series data entered into them, and based on the similarity value, the sampling rate decreases or increases. In the proposed algorithm 2, it adjusts the sampling rate based on the patient's condition. When the patient's situation is bad, the algorithm adjusts the sampling rate to the maximum, while in normal conditions, the sampling rate can be adjusted to the minimum. The sampling algorithm 2 depends on adjusting the sampling rate based on the scoring approach to forecast the illness of the patient, which was calculated as shown in the algorithm 2.

Algorithm 2: *Adaptive sampling algorithm*

Require: VS: *set of vital sign values, samMax: maximum sampling rate, samMin: minimum sampling rate,* Wgt_j: *weights of scores (j= 0, 1, 2, and 3),(r0Min, r0Max, r1Min, r1Max, r2Min, r2Max, r2Min, r2Max): score ranges of weights, (ν1,ν2): application-specific parameters, ρ: total number of vital signs in the period*
Ensure: $samRate$: *the new sampling rate*
for each period p **do**
Set δ_j to 0, $0 \geq$ j ≤ 3. ;
for $i \leftarrow 1$ to ρ **do**
$scoreList_i \leftarrow$ ELiDaT Algorithm(vs_i) ;
for $j \leftarrow 0$ to 3 **do**
if $scoreList_i =$ j **then**
$\delta_j \leftarrow \delta_j$ +1 ;
end if
end for
end for
for $j \leftarrow 0$ to 3 **do**
$\alpha_j \leftarrow \delta_j * Wgt_j$;
end for
samR $\leftarrow \sum_{j=0}^{3} \alpha_j$;
end for
if samR $\leq$ r0Max and samR $\geq$ r0Min **then**
samRate $\leftarrow$ samMin;
else if samR $\leq$ r1Max and samR $\geq$ r1Min **then**
samRate $\leftarrow$ samMin + ν1;
else if samR $\leq$ r2Max and samR $\geq$ r2Min **then**
samRate $\leftarrow$ samMin +ν2;
else if samR $\leq$ r3Max and samR $\geq$ r3Min **then**
samRate $\leftarrow$ samMax;
end if
return $samRate$;

This scoring scheme idea was inspired from the research [18] with some modifications.

The score weights Wgt_0, Wgt_1, Wgt_2, and Wgt_3 in Algorithm 2 are defined as follows.

$$Wgt_0 \leftarrow 1 \tag{7}$$

$$Wgt_1 \leftarrow 2 \tag{8}$$

$$Wgt_2 \leftarrow samMax + 2 \tag{9}$$

$$Wgt_3 \leftarrow samMax^2 + samMax + 2 \tag{10}$$

The weight ranges of scores r0Min, r0Max, r1Min, r1Max, r2Min, r2Max, r3Min, and r3Max are defined as follows.

$$r0Min \leftarrow samMin \tag{11}$$

$$r0Max \leftarrow samMax \tag{12}$$

$$r1Min \leftarrow samMax + 1 \tag{13}$$

$$r1Max \leftarrow 2 * samMax \tag{14}$$

$$r2Min \leftarrow 2 * samMax + 1 \tag{15}$$

$$r2Max \leftarrow samMax^2 + 2 * samMax \tag{16}$$

$$r3Min \leftarrow samMax^2 + 2 * samMax + 1 \tag{17}$$

$$r3Max \leftarrow samMax^3 + samMax^2 + 2 * samMax \tag{18}$$

In this algorithm, the parameters samMin and samMax are set to 30 and 70, respectively. The application-specific parameters $\nu 1$ and $\nu 2$ can be set according to the application requirements, where in this paper they are set to 10 and 20 respectively. This algorithm is executed at the end of each period to adapt the sampling rate of the biosensor device for the next period. Steps 2–10 calculate the number of occurrences of scores 0, 1, 2, and 3 in the $scoreList$ and save it in δ. Then, multiplying each value in δ with the weight assigned to it and saving it in α is done in steps 11–13. Step 14 computes the sum of α and saves it in samR. In steps 16–24, the resulted samR value is checked within the weight ranges of scores to assign the appropriate sampling rate according to the status of the patient. The output of this algorithm at the end of each period is a new sampling rate $samRate$ that will be used by the biosensor to sense the data for the next period.

3) Computational complexity: The time complexity for ELiDaT algorithm 1 is $\theta(1)$, while the space requirement is $\theta(1)$. Algorithm 2 requires $\theta(\rho)$ of time complexity and it requires $\theta(\rho)$ of storage requirement.

B. Fog gateway level

The MuDaSaTReD approach analyzes, updates, and aggregates the received data from biosensors at the fog gateway and then uses the machine learning technique to provide the appropriate decision according to the status of the patient. For each slot time in the period, the received vital signs at the fog gateway from different biosensor devices will be used to calculate the updated scores for every biosensor. Each vital sign converted to its score using NEWS. Hence, the updated score ξ^k for the biosensor k is computed as follows.

$$\xi_t^k \leftarrow \frac{\xi_{t-1}^k + \xi_t^k}{2} \tag{19}$$

The medical experts use the biosensors' aggregated score Λ to assess the condition of the observed patient. Hence, the aggregated score Λ is the summation of update scores of N biosensors and can be computed as follows.

$$\Lambda \leftarrow \sum_{k=1}^{N} \xi^k \tag{20}$$

Figure 3 depicts the clinical response chart. This chart displays five categories of patient risk levels, ranging from normal to urgent. The aggregated score Λ can be used to check if the patient falls into any of the five categories.

The decision about the situation of the patient can be taken by using the trained machine learning model. The machine learning model is trained using an almost 9-hour-long dataset for five biosensor nodes implanted on the patient's body. This dataset includes six features: ξ^1,...,ξ^5 and Λ. The labeled class of each of input (features) is represented as the decision's number according to the Table II. This table is derived from the table in Figure 3.

NEW score	Frequency of monitoring	Clinical response
0	Minimum 12 hourly	Continue routine NEWS monitoring
Total 1–4	Minimum 4–6 hourly	• Inform registered nurse, who must assess the patient • Registered nurse decides whether increased frequency of monitoring and/or escalation of care is required
3 in single parameter	Minimum 1 hourly	• Registered nurse to inform medical team caring for the patient, who will review and decide whether escalation of care is necessary
Total 5 or more Urgent response threshold	Minimum 1 hourly	• Registered nurse to immediately inform the medical team caring for the patient • Registered nurse to request urgent assessment by a clinician or team with core competencies in the care of acutely ill patients • Provide clinical care in an environment with monitoring facilities
Total 7 or more Emergency response threshold	Continuous monitoring of vital signs	• Registered nurse to immediately inform the medical team caring for the patient – this should be at least at specialist registrar level • Emergency assessment by a team with critical care competencies, including practitioner(s) with advanced airway management skills • Consider transfer of care to a level 2 or 3 clinical care facility, i.e., higher-dependency unit or ICU • Clinical care in an environment with monitoring facilities

Fig. 3. The clinical response chart.

TABLE II
THE DECISION'S NUMBER, CLINICAL RISK AND Λ

Decision's Number	Clinical Risk	Λ
1	Low	< 1
2	Low–medium	1- 4.99
3	medium	3 in one biosensor node
4	Medium-High	5 - 6.99
5	High	≥ 7

In this paper, we employed six machine learning methods such as Support Vector Machine (SVM), Naïve Bayes, Gradient Boosting, Random Forest, KNN, and Logistic Regression. The proposed machine learning-based model is evaluated by K-Fold cross-validation using real data of a patient dataset. We found from the results that the Gradient Boosting method produces better results compared with other methods. They are implemented by Python programming language using the "sklearn" library of machine learning. Hence, after training this model, it can be used later to predict the required decision according to the status of the patient and send it to the medical center office.

IV. Performance Evaluation

This section outlines the performance assessment of the proposed MuDaSaTReD approach. The simulation results can be obtained by a custom simulator built on the Python programming language. Real medical data from the PhysioNet datasets MIMIC I and MIMIC II (Multiple Intelligent Monitoring in Intensive Care) are utilized during the simulation. Each experiment's simulation time is roughly two hours (70 periods) and period = 100 seconds (i.e, 1 reading/ 1.43 second).

The parameters samMin and samMax are set to 30% and 70% respectively. The simulation results of MuDaFuDeC are conducted based on two records of patients: Patient 1 with the record s01840-3454-10-24-18-46n of MIMIC II dataset and patient 2 with the record 276n of MIMIC dataset. We used these records for the purpose of comparison with the related paper in [8]. The three different cases in [8] are respectively called as Dynamic Risk, Static Risk r = 0.4, and Static Risk r = 0.9.

A. Sampling rate adaptation

In this experiment, we explore the adaptation of the sampling rate for different biosensor devices deployed on patients 1 and 2 over 70 periods are applied. Figure 4 depicts the sampling rate adaptation of the HR biosensors for patients 1 and 2 for the proposed MuDaSaTReD approach compared to the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9. The three different cases in [8] employ the ANOVA model and the behavior function to adapt the sampling rate.

It can be observed from the results in Figure 4 that the overall number of captured data in Figure 4 (a) is lower than the total number of data in Figure 4 (b), making it easy to see the differences in the sampling rate adaptation between the two patients. Therefore, patient 1 has a better condition than patient 2 regarding HR biosensor throughout the 70 periods. The increase and decrease in the rate of sampling do not affect the quality of data at the fog gateway in the case of the local risk in the HR biosensor.

Comparing the two static scenarios for both patients (see Figures 4 (e), (f), (g), and (h)), the scenario with r = 0.9 provides larger sampling rates than the scenario with r = 0.4 during the adaptation of sampling rate. This is because the BV function definition leads to larger sample rates for the higher risk level values. For Patient 1, the number of sampled measurements was lower in the dynamic risk scenario than in the two static scenarios. It can be seen that the sampling rate adaptation in the proposed MuDaSaTReD approach results in lower sampling rates than the static cases and dynamic risk. This is due to the effectiveness of using the scoring scheme with the sampling algorithm of the MuDaSaTReD approach, which takes the situation of the patient into account and results in lower sampling rates for lower risk levels. In the case of patient 2, one can see that the dynamic risk gives an amount of samples higher than the static case with r = 0.4 and lower than the static case with r = 0.9. The proposed MuDaSaTReD approach provides sampling rates higher than the static case with r = 0.4 and the dynamic risk, while introducing sampling rates lower than the static case with r = 0.9. This demonstrates that our proposed MuDaSaTReD approach increases the sampling rates during the 70 periods due to the patient's worst situation. Hence, the proposed MuDaSaTReD approach outperforms the three different cases in [8] in terms of sampling rate adaptation. This is because it uses a good patient-weighted scoring system that reflects the patient's situation and changes the sampling rate based on the patient's situation.

B. Remaining Energy

Energy conservation is critical in devices with limited resources, such as biosensors. This section explores the impact of the proposed MuDaSaTReD approach on the energy of the biosensor device. Figure 5 shows the remaining energy comparison between the MuDaSaTReD approach and the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9 for both patient 1 and patient 2. The experiment is based on the same energy consumption model that is used in [8]. Hence, the sending, sensing, and computation consume 0.4, 0.04, and 0.16 units, respectively. Each vital sign that is picked up costs 0.6 units of energy to send to the fog gateway. The results in Figure 5 show that the proposed MuDaSaTReD approach saves more energy for the biosensor than the three different cases in [8] and for both patients 1 and 2. The initial energy of the biosensor, I_e, is set to 4000 units. In order to compute the percentage of consumed energy for the proposed MuDaSaTReD approach and the three different cases in [8], the following formula is used.

$$EnergyConsumptionPercentage \leftarrow \frac{I_e - RE}{I_e} * 100 \quad (21)$$

Where RE is the remaining energy of the biosensor at the end of the 70^{th} period. In Figure 5 (a), the MuDaSaTReD approach consumes 12.65% of the energy of the HR biosensor device, whereas the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9 consume 56.16%, 59%, and 62.16% of the energy of the HR biosensor, respectively. In Figure 5 (b), the proposed MuDaSaTReD approach consumes 22.83%, while the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9 consume 52.78%, 49.78%, and 56.78%, respectively. The proposed MuDaSaTReD approach outperforms the three different cases in [8] because it employs an energy-efficient lightweight data transmission algorithm in conjunction with an efficient sampling algorithm, which reduces the patient's sensed and transmitted data, particularly in normal situations.

C. Data Reduction

This experiment examines the rate of data reduction achieved by the proposed MuDaSaTReD approach by employing the lightweight data transmission reduction and adaptive sampling algorithms at the level of biosensor devices and throughout 70 periods for patient1. Figure 6 refers to the Data reduction percentage for the proposed MuDaSaTReD approach and the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9 for patient 1.

It can be observed from the results in Figure 6 that the proposed MuDaSaTReD approach increases the percentage of data reduction from 93.3% up to 99%, whereas the three different cases in [8]: dynamic risk, static risk r = 0.4, and static risk r = 0.9. introduced a data reduction percentage of 38 % up to 65%, 37 % up to 65%, and 34 % up to 65%, respectively. The proposed MuDaSaTReD approach outperforms the three different scenarios in [8] because it combines an energy-efficient lightweight data transmission algorithm with an efficient sampling strategy, which decreases

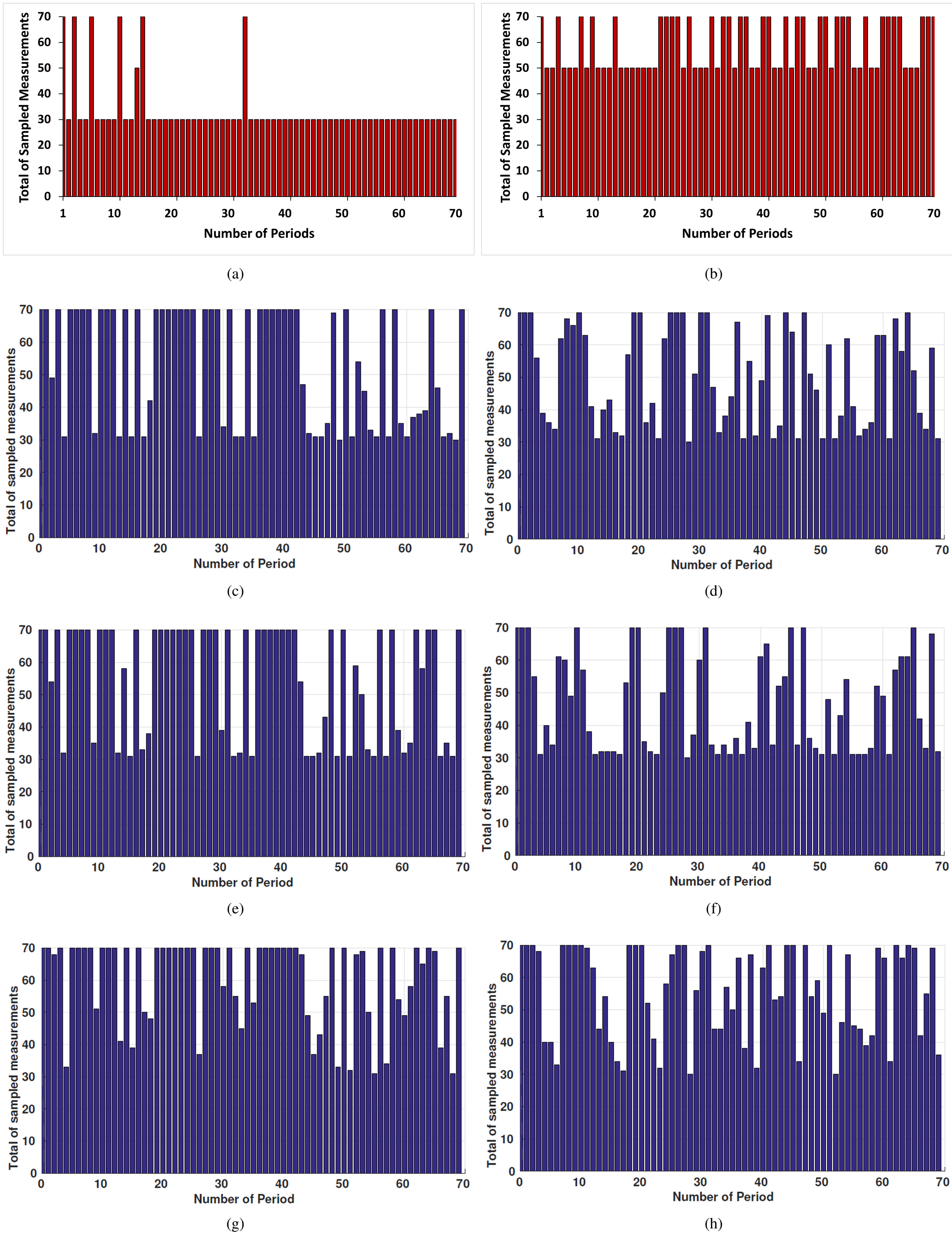
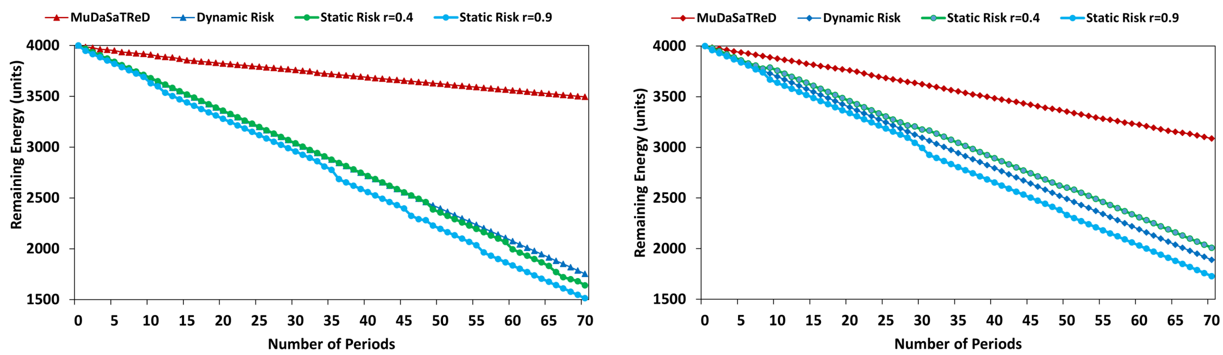


Fig. 4. Sampling rate adaptation. (a) Patient1: HR biosensor in MuDaSaTReD (b) Patient2: HR biosensor in MuDaSaTReD (c) Patient1: HR biosensor in Dynamic Risk (d) Patient2: HR biosensor in Dynamic Risk (e) Patient1: HR biosensor in Static Risk r = 0.4 (f) Patient2: HR biosensor in Static Risk r = 0.4 (g) Patient1: HR biosensor in Static Risk r = 0.9 (h) Patient2: HR biosensor in Static Risk r = 0.9.



(a) (b)

Fig. 5. Remaining Energy (a) Patient 1 (b) Patient 2.

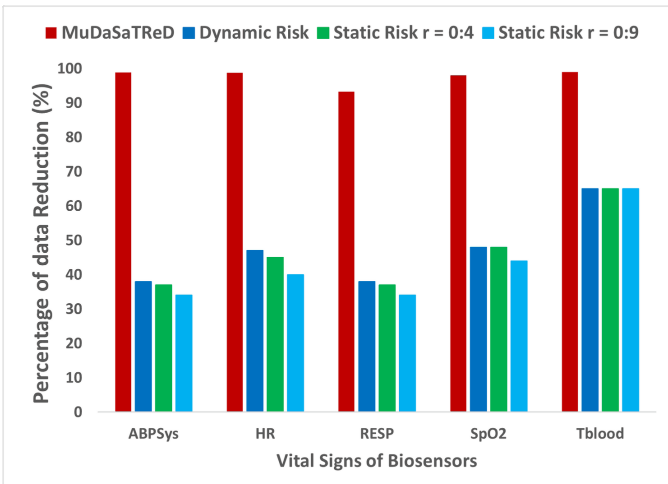


Fig. 6. Data Reduction for patient 1.

the patient's sensed and transmitted data, especially when the patients are in a normal situation. This will have a positive impact on the energy consumption of the biosensors.

D. Integrity of Data

This experiment explores the effect of the MuDaSaTReD method on data quality across 70 periods. Figure 7 depicts the data integrity for patients 1 and 2 separately. The Figures describe the distribution of the vital sign scores of the original and sensed data recorded by MuDaSaTReD for the biosensor devices of patients 1 and 2.

It can be seen from Figure 7 that the MuDaSaTReD provides data integrity at the fog gateway, preventing scores from being lost after applying the lightweight transmision reduction and adaptive sampling algorithms at the biosensor devices level. In spite of MuDaSaTReD is highly reduce the HR biosensor node data to 99% of the original (see Figure 6), but it preserves similar score distributions.

E. Aggregated scores with decision making

This study illustrates the aggregated score Λ and decisions made by the proposed MuDaSaTReD through employing the

TABLE III

PERFORMANCE EVALUATION METRICS OF EMPLOYED MACHINE LEARNING MODELS.

Machine learning model	Accuracy	Precision score	Recall score	F1 score macro	Hamming_loss
SVM	0.990415335	0.989241712	0.962855272	0.975293524	0.009584665
Gradient Boosting	0.99893617	0.999038462	0.985714286	0.992110665	0.00106383
Random Forest	0.99787234	0.995995091	0.919047619	0.950572718	0.00212766
Naïve Byse	0.774468085	0.767526983	0.833538599	0.778206503	0.225531915
KNN	0.980851064	0.77026948	0.767699707	0.768902309	0.019148936
Logistic Regression	0.984042553	0.784199546	0.768753988	0.776153447	0.015957447

machine learning model at the fog gateway across 70 periods. Figures 8 (a) and (b) display the total scores for patients 1 and 2 accordingly. The aggregated score is calculated by adding the scores of all biosensor nodes that have been updated. The greater the risk of the patient's situation, the greater the value of the summed aggregated score.

Decision-making for patients 1 and 2 is presented in Figures 8 (a) and (b), respectively. Each time received data from the biosensor devices at the fog gateway, the proposed MuDaSaTReD fuses, updates, and aggregates these data and passes them to the trained machine learning model to provide the decision about the status of the patient and then send the decision notification to the medical staff office. First, the machine learning model should be trained on the old received data from the biosensors where the decisions were taken based on the aggregated score and the chart of clinical response (see Figure3). The machine learning model is trained based on six features (updated scores and aggregated scoreΛ) and the label of the decision class is determined by matching each calculated aggregated score to the values in Table II that are inspired by the chart in Figure 3. As shown in this table, the decisions are labeled from 1 to 5 according to the level of patient risk. The machine learning model was trained on the patient data for nine hours. After that, the trained model will be used at the fog gateway to automatically send the decisions to the medical center office across the IoMTs Network.

We employed several machine learning models to make the decisions at the fog gateway and to provide these automated, fast, and accurate decisions remotely and continuously to the medical center office across the IoMTs network while monitoring the patient. Table III shows the performance evaluation metrics of employed machine learning models. The results show that the Gradient Boosting machine learning model

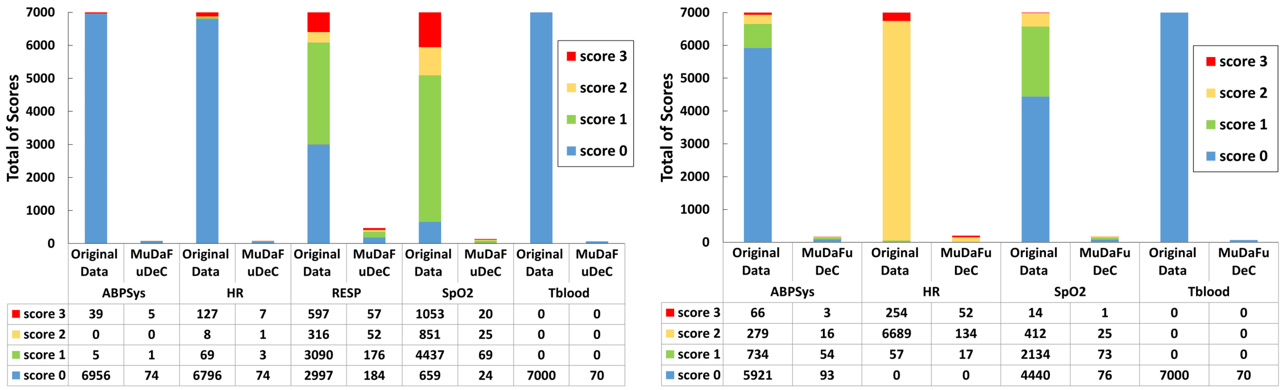


Fig. 7. Integrity of Data (a) Patient 1 (b) Patient 2.

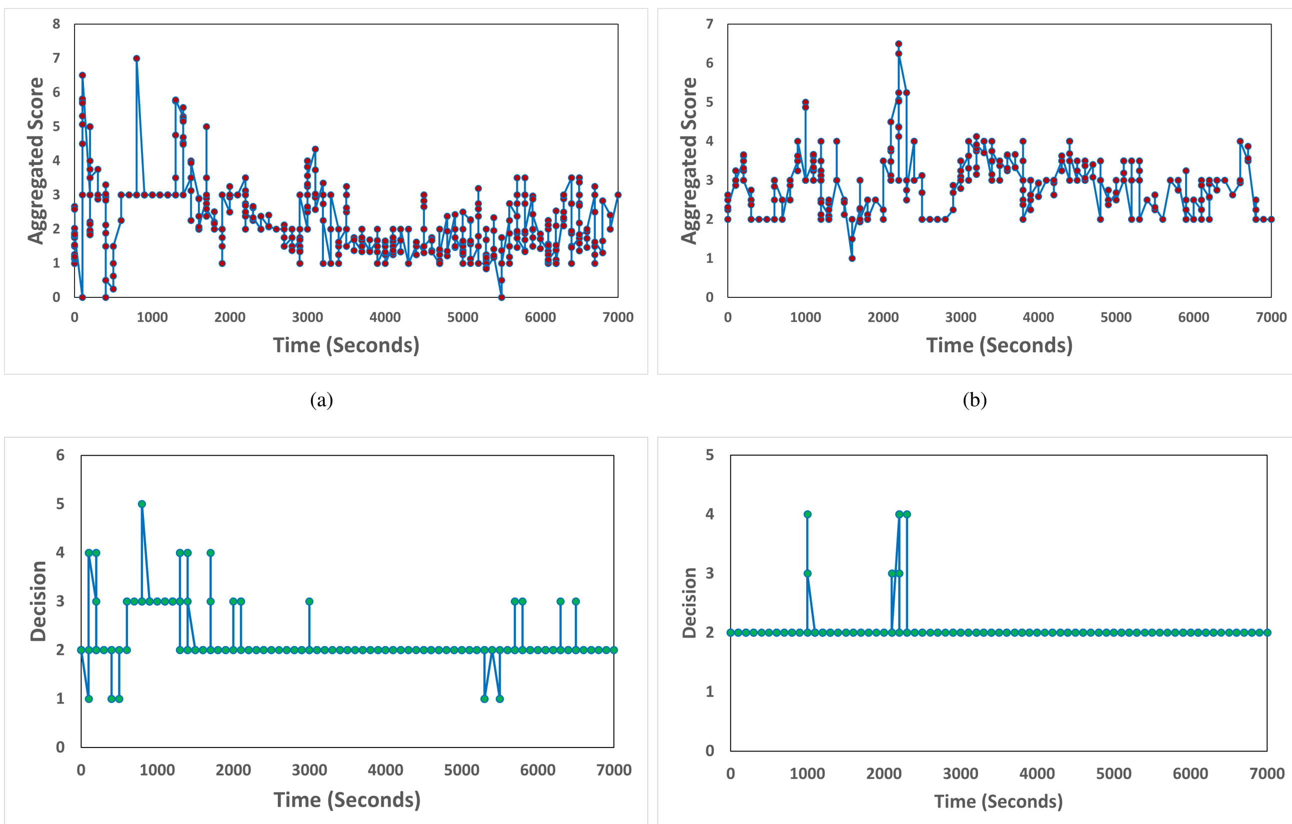


Fig. 8. (a) The aggregated score Λ for patient1 (b)The aggregated score Λ for patient2 (c) Decision making for patient1 (d)Decision making for patient2

introduced better results compared with other models. Hence, the proposed MuDaSaTReD approach can use the gradient boosting trained model as a decision maker at the fog gateway.

V. Further Results

In this section, we present more results to show the efficiency of the proposed MuDaSaTReD approach in comparison with another related work named "Modified LED*" [9]. Real medical data from the PhysioNet MIMIC dataset are used during the simulation. The simulation time is roughly two hours (70 periods), and a period is 100 seconds. The parameters samMin and samMax are set to 10% and 50% respectively. All simulation experiments are conducted based on the patient record (267n) using the respiration biosensor node. We used this record for the purpose of comparison with the related paper in [9]. Figure 9 refers to the Sampling rate adaptation and data reduction.

Using the same periods, the authors compare the findings for a normal patient (risk = 0.4) and a critical patient (risk = 0.49) in Figures 9 (c) and (d). Nevertheless, implementing various

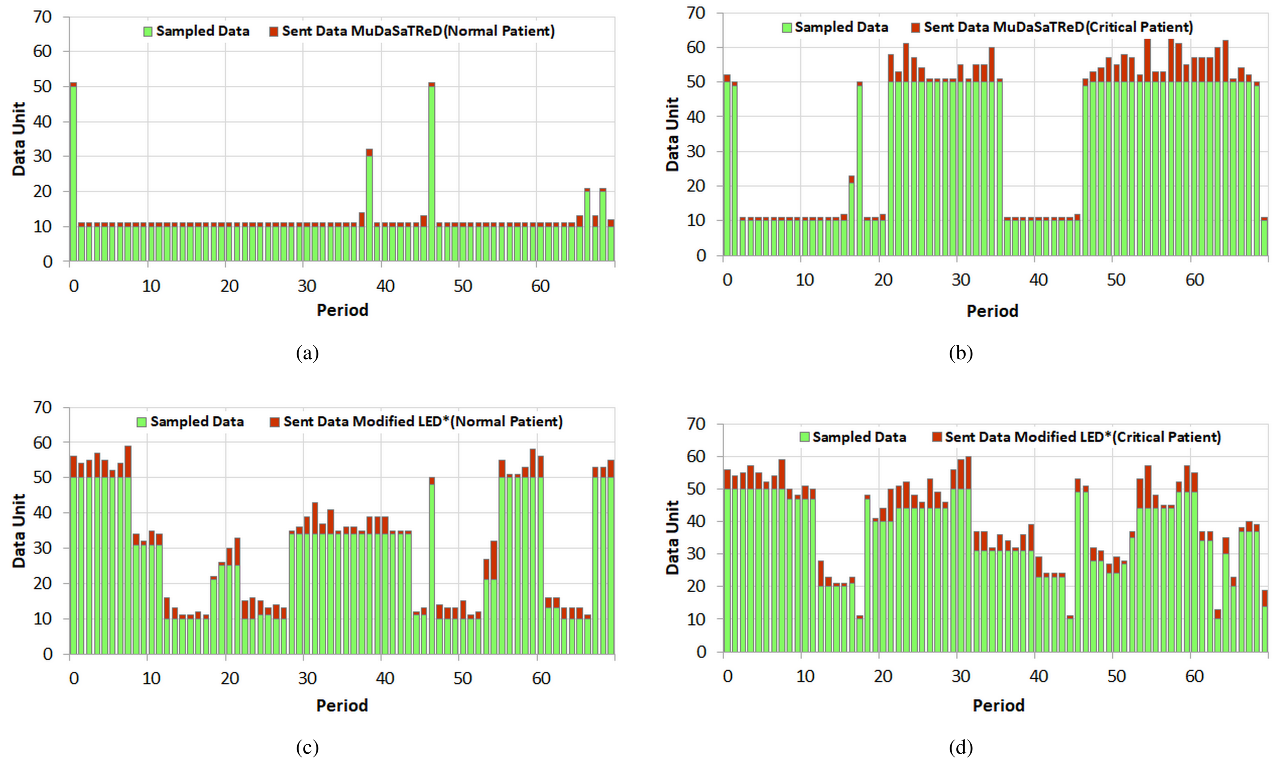


Fig. 9. Sampling rate adaptation and data reduction (a) MuDaSaTReD (Normal Patient) (b) MuDaSaTReD (Critical Patient) (c) Modified LED* (Normal Patient) (d) Modified LED* (Critical Patient).

risk values does not appear to be sufficient to demonstrate a significant difference in the adjusting of the sampling rate since it provides less information regarding the variation in severity of the patient's condition between both risk instances. On the other hand, Figures (a) and (b) illustrate a variation in adjusting the sampling rate to various cases of patient risk, with normal patients displaying lower values and critical patients displaying larger values over the same number of periods. The proposed MuDaSaTReD approach evaluates the level of RESP risk in accordance with the patient's actual situation, identifies a precise risk value at the present time, and changes the sampling rate based on this risk level. According to NEWS, the lower sampled data in Figure 9 (a) show that the vital signs are within the normal range. Consequently, the sampling rates will be reduced to their minimum values. Figure 9 (b) illustrates the variation in the sampling rates that results in varied values. Whenever a patient's condition is determined to be critical, it becomes necessary to examine the patient's physiological parameters with a high sampling rate in order to keep track of any changes that could have an impact on the patient's health state. Concerning the second issue, the amount of sent data to the fog gateway during each period is compared to how well both Modified LED* and the proposed MuDaSaTReD approach are adapted. With these two approaches, the amount of data sent to the fog gateway was kept to a minimum (only a small amount of the sampled data was sent), and only the first data of a given period was sent. The proposed MuDaSaTReD approach outperforms the Modified LED* method in the case of a normal patient, allowing for greater data reduction. Because there is no change in the patient's normal state, it only sends the first vital sign of each period to the fog gateway. Furthermore, in the case of a critical patient, the MuDaSaTReD method works better than the Modified LED* method, which means that more data can be reduced. All of these elements contribute to lowering the amount of data that does not need to be sent and improving the transmission process, which in turn reduces the amount of required power. Figure 10 compares the remaining energy for the proposed MuDaSaTReD approach to the Modified LED* method in normal and critical patient scenarios. The initial energy of the biosensor is set at 700 units. We used the same energy model as the Modified LED* method, with 0.3 and 1, respectively, for the sensed and transmitted vital signs.

It can be observed from the results in Figure 10 that the proposed MuDaSaTReD approach saves more energy than the Modified LED* method in both normal and critical patient scenarios. This is due to the effectiveness of the adaptive sampling algorithm and the ELiDaT algorithm used in the proposed MuDaSaTReD approach in reducing the sampling rates and data transmission according to the patient's situation. Figure 11 shows the amount of collected data and the distribution of scores after applying adaptive sampling (AS) to the respiration rate node vs. when no adaptive sampling is done (NS) for the proposed MuDaSaTReD approach for eight periods selected out of the 70 periods in normal and critical patients. Figure 12 shows the amount of collected data and the distribution of scores after applying adaptive sampling (AS) to the respiration rate node vs. when no adaptive sampling (NS) for the Modified

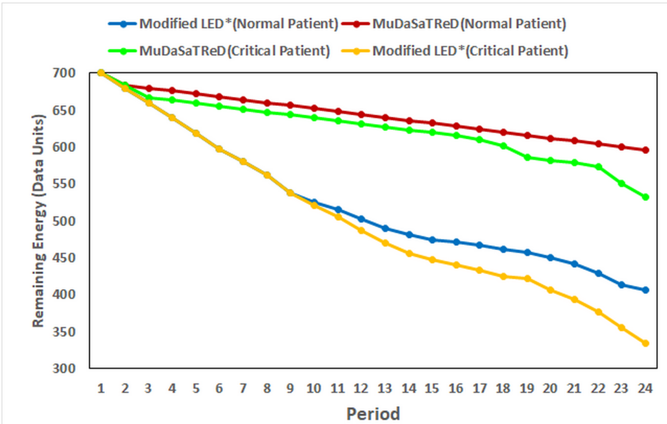


Fig. 10. Remaining energy.

LED* in a normal patient.

It can be seen from the results in Figure 11 (a) that the proposed MuDaSaTReD approach reduced the average of sensed data for eight periods to around 98.88%, whereas the Modified LED* method (see Figure 12) reduces the data by 64.5% for a normal patient. More reduction in the sampled data are shown in Figure 11 (a) when the patient is in a normal state, reflecting the minimum range score (mostly zero scores). Similarly, in Figure 11(b), when a patient is somewhat critical, there is a 95.5% reduction in sensed data. This shows the different score ranges and how bad the patient's health is since the maximum range score (2 and 3 scores) is included. It is obvious that adaptive sampling, as used by the proposed MuDaSaTReD approach, has no effect on the distribution of scores and, as a result, on the data and information required for decision-making. In spite of the high reduction in the sensed data by the proposed MuDaSaTReD approach for both normal and critical patients, it maintains a good representation of the scores after applying adaptive data sampling, and no score could be lost. This is necessary for the fog gateway to make an accurate decision about the patient's status. Figure 13 shows the data reduction for the proposed MuDaSaTReD approach and the Modified LED* method for eight periods selected out of the 70 periods. According to the results described in Figures 11(a), (b), and Figure 12, these percentages have been calculated.

It can be noticed from the results in Figure 13 that the proposed MuDaSaTReD approach reduced the sensed data from 98% up to 99%, whereas the the Modified LED* method reduced the sensed data from 50% up to 90% for the normal patient. The proposed MuDaSaTReD approach reduced the sensed data from 89% up to 99% for the critical patient. Also, because there is not a lot of variations in how scores are distributed, no important vital signs are wasted, and the way scores are distributed has not changed over the period. Therefore, the fog gateway's decisions are not affected.

VI. Conclusion and Perspectives

We have proposed Multibiosensor Data Sampling and Transmission Reduction with Decision-making (MuDaSaTReD) for Remote Patient Monitoring in the IoMTs Networks. The MuDaSaTReD approach implements the proposed ELiDaT and adaptive sampling algorithms at the biosensor level to eliminate the redundant data and save energy at the biosensor. Then, it fuses, updates, and provides fast, accurate, and automated decisions based on a machine learning model about the patient's situation at the fog gateway. The performance evaluation shows that the MuDaSaTReD outperforms the Dynamic risk [8] and the Modified LED* [9] methods in terms of the data reduction and energy consumption. It keeps a good representation of all the scores at the fog gateway and makes automated, fast, and accurate decisions based on the patient's condition.

In the future works, lightweight compression techniques will be incorporated into biosensors in order to compress readings and send them to the fog without affecting their meaning. In order to use the proposed approach, it is also planned to do real experiments with real biosensors and fog gateways.

References

[1] K. Dev, R. K. Poluru, R. L. Kumar, P. K. R. Maddikunta, and S. A. Khowaja, "Optimal radius for enhanced lifetime in iot using hybridization of rider and grey wolf optimization," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 2, pp. 635–644, 2021.

[2] P. K. R. Maddikunta, T. R. Gadekallu, R. Kaluri, G. Srivastava, R. M. Parizi, and M. S. Khan, "Green communication in iot networks using a hybrid optimization algorithm," *Computer Communications*, vol. 159, pp. 97–107, 2020.

[3] M. Liyanage, Q.-V. Pham, K. Dev, S. Bhattacharya, P. K. R. Maddikunta, T. R. Gadekallu, and G. Yenduri, "A survey on zero touch network and service (zsm) management for 5g and beyond networks," *Journal of Network and Computer Applications*, p. 103362, 2022.

[4] H. Harb, A. Mansour, A. Nasser, E. M. Cruz, and I. de la Torre Diez, "A sensor-based data analytics for patient monitoring in connected healthcare applications," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 974–984, 2020.

[5] Sharma, M. Mangla, S. N. Mohanty, D. Gupta, PrayagTiwari, M. Shorfuzzaman, and M. Rawashdeh, "A smart ontology-based iot framework for remote patient monitoring," *Biomedical Signal Processing and Control*, vol. 68, p. 102717, 2021.

[6] A. K. Idrees, S. K. Idrees, R. Couturier, and T. Ali-Yahiya, "An edge-fog computing enabled lossless eeg data compression with epileptic seizure detection in iomt networks," *IEEE Internet of Things Journal*, vol. 9, no. 15, pp. 13 327–13 337, 2022.

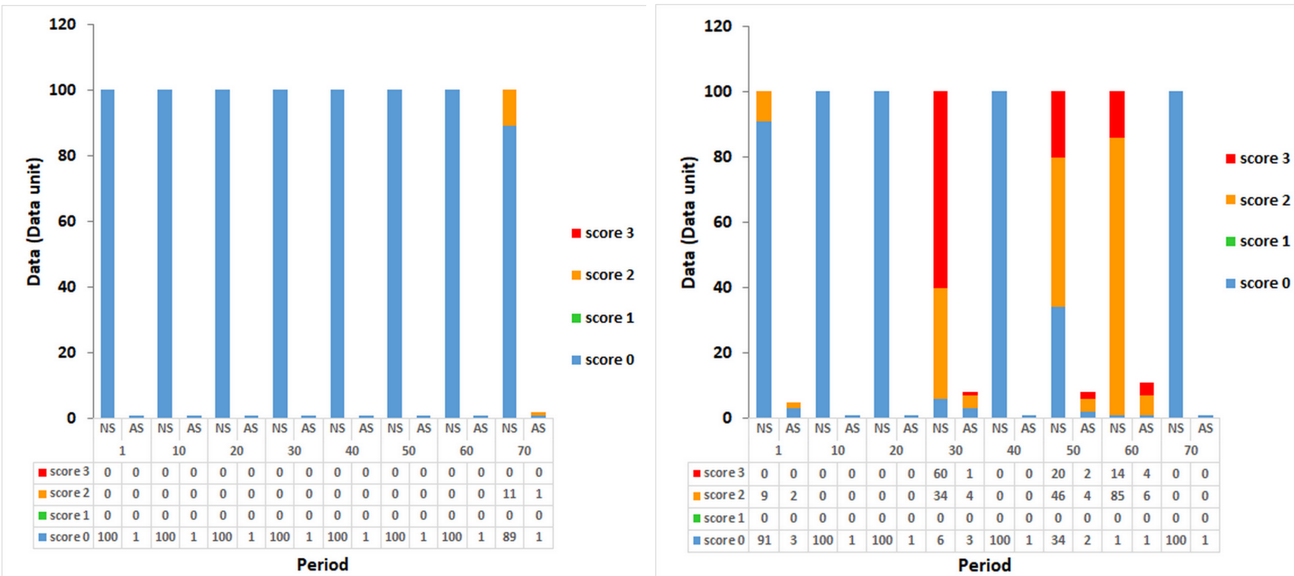
[7] L. G. J. M. H. P. C. I. R. G. M. J. E. M. G. B. M. C.-K. P. Ary L. Goldberger, Luis A. N. Amaral and H. E. Stanley, "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[8] C. Habib, A. Makhoul, R. Darazi, and R. Couturier, "Real-time sampling rate adaptation based on continuous risk level evaluation in wireless body sensor networks," in *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, 2017, pp. 1–8.

[9] C. Habib, A. Makhoul, R. Darazi, and C. Salim, "Self-adaptive data collection and fusion for health monitoring based on body sensor networks," *IEEE transactions on Industrial Informatics*, vol. 12, no. 6, pp. 2342–2352, 2016.

[10] T. Wang, M. Z. A. Bhuiyan, G. Wang, M. A. Rahman, J. Wu, and J. Cao, "Big data reduction for a smart city's critical infrastructural health monitoring," *IEEE Communications Magazine*, vol. 56, no. 3, pp. 128–133, 2018.

[11] M. Koussaifi, C. Habib, and A. Makhoul, "Real-time stress evaluation using wireless body sensor networks," in *2018 Wireless Days (WD)*. IEEE, 2018, pp. 37–39.



(a) (b)

Fig. 11. The amount of collected data and the distribution of scores after applying adaptive sampling (AS) to the respiration rate node vs when no adaptive sampling is done (NS): MuDaSaTReD (Normal Patient) (b) MuDaSaTReD (Critical Patient).

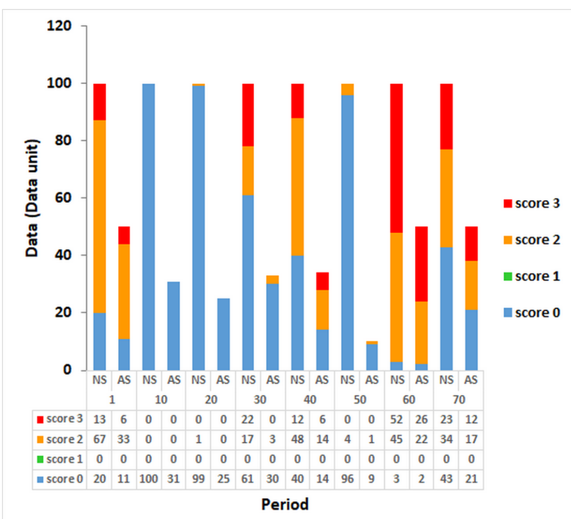


Fig. 12. The amount of collected data and the distribution of scores after applying adaptive sampling (AS) to the respiration rate node vs when no adaptive sampling is done (NS): Modified LED* (Normal Patient).

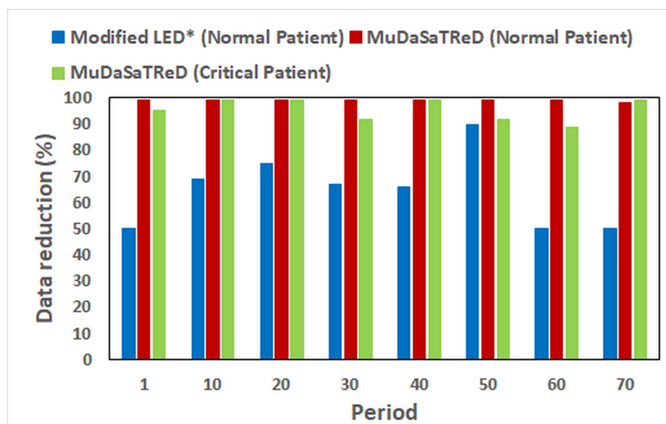


Fig. 13. Data reduction.

[12] Y. Qu, G. Zheng, H. Wu, B. Ji, and H. Ma, "An energy-efficient routing protocol for reliable data transmission in wireless body area networks," *Sensors*, vol. 19, no. 19, p. 4238, 2019.

[13] H. de Mello Dantas and C. M. de Farias, "A data fusion algorithm for clinically relevant anomaly detection in remote health monitoring," in *2020 International Symposium on Networks, Computers and Communications (ISNCC)*. IEEE, 2020, pp. 1–8.

[14] M. Chen, P. Zhou, D. Wu, L. Hu, M. M. Hassan, and A. Alamri, "Ai-skin: Skin disease recognition based on self-learning and wide data collection through a closed-loop framework," *Information Fusion*, vol. 54, pp. 1–9, 2020.

[15] A. Alameen and A. Gupta, "Optimization driven deep learning approach for health monitoring and risk assessment in wireless body sensor networks," *International Journal of Business Data Communications and Networking (IJBDCN)*, vol. 16, no. 1, pp. 70–93, 2020.

[16] R. C. of Physicians, "National early warning score (news) 2: standardising the assessment of acute-illness severity in the nhs. updated report of a working party 2017," 2021.

[17] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*. OTexts, 2018.

[18] T. R. Khan, K. M. Hossein, K. R. I. Maruf, A. Fukuda, and A. Ahmed, "Measurement of illness and wellness score of non-communicable disease patients," in *TENCON 2017-2017 IEEE Region 10 Conference*. IEEE, 2017, pp. 2253–2257.

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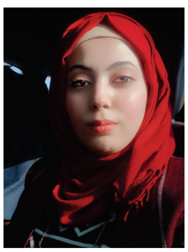

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