An Edge-Fog Computing Enabled Lossless EEG Data Compression with Epileptic Seizure Detection in IoMT Networks

Ali Kadhum Idrees[1,*], Sara Kadhum Idrees[2], Raphael Couturier[3], Tara Ali-Yahiya[4]

[1,2]*Dept. of Computer Science, University of Babylon, Babylon, Iraq.*
[3]*FEMTO-ST Institute/CNRS, Univ. Bourgogne Franche-Comte, Belfort, France.*
[4]*LISN Lab, Université Paris-Saclay, Orsay, France.*
Emails: ali.idrees@uobabylon.edu.iq, wsci.sara.idrees5@uobabylon.edu.iq, raphael.couturier@univ-fcomte.fr, tara.ali-yahiya@universite-paris-saclay.fr
[*]*Correspondant author*

Abstract

The need to improve smart health systems to monitor the health situation of patients has grown as a result of the spread of epidemic diseases, the ageing of the population, the increase in the number of patients and the lack of facilities to treat them. This led to an increased demand for remote healthcare systems using biosensors. These biosensors produce a large volume of sensed data that will be received by the edge of the Internet of Medical Things (IoMT) to be forwarded to the data centers of the Cloud for further treatment. An Edge-Fog Computing Enabled Lossless EEG data compression with Epileptic Seizure Detection in IoMT networks is proposed in this paper. The proposed approach achieves three functionalities. First, it reduces the amount of sent data from the Edge to the Fog gateway using lossless EEG data compression based on a hybrid approach of k-means Clustering and Huffman Encoding (KCHE) at the Edge Gateway. Second, it decides the epileptic seizure situation of the patient at the Fog gateway based on the Epileptic Seizure Detector based Naive Bayes (ESDNB) algorithm. Third, it reduces the size of IoMT EEG data delivered to the Cloud using the same lossless compression algorithm in the first step. Various measures implemented to show the effectiveness of the suggested approach and the comparison results confirm that the KCHE reduces the amount of EEG data transmitted to the Fog and Cloud platform and produces a suitable detection of an epileptic seizure. The average of compression power of the proposed KCHE is four times the average of compression power of other methods for all EEG records (Z, F, N, O, S). Furthermore, the proposed ESDNB outperforms the other methods in terms of accuracy, where it provides accuracy from 99.53 % up to 99.99 % using the dataset of Bonn University.

Keywords: IoMT, Edge-Fog Computing, Epileptic Seizure Detection, Lossless Compression, Machine Learning.

1. Introduction

The rapid growth in sensing and communication technologies make the network of IoT can connect many physical objects [1]. This led to the invention of many IoT applications like remote healthcare monitoring, environment control, intelligent transportation, smart home, etc [2, 3]. The health technology sector is invaded by IoT techniques and applications to produce a more brilliant future named the Internet of Medical Things (IoMT) [4, 5]. The growth of IoMT occasioned by the increased number of connected health devices that can gather, generate, fuse, analyze, send medical sensed data to Cloud computing. IoMT is composed of a collected data from medical and biosensor devices and applications [6]. These IoMT nodes are used to monitor the health situation of the patient, gather clinical data, and transmit it to the medical experts via the data centers of the remote Cloud platform [7]. The main goal of IoMT is to improve the healthcare systems. For instance, most healthcare applications require fast response and decision in case of emergency, high bandwidth over the IoMT network for sending the big data sensed from the patients every day. These requirements represent big challenges in the IoMT network. This led to the emergence of the concept of fog computing by which the intelligence and processing are brought near the source of data generators [8]. While, the Edge gateway is always close to the biosensors. The Edge gateway has no capability as the Cloud to train the machine learning algorithm and making a big analysis on the huge EEG data. The Fog gateway can be located in the middle between the Cloud and the data generators (biosensors). Figure 1 refers to the Edge-Fog computing architecture in IoMT Network.

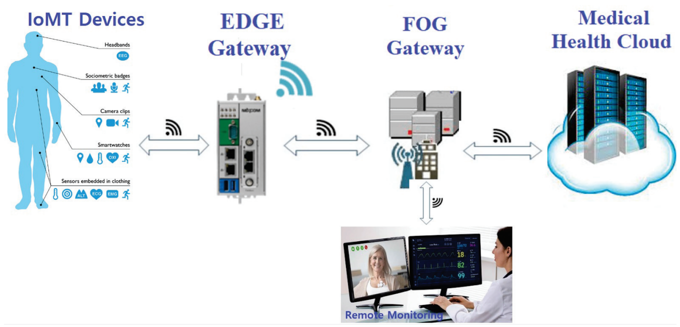

Figure 1: Edge-Fog computing architecture in IoMT Network.

Therefore, reducing the collected sensed data at the Edge gateway and make a decision at the Fog gateway can provide a fast response to the medical experts. In addition, it is conserving the IoMT network bandwidth by decreasing the amount of transferred data from Fog to the Cloud data centers. Table 1 shows the list of acronyms with corresponding full terms in this paper.

Various conditions have diagnosed by employing remote monitoring systems of electroencephalogram (EEG) like epileptic seizures detection, brain death testing, anesthesia, and movement disorders [9].

EEG refers to the electrophysiological process of registering the brain's electrical activity [10]. EEG evaluate variations in the electrical activity that the brain has produced. The ionic current between and within the neurons leads to these voltage changes. EEG signals are scanned by tiny discs of metal named electrodes that were placed on the head. The electrical activity of the brain captured and registered by these EEG electrodes. The gathered signals of EEG are amplified, digitized, and finally transmitted to the computer or mobile gateway for saving and processing these EEG data [11]. The EEG analysis supports the medical experts to verify the medical investigation, helps the scientists and researchers to understand the behavior of human, and people to enhance their

Table 1: The list of acronyms with corresponding full terms

Acronym	Full term
IoMT	Internet of Medical Things
EEG	Electroencephalogram
KCHE	k-means Clustering and Huffman Encoding
ESDNB	Epileptic Seizure Detector based Naive Bayes
IoT	Internet of Things
CNN	Convolutional Neural Network
TFA	Time–Frequency Analysis
ANN	Artificial Neural Network
DWT	Discrete Wavelet Transform
MLPNN	Multi-Layer Perceptron Neural Network
1D-LBP	One-Dimensional Local Binary Pattern
FT/BN	Functional Tree/BayesNet
NB/KNN	Naive Bayes/K-Nearest Neighbor
TQWT	Tunable-Q Wavelet Transform
KNNE	K-Nearest Neighbor Entropy
SVM	Support Vector Machine
LMD	Local Mean Decomposition
GA	Genetic Algorithm
M-V	Majority-Vote
CWT	Continuous Wavelet Transform
MEMD	Multivariate Empirical Mode Decomposition
1-D SPIHT	One Dimentional Set Partitioning In Hierarchical Trees
AC	Arithmetic Coding
JPEG	Joint Photographic Experts Group
SHORTEN	Simple lossless and near lossless waveform compression
DWT	Discrete Wavelet Transform
BCI	Brain Computer Interface
ASCII	American Standard Code for Information Interchange
MCTF	Motion Compensated Temporal Filtering
P-1D-CNN	Pyramidal one-Dimensional Convolutional Neural Network
HE	Huffman Encoding
LZW	Lempel–Ziv–Welch

wellness and productivity. These EEG signals require a large storage capacity to save, process, decision making about the patient situation, and transfer. To deal with these challenges, the compression techniques can be used at the Edge gateway and the machine learning at the Fog gateway to decrease the volume of EEG data before transmitting it to the Fog and to make a fast decision at the Fog level instead of Cloud data centers. Several research works have proposed in the literature either reducing the EEG data or making the decision about the status of the patient. Unlike the above-mentioned works, achieving efficient compression at the Edge layer and accurate decision about the seizure detection at the Fog layer can play important role in reducing the large size of data to the Cloud and decrease the energy consumption and latency. This paper includes the following contributions.

1. A hybrid approach of Edge-Fog Computing Enabled Lossless EEG data compression with Epileptic Seizure Detection in IoMT network is proposed. The proposed approach is based on the Edge-Fog computing architecture in IoMT Network (see Figure 1) and it achieves the lossless compression technique at the Edge gateway and the epileptic seizure detection using Machine Learning at the Fog gateway.

2. The proposed hybrid lossless compression technique combines two efficient methods: K-means Clustering and Huffman Encoding called (KCHE) to produce a larger lossless compression rate on the gathered data of EEG at the Edge gateway before transmitting it to the Fog gateway. This KCHE technique is employed at the Edge gateway in the proposed architecture of the Edge-Fog computing in IoMT Network. This can lead to improving the performance of the IoMT Network due to decreasing the transmitted EEG data of the patient toward the Fog gateway by proposed KCHE technique along with maintaining the integrity and the accuracy of EEG data at the Fog gateway.

3. Employing the machine learning based on the Naive Bayes algorithm at the Fog gateway for epileptic seizure detection. Naive Bayes algorithm has

been trained based on the received EEG data from the Edge gateway. The employed Naive Bayes algorithm introduced a strong detector for epileptic seizure and high accuracy while enhancing the response time concerning IoMT applications.

4. The performance improvement of the proposed work presented through several experiments using Python programming language and depending on real EEG captured data for patients with various records (Z, F, N, O, S) from Bonn University [12]. The proposed KCHE technique has compared with some existing methods like [13] and [14]. The results of comparison prove that the proposed KCHE technique outperformed the other approaches in terms of compression ratio. Furthermore, the results of the proposed Naive Bayes algorithm are better than the results of some existing related work such as Novel CNN [15], TFA +ANN [16], DWT+ Kmeans +MLPNN [17], 1D-LBP + FT/BN [18], DWT+ NB/KNN [19], TQWT+KNNE+SVM [20], LMD+ GA-SVM [21], CNN+ M-V [22], CWT+CNN [23], CNN [24], MEMD+ANN [25].

2. Literature review

One of the most important challenges in the IoMT networks is how to achieve remote patient health monitoring and decision making accurately and rapidly. To deal with this challenge, it is important to perform data reduction for the gathered EEG data at the Edge gateway using lossless compression before sending it to the Fog gateway and then implement machine learning for detecting the epileptic seizure at the Fog gateway. Several papers considered EEG data compression methods that introduced various algorithms and techniques. The work in [14] proposed a wavelet transform approach to achieve a real-time EEG data lossless compression. The authors in [13] introduced various EEG signals lossless compression methods like 1-D SPIHT, AC, 2-D SPIHT, JPEG2000, 1-D SHORTEN, and 2-D SPIHT + AC. The comparison has performed among these methods based on real medical data from the patients. The proposed work in [26] introduced a lossless compression approach based on the combination between Discrete Wavelet Transform (DWT) with lifting technique and polynomial interpolation. This method reduced the required bits to represent data before sending them. The authors in [27] presented an approach for dimensional reduction to decrease the EEG features by classifying the EEG data using various machine learning algorithms in the frequency domain. The principal component analysis is employed to compress the EEG data in [28]. The channel brain-computer interface is responsible for achieving this task. The electrical signals of the brain are splashed in electrophysiological monitoring. The authors in [29] provided the BCI based on the EEG feature classification. The motor imagery domain mapped the movements based on EEG signals classification. The recovery of feature is achieved after the data processing that includes two classes our limb and right hand. The authors in [30] proposed a lossless compression based on a normalized compression distance. The ASCII (American Standard Code for Information Interchange) objects utilized the calculated compression distance. Hierarchical clustering and multidimensional projection are employed by this method. A compression method based on discrete cosine transform and Huffman to compress data without loss has introduced by [31]. To increase the privacy of the data and reduce the complexity of data, the authors used inverse discrete cosine transform and discrete cosine transform, where the EEG data have sent efficiently. In [32], the author introduced a lossless Log2 sub band compression method to calculate the difference between two 24-bit samples. The bits are compressed in four cases: 8, 14, 20, 26. The data are compressed and sent serially. The work in [33] presented a new compression method for EEG signal that employs MCTF (motion-compensated temporal filtering) and DTW (discrete wavelet transform) to eliminate the intra-channel redundancy. The authors in [34] introduced lossless compression method for EEG data that based on two-level prediction, tri-entropy coding, and voting prediction. The two-level prediction used six functions and twenty-seven conditions to predict the current sample from previous samples. The best function with the best error is found by voting prediction. The binary code of the value of the error is generated by using Golomb-Rice coding and Huffman coding. The authors in [35] proposed the Fractals compression approach for decreasing the sent EEG data from patient to the Cloud. This can reduce network traffic and enhance the performance of the network.

The other related works are focused on the diagnosis and detection of epileptic seizure in EEG data by presenting various techniques and algorithms. The work in [36] suggested an approach for separating the seizure-free signals from epileptic seizure signals using discrete wavelet transform and computer-aided diagnostic method. The EEG data is decomposed by eliminating the non-significant coefficients to produce a fixed number of significant coefficients. The arithmetic coding converts the significant wavelet coefficients to bit streams. Finally, the set of compression feature is regulated, and then the classifiers detect the seizure activity. Authors in [37] proposed new automatic single-channel seizure detection by adding a new feature that does not need a full rebuilding of original EEGs. This feature employing an orthogonal matching pursuit method in an iterative way on the compressed EEG sensed data and calculate the ratio that increases the energies of the rebuilt EEG signals. The non-seizure and seizure cases are classified based on partial energy difference. The proposed method is improved to be used in the multichannel EEG signals. In [38], the authors proposed an adaptive-rate processing and level-crossing sampling for epileptic seizures detection automatically. This can reduce the EEG data transmission by achieving compression. The latency is not considered because the epileptic seizures classification is implemented in the Cloud. In [39], the authors proposed a lossy compression for EEG data using Discrete Cosine Transform, and then predict the epileptic seizure for the patients. They have studied the effect of lossy compression on the detector of the epileptic seizure.

Several techniques are introduced for epileptic seizure detection from the EEG data [15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25]. In [15], the authors proposed an epileptic seizure detector by using a deep neural network. This method includes three fully connected layers and three convolutional blocks. This method is applied to two, three, and five-class classification problem. Authors in [22] introduced a model named P-1D-CNN (Pyramidal one-dimensional convolutional neural network). The refined approach of the standard network model is used. The work in [24] applied the CNN for EEG data classification. The CNN utilized thirteen layers to detect three classes: seizure, normal, and preictal. Authors in [25] introduced a model based on MEMD (Multivariate extension of Empirical Mode Decomposition) and neural network for classifying the EEG data into non-ictal EEG and ictal signals. The non-stationary data sets are decomposed and analysed using MEMD. The work in [23] proposed a model combining Continuous Wavelet Transform (CWT) and CNN. The CWT converts the EEG data into five classes to produce two-dimensional frequency-time scalograms. The CNN is used for the classification of these five different classes.

SHORTCOMINGS. Despite presenting various methods for EEG data reduction and epileptic seizure detection, however, to the best of our knowledge, there is no integrated efficient method that combines reducing the volume of EEG data on the Edge network and providing a quick decision at the Fog gateway about the patient's health condition for remote monitoring applications. For instance, the proposed data reduction methods can affect the quality of reconstructed EEG data and they do not ensure a high EEG data reduction and accuracy at the same time. As for the methods used to detect epileptic seizures, they were not employed at the Fog gateway to monitor patients remotely; in addition to that, they did not provide acceptable percentages for the accuracy of the decision and did not take into account the delay in detecting seizures for remote applications.

OUR APPROACH. An edge-fog computing enabled lossless EEG data compression with epileptic seizure detection in IoMT Network is proposed. Three main functions have performed on the proposed Edge-Fog computing architecture. A hybrid lossless EEG data compression approach is composed of Huffman encoding and k-means algorithms at the Edge gateway to reduce EEG traffic transmitted from Edge to fog while maintaining the quality of received data. An epileptic seizure detector based on an efficient Naive Bayes machine learning algorithm is implemented at the Fog gateway to predict the patient's situation and notify the medical experts rapidly without introducing latency. Finally, the EEG data is compressed and then transmitted to the data centers of the Cloud for further analytic and archiving. The proposed approach can reduce the volume of data traffic on the network, keeping the quality of data, reduce the latency, and providing accurate decision about the patient's situation.

3. Proposed Techniques

This section introduced an edge-fog computing enabled lossless EEG data compression with epileptic seizure detection in IoMT Network. Figure 2 refers to the proposed approach based on Edge-Fog computing architecture.

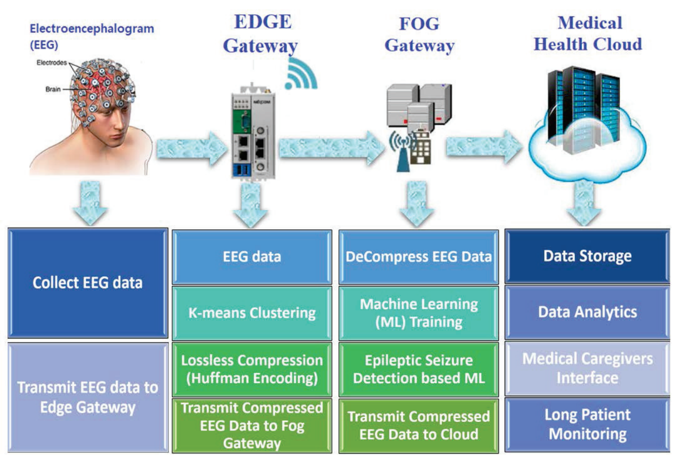

Figure 2: Proposed approach based on Edge-Fog computing architecture..

The EEG electrodes are located on the scalp of the patient to register the activity of the brain and delivering them to the Edge gateway wirelessly. The EEG headset captures the EEG signals from the patient and then transmit them to the Edge gateway in a periodic way.

3.1. Edge Gateway Level

After receiving the EEG data at the Edge gateway, a lossless hybrid compression method applied to decrease the gathered EEG data traffic size before transmitting it to the Fog gateway while maintaining the accuracy of received data at the Fog node. The hybrid lossless compression method is consisting of two efficient data reduction techniques: Huffman Encoding and K-means Clustering. The sensed data of EEG is periodically gathered at the Edge node from the electrodes devices on the head of the patient. There are two records of EEG data are handled at the Edge gateway in each period. They are denoted as $Y = y1, \ldots, ym$, where m represents the sensed data number of EEG values for the two records (i.e., 8194 EEG data values). In KCHE method, the EEG data of Y are grouped into many groups according to their similarity using K-means Clustering. The main reason behind implementing the K-means clustering by the proposed KCHE is that it is almost easy to implement, scalable for huge data, ensure convergence, simply adjusts to new instances, and generalizes to groups of various sizes and shapes. After that, the lossless Huffman Encoding is applied to each group of EEG data to compress it into a compressed file. Huffman encoding approach has utilized to accomplish a high range of compression between $20-90\%$ according to [31]. The proposed KCHE method implemented the Huffman encoding because it is a greedy method, and it requires less time of computation. It minimizes the code length on average to designate the alphabet's representatives. The code with variable length is employed to exchange each character based on the character's repetition. This can make the access time to the characters reduced. The Huffman coding provides the prefix codes to ensure the lossless EEG data compression and avoid the appearance of vagueness. Algorithm 1 refer to the suggested KCHE method.

In Algorithm 1, EEG data values are selected randomly as K centroids $a_1^t, ..., a_K^t$. After that, each EEG data in Y is allocated to the closest centroid a_i^t, where $i \in K$. Then the new centroids are calculated, and the algorithm continues until finding the optimal positions for the centroids. The algorithm converges either: there is no variation in the values of the centroids (i.e., it is stabilized)

Algorithm 1: KCHE Lossless Compression

Input: $Y = y_1, \ldots, y_m$: vector of EEG data values, m : size of vector Y, K : number of clusters

Output: C: compressed file of the clusters

$t \leftarrow 0$;
Initialize K clusters: $a_1^t, ..., a_K^t$;
Repeat;
$t \leftarrow t + 1$;
$CL_j \leftarrow \Phi$ // $\forall\ j \in K$;
for *each* $y_j \in Y$ **do**
    $s \leftarrow argMin_i\{||y_j - a_i^t\}$ // *allocate* y_j *to the closest point center*;
    $CL_s \leftarrow CL_s \cup y_j$;
end
for *each* $i \in K$ **do**
    $a_i^t \leftarrow \frac{1}{|CL_i|} \sum_{y_j \in CL_i} y_j$
end
Until Convergence;
$\{Group^1, \ldots, Group^K\} \leftarrow FetchGroups(CL, K)$;
GF $\leftarrow$ " " // empty file;
for $i \leftarrow 1$ **to** K **do**
    $FL_i \leftarrow$ *Huffman Encoding*$(Group^i, Length(Group^i))$;
    GF $\leftarrow$ *GF* $\cup\ FL_i$ // combine the compressed file FL_i with GF;
end
return GF ;

or the maximum number of iterations has reached. The FetchGroups(CL, K) function is to produce the needed groups depend on the supplied number of groups named K.

In Algorithm 2, each EEG value (leaf node) is created and put in the queue of priority. As shown in line (6), if there are many nodes in the queue, the loop will

Algorithm 2: Huffman Encoding

Input: $Group$, m

Output: FL: compressed file of the EEG data group

1 $Lef \leftarrow QueueStructure()$;
2 **for** $i \leftarrow 1$ **to** m **do**
3     $Num \leftarrow NodeStructure\{Group_i\}$;
4     $Lef.PUSH(Num)$;
5 **end**
6 **while** $Lef.Length() \neq 1$ **do**
7     $Num \leftarrow NovelNode()$;
8     $Num.Left \leftarrow X \leftarrow Lef.POP()$;
9     $Num.Right \leftarrow Y \leftarrow Lef.POP()$;
10     $Repetition(Num) \leftarrow Repetition(X) + Repetition(Y)$;
11     $Lef.PUSH(Num)$;
12 **end**
13 *return* Lef ;

continue. The nodes with the highest priority in the queue will be eliminated (see lines (7)-(11)). Then, a new node is built that contains these nodes and their frequency summation as a child. This novel node would be inserted into the queue. Eventually, the node's root is the remaining one in the queue and the tree is formed. Algorithm 2 consumes $O(nlogn)$ of time requirements.

In Algorithm 3, the prefix codes series converted to a particular byte value in decompression strategy. It accomplished through traversing the tree node by node as each bit collected from the input series. If the traversing arrives at the leaf node, the value of the byte realised, where the value of the leaf represents the needed value of EEG data.

Algorithm 3: Huffman Decoding

Input: Rot : Huffman tree's root, BS : the stream of bits is needed to be decoding.

Output: DF: reconstructed file from decompression process

$MS \leftarrow Length(BS)$;
for $j \leftarrow 1$ **to** MS **do**
    $DF \leftarrow Rot$;
    while $DF.LEFT \neq NULL$ *and* $DF.RIGHT \neq NULL$ **do**
        if $(BS_j = 0)$ **then**
            $DF \leftarrow DF.LEFT$;
        end
        else
            $DF \leftarrow DF.RIGHT$;
        end
        $j \leftarrow j + 1$;
    end
end
return DF ;

3.2. Fog Gateway Level

In the Fog gateway, the decompression process using Algorithm 3 achieved upon receiving the compressed data to reconstruct the original EEG data. These collected data can be used to learn a machine learning algorithm based on a Naive Bayes method to predict the epileptic seizure of the patients in IoMT Network. The Naïve Bayes is simple to construct and precise approach for prediction. The cost of computation of the Naive Bayes is low, consequently, it can be used efficiently on a massive dataset [40]. Algorithm 4 shows the Machine Learning based Naïve Bayes.

In Line (1) of Algorithm 4, the collected EEG dataset has spitted into K groups using the K-fold cross-validation approach. Each group contains training

Algorithm 4: Machine Learning based Naïve Bayes

Input: $DataSet$: dataset of EEG patients, K : Number of folds.

Output: $MeanAccuracy$: Mean Accuracy

1 $\{trainSet, testSet\} \leftarrow$ *Split Dataset using K-fold Cross Validation*$(DataSet, K)$;

2 **for** $j \leftarrow 1$ **to** K **do**

3   *Summarizing* $\leftarrow$ *SummarizingByClass*$(trainSet^j)$;

4   **for** *Row* $\in$ $testSet^j$ **do**

5         $Out \leftarrow Predicting(Summarizing, Row)$;

6   *Append Out to Predicted*;

7   **end**

8   *Actual* $\leftarrow$ *Get actual EEG data from dataset*;

9   *Accuracy* $\leftarrow$ *AccuracyMetric*$(Actual, Predicted)$;

10   *Append Accuracy to Scores*;

11 **end**

12 *MeanAccuracy* $\leftarrow \frac{\sum_{i=1}^{K} Scores_i}{K}$

13 *return* $MeanAccuracy$;

data set and a test data set. The lines (2)-(13) are used to evaluate the Naïve Bayes algorithm using the split of the cross validation. The lines (3)-(7) refer to the main steps of the Naïve Bayes algorithm. In line (3), the EEG training set has split by class, and the statistics have calculated for every row. These statistics include standard deviation, mean, and count for every column in the EEG dataset. In line (5), the predicting probabilities have calculated to predict the class for a yielded row. In line (9), the AccuracyMetric function returns the percentage of the accuracy that can be calculated as follow.

$$Accuracy(\%) \leftarrow \frac{Correct_{No}}{Length(actual)} * 100 \tag{1}$$

Where the $Correct_{No}$ is the number of matching between the $actual_i$ and $predicted_i$ for i=1,..., Length(actual).

After the training process, the trained model can be used to predict the patient's situation from newly received EEG data to detect the epileptic seizure of the patients and send a notification to the medical experts to take the appropriate decision according to the status of the patient.

Finally, the EEG data of the patients will be compressed using proposed KCHE lossless compression method and then transmitting to the data center of the Cloud platform for archiving and further analytic by the doctors to check the progress of the patients.

4. Performance Analysis and Simulation Results

This section introduces the performance assessment of the proposed Edge-Fog Computing Enabled Lossless EEG data compression with Epileptic Seizure Detection in IoMT networks. The simulation experiments have achieved using the EEG data of Bonn University. This EEG dataset includes several records (N, O, Z, F, S) [12]. A custom simulator-based Python programming language has used to perform the simulation experiments. In this paper, KCHE refers to the name of the proposed EGG compression technique implemented at the Edge node. The Huffman Encoding algorithm is named as HE, while the Lempel–Ziv–Welch compression algorithm is named as LZW. The Epileptic Seizure Detector based Naive Bayes method implemented at the Fog gateway is named ESDNB.

4.1. Simulation Results of KCHE at Edge Gateway

The proposed KCHE approach evaluated by achieving several performance measures like compression/decompression processing time, the volume of transmitted data, and Compression Ratio. To show the effectiveness of the proposed KCHE approach, some significant performance criteria are used to evaluate the proposed KCHE approach for EEG lossless compression. These metrics are defined as follow.

i) Compression Power: it is named the compression ratio. It is the ratio between the volume of uncompressed ($EEG^{Original}$) and compressed volume ($EEG^{Compressed}$) of data. It is formulated as follow.

$$CompressionPower = \frac{EEG^{Original}}{EEG^{Compressed}} \tag{2}$$

ii) Compression Ratio: it is formulated as follow.

$$CompressionRatio(\%) = \left(1 - \frac{EEG^{Compressed}}{EEG^{Original}}\right) * 100 \tag{3}$$

The $EEG^{Compressed}$ represents the volume of Compressed EEG data after implementing proposed KCHE. The $EEG^{Original}$ represents the volume of the original EEG data before process of compression.

iii) Decompression and Compression Processing Time (T): represents the total time of the process of compression and decompression respectively.

iv) Transmitted data volume(in KB): represents the volume of the EEG compressed data transferred to the data center of the Cloud platform from Edge gateway.

4.1.1. Number of groups

This section investigates the influence of the groups (clusters) number on the performance of suggested KCHE technique utilizing several metrics of performance. The results conducted by using several sizes of groups (K) like 10, 30, 50, 70, and 100. The record Z of the EEG dataset of Bonn University used during this experiment. The performance metrics versus the number of groups presented in Table 2.

As explained in Table 2, when the number of groups K increases, the compression ratio, compression power, and compression time increased while the transmitted EEG data and decompression time are reduced. Therefore, it is essential to select a suitable number of groups that can balance the compression ratio and the compression/decompression time. The suggested KCHE method assigns 100 to K, and this reduces the sent EEG data from the Edge gateway to the fog gateway and improves the performance of the IoMT network.

Table 2: Number of Groups vs Performance Metrics

Metric	**Number of Groups (K)**						
	10	**30**	**50**	**70**	**100**	**150**	**190**
Compression Ratio	85.89	87.14	88.15	88.80	89.46	90.37	90.74
Compression Power	7.09	7.78	8.45	8.94	9.52	10.41	10.82
Transmitted Data in KB	10.39	9.47	8.73	8.24	7.75	7.08	6.79
Compression time (Seconds)	0.03	0.06	0.07	0.08	0.13	0.22	2.82
Decompression time (Seconds)	0.07	0.10	0.18	0.21	0.28	0.31	3.42

4.1.2. Compression Ratio

This significant metric plays an essential role in the performance of the IoMT network. This experiment studies the impact of this measure using several EEG data records and compares the findings with other methods. Figure 3 presents the compression ratio using EEG records (Z, F, N, O, S) for different approaches. The proposed KCHE method introduces a better compression ratio compared with HE and LZW. KCHE compressed the EEG data from 85.5% up to 89.5% for all records. HE and LZW compressed the EEG data from 65.9% up to 68.8% and from 42.7% up to 48.4% respectively.

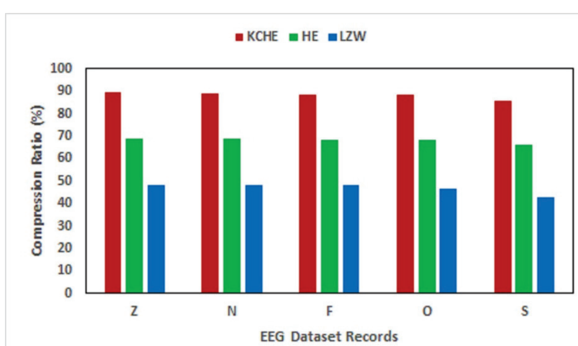

Figure 3: The compression ratio.

4.1.3. Transmitted EEG Data

This section studies the influence of the suggested KCHE on the transmitted EEG data to the Edge gateway. Figure 4 exhibits the volume of sent EEG data of various records such as (Z, F, N, O, S) after applying KCHE, HE, and LZW. As shown in this Figure, the proposed KCHE outperforms the other methods in terms of transmitted EEG data size to the Edge gateway. KCHE transmitted from 7.7% up to 11.9% (in KB) for different records. HE and LZW sent from 11.4% up to 14.1% and from 18.5% up to 23.7% respectively. Hence, the proposed KCHE reduced the size of transmitted EEG data efficiently at the Edge gateway before sending it to the Fog gateway.

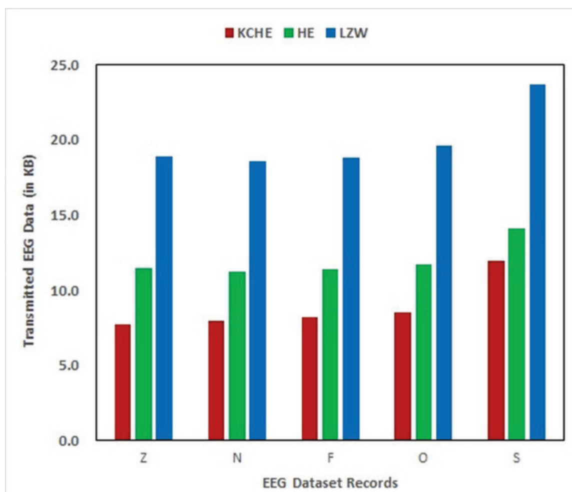

Figure 4: The transmitted EEG Data.

4.1.4. Compression Time

This study investigates the influence of the suggested KCHE on the time required to compressing the EEG data. Figure 5 gives the time of compression for KCHE, HE, and LZW using different EEG records (Z, F, N, O, S). As illustrated in Figure 5, the proposed KCHE consumed little time for compression compared with LZW, while it consumed a little more time for EEG data compression compared with HE. However, the proposed KCHE presented a higher performance especially, in compression ratio and sent EEG data. KCHE improved the performance of the IoMT network.

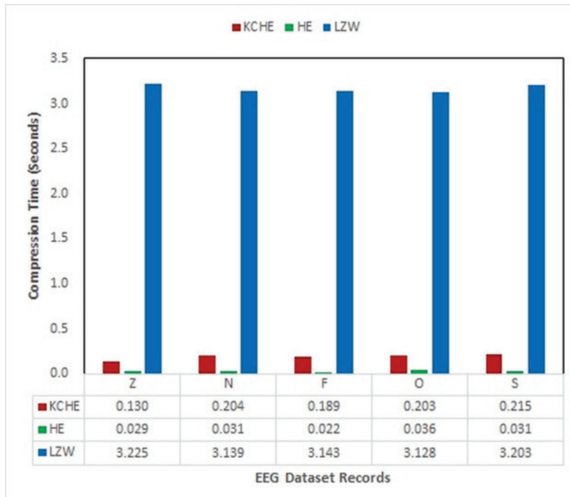

Figure 5: The compression Time.

4.1.5. Decompression Time

This section studies the impact of the proposed KCHE on the time of the decompression process. Figure 6 shows the time required for a decompression process of different methods using EEG records (Z, F, N, O, S). The presented results in Figure 6 showed that the proposed KCHE spent a lower time for decompression compared with LZW whilst it spent a little bit higher time for decompression compared with HE.

4.1.6. Compression Power

This experiment studied the compression power for several methods of lossless compression such as the proposed KCHE approach, JPEG2000 [13], 2-D SPIHT + AC [13], 1-D SHORTEN [13], 2-D SPIHT [14], AC [13], and 1-D SPIHT [14]. Figure 7 explains the compression power for different lossless compression algorithms.

The introduced results of Figure 7 shows that the proposed KCHE lossless

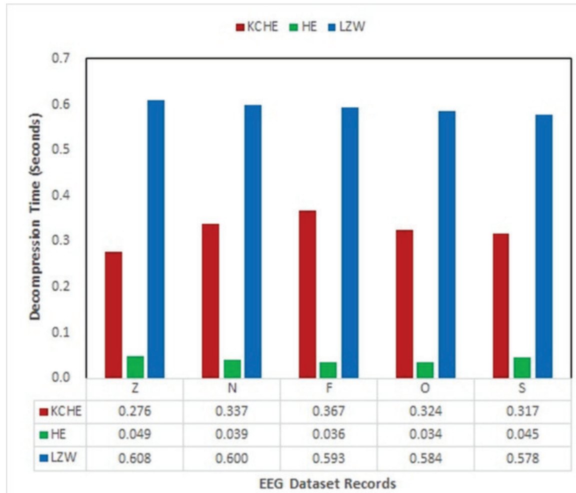

Figure 6: The Decompression Time.

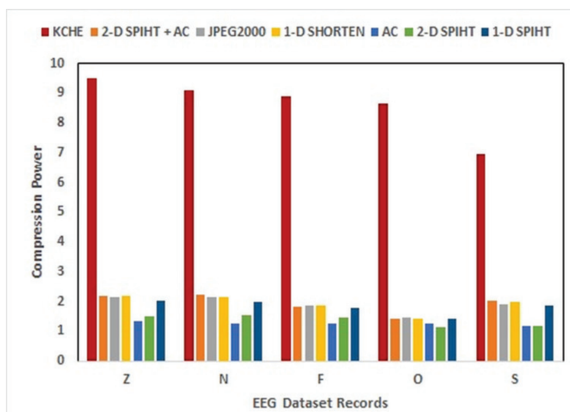

Figure 7: The Compression Power.

compression approach outperforms the other existing methods by providing a better compression power while keeping the quality of the received EEG data at the Fog gateway. The average of compression power of KCHE is four times the average of compression power of other methods for all EEG records (Z, F, N, O, S). The spatial similarity between the received EEG data at the Edge gateway is exploited by the proposed KCHE to reduce the EEG data before sending them to the Fog gateway.

4.2. Simulation Results of ESDNB at Fog Gateway

In this section, The proposed ESDNB (Epileptic Seizure Detector based Naive Bayes) approach is evaluated using different performance metrics such as Accuracy (Acc), Mean Square Error (MSE), F-Score (F), Sensitivity(Sen), Specificity(Sp), and Precision(Pr) to show the effectiveness of the proposed ESDNB. The performance of the proposed ESDNB is compared to some existing related work such as Novel CNN [15], TFA +ANN [16], DWT+ Kmeans +MLPNN [17], 1-D-LBP + FT/BN [18], DWT+ NB/KNN [19], TQWT+KNNE+SVM [20], LMD+ GA-SVM [21], CNN+ M-V [22], CWT+CNN [23], CNN [24], MEMD+ANN [25]. There are three activities in epileptiform EEG: ictal (during a seizure), interictal (between seizures), and postictal (after a seizure). Table 3 shows the average values of the performance metrics using 5-fold cross-validation. The EEG datasets merged in various combinations to explore the global classification model of the proposed ESDNB approach. Two classes (seizures, nonseizures), three classes (ictal, normal, and interictal), five classes (Z, O, N, F, and S). can be classified by this model.

As shown in Table 3, the proposed ESDNB approach can provide an accuracy from 99.95% up to 99.99% for two classes classification and from 99.53% up to 99.98% for three classes classification. The five classes classification is more complex and difficult to solve compared to other classes of classification and the proposed ESDNB still introduce an accuracy of 99.98%. In two classes classification, the proposed ESDNB provides MSE between 0.02% and 0.12%, while for three classes classification, ESDNB provides MSE between 0.02% and 0.49% and for five classifications, ESDNB provides 0.08 of MSE. Moreover, the MSE for the five classes classification of the proposed ESDNB is 0.08. Hence, the proposed ESDNB model has a powerful generalization capability and is appropriate for different problems of classification.

Table 4 refers to the comparison between the proposed ESDNB approach and some other existing related works in terms of accuracy. As shown in Table 4, the proposed ESDNB approach provides accuracy from 99.53 % up to 99.99 % using the dataset of Bonn University. In the problem of two-class classification, the

Table 3: Performance metrics using 5-fold cross-validation.

Data sets combination	**Acc**	**MSE**	**F**	**Sen**	**Sp**	**Pr**
Z_S	99.99	0.01	99.99	99.99	99.99	99.99
O_S	99.95	0.05	99.95	99.95	99.95	99.95
N_S	99.95	0.05	99.95	99.95	99.95	99.95
F_S	99.95	0.05	99.95	99.95	99.95	99.95
ZO_S	99.98	0.02	99.97	99.96	99.96	99.98
ZN_S	99.98	0.02	99.97	99.96	99.96	99.98
ZF_S	99.98	0.02	99.97	99.96	99.96	99.98
ON_S	99.98	0.02	99.97	99.96	99.96	99.98
OF_S	99.98	0.02	99.97	99.96	99.96	99.98
NF_S	99.98	0.02	99.97	99.96	99.96	99.98
ZON_S	99.98	0.02	99.97	99.95	99.95	99.98
ZOF_S	99.95	0.12	99.95	99.93	99.97	99.97
ONF_S	99.98	0.02	99.97	99.95	99.95	99.98
ZONF_S	99.95	0.05	99.92	99.93	99.93	99.91
Z_N_S	99.96	0.07	99.96	99.96	99.98	99.96
Z_F_S	99.96	0.07	99.96	99.96	99.98	99.96
O_N_S	99.98	0.02	99.98	99.98	99.99	99.98
O_F_S	99.98	0.02	99.98	99.98	99.99	99.98
ZO_NF_S	99.53	0.49	99.60	99.59	99.74	99.61
Z_O_N_F_S	99.98	0.08	99.98	99.98	100.00	99.98

accuracy of the ictal and interictal by the proposed ESDNB approach and for the datasets combinations N_S,F_S, ZO_S, NF_S, and $ZONF\_S$ is better than all other methods while it is slightly lower than some methods for Z_S and O_S. In a three-class classification problem, the proposed ESDNB approach provides better accuracy than other methods for O_F_S and ZO_NF_S datasets combination. Moreover, the proposed ESDNB approach introduced a

Table 4: Comparison between proposed ESDNB approach and some existing methods in terms of accuracy.

Data sets combination	Existing Methods	Acc	Acc of ESDNB
Z_S	Novel CNN	99.52	99.99
	TFA +ANN	100	
	DWT+ Kmeans +MLPNN	100	
	1-D-LBP + FT/BN	99.50	
	DWT+ NB/KNN	100	
	TQWT+KNNE+SVM	100	
	LMD+ GA-SVM	100	
	CNN+ M-V	100	
	CWT+CNN	99.50	
O_S	Novel CNN	99.11	99.95
	DWT+ NB/KNN	99.25	
	TQWT+KNNE+SVM	100	
	CNN+ M-V	99.6	
	CWT+CNN	99.50	
N_S	Novel CNN	98.02	99.95
	DWT+ NB/KNN	99.62	
	TQWT+KNNE+SVM	99.50	
	CNN+ M-V	99.1	
	CWT+CNN	98.50	
F_S	Novel CNN	97.63	99.95
	1-D-LBP + FT/BN	95.50	
	DWT+ NB/KNN	95.62	
	TQWT+KNNE+SVM	98	
	LMD+ GA-SVM	98.10	
	CNN+ M-V	99.4	
	CWT+CNN	98.50	
ZO_S	Novel CNN	99.38	99.97
	DWT+ NB/KNN	99.16	
	CNN+ M-V	99.8	
NF_S	Novel CNN	98.03	99.98
	1-D-LBP + FT/BN	97.00	
	DWT+ NB/KNN	98.75	
	CNN+ M-V	99.7	

higher accuracy compared with other methods for the five-class classification using the dataset combination $Z\_O\_N\_F\_S$. The problem of two (binary) classification is to detect the seizures and nonseizures from the EEG data of the patient. The results in Table 4 proved that the proposed ESDNB approach can be used as a strong seizures detector because it provides a suitable accuracy for binary classification and other types of classifications.

4.3. Further Results and Discussion

This section introduces further results, analysis, and discussion to prove the efficiency of the work proposed in this paper. Figure 8 shows the comparison between the EEG data size of both compressed EEG data (by KCHE) and Non-compressed EEG data. The results introduced in Figure 8 show that the

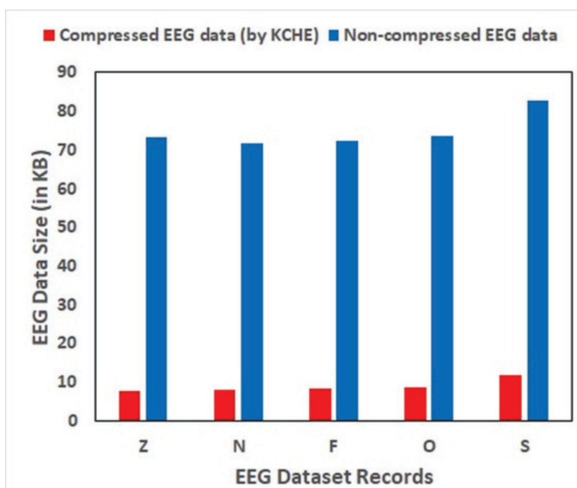

Figure 8: The EEG Data Size:Compressed EEG data (by KCHE) vs Non-compressed EEG data.

KCHE approach reduces the EEG data size after the compression from 85.6 % up to 89.2% compared with Non-compressed EEG data for different EEG data records. These results ensure the efficiency of the proposed lossless KCHE approach in compressing and reducing the EEG data before transmitting them to the Fog gateway while keeping the quality of data of the original.

Figure 9 shows the energy consumption at the edge node for both approaches: compressed EEG data (by KCHE) and Non-compressed EEG data. In this paper, the employed energy consumption model is based on the Medusa II sensor device [41]. It uses the microcontroller called Atmel's AVR ATmega103L. There are four units inside this device: processing, communication, sensing, and power supply. Table 5 summarizes the consumed energy (denoted in milliWatt/second) for various states of the sensor device. The packet size is 1024 bits.

Table 5: The consumed power values

Device Status	**Sensing**	**Microcontroller**	**Radio**	**Power (mW)**
Processing	ON	ON	ON	**26.83**
Listening	ON	ON	ON	**20.05**
Active	ON	ON	OFF	**9.72**
Sleep	OFF	OFF	OFF	**0.02**
The energy required to transmit or receive one bit is 0:2575 Joule				

The simulations were achieved on HP laptop with processor Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz (4 CPUs) whose Million Instructions Per Second(MIPS) rate is 49,360. To be compatible with the use of a sensor device (Edge node) based on a microcontroller (Atmels AVR ATmega103L) with 6MHz owning a MIPS rate equivalent to 6, the original time of execution on this laptop is multiplied by 2056.67 ([49,360/4] * [1/6]) and this value represented as the parameter T_{Diff} . The EEG data is composed of 5 data records (Z, F, S, N, O). Each one includes 100 files of EEG data. Each EEG data file includes 4097 EEG data that require 23.6 seconds to be captured. This paper combines the data of each two files to constitute 50 periods for each record. Hence, the average of energy consumption ($E_{EdgeNode}$) at the Edge node is calculated as follows.

$$E_{EdgeNode} = \frac{\sum_{i=1}^{P} E_S^i * T_S^i + E_{Pr}^i * T_{Compr}^i * T_{Diff} + E_C^i * D_{Bits}^i}{P} \tag{4}$$

Where P is the total number of periods (P=50), E_S^i refers to the energy of sensing at period i, T_S^i refers to the time required to sense the EEG data during period i ($T_S^i = 47.2$ seconds), E_{Pr}^i is the energy needed to process while applying the compression algorithm, T_{Compr}^i refers to the compression time, E_C^i is the energy required to transmit one bit in period i ($E_C^i = 0.2575$), D_{Bits}^i refers to the total number of transmitted bits by the Edge node.

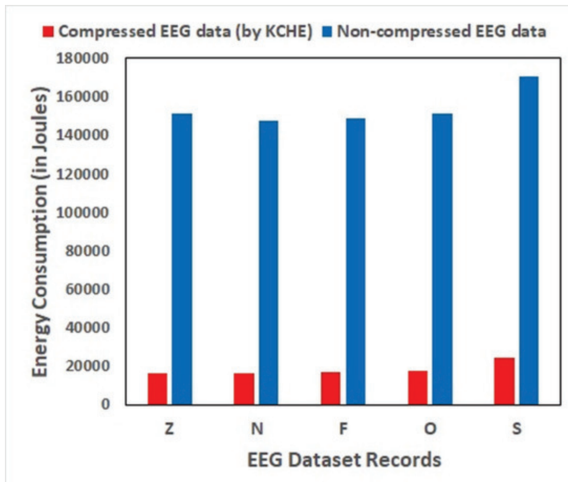

Figure 9: The Energy Consumption at the Edge node.

The results confirm that the KCHE approach reduces the consumed energy at the Edge device from 86 % up to 89% compared with the Non-compressed EEG data approach for different EEG data records. One might think that the proposed lossless KCHE approach is too costly in terms of energy due to the time required for compression, but the results show that it is very useful to lose as little time as possible during the compression to highly reduce the transmitted data without affecting the quality of received data at the Fog gateway.

In this paper, latency is defined as the time required by the EEG data to travel from the Edge node to the Fog gateway. The EEG data represents a collection of data packets belonging to the same period. The main purpose of reducing the latency is to provide a fast decision response to the medical staff about the situation of the patient. The latency is directly proportional to EEG data size. Therefore, larger EEG data sizes have higher latencies. The latency time T_L can be calculated as follows.

$$T_L = T_{Trans}^{Edge} + T_{Link} + T_{Queue}^{Fog} + T_{Pr}^{Fog}. \tag{5}$$

The T_{Trans}^{Edge} is the time required to transmit EEG data ($T_{Trans}^{Edge} = \sum_{i=1}^{PktNo} L/R$), where PktNo is the total number of packets in the period. The T_{Link} refers to the time required to transfer the EEG data across the communication link to Fog gateway ($T_{Link} = \sum_{i=1}^{PktNo} TL$), where TL is the time required by one packet to travel over the communication link to reach the Fog node. The T_{Queue}^{Fog} is the waiting time for the received EEG data at the queue of the Fog gateway, and T_{Pr}^{Fog} is the processing time at the Fog node. In this experiment, the packet length (L) is set to 128 Bytes and the transmission data rate (R) is 250 Kbps. For simplicity's sake, it is assumed that there is only one hop and the TL is 0.05 second, and the waiting time for each packet at the queue of the Fog node (T_{Queue}^{Fog}) is 0.001 second. It is assumed there is no packet loss during the simulation. Figure 10 shows the latency time for both approaches: the Compressed EEG data (by KCHE) and the Non-compressed EEG data for different EEG data records.

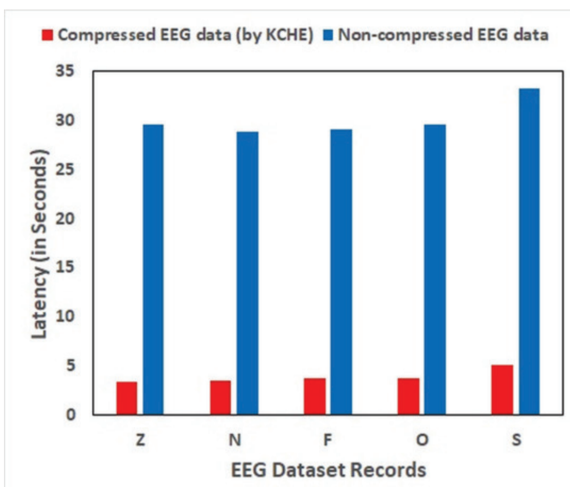

Figure 10: The latency time.

It can be seen from the results that the KCHE approach decreases the latency time between the edge and Fog nodes due to the high reduction of the EEG data at the Edge node while keeping the quality of received EEG data at the Fog gateway. The KCHE reduces the latency time from 84.6 % up to 88.2% compared with the Non-compressed EEG data approach for different EEG data records. This will help the medical staff to make fast decisions concerning their patients.

5. Conclusion and perspectives

This paper proposed an Edge-Fog Computing Enabled Lossless EEG data compression with Epileptic Seizure Detection in IoMT networks. The proposed approach applies two efficient algorithms. The KCHE lossless compression algorithm is implemented at the Edge gateway to reduce a large amount of the EEG data before sending it to the Fog gateway. The Epileptic Seizure Detector based Naive Bayes (ESDNB) designed for predicting the Epileptic Seizure at the Fog node from the received EEG data. Finally, the EEG data at Fog node is compressed to send them to the Cloud platform for archiving and further analysis. The results show that the proposed KCHE approach outperforms other existing methods in terms of compression power and compression ratio. The suggested ESDNB approach outperformed the other algorithms in terms of accuracy. In future works, the lossless compression method will be improved to increase the compression power. Furthermore, a new machine learning approach can be developed to introduce a higher accuracy and robust seizure detection.

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