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A physiological signal compression approach using optimized Spindle Convolutional Auto-encoder in mHealth applications

Vishal Barot a,*, Dr. Ritesh Patel b

a LDRP Institute of Technology and Research, KSV University, Gujarat, India
b U & P U. Patel Department of Computer Engineering, CSPIT, Charotar University of Science and Technology, Gujarat, India

ARTICLE INFO

Keywords:
Data compression
Energy efficiency
mHealth applications
Physiological signal compression
Spindle Convolutional Auto-encoder

ABSTRACT

Background and Objectives: The COVID-19 pandemic manifested the need of developing robust digital platforms for facilitating healthcare services such as consultancy, clinical therapies, real time remote monitoring, early diagnosis and future predictions. Innovations made using technologies such as Internet of Things (IoT), edge computing, cloud computing and artificial intelligence are helping address this crisis. The urge for remote monitoring, symptom analysis and early detection of diseases lead to tremendous increase in the deployment of wearable sensor devices. They facilitate seamless gathering of physiological data such as electrocardiogram (ECG) signals, respiration traces (RESP), galvanic skin response (GSR), pulse rate, body temperature, photo-plethysmograms (PPG), oxygen saturation (SpO2) etc. For diagnosis and analysis purpose, the gathered data needs to be stored. Wearable devices operate on batteries and have a memory constraint. In mHealth application architectures, this gathered data is hence stored on cloud based servers. While transmitting data from wearable devices to cloud servers via edge devices, a lot of energy is consumed. This paper proposes a deep learning based compression model SCAElite that reduces the data volume, enabling energy efficient transmission.

Results: Stress Recognition in Automobile Drivers dataset and MIT-BIH dataset from PhysioNet are used for validation of algorithm performance. The model achieves a compression ratio of up to 300 fold with reconstruction errors within 8% over the stress recognition dataset and 106.34-fold with reconstruction errors within 8% over the MIT-BIH dataset. The computational complexity of SCAElite is 51.65% less compared to state-of-the-art deep compressive model.

Conclusion: It is experimentally validated that SCAElite guarantees a high compression ratio with good quality restoration capabilities for physiological signal compression in mHealth applications. It has a compact architecture and is computationally more efficient compared to state-of-the-art deep compressive model.

1. Introduction

Wearable devices are computing devices that are a combination of electronics such as sensors and controller boards. These devices can be worn or stuck to human bodies for example watches, bands and glasses etc. The COVID-19 pandemic made us understand the need of continuous remote monitoring, early diagnosis and in time treatment, with limited resources. This has led to an increase in the use of IoT based wearable devices. As reported in [1], the healthcare domain is expected to spend around 20 billion dollars each year till 2023 on IoT based wearable devices. In mHealth applications, the wearable devices are connected to the patient’s mobile phone via Bluetooth. The mobile phone acts as the edge device that relays the information gathered by the wearable device to cloud based medical server. The healthcare providers can keep a check on patient’s vitals using a web interface. Additionally, if the measured vitals are higher or lower than the normal range, an alert or a notification can be sent to the authorities [2]. However, the mHealth architecture is resource constrained. Both wearable devices and edge devices are battery backed and have energy and memory constraint [1]. To address this challenge, we propose compression of the gathered time series - physiological data on the edge device so as to reduce the volume of gathered data. This thereby would reduce the energy consumed in transmission.

We propose Spindle Convolution Auto-encoder Lite (SCAEelite) data compression model that is a deep compressive Auto-encoder. It is built with functional layers that extract the local information from

* Corresponding author.
E-mail addresses: barotvishal47@gmail.com (V. Barot), riteshpatel ce@charusat.ac.in (Dr.R. Patel).

https://doi.org/10.1016/j.bspc.2021.103436
Received 14 July 2021; Received in revised form 16 November 2021; Accepted 29 November 2021
Available online 8 December 2021
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physiological signals using convolution operation. The model has two components - convolutional encoder and convolutional decoder. While encoder is deployed on the edge device, decoder is deployed over cloud. As the dimensions increase in the initial few layers, sufficient amount of information is gathered from the physiological signals so as to make sure a quality compression. In the last few layers, the dimensions gradually decrease so as to merge the gathered information into codes, guaranteeing a high compression ratio. This gradual increase and then a decrease in dimensions in the architecture define the spindle structure of the auto-encoder. With the objective of improving the quality of reconstructed signals, the model obtains optimal set of encodings for compression.

Our major contributions are: (1) A deep learning based compression algorithm SCAElite that substantially reduces the data size of physiological signals including quasi-periodic signals such as respiration traces (RESP), electrocardiogram (ECG) etc. (2) Experimental validation of the proposed model over two datasets from PhysioNet - Stress recognition in automobile drivers dataset and MIT-BIH dataset. (3) A thorough performance evaluation of the proposed compression model with a detailed comparison with state-of-the-art deep compressive models in terms of compression ratio, reconstruction error, computational complexity and prediction accuracy.

For validation of the efficacy, we compressed the Stress Recognition in Automobile Drivers dataset from PhysioNet [3] using the proposed SCAElite compression model. This dataset contained physiological signal data such as Electrocardiogram (ECG), Electromyogram (EMG), Galvanic skin response (GSR), Heart rate (HR) and Respiration traces (RESP). The dataset was compressed using SCAElite encoder and the signals were reconstructed from the compressed file using SCAElite decoder. The original volume of dataset was compared with the compressed version to estimate the compression ratio. Root mean squared (RMS) error and Percentage RMS Difference (PRD) were calculated for the signals reconstructed using the decoder. Stress prediction was made over the reconstructed signal data and the accuracy of prediction was compared to that obtained with predictions made on original dataset. Flops were calculated to estimate the computational complexity of the compression model. SCAElite achieves a compression ratio of up to 300 folds, PRD within 8%, prediction accuracy of 98.06% on the reconstructed signals and a reduction in 51.65% in the computational complexity when compared other deep compressive auto-encoders.

For performance comparison with the reference SCAE model [4], SCAElite compression was performed over the MIT-BIH dataset [5] from PhysioNet. ECG signals from the dataset were preprocessed for noise filtering and centralisation and were then compressed using SCAElite encoder. The original volume of dataset was compared with the compressed version to estimate the compression ratio. PRD was calculated for the signals reconstructed using decoder. The model achieved a compression ratio of 106.34, PRD of 8% and a reduction of 51.65% in the computational complexity compared to the SCAE compression model on the same dataset.

The paper is organized as follows: Section 2 provides a review of the existing mHealth applications and compression techniques. Section 3 details the methodology adopted for conducting this research. Section 4 details the SCAElite architecture and the trials conducted for hyper-parameter optimization. Section 5 discusses the dataset details. The results in terms of various performance evaluation metrics are presented in Section 6. Section 7 summarizes the results and discusses the efficacy of the model. Section 8 discusses the limitation of the model and concludes the paper.

2. Related work

While COVID-19 spread became a challenge at the global level, the advancements in technology and communication networks contributed in enhancing the global response. Wearable sensor devices and mHealth applications have become more popular due to the continuous remote monitoring capabilities and the facilitated early detection of symptoms and future prediction of a disease. An IoT based smart wearable device called the quarantine band (IoT - Q - Band) was designed to monitor the patient vitals as well as to detect the abscinding quarantined subjects [6]. Smart wearable devices were used for designing an IoT framework that would help remotely screen COVID-19 in subjects on the basis of real time data. The evaluation was done by capturing the subject’s heartbeats, body temperature, oxygen saturation (SpO2) and respiration traces (RESP) [7]. Wearable devices were used for analysis of symptoms and the risk factors influencing the COVID-19 virus; generating early predictions on the basis of oxygen saturation (SpO2) and respiration traces (RESP) [8]. A biometric bracelet with infrared thermometer, global positioning system (GPS) module and radio frequency identification (RFID) transferred real time monitoring data to a web based interactive interface helping track the COVID-19 patients real time [9].

Although COVID-19 has accelerated the need of developing a digital framework for remote patient monitoring, devices such as Whoop Strap, VivaLNK Vital Scout, Zephyr BioHarness, Apple Watch, Fitbit, etc. have had a significant impact in the routine lives, improving user experience over time [10-12]. Biometrics such as electrocardiogram, oxygen level, respiration rate, heart rate, blood pressure, blood glucose etc. can be acquired using wearable devices [13]. Activities such as sleeping, walking, eating, etc. can be recognized tracking hands and legs gestures using smart assistive devices [14]. Apart from healthcare domain, smart home [15], rehabilitation centers [16] as well as skill and working hours assessment in industries [17] make use of wearable devices.

Electrocardiogram (ECG) signal monitoring done at a frequency of 1Mbps generates 80 GBs of data each day for one patient [18]. Applications like fall detection or heart rate monitoring of a patient require instant reporting of data. Other analytical applications like a model for cardiac arrest chances prediction based on ECG pattern or symptom analysis of a disease require storage of data collected over time for future analysis. In mHealth application architecture, both wearable devices and edge devices are battery backed and have a energy and memory constraint [1]. The transmission as well as storage of this huge amount of data generated using wearable devices therefore becomes challenging. Hence, there is a need of an energy efficient data compression technique that would compress the data at edge device so as to minimize total energy consumed in data transmission and volume consumed in storage over cloud [18].

Some of the techniques used for compression are lossless such as the compression using quantizing vectors. It sends codebook indexes instead of original time series [19]. It offers a high compression ratio and low computational complexity but is inefficient for Electrocardiogram (ECG) signal compression due to non-stationarity constraint. A combination of Pulse Code Modulation (PCM), K-means clustering and arithmetic coding techniques can also be used for signal compression [20]. As the demand for robust compression and reconstruction of signals increased, lossy compression algorithms became popular. They offered a high compression with an acceptable quality reconstruction minimizing the power consumed by wearable devices [21,22].

Lossy compression techniques offer high compression ratio but distortion leads to loss of information that cannot be recovered [23]. Techniques such as Wavelet Transform, Discrete Fourier Transform, Shearlet Transform, and Discrete Cosine Transform were conventionally used for data compression but were later replaced by compressed sensing (CS) based reconstruction techniques [24]. Although these compressed sensing (CS) based techniques were computationally more efficient than wavelet based techniques, they were still complex, took a considerable amount of CPU time for execution [25] and were not suitable for applications requiring reconstruction of real time non-sparse signals. Lossy compression techniques suffer from loss of information and lossless compression techniques suffer from lower compression ratios, striking a trade off. Data driven algorithms such as neural networks have recently found a wide applicability in image compression [26], audio compression [27] as well physiological signals compression [28].
Auto-encoders are neural networks that approximate the identity function such that they are able to reconstruct the input signal as much similar with minimum reconstruction error [26]. The study conducted in [27] suggested that Auto-encoders showed reliable compression over Electrocardiogram (ECG) signals. Convolutional Auto-encoders (CAE) are variants of Auto-encoders that produce a good quality restoration of low dimensional signals providing efficient information retrieval [29]. The convolutional neural networks not only preserve the local information but also facilitate expansion of dimensions for extracting features to obtain high level information. They also facilitate reduction in the dimensionality to result in a high ratio compression [4]. Stacked Denoising Auto-encoders (SDAE) is used for reconstruction of Fetal electrocardiogram (FECG) signals [21] from a PhysioNet database. Spindle Convolutional Auto-encoders (SCAE) deep neural network based model compresses the input to a low dimensional code offering a high ratio compression of ECG signals with quality reconstruction [4]. With near lossless compression, accurate predictions can be made over the reconstructed signals. The other way around accuracy of prediction can prove a good estimate of the information loss suffered by a high dimensionality to result in a high ratio compression [4]. Supervised classifiers such as Support Vector Machine [30] and k-Nearest Neighbors (kNN) [31] were used for emotional stress detection over reconstructed physiological signals. Earlier, these deep compressive neural networks were suitable for deployment on server platforms over cloud only [32]. But, the recent development of the AI chip also known as the Bionic chip or the Neural Processing Unit (NPU) has made deployment of these compute intensive models over mobile devices easy. This has not only reduced response times due to local processing but also reduced the energy consumption increasing battery lives of wearable and edge devices [33].

3. Methodology

In the mHealth application architecture, the subjects were made to wear wearable sensor devices such as smart bracelet, smart belt, smart watch, smart ring, smart shoes etc. These devices measured the subject’s vitals at a preset frequency. The aggregated information was transmitted in the form of signals to the subject’s mobile phone or any other personal digital assistant, acting as the edge device. This wireless communication took place using technologies such as Bluetooth, Zigbee, RFID etc. At the edge device, local conditioning was performed over the measured vitals and if an abnormality was noticed, a notification was sent to the respective healthcare authorities. The data from the edge devices was then relayed via internet to the cloud based medical web server. The data could be displayed on an interactive web interface through which the medical authorities could keep a track of the subject’s health via the medical server. This data can be stored and used for future predictions and analysis in the longer run. As wearable devices and edge devices are battery backed and have energy and memory constraint, we propose compression of the gathered time series - physiological data on the edge device so as to reduce the volume of data gathered thereby reducing the energy consumed in transmission. Fig. 1 depicts the mHealth application architecture.

The proposed SCAElite compression model has two components - convolutional encoder and convolutional decoder. While encoder is deployed on the edge device, decoder is deployed over cloud. Through compression, encoder reduces the data volume enabling energy efficient transmission. On the cloud server, the signals can be reconstructed using the decoder. SCAElite guarantees high compression ratio with a low reconstruction error. As the prediction accuracy over reconstructed signals is higher than that obtained on original dataset, it proves this is a lossless compression approach.

For validation of the efficacy of the model, we compressed the Stress Recognition in Automobile Drivers dataset from PhysioNet [3] using SCAElite compression model. The dataset was compressed using SCAElite encoder and the signals were reconstructed from the compressed file using SCAElite decoder. Its performance was compared with the state-of-the-art deep compressive models such as Fully Connected Neural Network Auto-encoder (FCNN-AE), Convolutional Auto-encoder (CAE) and Spindle Convolutional Auto-encoder (SCAE) [4].

3.1. Performance Metrics

The original volume of dataset was compared with the compressed version to estimate the compression ratio. As stated in [34], compression ratio is defined as follows:

$$\text{CompressionRatio} : CR = \frac{C_0}{C_1}$$

where CR is the compression ration achieved, C0 is the size of the original signal and C1 is the size of the reconstructed signal.

PRD helps estimate the compression loss suffered by the model. It includes in its computation the variance in between the original signal and the reconstructed signal. It can be computed using
the following formula:

\[
PRD = \sqrt{\frac{(G_0 - GR)^2}{G_0^2}} \times 100 \tag{2}
\]

where \(G_0\) is the original signal and \(GR\) is the reconstructed signal.

Stress prediction was made over the reconstructed signal data and the accuracy of prediction was compared to that obtained with predictions made on original dataset and the accuracies were compared. Fully Connected Neural Network (FCNN) [35] was made use of for stress prediction over the dataset both original as well as the reconstructed one. This neural network had 16 neurons in the input layer, 32 neurons in the hidden layer and 1 neuron in the output layer; binary cross entropy used as a loss function with Adam optimizer; ReLU as the activation function in hidden layers while sigmoid activation in the output layer; trained for 10 epochs at 0.01 learning rate. Flops were calculated to estimate the computational complexity of the compression model to compare their computational efficiency. SCAElite achieves a compression ratio of up to 300 folds, percentage root mean square difference within 5%, prediction accuracy of 98.06% on the reconstructed signals and a reduction in 51.65% in the computational complexity when compared other deep compressive auto-encoders.

For performance comparison with the reference SCAE model, SCAElite compression was performed over the MIT-BHI dataset [5] from PhysioNet. ECG signals from the dataset were preprocessed for noise filtering and centralisation and were then compressed using SCAElite encoder. The original volume of dataset was compared with the compressed version to estimate the compression ratio. PRD was calculated for the signals reconstructed using decoder. The model achieved a compression ratio of 106.34, a percentage root mean square difference of 8% and a reduction in 51.65% in the computational complexity compared to the SCAE compression model on the same dataset.

4. SCAElite architecture

Spindle Convolution Auto-Encoder Lite (SCAElite) is made up of two components - Convolutional Encoder (CE) and Convolutional Decoder (CD). The hidden layers of convolutional encoder and pooling layers contribute in reducing the size of the input signal. Spindle structure is designed with the objective of obtaining high ratio compression with no information loss. By changing the number of kernels, the structure balances expansion and reduction of signal features. In convolutional encoder, there are 1D convolution layers, max pooling layers, batch normalization and 1*1 convolutional layers [36]. The kernel size is gradually increased in the first few layers to expand dimensionality compressing high level features into codes thereby guaranteeing a good quality compression. Next, kernels are gradually removed reducing their number to merge features representing compressed data, resulting in lower dimension. Hence using convolutional encoder, the input signals are converted to compressed codes which are one kernel outputs. This compression is enhanced by max pooling layer and 1*1 convolutional layers.

\[
\text{Compression} : c = g_{\theta(a)}(a) \tag{3}
\]

where \(c\) is the compressed code, \(a\) is the input signal, \(w\) is the weight, \(b\) is the bias in hidden layers and \(g(a)\) is the mapping compression function.

In the convolutional decoder, compressed signal are decoded into features for reconstruction of the original signal. Transposed convolution and max pooling layers are used [37]. There is a linear layer for transformation of features back to original signals. Here again initially dimensions are increased for decoding compressed data and then dimensions are reduced for merging features so as to reconstruct original signal using linear combination.

\[
\text{Decompression} : a' = f_{w', b'}(c) \tag{4}
\]

where \(a'\) is the reconstructed original signal, \(w'\) is the weight, \(b'\) is bias, \(c\) is the compressed code and \(f(y)\) is the mapping reconstruction function.

There are total 17 layers in the architecture. 8 layers in the convolutional encoder (CE) which includes 5 1D convolutional layers initially then one max pooling layer, 1 1D convolutional layer with batch normalization and 1 1D convolutional layer at the end. The convolutional decoder (CD) includes 9 layers namely 2 1D transposed convolutional layers in the beginning followed by a max pooling layer, followed by 5 1D transposed convolutional layers and a linear layer at the end. Fig. 2 shows the overall architecture of the SCAElite model and Table 1 details the model parameters.

4.1. Hyperparameter optimization

Using Spindle Convolutional Auto-Encoder [4] as the reference point, we attempted to propose a computationally effective thereby energy efficient model for compression of physiological signals captured using wearable devices, in mHealth applications. In the architecture of a deep neural network, batch normalization provides many different improvements such as speeding up the time spent in training [38]. It also improves the accuracy achieved over the same neural network. Another popular practice is the idea of cutting down certain weights on the basis of their importance. This is technically called pruning. Using pruning, if anything below a certain threshold is removed, it leads to a reduction in the number of parameters with a little impact on the accuracy [38]. This was seen when pruning was performed over Alexnet where parameters got reduced by 9 times and over VGGnet where parameters got reduced by 13 times [38].

There were 8 trials attempted during the phase of experimentation. Table 2 shows the architecture of each trial. Of these trials, trial 4 was the one that proved the best. The number of layers in encoder as well as decoder were 12. Activation function used was tanh and the kernel size increased with subsequent layers while making the forward pass. This model was trained for 2000 epochs.

5. Dataset

5.1. Stress recognition in automobile drivers dataset

Stress recognition in automobile drivers dataset published on PhysioNet [3] was used for validation of the efficacy of the proposed compression model. A wearable sensor body network was created to gather physiological signals of 17 different drivers while they drove on a predefined route in and around Boston, Massachusetts for a span of 50 to 90 min. The dataset had 9 attributes: elapsed time, driver, electrocardiogram (ECG), electromyography reading (EMG), foot galvanic skin response (GSR), hand galvanic skin response (GSR), heart rate (HR), marker and respiration traces (RESP). Table 3 depicts sample tuples from Driver 6’s dataset.

- Elapsed Time – Represents the time stamp of the recorded signals.
- Driver – Identifies each driver uniquely.
- ECG – Electrocardiogram Signal of the driver. For normal ECG rates, the heart must be beating at a regular sinus rhythm in between 60 to 100 beats per minute. More specifically, it is 82 beats per minute. Intervals such as P wave must have a normal duration of less than or equal to 0.11 s, PR interval must be between 0.12 to 0.20 s, QRS complex in duration less than 0.12 s, ST segment not depressed more than 0.5 mm, T wave in same direction as QRS complex and around 5 to 6 limbs leads and QT interval in duration less than or equal to 0.40 s for males and 0.44 s for females [39].
- EMG – Electromyography signal for muscles and nerve cells of the driver. Nerve conduction velocity between 50 to 60 meters per second is normal [40].
Foot GSR – Galvanic skin responses of the driver’s foot. GSR refers to the changes in sweat glands that indicate the intensity of a person’s emotional state which is also known as emotional arousal [34].

Hand GSR – Galvanic skin responses of the driver’s hand. Something scary, joyful or threatening is in environment leads to change of emotional state. Both negative and positive things can lead to this change in state. GSR hence detects arousal but does not measure the intensity of it [34].

HR – Driver’s heart rate. The normal range is 60 to 100 beats per minute for healthy adults [41].

Marker – Acts as a label depicting the level of stress the driver undergoes. After recording these biosignals, the drivers were put through a questionnaire that helped label the records. As per the dataset, there are 3 different labels as marked by the drivers wiz low stress, moderate stress and high stress [3]. The labels in marker attribute can be explained as:
1. The drivers are in “low stress” while at rest (before or after driving).
2. On highways, where there is average amount of traffic, the drivers are in “moderate stress”.
3. In city areas, where there are busy streets with a lot of traffic, the drivers are in “high stress”.

RESP – Respiration traces of the driver. Normal respiration rate for a healthy adult is 12 to 16 breaths per minute [41].

Hand GSR – Galvanic skin responses of the driver’s hand. Something scary, joyful or threatening is in environment leads to change of emotional state. Both negative and positive things can lead to this change in state. GSR hence detects arousal but does not measure the intensity of it [34].

HR – Driver’s heart rate. The normal range is 60 to 100 beats per minute for healthy adults [41].

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3. In city areas, where there are busy streets with a lot of traffic, the drivers are in “high stress”.

RESP – Respiration traces of the driver. Normal respiration rate for a healthy adult is 12 to 16 breaths per minute [41].

5.2. MIT-BIH Arrhythmia dataset

MIT-BIH Arrhythmia is a biological signal dataset available over PhysioNet [5]. It contains 48 half-hour excerpts of two channel ambulatory ECG readings. This is obtained from 47 subjects. 23 readings from a set of 4000 24-h ambulatory readings were chosen at random. These
were collected from a mixed population of inpatients and outpatients at the Boston’s Beth Israel Hospital. Rest 25 readings chosen belonged to the same set but were the ones with lesser common yet clinically significant arrhythmia that could not be captured in the random sample chosen earlier. To compare SCAElite with the reference model SCAE, ECG signals from the MIT-BIH arrhythmia database from PhysioNet [5] were used. These records were all sampled at 360 Hz with 11 bit/sample resolution. Signals were preprocessed for noise removal and centralisation, to achieve a higher compression ratio [4]. SCAElite compression model was applied over the dataset and the performance was evaluated in terms of compression ratio and reconstruction error so as to compare its performance with the state-of-the-art compression model SCAE [4].

6. Results

The training loss history for the FCNN-AE compression model, CAE compression model, SCAE compression model and the proposed SCAElite compression model over the Stress recognition in automobile drivers dataset is represented in the plots in Fig. 3. The plots include training and test (validation) loss per epoch for each of these models respectively.

6.1. Compression Ratio (CR)

The compression ratio achieved by FCNN-AE is 5.8, CAE is 31.75, SCAE is 300 and SCAElite is 300. Fig. 4 shows a comparison of the compression ratio achieved by these compression models over the PhysioNet dataset [3].

6.2. Computational complexity

The computational complexity of these compression models is measured in terms of Flops. Flop is a basic unit of computation which gives an estimate of how computationally heavy an algorithm is [41]. The computational complexity gives us an estimate of the energy consumed in the execution of an algorithm. FCNN-AE runs for 6065 Flops, CAE for 3280669 Flops, SCAE [4] for 379807 Flops while our proposed SCAElite runs for 184448 Flops. Fig. 5 shows a comparison between computational complexities of these models over the PhysioNet dataset [3].

6.3. Prediction accuracy

Stress prediction was made using a feed forward neural network (FCNN) with 16 neurons in the input layer, 32 neurons in the hidden layer and 1 neuron in the output layer; binary cross entropy used as a loss function with Adam optimizer, ReLU as the activation function in hidden layers while Sigmoid activation in the output layer; trained for...
shows performance comparison of SCAE and SCAElite models over the MIT-BIH dataset. The plot includes training and test (validation) loss per epoch. Table 4 shows a comparison of the accuracies achieved by SCAE and SCAElite compressed-reconstructed signals, the accuracy achieved was is 97.10%, with CAE it was 97.99%, with SCAE it was 98.01% and with our proposed SCAElite was 98.06%. Fig. 6 shows a comparison of the accuracies of these compression models. Fig. 7 shows the training and testing accuracies achieved over the reconstructed signals for each model.

6.4. Reconstruction error

The reconstruction error suffered by a compression model must be as low as possible. FCNN-AE suffers a reconstruction error of 15%, CAE of 9.3% while both SCAE and SCAElite suffer 8% reconstruction error. These are average PRD values calculated after conducting the same experiment with different number of samples. Fig. 8 shows a comparison of the reconstruction error suffered by these compression models over the PhysioNet dataset.

6.5. MIT-BIH dataset results

The compression ratio achieved by SCAE is 106.45 [4] while that achieved by SCAElite is 106.34. Both SCAE and SCAElite have a low percentage root mean square difference of 8% and the computational complexity of SCAElite is 51.65% less compared to SCAE. Fig. 9 shows the training loss history of SCAElite model over the MIT-BIH dataset. The plot includes training and test (validation) loss per epoch. Table 4 shows performance comparison of SCAE and SCAElite models over the MIT-BIH dataset in terms of compression ratio, reconstruction error and computational complexity.

7. Discussion

With the objective of achieving high quality compression, SCAElite compression model has been proposed. The model guarantees a high compression ratio with good quality restoration capabilities. It provides a more compact architecture compared to the state-of-the-art deep compressive model as it has lesser number of parameters with similar performance in terms of accuracy, compression ratio and reconstruction error. While the architecture ensures good quality compression, the less number of parameters assure there is no overfitting.

On implementing these compression models over the Stress Recognition in Automobile Drivers dataset from PhysioNet, the compression ratio achieved by SCAElite is higher compared to FCNN-AE and CAE while it is equal to the compression ratio achieved by SCAE. The proposed SCAElite model like other compression models minimises root mean square error. The RMS error suffered by FCNN-AE was 0.03, CAE is 0.0072 and SCAE is 0.0063. SCAElite suffers RMS of 0.0058. The stress prediction accuracy achieved over the original dataset was 97.10% while that achieved over the SCAElite compressed-reconstructed dataset is 98.06%. This is due to the pre-processing steps involved before compression, that include removal of noise from the signals. The prediction accuracy being more than that achieved over the original dataset confirms of no information loss making this a near lossless compression.

Table 5 summarizes the performance evaluation metrics for all the compression models experimented over the Stress Recognition in Automobile Drivers dataset from PhysioNet. Over the MIT-BIH dataset, the SCAElite compression model achieves a compression ratio of 106.34 and a low reconstruction error of 8%. Table 4 shows the comparison between SCAE and SCAElite in terms of the above performance metrics over the MIT-BIH dataset.

The Green500, November 2020 report [42] states that over a battery backed device like a smart wearable watch or an edge device like a mobile phone, one watt energy is consumed per 15.740 Gflops of an algorithm.

\[
G\text{flops} = \frac{F\text{lops}}{10^9}
\]

where Flops are the basic units of computation that an algorithm runs for.

\[
1 \text{ watt} = \frac{15.740}{G\text{flops}}
\]

where watt is the unit of energy. A single run of SCAE convolutional encoder [4] consumes 379807 Flops while that of our proposed SCAElite model consumes 184448 Flops. As per these statistics, the energy consumption calculation for SCAE and SCAElite models is presented as under:

For SCAE

\[
G\text{flops} = \frac{379807}{10^9}
\]

\[
\text{watts} = \frac{15.740}{379807 \times 10^{-9}} = 2.42 \times 10^{-5}
\]

For SCAElite

\[
G\text{flops} = \frac{184448}{10^9}
\]

\[
\text{watts} = \frac{15.740}{184448 \times 10^{-9}} = 1.17 \times 10^{-5}
\]

As per the calculations, energy consumed in a single run of the convolutional encoder of SCAE [4] is 2.42 * 10^{-5} watts while that
consumed by SCAElite is $1.17 \times 10^{-5}$ watts. This proves that the energy consumed in a single run of the convolutional encoder of SCAE is 51.65% more than that consumed by our proposed SCAElite model. Hence, although in terms of compression ratio, reconstruction error and prediction accuracy, SCAElite gave performance equivalent to SCAE over both the datasets, it proved 51.65% more computationally efficient compared to SCAE, thereby consuming 51.65% less energy.

8. Conclusion

The paper proposes a computationally effective and energy efficient compression model for physiological signal compression in mHealth applications. SCAElite compression model provides high-ratio compression with high quality restoration. The model was experimentally validated by stress recognition in automobile drivers dataset as well as MIT-BIH dataset from PhysioNet. On the stress recognition dataset SCAElite achieves a compression ratio of 300 and on MIT-BIH 106.34. The model provides a low PRD of 8%. SCAElite thus proves to be a promising compression model for physiological signal compression. The computational complexity of SCAElite is 51.65% less...
Table 5 Performance evaluation over Stress Recognition dataset.

| No. | Approach                  | Compression Ratio | Accuracy | Flops Error |
|-----|---------------------------|-------------------|----------|-------------|
| 1   | FCNN Auto-Encoder         | 5.8               | 81.1%    | 6065        |
| 2   | Convolutional Auto-       | 31.75             | 97.99%   | 32806669    |
|     | Encoder                  |                   |          | 9.3%        |
| 3   | Spindle Auto-Encoder      | 300               | 98.01%   | 379807      |
| 4   | Convolutional Auto-       |                   |          | 8%          |
|     | Encoder (SCAE)            |                   |          |             |

comparing to that of state-of-the-art deep compressive model. This makes it suitable for wearable devices and edge devices that have power budgets in microwatts or milliwatts ranges. With the use of "AI chips", implementation of this deep neural network based compression model on edge devices will become convenient. It will then help make the mHealth application architecture energy efficient. A downside of this model is that it is difficult designing a generic model. Thus in future work, there is a need of optimizing the model architecture to result in a generic compression model with guaranteed quality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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