

Received April 19, 2020, accepted May 13, 2020, date of publication May 18, 2020, date of current version June 2, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2995442

# Hybrid Deep Learning Model Assisted Data Compression and Classification for Efficient Data Delivery in Mobile Health Applications

YOSHEN CAO<sup>1</sup>, HANZHI ZHANG<sup>2</sup>, YONG-BAE CHOI<sup>1</sup>,  
HAO WANG<sup>3</sup>, AND SICHENG XIAO<sup>4</sup>

<sup>1</sup>College of Arts and Sports, Dong-A University, Busan 49315, South Korea

<sup>2</sup>College of Humanities, Dong-A University, Busan 49315, South Korea

<sup>3</sup>China Swimming Sports College, Beijing Sport University, Beijing 100084, China

<sup>4</sup>College of Sports, Shangqiu Normal University, Shangqiu 476000, China

Corresponding author: Youshen Cao (psjdong@hotmail.com)

**ABSTRACT** With the growing amount of chronic patients, consistent monitoring for health care professionals has been a major concern and a direct incentive to develop mobile health systems that are adaptive and energy-efficient. The data collected from these devices is extremely important and may be affected by wireless communication environments encouraging a preliminary stage that adapts transmission of data to network dynamics. The paper provides compression and classification schemes for data based on a Hybrid Deep Learning Model (HDLM) that represents data characteristics, acquired data, and energy efficiency data delivery dynamics. Further, the EEG and EMG signals are compressed and classified based on Hybrid Deep Learning Model (HDLM) has been mathematically analyzed. Hence, The system is specifically based on the Stacked Auto-Encoder (SAE) architecture which extracts discrimination in the multimodal representation of data; it reconstructs data from the latent description with the help of encoder-decoder layers for data analysis. Furthermore, Multi-Modality Adaptive Compression shows its performance, computational complexity and response to different network states has been experimentally analyzed at lab scale numerical analysis. This method is therefore appropriate for mHealth applications, which can improve energy efficiency, minimize capacity, and minimize transmission latency in the mHealth cloud with intelligent preprocessing.

**INDEX TERMS** Deep learning model, wireless network, auto-encoder, data compression, and classification.

## I. INTRODUCTION

In the present area of research, the global effort and growth for comprehensive healthcare is rapidly growing and demonstrates the need for efficient and precise systems to meet the increasing demand for better medical infrastructure for researchers and businesses [1]. Even if health surveillance systems are increasingly being introduced, they tend to be challenging in medical settings. Following this contentious accomplishment, the concept of how clinicians will respond in medical emergencies has changed in technology [2]. Transport incidents are becoming a major worldwide cause of death, requiring improved emergency care [3], [4]. The World health organization (WHO) estimated in 2012 that road accidents were the leading causes of death rates among people

between the ages of 15 to 29. The WHO has estimated by 2030, where road accidents will become the world's seventh-largest cause of death [5].

Besides, people with chronic and congenital diseases, especially as the elderly, need for better healthcare [6], [7]. The examples of chronic disease and congenital disorders that limit people from their daily exterior activity are diabetes, high blood pressure, and cardiovascular diseases. The development of better emergency and health care facilities is, therefore, the technical opportunity for people to live safely and economically [8], [9].

Monitoring of health care is one way of improving emergency services and health care. Health monitoring allows early disease diagnosis and prompt medical attention in emergencies, which can result in a reduction in injury and medical costs [11]. For recognizing patients at risk it is important to use sensors to track and transmit important symptoms of

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wei<sup>1</sup>.

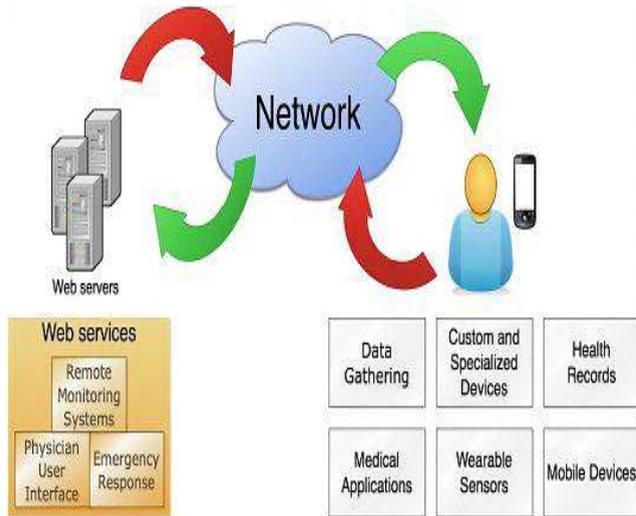


FIGURE 1. mHealth framework design [10].

the patient [12]. The medical staff can recognize measures to ensure the health of the patient utilizing sensor data. The availability of appropriate medical care could be the difference from life to death [13], [14].

Advances in mHealth systems incorporate wireless body sensor network (WBSN) (Figure 1) based technologies to provide a centralized resource for remote data transmission to medical facilities in emergencies [15]. The WBSN gathers data via a user-friendly interface from biomedical cameras and sensors. The WBSN enables images, physiological signals, and video transmission.

Data supply is generally prevented due to limitations on mobile devices and network resources. However, due to various wireless network impairments, congestion of a network, patient mobility, etc., network condition continually varies. Therefore, it must be adjusted to network dynamics for data compression to be effective [16]. Due to the availability of consumer wearable devices and variants coming from several methods, biomedical data has now become extensive. For commercial equipment, even the most complex medical monitoring systems that involve in bedding procedures are now feasible. For example, portable, noninvasive, accessible commercial devices such as Emotive headsets can record EEG [17], [18].

To overcome the above issues, and efficient data compression system using the Hybrid Deep Learning Model (HDLM) has been proposed for single and multiple data methods, following the edge computing paradigm that takes knowledge closer to patients to maximize performance [19], [20]. This system is dynamically customized to the differences in wireless networks to maximize overall energy consumption and to sustain application constraints. The main contributions of the paper are discussed as follows,

1. Provide an energy-efficient system to accommodate mHealth Cloud (mHC) multi-user data compression
2. The hybrid deep learning method (HDLM) has been suggested for PDA single and multiple data

compression modalities, it uses the interrelationship between multiple modalities to improve compression effectiveness.

3. Design a multi-user resource management system structure that determines the optimum compression ratio depends on network complexity while reducing overall energy consumption.
4. The suggested optimization system demonstrates that efficiency in reducing total energy consumption when optimizing the allocation to multiple users of network resources.

## II. RELATED WORK

The use of wireless devices in all aspects of human life around the world is growing every day. The majority of these devices are based on small sensors that automatically collect information from the environment without human intervention when deployed in the environment and create networks for wireless sensors. Due to their low battery capacity, storage, processing capacity, and communication, these small sensors are highly energy controlling. The constraint makes “Energy Efficiency” one of the issues most studied by wireless sensor networks researchers. In [21] the author presented a quantitative evaluation of the recent developments achieved in WSN information collection methods (ICM). The analysis categorizes each of the techniques based on the topology behind it. The energy savings strategy is used for a second level grouping of these techniques. For a qualitative assessment of these methods, a comparison is made.

In recent years, wireless sensor networks had developed a significant interest and represent several applications. The reliability of data collection is paramount as sensors are severe energy-controlled tools and current inequities of the protocol lead to substantial packet loss. In [22], the author reduced the information sensors required through the use of condensed detecting values. However, the principle of matrix completion effectively restores lack of information due to the loss of packets. The performance analysis shows that the reconstruction error for high compression and fairly large packet losses when such advanced signal processing methods are used simultaneously. At that same time, the network’s total energy consumption decreases significantly.

In [23], the author suggested energy-aware allocation heuristics that provide customer applications with data center resources to improve the data center’s energy effectiveness while providing established Quality of Service (QoS). Here, they define an architecture and design and energy-efficient cloud services mechanism. Based on this architecture, they present the vision, opening research challenges and resource algorithms to handle cloud systems energy efficiency. In particular, they are performing a research survey into energy-efficient technology in this paper, which proposes: (a) structural theory for energy-efficient cloud management; (b) energy-efficient allocation policy and system algorithms that take account of the efficiency and energy consumption requirements of facilities.

The Wireless Body Sensor Networks (WBSN) is the main enabler of patient-oriented or mobile cardiology information and information and communication to the next generation. The advanced WBSN-enabled ECG monitoring systems are nevertheless still less than necessary functionality, miniaturization and electricity performance. Energy efficiency can be increased, among other things, via integral ECG compression, to reduce the time slots through mobile connections [24], [25]. The paper estimates the potential on the state-of-art SHIMMER WBSN mote for low-complexity, energy efficiency ECG compression for the emerging compressed signal acquisition/compression design. The results indicate that CS needs to stand for a highly competitive approach to state-of-the-art DWT (digital wavelet transformation) WBSN-based ECG monitoring systems.

Based on the above survey, this paper proposed that the Hybrid Deep Learning Model (HDLM) has been proposed to improve the performance of Data compression and classification of EEG and EMG signals with efficient data delivery and better energy consumption.

### III. MOBILE HEALTHCARE APPLICATION AND ITS IMPORTANCE IN THE HEALTHCARE SECTOR

This section describes the main components of our health framework, explains individual or collective rules and addresses their needs in order to build a whole energy-efficient system for the requirement of critical signs. Figure 2, which contains three major systems, gives a high-level system overview:

- A. **Network Edge:** Most consumers of PDAs receive vital signals from wearable devices. The PDA uses the wearable device communication, collects, prepares and transfers data via the network infrastructure to the mHC subsystem. Preprocessing consists of a compression algorithm that converts original data into another image. It proposes a numerous method of hybrid deep learning compression that takes advantage of the accessibility of multiple modes of data and captures inter-modals in a compression strategy. In particular, it suggests compression schemes based on the Stacked AE (SAE), which are intended to compress medical records before they are sent to the mHC, taking the Quality of Service (QoS) condition and application-level into consideration.
- B. **Infrastructure for the network:** PDA communication with the mHC subsystem is enabled. The PDA is battery-operated; therefore it is important to maximize its transmission of energy. It reduces the cost to a minimum, by modeling the energy generated by the various systems entities and each allocated resources as per the wireless state of each user. In addition, with regard to the existing network structure, the feature model allows you to choose the compression configuration.
- C. **mHealth Cloud (mHC):** The medical system that collects, disconnects and stores patient data for review by medical personnel.

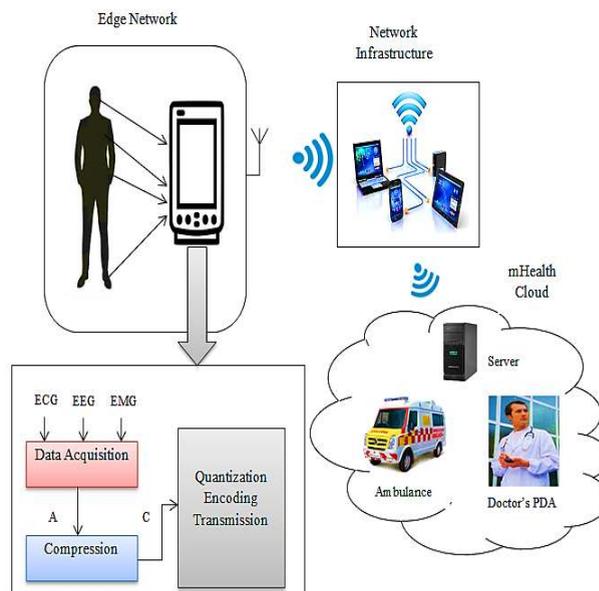


FIGURE 2. Structure of proposed model.

### IV. HYBRID DEEP LEARNING MODEL FOR DATA COMPRESSION

The design specifications and methods of the suggested compressor system are carried out in this section. In particular, it suggests the use of Stacked Auto-Encoders (SAE), and unique data compression technique. Instead, it expands the methodology suggested for a multi-modal case to address the changes in system performance achieved. Eventually, it discusses the efficiency of the proposed methodology in order to evaluate its performance for low system complexity.

#### A. DESIGN SPECIFICATIONS

The following criteria facilitate the development of a compression method, used in accordance with network and application requirements before transferring vital signs into the mHealth Network

- **Compression:** The dimensionality of the input data must be reduced to the level that the Network Identity and Capacities require.
- **Reversibility:** the reversal of the compression process (uncompressed) on the recipient's side should be possible in compliance with the application's efficiency requirements.
- **Effectiveness:** the necessary computational burden is to be divided into an edge node and the mHC.

#### 1) STACKED AUTO ENCODER (SAE)

For supervised learning applications, it is a specific type of neural network. This consists of an input layer, a hidden layer, and an output layer, as shown in Figure 3. Until the output layer is reached, the output of every layer is supplied with a next input layer. Within hidden layers, the level with both the minimal neuron number is defined as a bottleneck. The 1<sup>st</sup> layer obtained the 1<sup>st</sup> order functions, the 2<sup>nd</sup> layer received

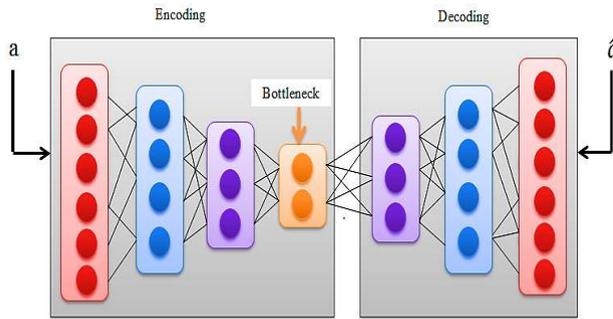


FIGURE 3. Stacked autoencoder.

the 2<sup>nd</sup> order attribute from the 1<sup>st</sup> order and more. SAE is designed to capture hierarchical knowledge abstractions.

SAE can be implemented in the mHealth model for compression because it meets the design specifications. Data can be compressed at different ratios by changing the bottleneck layer number of neurons (complying to S1), by reverting the compression process by optimal decoding (complying to S2), and specifically encoding that for the technical and expense burden between all the border network and the mHC during the training and decoding (complying with S3). Let's consider an Encoding SAE with a P layer and P layer with a decoding input  $a$  with  $m$  samples such as  $a = [a(1), a(2) \dots a(m)]^T$ . SAE aims to restore one through two operations: decoder and encoder, while mHC is capable of the first operation within an edge network, and mHC (S3 compliance). First of all, the encoder increasingly transforms the  $a$  of a bottleneck layer to the compressed representation,  $c = [c(1), c(2) \dots c(n)]^T$ , in which  $n < m$ . At each layer  $q$ , the intermediate compressed signal  $c_p$  is generated with the following terms of the encoding method:

$$c_p = f(Z_p c_{p-1} + x_p) \quad (1)$$

When the active function is  $f$ ,  $p = [1, 2, \dots, P]$ ,  $c_0 = a$ ,  $c_p$  has  $n_p$  samples have the following samples:  $n = n_p < \dots < n_1 < n_0 = m$ ,  $c^P = c$ ,  $Z_p = n_p - n_{p-1}$  vectors, and  $x_p$  is a  $n_{p-1} \times 1$ , bias vector.

The decoder then alters  $c$  slowly to generate a value of  $\hat{a}$ . Based on the decoding process, the following expression provides an intermediate approximation of  $\hat{a}_p$  at every layer  $p$ :

$$a_p = f(Z'_p a_{p-1} + x'_p) \quad (2)$$

When the active function is  $f$ ,  $p = [1, 2, \dots, P]$ ,  $c_0 = a$ ,  $c_p$  has  $m_p$  samples have the following samples:  $m = m_p < \dots < m_1 < m_0 = n$ ,  $c^P = c$ ,  $Z_p = m_p - m_{p-1}$  vectors, and  $x_p$  is a  $m_{p-1} \times 1$ .

The previous processes are simplified with greedy layer training for the SAE. Each layer is trained to minimize reconstruction of  $L_\theta(a, \hat{a})$  (compatibility to S2) by means of an optimal set of parameters  $\theta = [\theta_1, \theta_2, \dots, \theta_p]$  modified by Eq(4) and descent algorithm can be reduced at the minimum, with each layer weight and bias. Usually, this problem is

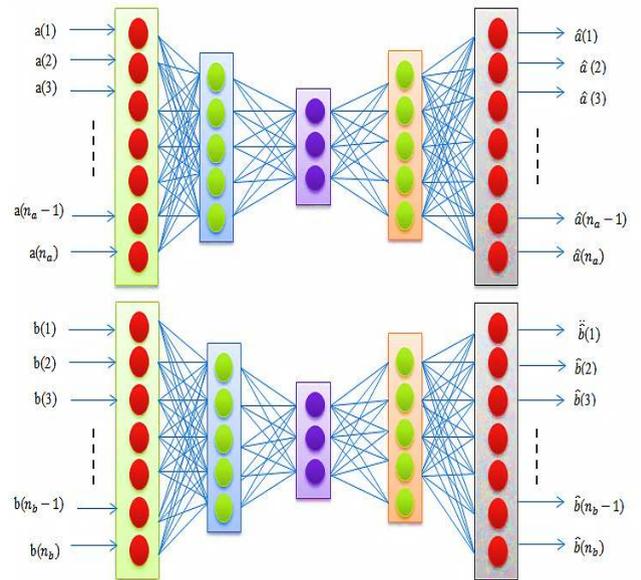


FIGURE 4. Data compression over single modality.

modeled using cross-entropy Eq(3) or Eq(4).

$$L_\theta(a, \hat{a}) = \|a - \hat{a}\|^2 \quad (3)$$

$$L_\theta(a, \hat{a}) = - \sum_j^m a_j \log(\hat{a}_j + (1 - a_j) \log(1 - \hat{a}_j)) \quad (4)$$

### 2) DATA COMPRESSION OVER SINGLE MODALITY

It is called the SAE-S method. In this sense, each signal of every device with a stacked autoencoder is compressed automatically. Let us take into consideration a scenario without loss of generality where two modality  $a$  and  $b$  signal with the number of samples  $ma$  and  $mb$  are present. Two different SAEs can be implemented to compress  $a$  and  $b$ , see Figure 4. It is called the SAE-S method. In this sense, each signal of every device with a stacked autoencoder is compressed automatically. Moreover, the drawbacks are mentioned as follows:

- For each modality, it is appropriate to store separate SAE models for each PDA.
- The SAE-S uses only the intra-correlation of the modality.

### 3) DATA COMPRESSION OVER MULTIPLE MODALITIES

This technique will be called SAE-M. In this regard, It uses one Stacked Auto-Encoder to compress acquired signals from several modes. SAE-M enables multiple modalities to be combined into a single definition, resulting in better compression by intermodality correlations. Two modes A and B are available. This vector is subjected to an SAE as shown in Figure 5 below. Multiple modal compressions are an easy solution that ensures ideal local conditions of health.

- For all modes for a specific application, only one SAE-M configuration needs to be saved on the PDA of the user.

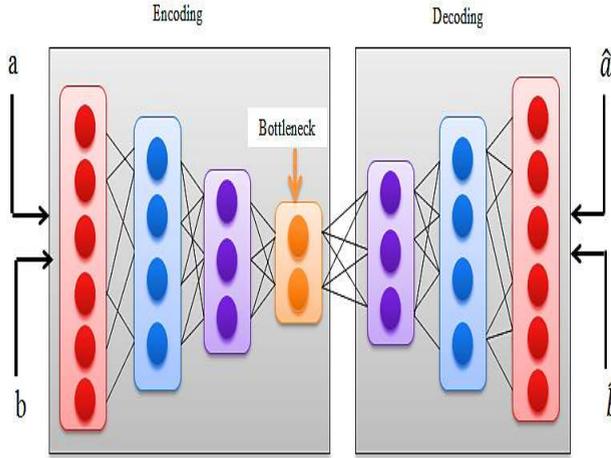


FIGURE 5. Data compression over multiple modalities.

- SAE-M operates together to optimize the use of both intra- and intermodal differences.

#### 4) EVALUATION OF COMPLEXITY

The SAE training is expensive which can be performed off-line on an mHC server-side to achieve maximum weight and preferences which can be displayed in real-time on the PDA of the patient. This evaluates the complexity of the device of the SAE-S and the SAE-M during evaluation:

If linear function activation  $f$  is taken as follows, write Eqs (1) and (2):

$$c = \left( \prod_{p=1}^P Z_{P-p+1} \right) a + \sum_{r=1}^P \left( \prod_{p=1}^{P-r} Z_{P-p+1} \right) x_r \quad (5)$$

$$c = \left( \prod_{p=1}^P Z'_{P-p+1} \right) a + \sum_{r=1}^P \left( \prod_{p=1}^{P-r} Z'_{P-p+1} \right) x'_r \quad (6)$$

$$\delta = Pn_P + \sum_{p=1}^P (pn_{p-1}n_p) \quad (7)$$

where  $n_0$  to  $n_P$  decay number of encoding samples or increase number of decoding samples.

#### 5) OPTIMIZATION OF ENERGY CONSUMPTION

It suggests a multi-user mHealth device design framework in this section that takes into account the requirements of the network and applications. In particular, it adapts the SAE-M methodology to the dynamic grid and the specifications of the application, to achieve optimum compression ratios, by choosing the DL configuration to ensure that the DL ratio is retained. First, the network/application limits are summarized and the necessary total energy consumption formalized. Formulate the problem of optimization then and use convex optimization techniques.

##### a: CONSTRAINTS ON NETWORK AND APPLICATION

The proposed scheme only aims to provide a methodology of compression with low complexity, hence it adapts to net-

work conditions and application requirements. The mHealth framework is designed to reduce total energy usage and to maximize the transfer rates and bandwidth of all PDAs. The following specific requirements should be satisfied for the given assignment: distortion threshold  $PRD_{th}$ .

##### b: CALCULATION OF ENERGY CONSUMPTION

Take mHealth multi-user with  $M$  users in which each of the samples (samples)  $A = [a_1, a_2, \dots, a_M]^T$  and  $M$  is collected in such a way that  $m = [m_1, m_2, \dots, m_M]$  and  $n = [n_1, n_2, \dots, n_M]$  and the number of bits transmitted by this device is  $L = \gamma n$ , where  $L = [l_1, l_2, \dots, l_M]$  contains the number of bits transmitted by whole customers, and  $\gamma = [\gamma_1, \gamma_2, \dots, \gamma_M]$ . Note that all vectors in this section use the same indexing form.

The total energy consumed by consumer  $I$  referred to as  $X^{(j)}$ , is as follows:

$$X^{(j)} = X_t^{(j)} + X_z^{(j)} + X_p^{(j)} \quad (8)$$

where  $X_t^{(j)}$ ,  $X_z^{(j)}$  and  $X_p^{(j)}$  are energy consumed in module  $j$  for the transmission, compression, and encoding of data. The following equations can be computed for  $X_t^{(j)}$ :

$$X_t^{(j)} = \frac{\vartheta_j l_j}{k_j h_j} (2^{\frac{k_j}{h_j}} - 1) \quad (9)$$

where  $k_j$  is the transmitted PDA  $j$  data rate over band-width  $\vartheta_j$  and  $h_j$  is the gain in the channel. In addition,  $X_t^{(j)}$  can be computed with its proportionality to the complexity of the compression algorithm is expressed as follows:

$$X_z^{(j)} = \delta_j X_c \quad (10)$$

where  $\delta_j$  is the complexity of compression algorithm,  $j$  encoder and  $X_c$  is the consumed energy per system. For  $r$  an SAE-M  $Q$ -layered module Eq(7) modifies Eq(10) to:

Where the compression algorithm  $j$  encoder is complex,  $X_c$  is the energy consumed by a system. Eq(7) changes Eq(10) to an SAE-M  $Q$  layered module:

$$X_z^{(j)} = \left( Pn_j^{(P)} + \sum_{p=1}^P [pn_j^{(p-1)}n_j^{(p)}] \right) X_c \quad (11)$$

Finally, the number of converting steps proportional to  $n_j$  is required and the energy consumed by  $X_s$  depends on  $X_p^{(j)}$ . Therefore  $X_p^{(j)}$  can be defined as follows:

$$X_p^{(j)} = n_j X_s \quad (12)$$

##### c: PROBLEM DEFINITION

Compression efficiency is quantified by the compression ratio (CR) and distortion by the Root Medium Square Difference (PRD) for the following reasons:

$$CR^j = 100 \times \left( 1 - \frac{n_j}{m_j} \right) \quad (13)$$

$$PRD^j = 100 \times \frac{\|a_j - \hat{a}_j\|}{\|a_j\|} \quad (14)$$

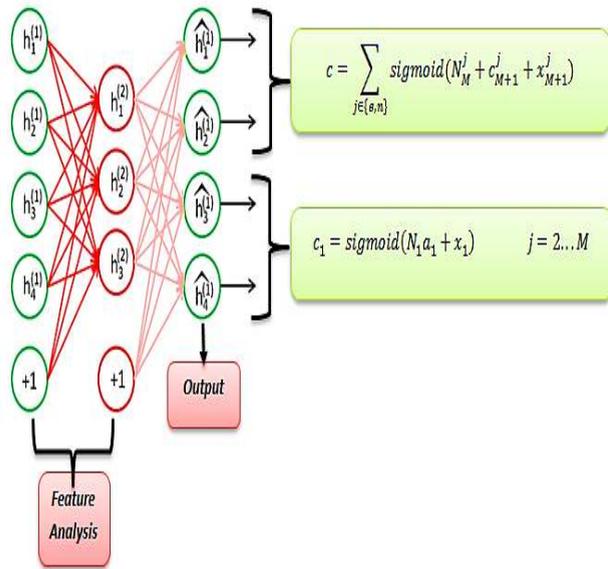


FIGURE 6. Hybrid deep learning for intermodal correlation.

The exponential operator  $d$  will estimate PRD from CR using regression analysis, such that:

$$PRD^j = d \{ CR^j \} = x e^{y CR^j} \quad (15)$$

where  $x$  and  $y$  are the parameters of regression.

Considering the application specifications and network constraints i.e. maximum permissible distortions  $PRD_{th}^j$ , time period  $D_{th}^j$  and total bandwidth  $\beta_t$ , It is expressed as follows,

$$\min_{CR^j, k_j h_j} \left( \frac{\partial_j l_j}{k_j h_j} \left( 2^{\frac{k_j}{h_j}} - 1 \right) + P n_j^{(p)} + \sum_{p=1}^P \left[ p n_j^{(p-1)} n_j^{(p)} \right] X_r + n_j X_s \right) \quad (16)$$

where,

$$x e^{y CR^j} \leq PRD_{th}^j \quad (17)$$

$$\frac{l_j}{h_j} \leq D_{th}^j \quad (18)$$

$$\sum_{j=1}^M \beta_j \leq \beta_t \quad (19)$$

## V. APPLICATION OF THE EEG AND EMG DATA COMPRESSION AND CLASSIFICATION BASED ON HYBRID DEEP LEARNING MODEL

Multimodal auto-encoder architecture is shown in Figure 5. It consists of two processes of EEG and EMG. Each route indicates a unimodal auto encoder associated with the correlation between data and intra-modality while the joint level merges the functions at a higher level.

### A. PRE-TRAINING OF UNIMODAL DATA

The SAE is applied separately for each model; the sigmoid activation function and Euclidean square distance are used as

a loss feature that is controlled by the term for weight loss.

$$c_1 = \text{sigmoid}(N_1 a_1 + x_1) \quad j = 1 \quad (20)$$

$$c_1 = \text{sigmoid}(N_1 a_1 + x_1) \quad j = 2 \dots M \quad (21)$$

The SAE is formed with a training technique in soft layers which feeds the latent representation of the auto-encoder to the layer below. This deep architecture makes the system scalable and efficient while the data are extracting higher functionality progressively.

### B. HYBRID DEEP LEARNING

Intermodal correlation (Figure 6), which can relate to proper representation of the high-level features, is not involved throughout the single modal pre-training. This allows, in particular, the encoding of the various modalities by a single joint layer common representation. The consequence of this layer involves the input in the code representing the compressed data for each modality. The common representation is achieved as follows:

$$c = \sum_{j \in \{e,n\}} \text{sigmoid}(N_M^j + c_{M+1}^j + x_{M+1}^j) \quad (22)$$

where  $e$  and  $n$  relate individually to EEG and EMG. In addition, the multi-modal autoencoder is trained in increased noise, in which additional examples lead to individual sample modes. In practice, it adds zero in value to one model, while maintaining the original in the other model and vice versa. Consequently, only a third of the training data is EEG, a third is EMG, and the remaining data are EEG and EMG. The framework that denotes the autoencoder is justified in two ways:

- It is very likely that the association between multiple modes is nonlinear.
- This non-linearity contributes to the activation of hidden units by a single-mode.

Subsequently, the initial and corrupted input is distributed separately to high levels, which are then slowly reconstructed on both inputs to regenerate the clean image.

### C. FINE-TUNING

The compressed data can be used for classification by attaching the bottleneck layer to a softmax classification, according to a monitoring criterion.

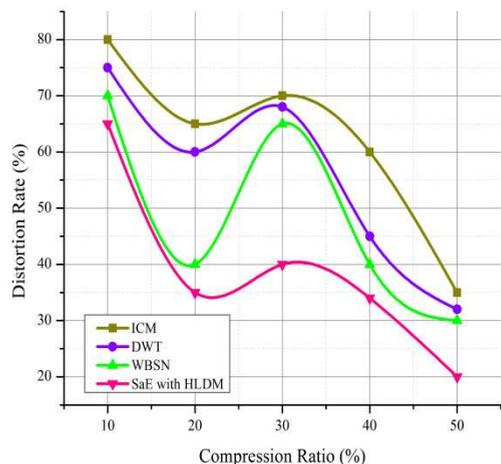
$$\hat{Q} = \frac{\exp(Xb + y)}{\sum_{t=0}^T \exp(X^t b + y^t)} \quad (23)$$

where  $\hat{Q}$  is the predicted label for the object,  $y$  describes the compressed information and  $T$  is the number of labels for classification. The performance of the Hybrid Deep Learning Model (HLDM) is evaluated using different metrics as mentioned below.

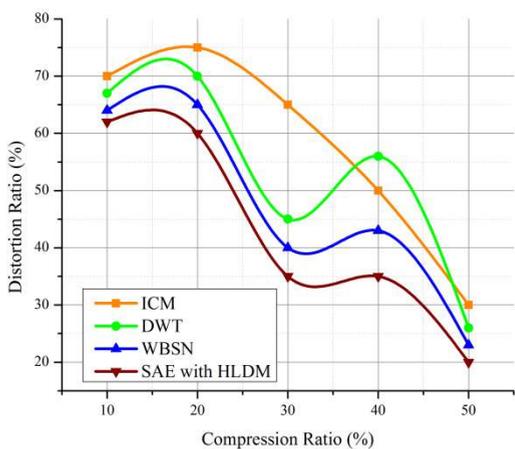
## VI. RESULTS AND DISCUSSIONS

### A. DATA COMPRESSION OVER SINGLE MODALITY

Figures 7 (a&b) demonstrate ICM, DWT, WBSN, and SAE with HDLM compression distortions at various EEG and



(a)



(b)

FIGURE 7. (a). EEG compression performance (b). EMG compression performance.

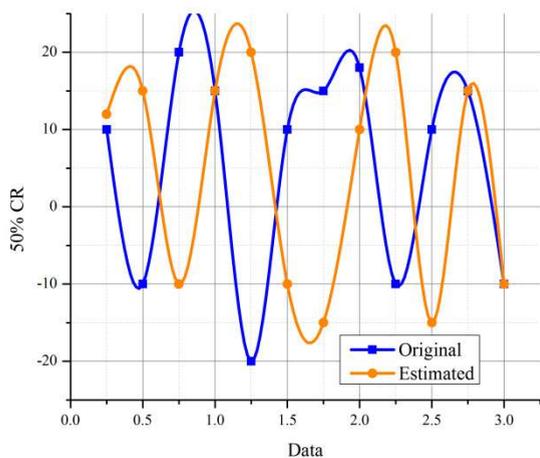
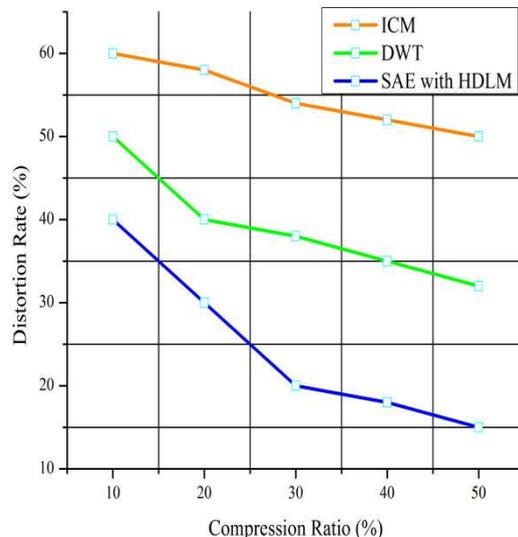
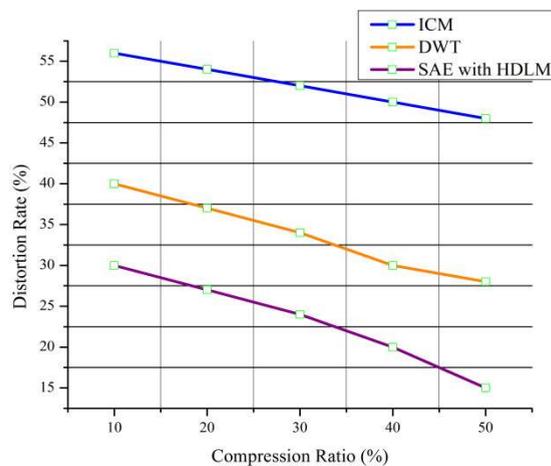


FIGURE 8. 50% compression ratio of EEG using SAE.

EMG compression ratios, respectively. Figure 7(a) reveals, on the one hand, that the findings of DWT and WBSN are similar together without a huge difference and that SAE with HDLM increases output at a high compression rate



(a)



(b)

FIGURE 9. (a). EEG compression performance (b). EMG compression performance.

with a 20.04% average distortion, demonstrating that it can compress non-stationary signaling. In Figure 7(b), however, DWT and ICM show a contrasting performance of up to 80% compression, with lower distortions than 80% compression. The latter shows a better performance than compression. SAE with HDLM both show higher performance than the former for stationary signals.

Ultimately, figures 8 display the compressed versus the initial EEG signals by 50% SAE, respectively, hence a perceptual evaluation for the low distortions can be obtained by SAE

### B. DATA COMPRESSION OVER MULTIPLE MODALITIES

Figures 9(a) and 9(b) show multiple DWT, ICM, and SAE with HDLM modality distortions at different compression ratios. Averaging results of the individual modalities by linear interpolation are determined for multiple modal results of

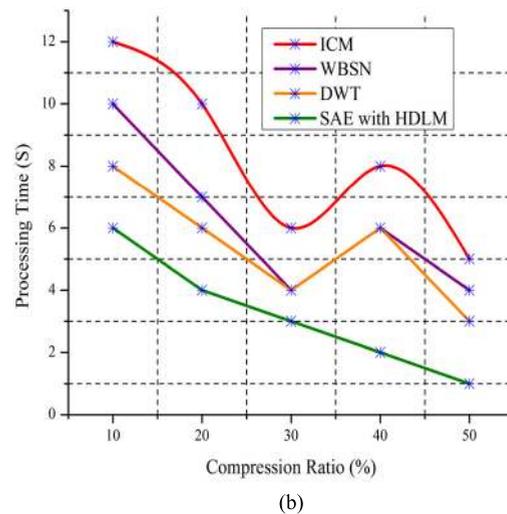
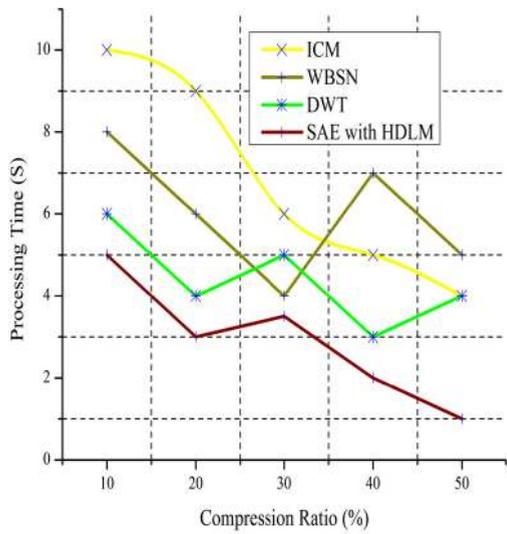
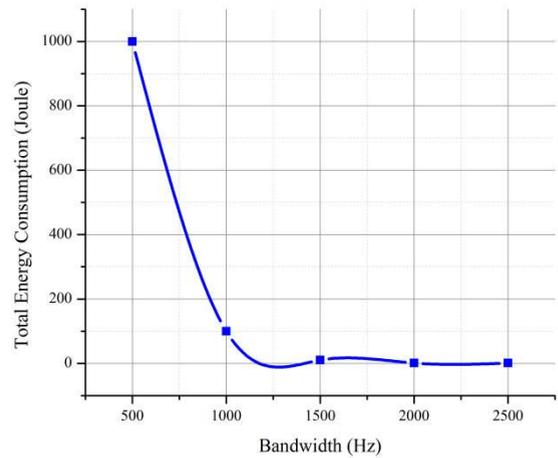


FIGURE 10. (a). EEG compression computational complexity (b). EMG compression computational complexity.

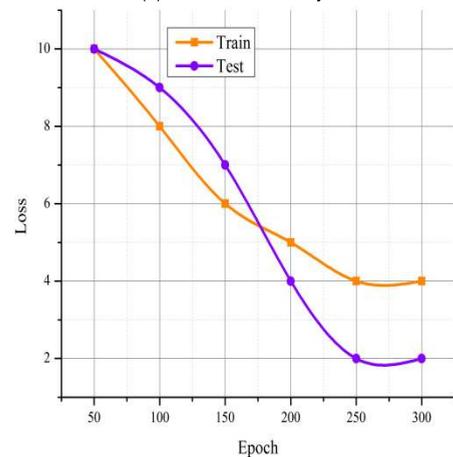
the DWT and ICM. When you analyze the data, SAE with HDLM shows improved overall performance with an average distortion of 15.05% at all compression ratios. It shows the effectiveness of SAE with HDLM for multimodality compression, showing relative performance improvements compared to DWT and ICM.

C. OPTIMIZED COMPRESSION COMPUTATIONAL COMPLEXITY

The processing times required for each modality algorithm are shown in figures 10(a) and 10(b) at different EEG and EMG compression rates, respectively. Firstly, all compression scenarios (EEG and EMG compression) need less time to work. Further, the compression rate depends on the WBSN and DWT curves, while the compression rate decreases and increases with ICM and SAE in HDLM compression compliance. Therefore, with HDLM Data form time (EEG and EMG) ICM and SAE do not change significantly, Therefore



(a) Bandwidth analysis



(b) Train Vs Test analysis

FIGURE 11. Total energy consumption validation.

in each modality DWT changes because of the different optimum parameters.

D. TOTAL ENERGY CONSUMPTION

It illustrates how the proposed SAE-M methodology leads to a reduction in energy consumption in different network areas. Energy use is assessed on the basis of the network topology in Figure 2 using simulated conditions at different distortion levels and usable bandwidths. Figure 11 (a) illustrates the energy consumed at multiple distortion thresholds. SAE can significantly decrease the overall energy consumption with HDLM, as is shown by greater tolerance for high distortion. SAE with HDLM enables multiple modalities to be combined into a single definition, resulting in better test and training rates by intermodality correlations. Figure 11(b) shows the test and training analysis of SAE with HDLM.

The above result analysis shows the Hybrid Deep Learning Model (HDLM) has better performance in EEG and EMG signals compression and classification. The system is specifically based on the Stacked Auto-Encoder (SAE) architecture which extracts discrimination in the multimodal representation of data.



## VII. CONCLUSION AND FUTURE WORK

This paper proposed the use of Stacked Auto-Encoder techniques for mHealth systems. It examined the compression of single and several modes of data for use intra and inter-relation modalities. It suggested a medical data provision Energy and resource-sensitive system given ongoing changes in network dynamics. The algorithm has been adapted to the following network limitations: the time limit, the available bandwidth and the application conditions for the maximum distortion. Our methods are analyzed by standard compression methods like ICM, DWT, and WBSN. They proved that the proposed single-and multiple-modal compression techniques are respectively adapted to network and application constraints. Results from single SAE with HDLM show that it can disjoint stationary and non-stationary compression signals while multiple SAE and HDLM can combine inter-signal correlations and make them important in real-life applications. Single SAE with HDLM and multiple SAE with HDLM light computer complexity allow for the installation on an edge device and optimization in real-time for applications. The SAEM technique reduced the total energy consumption when adapted to its compression ratio based on different network conditions. In future, improved version of algorithm will be implemented in mHealth Applications for data compression and classifications.

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**YOUSHEN CAO** was born in Xi'an, China, in 1995. He received the bachelor's degree from Shaanxi Normal University, in 2017. He is currently pursuing the Ph.D. degree with Dong-A University, South Korea. He has published two articles, one of which has been indexed by SCIE. His research directions are physical education and training, and exercise prescription rehabilitation.



**HANZHI ZHANG** was born in Xianyang, China, in 1994. She received the bachelor's degree from Dong-A University, South Korea, in 2018, where she is currently pursuing the master's degree. She has published a total of one article. Her research interest is included infant education.



**YONG-BAE CHOI** was born in Busan, South Korea. He received the bachelor's degree from Dongseo University, South Korea, in 2005, the master's degree from Joongbu University, South Korea, in 2008, and the Ph.D. degree from Dong-A University, South Korea, in 2013. He is currently working with Dong-A University. He has published three articles. His research interest is taekwondo training.



**SICHENG XIAO** was born in Shangqiu, China, in 1988. He received the bachelor's degree from the Zhongyuan University of Technology, in 2010, the master's degree from Zhengzhou University, in 2013, and the Ph.D. degree with Sangmyung University, South Korea, in 2018. From 2013 to 2018, he worked with Shangqiu Normal University. He has published five articles, one of which has been indexed by CSSCI. His research interests include sports humanities sociology and sport industry.

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**HAO WANG** was born in Tianjin, China, in 1993. She received the bachelor's degree from Tianjin University of Sport, in 2018. She is currently pursuing the master's degree with Beijing Sport University. She has published a total of two articles. Her research interests are included physical education and training.