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Review

Review on Compressive Sensing Algorithms for ECG Signal for IoT Based Deep Learning Framework

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Abstract: Nowadays, healthcare is becoming very modern, and the support of Internet of Things (IoT) is inevitable in a personal healthcare system. A typical personal healthcare system acquires vital parameters from human users and stores them in a cloud platform for further analysis. Acquiring fundamental biomedical signal, such as with the Electrocardiograph (ECG), is also considered for specific disease analysis in personal healthcare systems. When such systems are scaled up, there is a heavy demand for internet channel capacity to accommodate real time seamless flow of discrete samples of biomedical signals. So, there is a keen need for real time data compression of biomedical signals. Compressive Sensing (CS) has recently attracted more interest due to its compactness and its feature of the faithful reconstruction of signals from fewer linear measurements, which facilitates less than Shannon's sampling rate by exploiting the signal sparsity. The most common biomedical signal that is to be analyzed is the ECG signal, as the prediction of heart failure at an early stage can save a human life. This review is for a vast use-case of IoT framework in which CS measurements of ECG are acquired, communicated through Internet to a server, and the arrhythmia are analyzed using Machine learning (ML). Assuming this use-case specific for ECG, in this review many technical aspects are considered regarding various research components. The key aspect is on the investigation of the best sensing method, and to address this, various sensing matrices are reviewed, analyzed and recommended. The next aspect is the selection of the optimal sparsifying method, and the review recommends unexplored ECG compression algorithms as sparsifying methods. The other aspects are optimum reconstruction algorithms, best hardware implementations, suitable ML methods and effective modality of IoT. In this review all these components are considered, and a detailed review is presented which enables us to orchestrate the use-case specified above. This review focuses on the current trends in CS algorithms for ECG signal compression and its hardware implementation. The key to successful reconstruction of the CS method is the right selection of sensing and sparsifying matrix, and there are many unexplored sparsifying methods for the ECG signal. In this review, we shed some light on new possible sparsifying techniques. A detailed comparison table of various CS algorithms, sensing matrix, sparsifying techniques with different ECG dataset is tabulated to quantify the capability of CS in terms of appropriate performance metrics. As per the use-case specified above, the CS reconstructed ECG signals are to be subjected to ML analysis, and in this review the compressive domain inference approach is discussed. The various datasets, methodologies and ML models for ECG applications are studied and their model accuracies are tabulated. Mostly, the previous research on CS had studied the performance of CS using numerical simulation, whereas there are some good attempts for hardware implementations for ECG applications, and we studied the uniqueness of each method and supported the study with a comparison table. As a consolidation, we recommend new possibilities of the research components in terms of new transforms, new sparsifying methods, suggestions for ML approaches and hardware implementation.

Keywords: compressed sensing (CS); electrocardiogram (ECG); biomedical signal; reconstruction; compression ratio; reconstruction accuracy

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1. Introduction

Internet of Things (IoT) is a digital revolution which happens to be larger than any other technological revolution and its presence is felt in each and every domain, from huge commercial applications to small domestic applications, and thanks to the usage of smart connected devices, the phenomenon tends to become Internet of Every Thing [1–3]. IoT is intended to connect things of the physical world to the Internet for the exchange of information with a framework that comprises of various sensors, actuators wireless link, communication protocols, and data processing technologies that interact with each other to provide greater communication ability for various applications [4,5]. This huge data collected from large sensor network causes a delay in network traffic which leads to the degradation of overall performance with respect to computational abilities, battery lifetime of devices and so on [6–8]. To optimize data transmission, various approaches have been explored, where CS seems to be a suitable contender to be incorporated [9–11]. The need for an IoT framework is vital in biomedical applications, especially in sharing the remote patient's body conditions and biomedical signals to a healthcare worker. One of the important biomedical signals under consideration is the Electrocardiograph (ECG) signal to diagnose the heart function of patients remotely. There is a compulsory need to compress the ECG signal before sending it to the cloud to meet the bandwidth capacity and to serve multiple parallel remote patients. It is also important that the quality of the decompressed signal should be good enough to yield accurate data analytics results in machine learning algorithms to predict arrhythmia [12,13].

In applying CS to the ECG signal and to communicate the information to IoT, a detailed study has to be carried out on the key research and technical aspects which includes the investigation of the best sensing phenomenon suitable for ECG, the selection of optimal sparsifying methods, the study of optimal reconstruction algorithms, the right choice of hardware for implementation, strategies of the ML methods and IoT modalities. These key points will be elaborated more in Section 6 after the fundamental background is elaborated upon in Sections 2–5. In a nutshell, the contribution of this paper is to address the above key research and technical aspects through a detailed review on various transforms and sensing matrices that are used for CS for ECG, a review on various sparsifying methods and compression algorithms for ECG, a review of CS reconstruction algorithms and the proper performance metrics, a review of ML models for ECG classification, a study of compressive learning and a review of hardware implementations and IoT methodologies. We have also recommended some possible outcomes from this review.

This review article is organized as follows: Section 2 gives the theoretical concepts of CS with basic mathematical formulation, summarizes CS algorithms with various performance metrics used for classification and evaluation of reconstructed signal quality and applications. Section 3 starts with introduction to ECG signal, heart and its related diseases and implementation of CS on the ECG Signal. Section 4 discusses the IoT Framework used for remote patient monitoring. Section 5 focusses on various Deep Learning algorithms and their application for Bio-Medical signal analysis. Section 6 presents a detailed survey of previous work on CS in compressing the ECG signal, its merits, demerits, application and comparative analysis to quantify better CS algorithm, revealing the path for new research directions. Finally, Section 7 outlines the paper's conclusions.

1.1. Compressive Sensing

A typical IoT framework with a CS block for remote ECG monitoring is given in Figure 1. The accurate reconstruction of ECG signal from digital compressed information is very vital to meet the requirement [14,15]. The emergence of compressive sensing (CS) or Compressed Sampling is acknowledged as a defining moment in the field of signal processing for sensing and reconstructing a digital signal at very low sampling rates [16,17]. CS has gathered a significant identity due to its potential to reconstruct signals from sampled data below the Nyquist rate [18,19]. CS works against the conventional signal compression algorithm principles [20–22]. The efficient l_1-minimization based CS method to reconstruct signal using a smaller number of samples is discussed in reference [23] with mathematical background and fundamental formulation of CS framework.

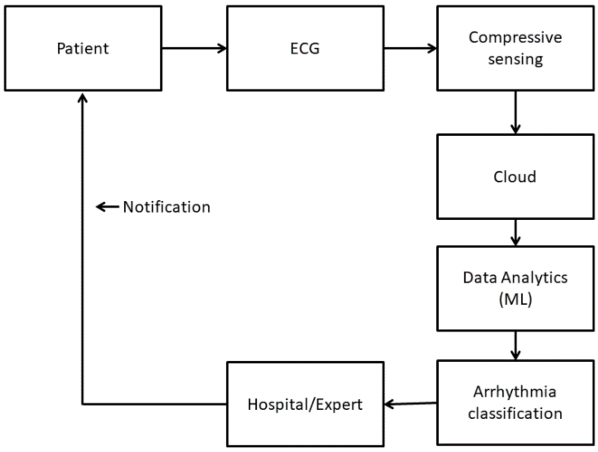

Figure 1. A generalized block diagram of an IoT-based healthcare system.

CS comprises of three process, sparse representation, sampling, and reconstruction of the signal [24]. A basic CS block diagram is shown in Figure 2. In 2004, CS obtained a new entity as David Donoho, Emmanuel Candes, Justin Romberg and Terence Tao came with a fundamental findings on a CS mathematical basis [25].

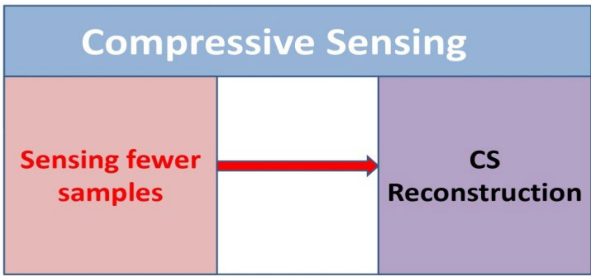

Figure 2. The CS compression scheme.

1.2. Need for CS in Bio Electric Signals

A continuous signal, sampled as per the Nyquist theorem, yields a large quantity of samples; hence, the traditional sampling method could be incapable for high-frequency signals [26]. Also, power consumption will be more due to the use of sensors in a large quantity. Hence, the compression techniques arise as an inevitable process in conventional signal processing. When monitoring bioelectric signals using WBSNs (wireless body sensor networks), some of the important parameters have to be considered such as power consumption, device cost and data compression [27–29]. In order to achieve the above limitations, data compression has to be done before transmission. However, conventional data compression methods are computationally intensive and fail to achieve these parameters. Hence, CS can be adopted as the efficient data compression methodology for bioelectric signals and other applications [30–33]. It should also be noted that in spite of all the benefits of CS, it has a demerit in that the reconstruction is an iterative process and requires more computation [24,25]. However, in an IoT framework, the computation is done in cloud support by cloud platforms.

2. Overview of Compressive Sensing Algorithm

CS is a data acquisition technique which results in reduction of transmitted power and data by combining sampling and compression through random projections. The signal could be recovered accurately if it has a low information rate and is sparse in nature either in time or in some transform domain. The number of samples required for precise recovery is determined by the sparsity of the signal. The reconstruction will be accurate if the signal being acquired has a lesser information rate which implies the signal is sparse in any of the transform domains. The number of samples required for precise recovery of the original signal also depends on reconstruction algorithm [34–37]. Moreover, CS manages noise in the measurements effectively.

2.1. CS Data Acquisition

CS theory can be expressed mathematically for signal acquisition, signal x being the original signal can be reconstructed by utilizing m << n patterns, where Φ_{m*n} being the sensing matrix through measurement vector. This sensing matrix is made up of 1 s and 0 s and to generate N-pixel random patterns through either Bernoulli or any other distribution patterns such as Hadamard, wavelet, and speckle which could be employed. Selecting the sensing matrix Φ is one of the important strategies in CS research; commonly, a random matrix is considered and the data is represented where the signal is more sparse [38–40]. Figure 3 gives an idea of the sensing matrices.

$$Y_{m*1} = \Phi_{m*n} X_{n*m} \ m << n \tag{1}$$

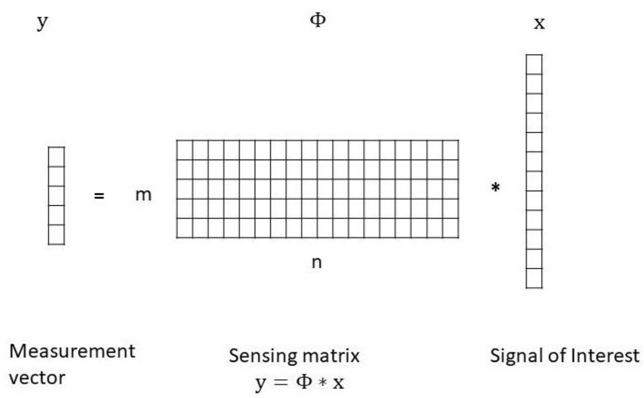

Figure 3. The CS sensing matrix.

Assuming x to be a large vector of N signal values. Consider Φ matrix, having dimension $m * n$ where $m \ll n$. The product $y = \Phi * x$ yields a much smaller, compressed vector of data $y = \Phi * x$, Φ is the sensing matrix, and y is the vector of measured values. It should be noted that m much lesser than n and when m is equal to n no compression takes place.

There are certain considerations in order to achieve faithful reconstruction; hence, the CS matrix should undergo the following properties [41,42].

- Null Space Property
- Restricted Isometry Property (RIP) and
- Incoherence

Figure 4 interprets the sparsifying matrix model which represents the signal of interest sparsely. A signal represented in sparse domain yields more desirable signal compression for efficient storage, data bandwidth and power usage, as it concentrates on the most related quality of data itself and also leads to a more effective signal detection, classification and other pattern recognition objectives. Original and Sparse representation of ECG signal is depicted in Figure 5 [43–45].

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 8 \\ 2 & 0 & 6 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 \end{bmatrix} \longrightarrow$$

Rows	Columns	Values
5	**4**	**4**
3	1	2
5	2	5
3	3	6
2	4	8

Figure 4. Sparsifying matrix.

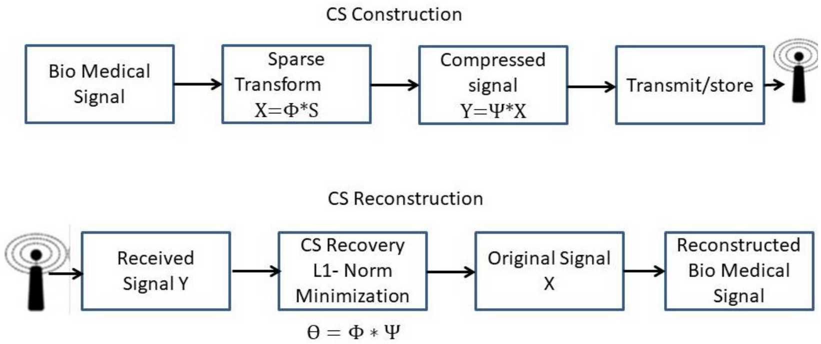

Figure 5. Communication framework using CS.

2.2. Sensing Matrices in CS

The sensing matrix plays a vital role in designing the CS algorithm, and the most important aspect in CS theory is to design efficient sensing matrices. A few important sensing matrices are the Random sensing matrix, the Deterministic sensing matrix, the Structural sensing matrix, the Optimized sensing matrix and the Binary sensing matrix.

Compressed sensing commonly makes use of random sensing matrices such as Gaussian and Bernoulli. These matrices are unstructured type and they need large memory storage and involve high computational complexity. Hence they are not feasible for hardware implementation. Contrary to this, the deterministic sensing matrix is simple to implement and widely used for practical applications. Though it does not satisfy RIP it is preferred due its compatibility with hardware application. Toeplitz and circulant are the types of structured sensing matrix with minimal parameters, and these measurement matrices can be accomplished for different applications [46–52].

2.3. Compressive Sensed Signal Reconstruction

The primary concept CS aims to reconstruct the original signal from a minimal number of measurements. To recover the original signal from the compressed domain, the signal x must have a sparse representation in any specific domain. The signal x can be modeled as $x = \Psi s$ the acquisition process can be modelled as

$$\mathrm{y} = \Phi x \tag{2}$$

where as y is incomplete measurement of x and Φ is the sensing matrix. Naturally, most of the signals are sparse, i.e., they have few non-zero elements or have a sparse representation in another domain. Here, s being the sparse representation of x and Ψ the sparsifying matrix, because it maps the signal into a domain where its representation is sparse. Ψ may be a transformation matrix (e.g., DWT, DCT) mapping to a sparse domain can be expressed mathematically as:

$$x = \Psi s \tag{3}$$

Considering s being the sparse representation of x, Equation (3) is obtained by combining Equations (2) and (3)

$$\mathrm{y} = \Phi \Psi s \tag{4}$$

By solving an optimization problem and using y, s can be retrieved. This can be found out using the l_0, l_1, and l_2 norms, though l_1-norm yields a precise result, as it is a nonprogrammable hard issue; it is rarely used and the l_2-norm is not recommended, as it creates significant errors. Since l_1 norm has less error, it is the most suitable and commonly used norm for this optimization problem [53–58]. It is denoted as in the following equation:

$$\underbrace{min}_{s} \frac{1}{2}\|y - \Phi\Psi s\|_2^2 + \tau\|s\|_1 \tag{5}$$

The CS reconstruction algorithms are classified into various categories, some of the most commonly used algorithms with their sub category are as listed in Table 1.

Table 1. The CS reconstruction algorithms and its subcategories.

CS Algorithm	Subcategories
Convex type Optimization [59]	Basis Pursuit (BP) Basis Pursuit denoising Dantzig Selector Total Variation denoising Bp-Simplex Bp-Interior Fixed Point Continuation Gradient Projection for Sparse Representation (GPRS)
Greedy Algorithm [60]	Matching Pursuit (MP) Gradient Pursuit (GP) Orthogonal MP (OMP) Regularized OMP (ROMP) Compressive Sampling MP (Cosamp) Subspace Pursuit (SP)
Thresholding Type [61]	Iterative Hard Thresholding (IHT) Iterative Soft Thresholding (IST) Approximate Message Passing (AMP)
Combinatorial/Sublinear Algorithm [62]	Fourier Sampling Algorithm Chaining Pursuits Heavy Hitters on Steroids (HHS)
Non-Convex Type [63]	Focal Underdetermined System Solution (FOCUSS) Iterative Re-weighted Least Squares Sparse Bayesian Learning Algorithms Monte-Carlo based algorithms
Bregman Iterative type [64]	Linearized Bregman Logistic Bregman Split Bregman

Each approach has certain pros and inherent cons, convex optimization can successfully reconstruct original signal form a smaller number of measurements. However, computational complexity is more [65–68]. Greedy algorithms are normally fast and time complexity is less, so it requires a matrix-inverse operation in each iteration, which requires more expensive hardware [69–74]. Combinational algorithms can quickly reconstruct data, but they require unusually structured samples, which could be difficult to obtain in practice [75–81]. The Non-Convex algorithm requires lesser measurements to recover a signal, performs better even under weaker RIP for larger signal and is difficult to implement, while the complexity is similar to that of convex optimization technique [82–85]. The Bregman algorithm is fast and gives a more sparse output, but computational cost is very high [86–88]. Figure 5 illustrates an overall communication framework using CS.

2.4. CS Performance Metrics

There are certain performance evaluation metrics that can be used to assess the reconstructed signal quality and amount of compression achieved. Some of the notable metrics that are extensively used in CS literature are the percentage root-mean-squared difference (PRD), Quality Score, Root mean square error, signal to noise ratio (SNR) and the compression ratio (CR) [89–91]. The mathematical definition of them is as follows

CR ratio of (N) original signals to (M) compressed signals

$$\mathrm{CR} = \frac{\mathrm{N}}{\mathrm{M}} \tag{6}$$

PRD ensures the quality of the reconstruction; thus, it is the measure of error between the reconstructed signal and the original signal,

$$\mathrm{PRD}(\%) = \frac{\mathrm{x} - \bar{\mathrm{x}}}{\mathrm{x}} * 10 \tag{7}$$

where $\bar{\mathrm{x}}$ is the reconstructed signal and x being the original signal.

Quality Score (QS): it is used to measure the overall performance of data compression, it considers both the CR and reconstructed signal quality, for better compression performance the QS should be higher.

$$\mathrm{QS} = \frac{\mathrm{CR}}{\mathrm{PRD}} \tag{8}$$

If the CR value is high, to recover the original signal less data is sufficient. The recovery signal quality and confidence are accessed through SNR and PRD values. If the PRD value is low the reconstructed signal has a high degree of confidence similarly the high value of SNR indicates that the reconstructed signal is of high quality. The other common measures widely used are reconstructed signal to noise ratio (RSNR), which represents differences between signals energy before and after the compression and root mean square error (RMSE).

Apart from CS performance metrics there are some other metrics to be considered in ECG signal classifications [92–94]

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{9}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{10}$$

$$\mathrm{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{11}$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{12}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{13}$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{Fp}} \tag{14}$$

$$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FN}} \tag{15}$$

TP, TN, FP, FN, PPV and NPV are the numbers of True Positive, True Negative, False Positive, False Negative, Positive Predictive Value and Negative Predictive Value respectively.

3. Compressive Sensing for ECG Signal

Knowing that many signals satisfy the sparsity property, the applications of CS can be listed as follows: speech and audio signal processing [95,96], underwater signal processing, power system monitoring [97,98], acoustic and linear frequency modulated signal processing [99], image reconstruction [100–103], radar and communications [104–106], pattern recognition [107–111], video processing [112,113], micro and nano electronics and VLSI [114–116] and biomedical applications [117–122].

As this paper relates to ECG signal compression, this section gives some basic ideas of the heart and its related function. The heart is divided into four chambers: the left and right atrium and the left and right ventricles, [123,124] and some of the most commonly occurring heart diseases are:

- Coronary artery disease (Blood vessel disease)
- Arrhythmias, problems related to rhythm of Heart
- Congenital heart disease (defects at birth)

Cardiovascular disease (CVD) refers to a group of illnesses that affect the heart and blood vessels [125–127]. The ECG records the electrical activity of the heart [128–130]. The history of the ECG dates back to 1781, and the machine traced the electrical exertion of the human heart for the first time [131–135].

It is common to use online public databases such as NYU Langone's Electronic Medical Record, MIT-BIH database, PhysioNet, Physikalisch-Technische Bundesanstalt (PTB), The American Heart Association (AHA) database etc. to evaluate CS algorithms for ECG signals [136]. Arrhythmia is one of the most frequent cardiological diseases [137–141]. Arrhythmias can be classified in many different ways but in general it can be categorized in two principal ways:

- Origination of arrhythmia in the heart
- Whether the arrhythmia increases or decreases the heart rate [142–144].

The domain conversion approach is a type of compression where the time domain signal is translated to a frequency or other domain, and data compression is applied following the conversion. Wavelet transforms, Fourier transforms, and discrete cosine transforms are some of the transform examples. The majority of lossy compression algorithms are based on domain conversion [145–147].

In general, the ECG signal is not sparse. The sparse representation approach will be used since the frequency domain ECG signal has appropriate sparse qualities. Figure 6 represents original ECG and its sparse representation [148].

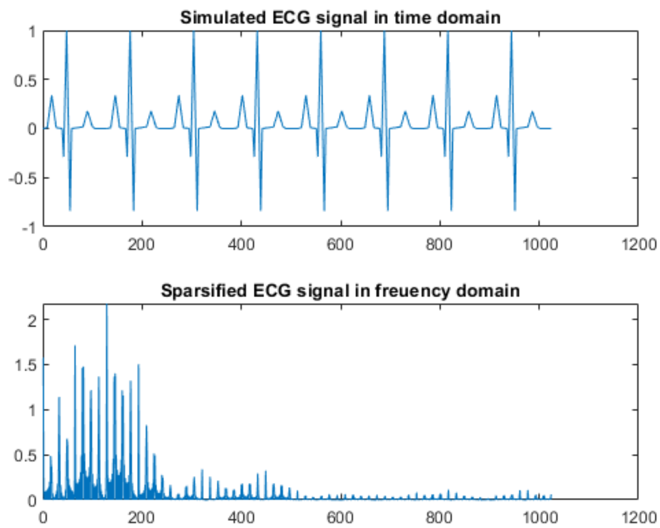

Figure 6. Original and Sparse representation of the ECG signal.

4. IoT Framework for Remote Patient Monitoring

The interconnection of computers by means of standard Internet protocol suite globally can be defined as Internet [149]. The traditional Internet focused on computers interestingly advancing from the Internet of PCs to the Internet of Things (IoT), which accentuates things instead of computers [150], which connect all things to the Internet. IoT is a network of devices that can communicate user data without human involvement and stays in line with predetermined protocols [151]. IoT has enabled a variety of applications pertaining to remote monitoring for patients where ECG monitoring has been extensively researched and implemented [152]. The exponential growth of internet-connected devices, by the means of connected wire or wireless, has caused IoT to gain popularity and become a growing topic of conversation both for commercial and non-commercial purposes which serves billions of users worldwide such as in government networks, academia, business, public and private networks [153]. IoT is the next phase of device-to-device communication where internet-connected smart devices and sensors are used to gather, transfer, store, and analyze various forms of data.

The architecture of IoT depends upon its functionality and implementation in different sectors, Figure 7 depicts the basic process flow of IoT. It can be divided into 4 Stage known as Sensing Layer, Network Layer, Data processing Layer, and Application Layer [154]. One of the most appealing uses of the Internet of Things is connected health, which allows patients to be observed and treated remotely from their residences rather than being forced to go to health facilities [155–160]. Hence, investigating compression strategies may be helpful to extend the life cycle of wearable sensors.

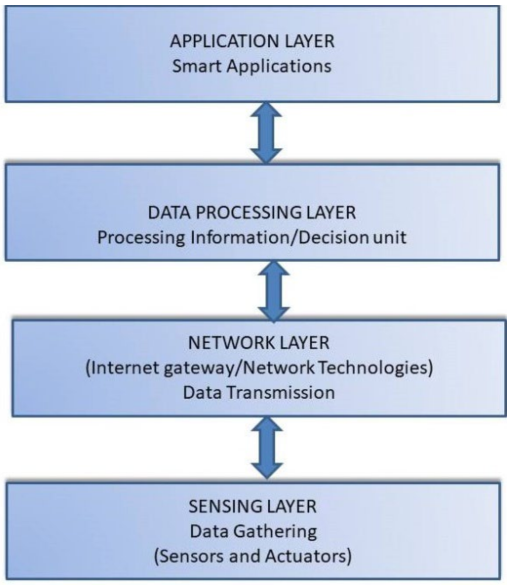

Figure 7. The fundamental architecture of IoT.

5. Deep Learning & Data Analytics for Bio-Medical Signal

The idea of an artificial neural network and its mathematical model was given by Warren McCulloch and Walter Pitts [161–164] and used in various applications [165,166] including biomedical signal classifications. Some of the commonly used Deep learning algorithms are discussed in [167,168] and are listed below.

- Convolutional Neural Networks (CNNs)
- Long Short-Term Memory Networks (LSTMs)
- Recurrent Neural Networks (RNNs)
- Generative Adversarial Networks (GANs)
- Radial Basis Function Networks (RBFNs)
- Multilayer Perceptrons (MLPs)

- Self Organizing Maps (SOMs)
- Deep Belief Networks (DBNs)
- Restricted Boltzmann Machines (RBMs)
- Gated Recurrent Unit (GRU)
- Auto Encoder (AE)
- Variational Auto Encoder (VAE)
- Denoising Auto Encoder (DAE)
- Sparse Auto Encoder (SAE)

CNN introduces learning filters that perform operations on each input sub-region. Basic CNN architecture is comprised of convolution layers, the normalization layer, pooling and the fully connected layer. The first three layers are used for feature extraction and for classification of signal fully connected layer takes the responsibility [169,170]. Some of the popularly used CNN architectures in the classification of physiological signals are AlexNet, which uses 5 convolutional layers and 3 fully connected layers, Visual Geometry Group (VGG), which was constructed with the help of 13–15 convolutional and three fully-connected layers, GoogLeNet, which utilizes 21 convolutional layers with three fully-connected layers, ResNet, which employed 152 convolutional layers, DenseNet, which used 121 convolutional layers and only 1 fully-connected layer, etc. [171–174]. The various biomedical signals acquired in an IoT framework are classified generally using CNN, and there are new trends to learn information in the compressed domain. Many more such use cases will be discussed in the next section.

6. Detailed Review of CS Based ECG IoT Framework and Analysis

In the discussion so far, we have discussed how CS can be applied for the use-case of IoT framework to acquire an ECG signal and be processed in a remote cloud for further analytics using ML algorithms. Let us revisit the key research and technical aspects mentioned in Section 1. The primary task is the investigation of the best sensing matrix of CS for ECG. This involves reviewing various sensing matrices used in literature. In this review several sensing matrices are discussed, and the best method is recommended in Section 6.4. The next task is the selection of optimum sparsifying methods which involves the analysis of all sparsifying techniques used in literature. As any best compression algorithm can be used as a sparsifier, some novel compression methods are recommended as sparsifying methods in Section 6.4 based on our review. To support the process of selection of optimum reconstruction algorithm, several reconstruction algorithms are discussed and tabulated, and the appropriate algorithm can be selected based on the platform. We also consider the right choice of hardware and IoT modalities in our review, and the tabulated results will be helpful for hardware choice and IoT modality. In applying ML for decision making, there are two different strategies: one is to learn ML models from the reconstructed signals, and the other one is to learn ML models from the CS measurements. We discussed both strategies in the review. All the aspects we mentioned in Section 1 are considered in our review, and Section 6.4 discusses more on recommendations that are given based on the review. In this section, we did a literature review on the work assuming the following research components: (i) CS sensing matrix and the sparsifying techniques (ii) ML algorithms for ECG analysis in CS framework (iii) IoT and real time CS implementation. For every research component the performance metrics of the implementation are compared and tabulated. The goal of this study is to enable to architect the use-case with the best sensing matrix, novel sparsifying techniques, optimal and effective ML algorithms, efficient hardware implementation and IoT deployment.

6.1. CS Implementations-Sensing and Sparsifying Matrices

The signal that has redundant information is said to be compressible and there are lot of compression methods for ECG signals. CS is also a method to compress the signal, but it is performed in the sensing stage where only required number samples or measurements are done on the signal and the original signal is reconstructed from the incomplete linear measurements by exploiting the sparsity of the signal. If the signal is not sparse it can be represented as a sparse signal using a sparsifying matrix. Any prevailing conventional compression techniques can be used as a sparsifier. Let us discuss some sparsifying techniques that have been used for ECG signal compression which is already used in CSA.

Let us consider some novel compression techniques that had been used for ECG and explore the method of using it in CS. One such method is Discrete Anamorphic Stretch Transform. In this study, Thilagavathy R et al. [175] have investigated a technique on compression using the 1D complex Discrete Anamorphic Stretch Transform (DAST). Here, for pre compression of ECG signal 1D DAST with three different kernel functions (Superlinear, Sublinear and Linear) it is proposed. DAST stretches and warps the ECG signal which results in the allocation of huge samples for sharp features, decreased the occupied bandwidth (OBW) and data required for storage. For inverse DAST two tap phase recovery filter is used to recover the phase of the DAST. Their experiment using MIT-BIH arrhythmia database shows that the highest average CR obtained for 3 and 6 level DWT is 3.25 and 2.8 respectively. Authors claim that the pre compression using DAST improves the compression attained using the secondary compression scheme such as Discrete Wavelet Transform (DWT) and (RLE) Run-length encoding. The proposed scheme achieved a higher CR and is suitable for cardiac patient monitoring remotely.

Fatemeh Mohammadi et al. proposed another non-invasive technique [176] to determine whether the ectopic foci located in the right or left atrium and also to identify the exact anatomical location of the ectopic foci inside the atrium. 12 lead ECG signal dataset was exploited from Tehran arrhythmia clinic database and estimation and optimization of sparse coefficients was contributed by the use of Gradient Projection for Sparse Reconstruction algorithm (GPSR) that performed well in locating arrhythmias in the right and left atria accurately.

Another work [177], addresses two MAXimum Feasible Subsystem which have been implemented and investigated for reconstruction of compressed ECG signals. For signal compression, Random Normalized Matrices (RNM) is used and in recovery of ECG signals it out preformed the state-of-the-art CS sparse recovery algorithms such as Smoothed l_0 Norm (sl_0) and BP.

Hongqing Liu addresses [178] the power line interference (PLI) that is present in ECG signal while reconstructing. They utilized the sparsity of signals to execute PLI suppression and as well as to reconstruct the ECG signal. Joint optimization estimation was formulated to simultaneously perform the PLI suppression and ECG recovery in the transform domains. Optimization problem was solved with the help of two popular efficient greedy algorithms such as BP and CoSaMP for ECG reconstruction and PLI suppression using MIT-BIH PTB diagnostic ECG database.

In [179], Chandan Kumar Jha et al. demonstrated the ECG data compression technique based on the tunable Q-wavelet transform (TQWT) which provides modifiable parameters to attain better compression. The performance of the TQWT compression technique was evaluated on various records of MIT-BIH arrhythmia dataset the performance result obtained for 48 first lead ECG records of duration 1 min in terms of CR, PRD, PRD1, QS, QS1 and SNR are 20.61, 4.43, 6.37, 5.88, 3.46, and 55.93 dB respectively and for 48 first lead ECG records of duration 30 min was 21.98, 7.11, 9.23, 4.24, 2.57 and 48.48, respectively.

Tsung-Han Tsai et al. [180] investigates the lossless compression technique for multichannel ECG, which utilizes the adaptive linear prediction for intra channel and inter channel decorrelation to remove redundancy in lossless mode with an adaptive Golomb–Rice codec for entropy coding and achieved an average CR of 2.809 saved average power of 36.5 mW.

Asma Maalej et al. [181] discusses the innovative wavelet-based compression scheme for ECG signals in e-Health cardiac online diagnostic applications. The compressibility of continuous-time sampled ECG signals has been investigated in this research using 75 ECG signals which are normal and pathologic and 54 different orthogonal and biorthogonal wavelets to determine the best wavelet for ECG compression. After the (level-crossing analog to digital converter) LC-ADC model sampling, OMP algorithm is used to compress. The effectiveness of both LC-ADC and bior3.1 wavelet decomposition, followed by thresholding, is computed and is compared with conventional ADC. This resulted in 33% bits reduction compared to conventional ADC with PRD ranging from 0.1 to 2.1 percent and an acceptable diagnostic quality.

In her research work [182], Luisa F. Polania et al. utilized the correlation between consecutive heartbeats to determine the magnitude of the coefficients of the sparse representation in support of the signal. In this proposed scheme, normalization, sampling and quantization of ECG signal is carried out at the encoder stage, and most of the computational process is done at the decoder side using block sparse Bayesian learning (bSBL) algorithm. Daubechies db4 wavelets were used, and the effectiveness of the proposed bSBL algorithm for reconstruction of original signal is evaluated. The superiority of the proposed scheme was compared with SPIHT algorithm where the proposed method outperformed for low PRD values and reconstruction SNR. When compared with SOMP, MSBL and CoSOMP this method was capable of recovering the ECG signal with lesser measurements.

Another article [183] proposes an ECG compression algorithm which relies on residual error coding based on variable-length classified signature, envelope vector sets (VL-CSEVS) and wavelet transform. The suggested approach used an energy-based segmentation technique where a high-energy ECG frame possessing important clinical information as QRS complex was represented with short segments and a low-energy ECG frame with or without clinical information with large segments and tested on the MIT-BIH Arrhythmia and MIT-BIH Compression Test Dataset to get high CR with low reconstruction error, and the average time taken for compression and reconstruction was 0.619 and 0.279 s respectively, retaining the diagnostic information of the reconstructed signal.

The authors of [184] Israa Tawfic et al. explored CS for wireless ECG system with iterative method using WBAN and DWT sparsification. They presented two greedy pursuit techniques named Least Support Orthogonal Matching Pursuit (LS-OMP) and Least Support Denoising-Orthogonal Matching Pursuit (LSD-OMP). The effectiveness of the LS-OMP is tested from Physio Bank ATM records and to get a sparse signal DWT was used. The stopping condition in the algorithm successfully found the correct signal in a smaller number of iterations. Similarly, this was experimented for other record using three level DWT with filter type Symlets8. The transmitted signal was affected with WGN = 10 dB noise, reconstructed signal is achieved with RSNR = 25.0677. Three performance measures were used to check the ability of proposed algorithm and compared with the other three greedy methods such as MP, OMP and (Compressive Sampling Matching Pursuit) CoSaMP. Results showed that there is a significant performance in terms of reconstruction quality and compression rate.

Michael Melek et al. [185] proposed an ECG compression method in wavelet domain based on adaptive greedy reduced-set matching pursuit with partially known support (ARMP-PKS). The ECG signal is segmented into non-overlapping blocks of definite length and sparcification of the signal is performed on each block using Daubechies 5 DWT. The wavelet coefficients are thresholded to improve the performance, keeping only the top magnitude coefficients. CS is applied to the wavelet coefficients of each block and the reconstruction capability of ARMP-PKS is evaluated on MIT-BIH Arrhythmia Database. ARMP-PKS displayed a significant improvement in reconstruction time and SNR.

Javad Afshar Jahanshahi et al. [186] discussed a CS technique with lower-rank limitation for efficient data acquisition and signal recovery for multichannel ECG in WBSN. For effective signal recovery, an analytical method is implemented based on alternating direction method of multipliers (ADMM) to effectively solve the optimization problem. Specifically, two optimization methods are defined l_1 norm and nuclear norm for sparsity and the low-rank constraint respectively. Daubechies-4 (db4) wavelets and DCT are used as the temporal and spatial sparsifying bases for reconstruction of MECG signals using MIT-BIH and PTB database. Considering the additive white Gaussian noise (SNR = 10 dB) to all the experiments, the proposed algorithm achieved higher reconstruction accuracy with a smaller number of required transmission packets and lesser computational complexity with low reconstruction error.

Shuang Sun et al. [187] makes a study on the acquisition of heart sound (HS) signals by CS in WBSN. The main purpose is to find the best sparsifying basis among the wavelet family, the best reconstruction techniques and frame size among the widely used ones. BP was considered as recovery algorithm, setting the frame size to 1024 and it is implemented over 52 different types of wavelet basis. The experimental results conclude that with the reduction of CR, PRD decreases significantly. The results demonstrate that rbio3.1, bior3.1 and bior3.3 had bad recovery performance when CR is greater than 35%. Keeping db2 as sparsifying matrix and the frame size to 1024 for fair comparison, different reconstruction algorithms bring about different signal qualities. PRD for almost every CR region and the best efficiency was obtained by BP. OMP algorithm gave satisfactory result for 35% of CR value. However, when CR is greater than 50%, PRDs and SSIMs of OMP and CoSaMP methods are unsatisfactory, and analysis of frame size concluded that the frame size from 256 to 4096 has little influence on the reconstruction quality. The different frame sizes have undefined differences in terms of PRD and SSIM.

Another paper [188] addresses the design of bi orthogonal wavelet filters to increase the sparsity of ECG signal in CS domain in ECG and fetal ECG compression based on double exponential wavelet 2 (dew2). From the observed result it can be noted that the sparse representation in fetal ECGs was better compared to other wavelets where the obtained reconstruction quality was enhanced as there was an improvement in PRD and PSNR. In some dataset dew1 performed better than dew2 as the prior had good sparse representation.

Fabio Pareschi et al. [189] investigated on Rakeness-Based CS optimization techniques for improving reconstruction performance of an ECG Signal using three iterative algorithms such as OMP, CoSaMP and Iterative Hard Thresholding (IHT) at decoder and evaluated their performance in terms of energy required for reconstruction. On two separate ARM architectures, three iterative techniques were explored, and certain trade-offs were considered, OMP emerges as the best reconstruction algorithm, both in terms of energy consumption and reconstruction quality.

In [190] Zhimin Zhang et al. examined the four commonly used CS recovery algorithms such as CoSaMP, OMP, Expectation Maximum-based block sparse Bayesian learning (BSBL-EM) and Bound-Optimization-based block sparse Bayesian learning (BSBL-BO) to identify the suitable algorithm for real-time application for CS-based ECG signal processing. PRD and Reconstructing time (RT) were chosen as performance metrics. For various values of CR BSBL-BO and BSBL-EM algorithms performed superiorly, specifically BSBL-BO resulted in giving the best PRD while BSBL-EM attained the better RT at various CR. It resulted in saving more hardware resources and reducing the burden of sampling and storing.

Article [191] discusses the aim of enhancing the reconstruction quality of ECG signals in CS algorithm. Enrico Picariello et al. proposed a new method for dictionary matrix optimization. The dimensions of the dictionary matrix were reduced by using a Multiple Orthogonal Matching Pursuit (M-OMP) algorithm in an initial training phase. As a result, the OMP algorithm used in reconstruction estimates the signal coefficients in a reduced domain, which in turn increased the signal's quality and execution time was also reduced. PhysioNet and MIT-BIH Arrhythmia Database were explored for evaluation, and this method achieved greater performance in terms of PRD and also exhibited a better reconstruction quality.

The work performed by Ruixia Liu et al. in [192] discusses about ECG signal corrupted with different noise signals and efficient way of denoising and recovering. They considered two noises baseline wander interference and Gaussian white noise and overcame the noise by using the low-pass filtering method and alternating direction method of multipliers (ADMM) optimization algorithm. This BP-ADMM is based on the conventional BP algorithm, which can reconstruct the ECG signals with denoising. To improve the original variables and dual variables at the same time this scheme adds a secondary penalty term and reduces constraint conditions. By decomposing the objective function in parallel the calculation speed is improved by dual decomposition method, the simulation results conclude that the proposed algorithm gave its best in ECG denoising with higher SNR and lesser mean square error (MSE).

Yih-Chun Cheng et al. [193] proposed low-complexity CS techniques in WBSN for monitoring ECG signals. To simplify the support augmentation and to estimate the efforts in the recovery algorithm, properties of ECG were utilized in the wavelet domain to extend the partially known support set (PKS). OMP algorithm based variable orthogonal multi-matching pursuit (vOMMP) that combines the advantages of OMP and orthogonal multi-matching pursuit (OMMP) is proposed to successfully augment the support set with reliable supports as a first step and as a second phase. The OMMP is used to increase the probability of recovering the missing supports to increase the reconstruction performance. For reducing the computation complexity matrix-inversion-free scheme based on QR decomposition was utilized to implement pseudo-inverse operation. The performance of the proposed scheme was evaluated, complexity analysis and simulation results proved to attain good performance with less complexity.

Yaguang Yang et al. [194] conducted study on adaptive ECG signal processing system adapting the quantity of data transmitted based on the channel status. Partial DCT matrices and LDPC matrices were used as measurement matrices. Later, performances of various recovery algorithms were evaluated using CR, MSE, PRD and SNR. BSBL algorithm gave the best result with low data rate.

Wireless body area network (WBAN) is a trending technology which allows examining and collecting patient health data using wearable sensors. WBAN communicates through the Internet and other wireless technologies like Bluetooth, ZigBee, Wireless Sensor Networks (WSNs) etc. Here are a few studies which are carried out using CS on WBSN.

This approach by Yue-Bin Zhou [195] initiated to cut down the energy consumption of WBAN node, a data compression energy-saving strategy was presented. Using CS technique for signal compression, Sparse Representation Classification (SRC) algorithm was selected to recognize the normal and abnormal signal. SRC identifies the nodes that are collecting normal signals and set them to dormant state these normal physiological signals collected by WBAN nodes will not be transmitted and put the nodes to sleep state which reduces the amount of data acquisition and transmission, which in turn reduces the data transmission energy consumption of WBAN node. Similarly, if the abnormal signal is identified it is sent directly to the central base station, and reconstruction of the signal is done through CS reconstruction algorithm. FFT was chosen as transformation matrix, and sparse random matrix was selected as measurement matrix. Signal recognition simulation result shows the effectiveness of proposed model based on the PRD and SNR evaluation index. The minimum l_0 algorithm has faster computing speed compared with l_1 minimum convex optimization algorithm. Considering both recognition time and data rate, greedy algorithm is a preferable algorithm for the ECG SRC algorithm.

This paper [196] by Yunfei Cheng et al. proposes a fast and accurate non-sparse ECG signal recovery algorithm based on BSBL known as BSBL-Alternating direction method of multipliers algorithm (ADMM) for ECG tele-monitoring system. The proposed BSBL-ADMM method can recover non-sparse ECG signals in the time domain with high accuracy and speed. A digital CS based practical wearable ECG tele-monitoring system was built and the experimental outcome demonstrated that the proposed approach can directly recover ECG signals in the time domain without the need of a dictionary matrix with fast speed and acceptable accuracy. The suggested technique is quick and resilient for various ECG datasets because of ADMM.

This study [197] by Zhimin Zhang et al. recommended CS algorithms for reconstructing under-sampled and compressed ECG signal. This method involved two steps: ECG signal subsampling and reconstruction. Initially sparsity enhancement was done by sub-sampling the ECG signal and using Cut and Align (CAB) it was mapped onto a two-dimensional (2D) space, later using nonlinear optimization model 2D signal was reconstructed. Compression of original signal was achieved using Gaussian random matrix and recovery of signal is done using four well known algorithms, two from MP that is OMP and CoSaMP and another two from BSBL method such as Bound-Optimization based Block Sparse Bayesian Learning (BO-BSBL) and Expectation-Maximum-based Block Sparse Bayesian Learning (EM-BSBL). Performance evaluation was carried out by PRD and Reconstruction Time (RT) is also considered. The suggested CS technique demonstrated to be capable of reconstructing original signals faithfully with just 30% data acquisition. The obtained results prove that the reconstruction accuracy was better in BSBL methods and for implementation MP methods proved to be very efficient.

Anurag Singh et al. [198] proposed a work in which a joint CS method is considered for compression and recovery of multi-channel ECG (MECG) signals for tele-monitoring applications. Here two specific sparse recovery algorithms are jointly used from weighted mixed-norm minimization (WMNM) algorithms, one is iterative and referred as Sub-band weighted MNM (SWMNM), and the other is a non-iterative algorithm called Prior weighted MNM (PWMNM). The proposed recovery algorithms exploit multi-scale signal information through a sub band weighting strategy. This weighting strategy incorporates additional information about diagnostically relevant wavelet coefficients in the optimization problem formulation and emphasizes them in the final reconstruction. Results are averaged for PTB database, PRD = 6.60, SNR = 23.67, WEDD = 6.07 and CSE data base, PRD = 16.74, WEDD = 13.96. It has a capability of achieving classification accuracy of 73.2% when MECG signals are jointly reconstructed using only about 10% of compressed measurements. The proposed method was capable of reducing the number of CS measurements required for effective reconstruction.

Mohammadreza Balouchestani et al. [199] discuss a modified low sampling rate approach based on CS theory with incorporation of BSBL framework for classification of normal and abnormal ECG signals. Sparse reconstruction algorithm was evaluated using SPARCO toolbox. ECG databases were subjected to a random sensing matrix, this random sensing matrix was examined with three different sensing matrix variants concluded that with minimum energy consumption the Binary Toeplitz matrix provided good SNR and better compression performance. The recovery of sparse signals from quantized random measurements is validated through BPBQ (Basis Pursuit De Quantizer) toolbox, and performed better on CR, and PRD with high probability and with reasonable accuracy.

Shengxing Liu et al. [200] proposed a self-training dictionary scheme (STDS) based on an approximated l_0 norm constraint method (Al_0CM), it is designed by making use of an accelerated gradient descent method for ECG signal compression and reconstruction to attain better accurate sparse representation. In the compression stage, the original ECG signal is recorded and compressed by sampling matrix. Then the compressed data is transmitted through IoT platform and received by the data center for reconstruction of original ECG signals. In this work STDS is used for sparse representation. A training step is required for the learned dictionary; training data is taken from the original ECG signal. This method performed superior in terms of the RSNR, for both low and high CR. It provided a better precise estimation of the ECG signal even when CR = 0.2, RNSR was high compared to other methods.

Jeevan K. Pant et al. [201] proposed ECG Signal Compressive Sampling by Encouraging Second-Order Sparsity Differences and with the aid of using a Dictionary Learning. The regularised least-squares (l_p^{2d}-RLS) algorithm, for the reconstruction of ECG signals and dictionary learning algorithm for improving the l_p^{2d}-RLS algorithm is proposed in this study, On the second-order difference of the signal, the pseudo-norm is employed to promote sparsity. The l_p^{2d}-RLS algorithm is associated with the reduction of a pseudo-norm regularised square error. A sequential variant of the basic conjugate-gradient (BCG) approach is used to perform the optimization. The l_p^{2d}-RLS technique is used to reconstruct signals, and the linear least-squares method is used to update the dictionary. Simulation results shows that the l_p^{2d}-RLS approach improves signal reconstruction performance, and the average computation time was also less.

Tohid Yousefi Rezaii et al. [202] investigated a new method to find out the sparsity order of the signal by reducing the reconstruction error, the Optimum Sparsity Order Selection (OSOS). Using the dictionary matrices based on Gaussian kernel functions representation of the sparse signal is obtained, the OMP algorithm was used to estimate the active coefficients of the model. By knowing the optimum sparsity order, a sensing matrix which has RIP property was used to achieve compressed ECG signal. The proposed algorithm provided fair compression ratio, parameter error, efficient denoising and good improvement in SNR. The raised Cosine dictionary represented more sparsifying dictionary, it is much more efficient than Gaussian kernel and this method can work with any sparsifying kernel.

Luisa F. Polanía et al. [203] investigated the (Restricted Boltzmann machines) RBM-OMP-like algorithm wavelets and "learned overcomplete dictionaries" are utilized to sparsify ECG signals. RBM is a type of undirected graphical model made up of layer of binary stochastic hidden units and a layer of stochastic visible units. Daubechies-4 wavelet transform used as the sparsifying transform at decomposition level L = 4. Simulation result revealed that the RBM-OMP-like algorithm performed better when using learned overcomplete dictionaries than wavelets.

Another proposal by Manas Rakshit et al. [204], discusses CS based efficient beat type dictionary learning. For individual ECG records, the proposed algorithm provides high-quality reconstructed signal without training stage. It incorporates both beat type dictionary and non-uniform random sensing matrix. Based on the morphology of the ECG beats the matching beat type dictionary is employed for recovery of the ECG signals. A cross-correlation based template matching approach is used to determine the type of ECG beat in the recovered signal. The kind of the beat is identified by determining the greatest cross-correlation coefficient. The qualitative and quantitative analysis concluded efficiency by analyzing CR, PRD, PRD1, RMSE, SNR and (fractional distortion measure) FDM. It produced greater CR and the power consumed by the proposed scheme was 11.35 µW which is very less.

The authors Dana Černá et al. [205] provided the complete description to build wavelet dictionaries with reduced dimensionality for modelling the ECG signals, these dictionaries are created from known wavelet families. Each dictionary is created by taking the models from a wavelet basis and translating them in a smaller step than the wavelet basis itself. There are two parts to each of the suggested dictionaries. A discrete cosine basis denoted as matrix D_c, is used in one of the components few elements, and the Wavelet dictionary denoted as matrix D_w is the other component. As a result of the horizontal concatenation of D_c and D_w matrices, the full dictionary D modeling is built as $D = [D_c * D_w]$ and it was illustrated to reduce the dimensionality of three records from the Arrhythmia database. The wavelet dictionary is constructed for different scales with translation parameter b = 1 and b = ¼ and approximation was realized.

Pasquale Daponte et al. [206] this paper presents a dynamic CS method for monitoring ECG signal with multiple lead, and transfer of information through IoT networks. The CS algorithm utilizes a sensing matrix that is constructed from a vector obtained by precisely integrating ECG signals from two separate leads. The sensor node obtains a compressed signal for every ECG frame and sends it to the cloud server, together with the vector defining the sensing matrix. As a result, the sensing matrix can be reconstructed in the cloud server, and all of the ECG leads can be recovered, Mexican hat wavelet kernel is used as sparsity matrix and to solve the reconstruction problem this method utilized two minimization algorithms the Multiple Sparse Bayesian Learning (M-SBL) and the Multiple FOCal Underdetermined System Solver (M-FOCUSS). The proposed method obtained low PRD.

Mohammed M. Abo-Zahhad et al. [207] exploit a single-lead ECG compression method in which the Q, R and S wave peaks and periods are detected for each heartbeat in pre-processing stage, later this QRS complex is estimated these estimated QRS complex is compared with original ECG signal and the difference signal is considered as error where these error signal is compressed with CS method. DWT sparsifying dictionaries (The bi-orthogonal wavelet filter "bior4.4") is adopted for entire process. The results indicate that an average compression ratio of 11:1 with PRD1 = 1.2% are obtained and proved an improved result in compression ratio.

Jan Saliga et al. [208] presented an alternate method for CS and reconstruction of ECG signal, which offers a high CR. This is achieved by high decimation and requantizing the measurement signal. QRS detector algorithm using Hilbert transform was used to detect exact R wave position for signal segmentation, the reconstruction employed a dynamic ECG model, based on Differential Evolution (DE) algorithm to find the ECG model parameters for signal reconstruction. It had been experimented varying the decimation factor D for different CR values and achieved better results for higher D. The results indicated the similar quality of reconstruction for l_1 and l_2, based on error function minimization. Experimental results validate the l_2 norm as the better choice for the reconstruction. It reduces the noise interfering with ECG signals and minimizes the loss of diagnostic information.

In another method employed by Fahimeh Nasimi et al. [209] the sparsity of an ECG frame was increased by removing the redundancy in a normal frame to detect heart rate variability (HRV). The ECG signal is divided into frames of equal duration. Uniform sensing matrix is used for sensing the signal and later Selective compression is done. The reconstruction of original Signal is performed using basic pursuit. The performance evaluation was performed on HRV analysis and energy-based distortion analysis, and this method reached an accuracy of 99.9%, for a CR of 25. The average PRD is less than 10 for all compression ratios.

The work proposed by Ashok Naganath Shinde et al. [210] explores CS reconstruction of biomedical signals using Haar Wavelet Matrix through 'Average Fitness-based Glow-worm Swarm Optimization' (AF-GSO) model. Compression of signals were processed by transformation, evaluation and normalization stages and the statistical analysis and error performance are performed.

Another such paper proposed by Grazia Iadarola et al. [211] discusses a dynamic method for reconstructing multi-lead ECG signal based on CS with Internet of Medical Things (IoMT) using the circulant matrix as sensing matrix which was dynamically analyzed through the signal samples collected by the first lead and Mexican hat wavelet was used for signal sparsification. The suggested dynamic technique has a better signal reconstruction than the conventional CS multi-lead method employing a random sensing matrix. The effectiveness of the recommended system is evaluated using ECG signals from the Physikalisch-Technische Bundesanstalt (PTB) Database. At CR = 10 obtained a reasonable value of PRD equal to 7.05%.

Pasquale Daponte et al. [212] investigated his study on heart sound signals based on CS using Deterministic Binary Block Diagonal (DBBD) matrix as sensing matrix. The major benefit of using this is that it does not require generation of random numbers in the acquisition node and the computational complexity is also less at the compression phase. DCT and the Mexican Hat wavelet are the two different sparsity matrices were used in this method. The method was evaluated on a wide set of heart sound signals available from the PhysioNet database and compared the result with another CS methods. DBBD matrix gave its best result when used with DCT matrix and Mexican Hat matrix performance was also convincible demonstrated result gave an outstanding performance achieving PRD = 23.88% for CR = 10.

Table 2 contains the literature survey discussions with respect to various applications and CS implementation on ECG signal and its reconstruction algorithm.

Table 2. CS Models and the Reconstruction algorithm. *Note: when a quantifiable data is not available it is marked as -.*

Author	Sensing Matrix	Signal Sparsification	Reconstruction Algorithm	Data Set	Result/Remarks
Thilagavathy R et al. [175]	1D complex DAST	DWT and Run-length encoding (RLE)	IDWT and Run-length Decoding	MIT-BIH arrhythmia database	Average CR = 99.97% Execution time = 0.4568 s and 0.3857 s with and without DAST. Not exact CS but lot of potential to be CS
Fatemeh Mohammadi et al. [176]	Independent component analysis (ICA)	sparse coefficients based on the learning dictionary	GPSR	Tehran arrhythmia clinic database	Average accuracy = 70.24%
Fereshteh Fakhar Firouzeh et al. [177]	Random Normalized Matrices (RNM)	DCT	Smoothed l_0 Norm (sl_0) and BP	MIT-BIH arrhythmia	CR = 50% PRD for sl_0 = 8:36 BP = 16:25
Hongqing Liu et al. [178]	-	Daubechies4 Wavelet	BP and CoSaMP	MIT-BIH PTB diagnostic ECG	suppression ratio = 18 dB and MSE = −130 dB
Chandan Kumar Jha et al. [179]	-	dead-zone quantization and run-length encoding	Tunable Q-wavelet transform (TQWT)	MIT-BIH arrhythmia database	Accuracy = 98.35% Sensitivity = 95.77% Specificity = 99.19%
Tsung-Han Tsai et al. [180]	Multi-channel Linear Prediction unit(MLP) and LP	Golomb-Rice encoding algorithm	Golomb-Rice Decoder	MIT-BIH & PTB	Multichannel Average CR = 4.073 CR improved by 33%
Asma Maalej et al. [181]	LC-ADC	DWT	OMP algorithm	PTB-diagnostic	Average CR = 63%
Luisa F. Polania et al. [182]	Gaussian sensing matrix	Daubechies db4 wavelet	BSBL	MIT-BIH Arrhythmia	PRD = 3.55, CR = 10. PRD = 2.07, CR = 14
Hakan Gurkan et al. [183]	variable-length classified signature and envelope vector sets VL-CSEVS	wavelet transform	Huffmn decoder	MIT-BIH Compression Test Database	PRD = 1.2 to 5.6% MPRD = 1.627 to 8.631% average CRs = 4:1 to 20:1
Israa Tawfic et al. [184]	Random Gaussian matrix	DWT sparsification	LS-OMP and LSD-OMP	Physio Bank ATM	RSNR = 31.0543
Michael Melek et al. [185]	Gaussian matrix	Daubechies 5 DWT	ARMP-PKS algorithm	MIT-BIH Arrhythmia	RSNR ARMP-PKS = 22.6, 3.7 & 14.4 dB
Javad Afshar Jahanshahia.b et al. [186]	Random binary measurement matrix	Kronecker sparsifying db4 wavelet and DCT	ADMM	MIT-BIH and PTB database	CR = 8, time = 0.061 s PRD = 3.32, PRDN = 7.48, QS = 1.95

Table 2. *Cont.*

Author	Sensing Matrix	Signal Sparsification	Reconstruction Algorithm	Data Set	Result/Remarks
Shuang Sun et al. [187]	Bernoulli matrix	db2	BP	PhysioNet Database	Irls for best reconstruction quality and BP for efficient algorithm
S. Abhishek et al. [188]	Random sensing matrix	dew2	M-SBL (Multiple sparse Bayesian learning algorithm)	MIT-BIH and MIT challenge data set	Average performance of 'dew2' is higher in fetal ECGs
Fabio Pareschi et al. [189]	Rakeness-Based CS optimization	Symlet 6 wavelet	OMP, CoSaMP and IHT	MIT-BIH Arrhythmia Database	OMP preferred for lower energy and high reconstruction quality
Zhimin Zhang et al. [190]	Gaussian random matrix (GRM) used as measurement matrix	Fourier transform	CoSaMP, OMP, BSBL-EM and BSBL-BO	MIT-BIH Normal Sinus Rhythm Database	PRD for OMP = 7.51% to 81.95%, CoSaMP = 6.07% to 71.09%, BSBL-BO = 1.75% to 15.33% BSBL-EM = 1.79% to 38.09%.
Enrico Picariello et al. [191]	Binary Matrix	Dictionary matrix	OMP algorithm	MIT-BIH Arrhythmia	PRD < 9% for various CR
Ruixia Liu et al. [192]	Gaussian random matrix	STFT analysis dictionary	BP-ADMM algorithm	MIT-BIH ECG	5 dB noise mean SNR = 7.129
Yih-Chun Cheng et al. [193]	Binary sensing matrix	DWT	PKS-vOMMP algorithm	MIT-BIH Arrhythmia	Achieved better SNR
Yaguang Yang et al. [194]	Gaussian matrix	Partial DCT and low-density parity check (LDPC) matrices	BP, OMP, CoSaMP, and BSBL	MLII-type data from MIT-BIH	CR < 60% BSBL algorithm gave best result
Yue-Bin Zhou [195]	Sparse random matrix	Sparse Representation Classification (SRC)	Greedy algorithms	MIT-BIH database	RT = 50 ms
Yunfei Cheng et al. [196]	Sparse binary matrix	without dictionary	BSBL-ADMM	MIT-BIH and MIT-BIH Long-Term	Recovery speed was 0.0629 s for CR = 60% Mean PRD = 6.92
Zhimin Zhang et al. [197]	Gaussian random matrix	Fourier transform	OMP and CoSaMP BO-BSBL and EM-BSBL	MIT-BIH Normal Sinus Rhythm	PRD $\leq$ 9%
Anurag Singh et al. [198]	Random binary sensing matrix	Wavelet	SWMNM and Non-iterative algorithm PWMNM	PTB and MIT-BIH database	PRD1 = 1.31, QS = 4.88 for MIT-BIH, classification accuracy = 73.2% for 10% of compressed data
Mohammadreza Balouchestani et al. [199]	Random sensing matrix	Dictionary	BSBL framework	MIT-BIH database	65% reduction in power and 15% incensement on SNR

Table 2. *Cont.*

Author	Sensing Matrix	Signal Sparsification	Reconstruction Algorithm	Data Set	Result/Remarks
Shengxing Liu et al. [200]	Binary matrix	Self-training dictionary scheme (STDS)	Al_0CM frameworks	MIT-BIH Arrhythmia database	CR = 0.5 Running time = 0.0039 s PND = 0.2454% RSNR = 53.0814 dB
Jeevan K. Pant et al. [201]	Basic conjugate gradient	Dictionary learning	l_p^{2d}-RLS algorithm	MIT-BIH database	reduction in computational time
Tohid Yousefi Rezaii et al. [202]	OSOS	Dictionary based	OMP algorithm	Physionet ATM	Gaussian matrix SNR = 9.5078 dB, cosine matrix SNR = 7.9655 dB
Luisa F. Polanía et al. [203]	RBM	wavelets and learned overcomplete dictionaries	OMP	MIT-BIH and European ST-T	Average recall = 96.34% Precision = 93.92%
Manas Rakshit et al. [204]	Non-uniform Random sensing matrix	Beat type dictionary	a beat type dictionary	MIT-BIH and NSRDB	33.5% greater CR PRD1 = 9%
Dana ˇCerná et al. [205]	-	Wavelet dictionaries and DCT	OOMP	MIT-BIH	PRD = 0.51%
Pasquale Daponte et al. [206]	Dynamic sensing matrix	Mexican hat wavelet	M-SBL and M-FOCUSS	MIT-BIH Arrhythmia	PRD = 0.71%, CR = 2 PRD = 2.82% CR = 10
Mohammed M. Abo-Zahhad et al. [207]	Random Gaussian Matrix	DWT, bior4.4		MIT-BIH database	CR = 11:1 PRD1 = 1.2%
Jan Saliga et al. [208]	Bernoulli matrix	The Mexican Hat and the Symlet-4 wavelet	Differential Evolution	MIT-BIH arrhythmia database	l_2 norm as the better choice
Fahimeh Nasimi et al. [209]	Uniform sensing matrix	DWT technique	Basic pursuit	MIT-BIH and MIT-BIH Long Term	Accuracy = 99.9%, for a CR = 25 PRD < 10
Ashok Naganath Shinde et al. [210]	Gaussian matrix	Haar Wavelet matrix	AF-GSO	Physiobank database	attained less error for neighbour count is equal to 2
Grazia Iadarola et al. [211]	Circulant matrix	Mexican hat wavelet	M-FOCUSS	PTB Database	PRD = 7.05% with Less error.
Pasquale Daponte et al. [212]	DBBD matrix	DCT and Mexican hat wavelet matrix	OMP	Physiobank database	PRD = 23.88% for CR = 10. less computational complexity

6.2. Learning Algorithms on ECG

The important block of the use-case of our interest is the decision-making block and in case of CS for ECG there are 2 approaches in implementing the learning algorithms (i) learning from the ECG signal reconstructed from CS measurements (ii) Learning directly from the CS measurements.

6.2.1. Learning on Reconstructed ECG Signal

The IoT framework considered for the review has an important decision-making block implemented using AI. Hongpo Zhang et al. [213] quantified the effect of CS for monitoring ECG remotely using deep learning technique based on non-iterative method. The combination of CNN and LSTM was made to learn directly the mapping relationship between the original signal and the measurements. This method has the ability to reconstruct original ECG signal more accurately without any prior knowledge. The results proved the reconstruction error is lower than other methods. The clinical requirement was achieved at CR $\leq$ 70%, for Normal Sinus Rhythm Database (NSRDB), MIT-BIH Atrial Fibrillation Database (AFDB) and CR $\leq$ 90% for EDB dataset.

Lijuan Zheng et al. [214] implemented a singular value decomposition (SVD) based compression procedure including period normalization, for ECG Arrhythmia signals. The decompressed data is given to a CNN and SVM models to classify abnormal ECG signal, certain commonly used indicators such as CR, PRD, PRDN, Root Mean Square Error (RMS), SNR and Quality Score (QS) achieved an Average value of 53.77, 9.23, 12.81, 5.28, 18.07 and 5.83 respectively. Even if some information is lost, a high-quality classification result can be achieved

The study proposed by Bo Zhang et al. [215] relates to multi-objective optimization-based ECG signal compression using a neural network. The neural network learns the changes in ECG characteristics and its structural parameters are adjusted under the guidance of the multi-objective function. By learning the diverse properties of ECG data compression, neural networks will adapt the parameters of network structure. The computational time required for obtaining original signal was less. For CR = 9, average PRD = 20 and average encoding time taken was around 7 s.

In [216] Wenzhuo Li et al. proposed 1-D CNN based Compressed Learning algorithm to classify compressed on-device multi-class ECG signal directly without reconstruction. Consequently, the processing power is drastically reduced and the performance of the proposed hardware design is validated by implementing the algorithm on various hardware design such as FPGA, Artix-7 Low power board and UMC 40 nm Low Power Process technology, the hardware architecture with the 1-D CL classifier achieves an energy efficiency of 0.83 μJ/Classification under a 1.1 volt power supply at a frequency of 5 MHz, This strategy yielded a significant performance boost with an average accuracy of 98.35%, under CR = 0.2 and displayed an increase in average accuracy.

Article [217] quantifies the impact of compressed sensing and reconstruction methods on ECG arrhythmia detection with SVM classifiers. Sophie Zareei et al. focused their work to determine acceptable compression ratios for ECG signals that retain critical information. Reconstruction of original signal is done through two widely used algorithms, such as BP and OMP and identification of the suitable CR which retains the necessary information of ECG signal. Outcome of the investigation illustrates that few sparsely sampled signals are sufficient for SVM classifier to detect type of arrhythmia, for the CR value up to around 1:7 ECG signals are recovered and then classified with the same quality for BP and OMP algorithms. Thereafter, after increasing the compression ratio BP outperformed OMP in detecting the arrhythmia for ECG signal, as a trade-off negative correlation was witnessed.

In order to deal with missing data, Vanika Singhal et al. [218] proposed unsupervised deep blind compressed sensing concept and combined the signal reconstruction and classification in a single frame. The analysis of the signals is done directly from the partially observed or compressed domain. The results concluded that this method outperformed compared to other methods for 2:1 compression the average classification accuracy was 100% which contributed a superior result.

Jia Li et al. [219] proposed ECG signal Classification based on CNN using the ADADELTA and biased dropout algorithms to improve performance where the ADADELTA optimizer is used to increase the learning rate and convergence speed. The 1D information fusion vector was transformed into a 2D image with the help of one-hot encoding technique to improve the accuracy and speed of classification. This model was experimented on the

MIT-BIH arrhythmia database, which was capable of achieving an average accuracy of 99.1% and 97% which displayed a fair performance in terms of the sensitivity and positive predictive rate.

A deep-learning strategy has been presented by Shadhon Chandra Mohonta et al. [220] in which the network classifies the scalogram image obtained by CWT based on the signature associated to arrhythmia. The 2D CNN is trained for automated arrhythmia identification using the recordings of CWT. The suggested method is trained and tested to identify five various types of heartbeats. The proposed method displayed an average sensitivity, specificity, and accuracy of 98.87%, 99.85%, and 99.65%, respectively. The outcome demonstrated that the proposed model can effectively identify arrhythmia for small segments of ECG signal which made the model computationally faster and simpler.

Roberta Avanzato et al. [167] proposed an automated heart disease recognition technique based on 1-D CNN 5-layer architecture using ECG signals. Here the signals were directly fed to a well-trained CNN network. This model was validated using the MIT-BIH Arrhythmia Database, which consisted of more than 4000 ECG signal samples extracted from 25 male and 22 female subjects. The experimented output result gave an outstanding result of an average classification accuracy of 98.33%. The confusion matrix from the testing dataset indicated 99% accuracy. The sensitivity and the specificity were 98.33% and 98.35%, respectively.

V. Jahmunah et al. [221] developed an automated system for ECG classification which classifies 4 classes of ECG signal which are normal, coronary artery disease (CAD), myocardial infarction (MI) and congestive heart failure (CHF) classes. The classification is done by using CNN and unique GaborCNN models. Weight balancing was used to balance the dataset, as the ECG data used in this work were imbalanced. Lead II ECG signals from 92 healthy controls, 7 CAD, 148 MI and 15 CHF patients were considered for categorization. The performance of GaborCNN was better due to its less computational complexity and the classification accuracy was more than 98.5% for all the 4-classes, while on the other hand, CNN also gave its best performance.

Xue xu et al. [222] proposed a combined network of CNN and RNN designed for 5 classes of ECG signal classification. This model consists of 2 convolutional layers, ReLU layer, residual blocks, 2 bidirectional long short-term memory (biLSTM) layers and 2 fully connected layers where each residual block involved the structure of a Squeeze-and-Excitation Network (SENet) with lightweight property to recalibrate the feature map of the network. The last dense layer has 5 outputs equivalent to the classes considered. Experimentation on an MIT-BIH dataset the developed network achieved a sensitivity, accuracy and specificity of 95.90%, 95.90% 96.34% for classification of 5 ECG classes and compared the obtained result with other existing models where the proposed method exhibited better performance.

Yunqing Liu et al. [223] proposed an inverted residual block-embedded deep neural network (IRBEDNN) to classify arrhythmia diseases based on processed ECGs. VGG-like architecture was used for extracting the features of different arrhythmia diseases and on the other hand inverted residual block was used to reduce network complexity. The effectiveness of the proposed system was verified by conducting experiments on the MIT-BIH database and achieved the overall classification accuracy of 96.326% and compared the result with other methods. This model has also been tested on the INCARTDB and achieves an overall accuracy of 97.110%.

Ali Mohammad Alqudah et al. [224] developed an efficient and fast deep learning method for classification of cardiac arrhythmias in up to 17 classes. This method used beat-wise ECG signal analysis using iris spectrogram where a single ECG beat was analyzed and calculated the iris spectrogram. Later, this spectrogram was given to 2D CNN for classification. This model was implemented using 744 ECG signals from 45 different persons and was able to obtain an overall classification accuracy of 99.13. This approach was found to be faster and more efficient for classification and can be implemented for real-time arrhythmia detection.

The study proposed by Rui Fang et al. [225] developed an automatic classification method for identifying myocardial infarction using 3-D ECG image and a Grad-CAM ++ method based on a VGG network. Here the ECG data were segmented into heartbeats based on the R-peak and normalized. Then, the heartbeat data was converted into a top view of a colored 3-D ECG and divided into three parts: ST, whole heartbeat, and QRS images for a multi-VGG19BN for training and classification. Later, the classification outputs were summed to obtain the final results. Grad-Cam ++ method was used to provide visually interpretable heatmaps. The experimented output demonstrated that the proposed model effectively classified 3-D ECG images with high accuracy and obtained accuracy, sensitivity and specificity of 95.65%, 97.34% and 90.80% for the PTB database.

Another such paper based on CNN by Ali Sellami et al. [226] for heartbeat classification was proposed. In order to overcome the imbalance between classes a batch-weighted loss function was used to quantify the loss. Experiments were carried out on a single-lead raw ECG signal as it is without any data preprocessing and feature extraction and multiple heartbeats were also considered for more effective classification. This method outperformed existing methods for intra-patient and inter-patient paradigm and achieved an accuracy, positive productivity, sensitivity and specificity of 99.48%, 98.83%, 96.97% and 99.87% for intra-patient and 88.34%, 48.25%, 90.90% and 88.51% for inter-patient respectively.

This paper by Amin Ullah et al. [227] developed a robust algorithm to classify the ECG signal effectively in the presence of environmental noise. 1D CNN with two convolutional layers, two down-sampling layers, and a fully connected layer was used in the proposed model. Classification accuracy was improved by transforming the 1D data into 2D images. Later the 2D CNN model consisting of three 2D-convolutional layers, three down-sampling layers, and a fully connected layer was also used. The effectiveness of the proposed method was tested on MIT-BIH arrhythmia database and achieved the classification accuracy of 97.38% and 99.02% for 1D and 2D model respectively. The obtained performance indicates that the 2D CNN model is more effective than 1D for classification.

The paper proposed by Monica fira et al. [228] discusses the study on dictionary selection for ECG signals in CS domain. This article proposes the construction of dictionaries which are directly constructed from R waves. Authors examined three different types of projection matrices in various types of dictionaries. The K-nearest neighbors (KNN) classifiers are used to classify the reconstructed signals and in addition to this an MLP was also used to classify the recovered signals. Experiments were carried out using MIT-BIH database for cardiac patterns compressed sensing (CPCS) and Patient specific classical compressed sensing methods (PSCCS). Authors concluded that the dictionaries-based method used for reconstruction has more impact for reconstructing the original signal.

Another approach presented by Weibin Cao et al. [229] discusses an effective method for Real-Time ECG signal reconstruction based on CS. In this work CS and Generative adversarial networks (GAN) are concatenated with each other for recovery of signals over long time period. Sparse binary matrix was used as sensing matrix. The concepts are experimented upon MIT-BIH and PTB datasets where all the experiments were carried out directly on time domain, and the obtained result demonstrated that this method achieved better performance compared to other existing models with respect to reconstruction time and accuracy. The reconstruction accuracy of the ECG signal was evaluated using PRD. The proposed model enhanced the reconstruction accuracy by 2% and the PRD value is equal to 0.39%.

The discussions have been tabulated in Table 3 with respect to various applications, CS implementation on ECG signal classification using various Deep learning algorithms.

Table 3. Models based on the convolutional neural network and hybrid models.

Author	Application	DL Algorithm	Database	Result	Remark
Hongpo Zhang et al. [213]	QRS detection	CNN and LSTM	MIT-BIH NSRDB, MIT-BIH AFDB and European ST-T	Average reconstruction quality = 85% Average time = 0.1265 s	lower reconstruction error
Lijuan Zheng et al. [214]	Normal, LBBB, RBBB and PVC	CNN and SVM	MIT-BIH cardiac arrhythmia	Average accuracy = 99.39%	low quality signal, achieved high accurate classification
Bo Zhang et al. [215]	ECG data compression	multi-objective optimization neural network	MIT BIH ECG database	data compression ratio is 1:19, PRD = 12% and CC = 99%,	lesser computational time
Wenzhuo Li et al. [216]	Arrhythmia Classification	1-D CNN	MIT-BIH	Average precision = 91.73% sensitivity = 91.55% & specificity = 98.65%	implemented on FPGA, Artix-7 and UMC 40
Sophie Zareei et al. [217]	Arrhythmia detection	SVM classifiers	MIT-BIH Arrhythmia database	CR up to 9.77 can be classified with precision and sensitivity > 90%	negative correlation between CR and reconstructed signal quality
Vanika Singhal et al. [218]	ECG signal classification	CNN	MIT-BIH Arrhythmia database	Average accuracy = 98%	Reconstruction & classification stages are combined as single frame
Jia Li et al. [219]	cardiovascular disease detection	CNN (LeNet-5)	MIT-BIH arrhythmia	Achieved sensitivity and specificity of 99.4% 99.9%	To increase the convergence speed of the learning rate ADADELTA optimizer is used.
Shadhon Chandra Mohonta et al. [220]	5 types of Heartbeat classification	2D CNN	MIT-BIH arrhythmia database	The average accuracy for TN4 model is 99.65%	Pan Tompkins algorithm was used for ECG wave R peak detection
Roberta Avanzato et al. [167]	Automated heart disease recognition	1D CNN	MIT-BIH arrhythmia database	F1 Score Mean Accuracy = 98.33%	Considered three classes database Normal, Atrial premature beat and Premature ventricular contraction.
V. Jahmunah et al. [221]	Automated ECG classification	CNN and GaborCNN	Fantasia and St. Petersburg databases	Average success rate CNN = 99.55% GaborCNN = 98.74%	CAD, MI and CHF heart diseases were considered for classification
Xue xu et al. [222]	ECG heart Signal classification	CNN and RNN	MIT-BIH dataset	Accuracy = 95.90%	cardiac health application
Yunqing Liu et al. [223]	arrhythmia detection	CNN and inverted residual block (IRB)	MIT-BIH arrhythmia	classification accuracy was 100%,	clinical applications.
Ali Mohammad Alqudah et al. [224]	cardiac arrhythmia classification	2D CNN	MIT-BIH dataset	overall accuracy = 99.13%	Real-time arrhythmia detection Application

Table 3. *Cont.*

Author	Application	DL Algorithm	Database	Result	Remark
Rui Fang et al. [225]	Arrhythmia classification	multi-VGG	PTB-XL diagnostic ECG database	inter-patient accuracy = 97.23%	3-D ECG images was capable of diagnosing heart disease with more accurately and visual interpretability
Ali Sellami et al. [226]	heartbeat classification	9-layer CNN	MIT-BIH arrhythmia dataset	Accuracy = 99.79%	Achieved high classification accuracy for single-lead raw ECG data
Amin Ullah et al. [227]	ECG signal classification	1D CNN and 2D CNN	MIT-BIH arrhythmia	Accuracy for 1D and 2D CNN was 97.38% and 99.02% respectively	Performance of 2D CNN was better compared to 1D CNN
Monica fira et al. [228]	Normal and abnormal heartbeat classification	KNN and MLP	MIT-BIH database	Classification accuracy for KNN and MLP = 92.5% and 93.1% respectively	Quality Score for CPCS and PSCCS Methods are 17.04 and 15.46
Weibin Cao et al. [229]	Real time ECG monitoring	GAN	MIT-BIH and PTB datasets	RT = 0.014 s	Reconstruction time (RT) improved by 50%

6.2.2. Learning on Direct CS Measurements

At the decision-making block, the reconstruction of ECG signal is time consuming and in order to reduce the time and power usage various researches have carried out to analyze the signal directly on CS measurements without reconstructing the signal. Fundamentally CS reconstruction is all about learning the signal using iterative algorithms from the linear CS measurements [24,25] and it would be a smart way to integrate the learning along with ML. Anyway, a systematic approach of compressed learning of ECG signal had not been done, but few have implemented compressed learning on ECG. Ching-Yao Chou et al. [230] proposed a biometric user identification using ECG known as Compressed alignment-aided compressive analysis (CA-CA) algorithm, this CA-CA algorithm uses PCA based dictionary in compressed domain, where the reconstruction of ECG signal is avoided and the information is directly recovered from compressed domain resulted in a reduction of computation time by 81.08% and classified the compressed ECG signal with high accuracy. Compared to compressed learning (CL), the accuracy of the proposed algorithm was improved by 7.11%, the accuracy dropped with respect to Reconstruction learning with alignment (RL-A) and this algorithm was tested only on a small ECG database.

Another article related to compressed domain by Giulia Da Poian et al. [231] investigates the problem of heart rate estimation from ECG recordings, on compressed signal. QRS complex locations are detected directly in the compressed sensed domain; a template matched filtering based QRS detection approach is considered, by calculating the correlation of the known QRS template and a compressed ECG. Orthogonal Daubechies 4 wavelet was considered as a sparsifying transform. Using the cross correlation and matched-filtering detection method we compared the results with the Pan-Tompkins (PT) detection algorithm for CR = 75% average Sensitivity and the Positive Predictive value was about 95%.

Jing Hua et al. [232] discussed the heartbeat classification on wearable devices in CS domain. The original ECG signal is observed using a sparse binary random matrix, a template based QRS detection algorithm was developed to locate the QRS complexes directly by calculating the correlation of the compressive ECG measurements. Here signal reconstruction is avoided. Based on the detected QRS complexes from the compressed

ECG signals, the deep Boltzmann machine is used for heartbeat classification algorithms under varying CRs, compared to the benchmarking method the performance was slightly reduced. However, it achieved lower energy consumption and is thus suitable for wearable devices.

Table 4 lists down the summary of these publications and their performance in compressed domain.

Table 4. CS Models without the Reconstruction algorithm.

Author	Application	Algorithm	Database	Result	Remark
Ching-Yao Chou et al. [230]	biometric user identification	CA-CA	ECG-ID and PhysioNet QT	Accuracy = 94.16% CT = 6.55 s CR = 0.5	Computation complexity and power reduced
Giulia Da Poian et al. [231]	Hearth rate estimation	template matched filtering	MIT Arrhythmia Database	F measure PT = 98.7% MF = 98.9%	Detection of R-peak directly on the CS Measurements
Jing Hua et al. [232]	Heartbeat Classification	Template based algorithm	MIT-BIH arrhythmia	Accuracy 90.00% & 81.88% CR = 40%	DBM for classification

6.3. CS Realtime Implementations and IoT Framework

Technologies such as the IoT and robotics systems will be essential in modernizing the healthcare system. Certain researches that are carried out by implementing hardware through IoT platform is discussed in this section. Low-complexity Field Programmable Gate Array (FPGA) hardware implementation was proposed for healthcare applications by Oussama Kerdjidj et al. in [233] in which the design was based on pipeline optimization of the Programmable Logic (PL). Simulation of MP algorithm was carried out by Vivado tools, and MATLAB. A low-cost Xilinx board was utilized to examine the MP algorithm and the above scheme was capable of attaining reduced computational time and energy consumption. Though OMP is more complex than the MP algorithm, the result obtained was similar when compared to the former one.

Authors Hamza Djelouat et al. [234] aim to address issues such as power consumption and medical record security in an IoT-based health monitoring system based on CS technique. A unique sparse sensing matrix was constructed, with sparse Bernoulli matrix and linear shift feedback registers (LFSRs) architectures to realize an efficient encryption module. Based on an orthonormal Symlet-4 wavelet matrix representation matrix, a sparsifying matrix was constructed and OMP algorithm was considered for reconstruction of the ECG signal. This research displayed that transmission is kept secure even if the attacker can acquire 95% of the information. The reconstructed ECG signal in the high quality (HQ) had minimal inaccuracy and can be used directly for human diagnosis. The quality of the reconstructed ECG in the low quality (LQ) scenario is susceptible to degradation and the ECG features can still be detected and utilized.

In another hardware implementation, Yun-Hua Tseng et al. [235] identified the changes present in original and reconstructed signal of QRS complex in ECG signal. To overcome the above issues the authors presented a novel approach by concatenating the high accurate method known as Near-Precise Compressed (NPC) algorithm and CS algorithms together for the compression of ECG signal. NCP can be easily implemented using low-cost hardware. Here, hardware has been implemented using VLSI technology, Taiwan Semiconductor Manufacturing Company's (TSMC) 0.18 µm Complementary Metal-Oxide-Semiconductor (CMOS) technology. NCP compresses the region of high change between the original and recovered signal and CS algorithm takes care of other regions of ECG signal compression. SNR and PRD are identified as evaluation matrics. Compared the results with other algorithms such as OMP, BSBL-BO and BSBL-EM and obtained a notable improvement in SNR and CR.

In order to overcome certain limits such as energy-efficiency, cost and proper compression technique, Kan Luo et al. [236] implemented a low power wireless single lead Bluetooth ECG monitoring device based on CS. A sparse binary matrix was explored to realize the CS compression. This compression technique with sleep and wake-up strategy aims to reduce the transmitted data size and consumed power. Utilization of sleep/wake-up scheme and CS compression reduced power consumption compared to other commercially available devices. The advantages of the proposed device are lesser weight, small size, low-cost, single-spot, real-time and wireless module with a good battery lifetime.

A study by Hamza Djelouat et al. [237] investigates the efficiency of CS-based real-time ECG signal reconsruction on an IoT gateway embedded with heterogeneous multicore platform (HMP) featuring ARM. Patients ECG data is compressed and sent to the gateway through Bluetooth. The data is reconstructed and categorized at the gateway in order to identify irregularities in the patient's heartbeat. The odroid xu4 is used for data processing, while the Shimmer3 device is used for data collecting. This technique was capable of handling computing latency, security and privacy issues related to cloud-based models. Comparison results between OMP and SP in terms of PRD shows that SP have lower reconstruction error and OMP performed better than SP at most CRs, increasing number of cores and cores frequency resulted in faster reconstruction.

In terms of significantly reducing the hardware complexity of the CS reconstruction OMP algorithm, Amey Kulkarni et al. [238] proposed two different modifications to the OMP algorithm, Thresholding technique for OMP (tOMP) and Gradient Descent OMP (GDOMP). To reduce reconstruction time, tOMP was used, to modify identification stage in OMP algorithm and to reduce chip area GDOMP was considered. For all three algorithms, they implemented reconfigurable, parallel, and pipelined architectures which were capable of reconstructing various data vector sizes on 65 nm CMOS technology. This resulted in less reconstruction time and chip area for tOMP and GDOMP compared to OMP ASIC design.

Table 5 summarizes hardware implementation on CS models and its result on various applications.

6.4. Recommendations and Research Directions

This review is all about minimizing the sampling rate of ECG for an IoT framework and efficient decision making on users' heart health using CS. In this review, key research components are considered and, in this section, new research directions and recommendations are given. Our review shows that in CS there are so many sensing matrices deployed and the best sensing matrix will be the one that is easy to practically implement and effectively reconstruct the signal. The most commonly sensing matrix used is the Gaussian Random matrix. Our study shows that any transforms such as FFT, DCT can also be used as a sensing matrix by retaining some percentage of the coefficients and forcing others to zero. As the sparsity of the signal is the key requirement of CS, the right selection of sparsifying matrix is very important, and our study shows that any transform that is used in ECG signal compression can be used as a sparsifying operator. Few of such transforms are wavelet, DCT, STFT etc. The novel transforms such as 1D-DAST as a sparsifier in CS are unexplored and future work can lead in this direction. QRS-based signal representation and sparsification is much customized for ECG and dictionary based sparsification is also suitable for ECG. As far as the decision making is concerned, learning directly from CS measurements of ECG, which is called compressive learning, is more effective in terms of computation time. CS reconstruction is computationally intensive task and compressive learning eliminates the need for reconstruction and thus is much suitable for CS framework. The functional requirements of CS are the speed and power of operation and the Table 5 depicted in our review helps to identify hardware implementations that are faster and low power.

Table 5. CS models with hardware implementation. *Note: when quantifiable data is not available it is marked as-.*

Author	Reconstruction Algorithm	Simulation	Synthesis	Hardware	Result	Remarks
Oussama Kerdjidj et al. [233]	MP	MATLAB	-	Zynq FPGA	Peak Signal to Noise Ratio (PSNR) of 23.8 db	Utilized Static and Dynamic power
Djelouat et al. [234]	OMP algorithm	MATLAB	-	Shimmer-3 wearable device	CR = 0.5 PRD = 9 & CR = 0.4, PRD = 2.55	Reduced 35% of power
Yun-Hua Tseng et al. [235]	Near-Precise Compressed (NPC) and CS	-	Synopsys Design Complier, Cadence	TSMC 0.18 µm CMOS technology 60 MHz	CR = 40 QS = 0.85	Implemented into Xilinx Kintex-7 FPGA
Kan Luo et al. [236]	BSBL and DCT	Matlab and LabVIEW		BLE, Analog front-end chips AD8232, MSP430F1611	reduced power consumption by 77.37%	Recovered undistorted signal.
Hamza Djelouat et al. [237]	OMP and SP Algorithm	MATLAB	Code Composer studio (TI 4.4.8 compiler)	Odroid xu4 and Shimmer-3	achieved maximum of 47% faster reconstrtion	computational complexity was overcome
Amey Kulkarni et al. [238]	tOMP and GDOMP	MATLAB	Cadence® RTL compiler	65 nm, 1 V6 M CMOS Technology	33% less RT for tOMP and 44% less chip area for GDOMP	Reduction in hardware complexity for OMP algorithm

7. Conclusions

In this review, a use-case of using CS measurements of ECG signal in the IoT framework is developed. The basic research and technical aspects are considered on this use-case based on the CS need. The theoretical key concepts of CS with mathematical formulations are discussed to shed some light on selection strategies of sensing matrix and reconstruction algorithms, as well as compression ratio to assure the quality of a reconstructed ECG signal. Numerous CS construction (Measurement and Transformation matrix) and reconstruction algorithms with performance metrics aiming to achieve better classification accuracy, computational efficiency, high speed, low power and less area usage are also analyzed. The most appropriate sensing matrix, which has been examined by several CS approaches and techniques adapted to enhance the sparsity of the signal in order to improve the reconstruction quality, were also highlighted. Furthermore, deep learning algorithms, datasets, hardware implementation, and IoT framework on CS are also studied. Based on the review, recommendations and future research directions are given to select the best sensing matrix, novel deployment of sparsifying process, compressive learning algorithms and faster hardware implementations that consume less power. The results are tabulated, and the tables shed light on the research and technical aspects we considered. Some of the important recommendations given are to use novel compression techniques such as 1D-DAST as a sparsifying method, QRS based sparsification, DCT and DFT based sensing methods, as well compressed domain ML models. Specifically, this paper proposes a generalized CS based ECG framework and provides open research directions that should be considered when developing a CS algorithm for achieving better classification and reconstruction quality of the ECG signal.

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