Edge-Based Computation of Super-Resolution Superlet Spectrograms for Real-Time Estimation of Heart Rate Using an IoMT-Based Reference-Signal-Less PPG Sensor

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***Abstract*—Cardiovascular disease (CVD) is one of the leading causes of the mortality rate increase. To effectively analyze wearable sensor data for providing accurate and reliable estimation of vital signs, such as heart rate (HR), the use of artificial intelligence (AI) in wearable devices is increasing. The use of AI in designing healthcare wearable sensors is crucial to the uprising of the Internet of Medical Things (IoMT). The appearance of IoMT sensor technologies lets the healthcare industry shift from vis-a-vis consulting to telemedicine. IoMT sensors have transformed the healthcare industry by improving patient safety and reducing healthcare costs. This article proposes a photoplethysmogram (PPG) enabled wearable device in an edge-IoMT computing environment that enables users to monitor their real-time health status. A deep learning approach for automatic feature extraction is proposed in this work. The deep learning algorithm learns features from a super-resolution spectrogram computed using superlet transform. In the proposed system, a PPG signal is input, and the output layer provides information on HR. The proposed framework uses two publicly available PPG data sets to train and test the proposed edge-assisted model. The model is further evaluated using an in-house acquired PPG signal data set. The proposed framework obtained a mean absolute error of 0.76, 1.01, 1.46, and 1.79 BPM for IEEE Signal Processing Cup 2015 (IEEE SPC) training, IEEE SPC test, BAMI-I, and BAMI-II data sets, respectively. The proposed edge-based IoMT framework satisfactorily predicts HR in real time using reference-signal-less PPG sensor signal.**

***Index Terms*—Edge computing, healthcare devices, heart rate (HR) estimation, Internet of Medical Things (IoMT) sensor, photoplethysmogram (PPG), super-resolution, wearable device.**

I. Introduction

CARDIOVASCULAR disease (CVD) is primarily a chronic disease and the leading cause of death worldwide, per the World Health Organization (WHO) reports. Out of the deaths due to CVD, four out of five are due to heart attacks and heart strokes [1].

Several effective strategies suggest reducing CVD through a healthy lifestyle and proper medication. However, the approaches to early detection of CVD risk can help society reduce the trauma of mortality and health costs. Hence, regular monitoring of cardiac health status is vital for early diagnosis and timely treatment of CVD. Therefore, continuous and reliable monitoring of vital body signs, such as heart rate (HR), is crucial in designing wearable healthcare systems [2]. Estimation of HR in real time using wearable devices has been steadily growing. An electrocardiogram (ECG) signal is used as a gold standard technique to measure HR. However, challenges associated with long-term usage to monitor cardiac health have resulted in the acceptance of the photoplethysmogram (PPG) signal as an alternative approach [3]. The demand for wearable health monitoring devices based on PPG is ever-increasing due to its noninvasive nature, easy-to-use, simple operation, and low cost.

There are two different ways to measure vital signs using a PPG signal. They are contact PPG and contactless PPG [4]. In contactless PPG, light focused from a distance records the PPG signal. A contact PPG measurement uses a light-emitting diode (LED) and a photodetector to record the signal. The contact PPG provides continuous real-time monitoring of vital body signs, which is impossible in contactless PPG measurements. This article uses a contact PPG to record the PPG signal to estimate HR. The wrist is a commonly preferred site to record PPG signals using a wearable device [5]. The design of a PPG-enabled wearable health monitoring device focuses on factors, such as ease of use and cost from the user perspective and computational complexity from the design perspective. It is a

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reality that motion artifact noises exist in every PPG signal acquired using a wearable device [6].

Motion artifacts degrade the quality of a PPG signal. Thus, for accurate and reliable estimation of vital signs, such as HR, the motion artifacts spectrum must be separated from the recorded PPG signal [7]. Thus, denoising techniques suppress motion artifact components from the acquired PPG signals. The methods to remove motion artifacts from a PPG signal are divided into two categories. The first method requires a reference motion signal simultaneously recorded using additional hardware, and the second does not require a reference signal [8]. The PPG sensors available in the market use the first type to reduce the effect of motion artifacts on the PPG signal. The performance of the PPG health monitoring devices available in the market depends on the accuracy of the additional accelerometer sensor signal used to provide a reference noise signal. However, using an additional sensor to acquire a reference motion signal increases the complexity and energy requirements of the device [9]. The proposed method transforms a PPG signal into a time-frequency super-resolution spectrogram using superlet transform to improve detection accuracy. The superlet transform separates the HR and motion artifact components. The proposed method does not require additional accelerometers or sensors to eliminate motion artifacts.

The features of a super-resolution spectrogram are learned through a deep convolutional neural network (CNN) model to estimate HR in real time. Recently, interest in personalized wearable health monitoring systems has been gaining importance due to the association of edge computing and sensor technologies [10]. Wearable devices allow users to monitor HR with daily routine activities and act as emerging tools to detect cardiac abnormalities at an initial stage. The proposed device shows the potential of wearable PPG signal analysis to track CVD in real time. To the best of the author's knowledge, the proposed framework is the first of its kind, showing a complete model from data acquisition to HR estimation in real time.

The remainder of the proposed work is organized as the following. Section II describes the background and objective. Section III provides details on the architecture of the proposed system. The proposed methodology highlighting the potential of the super-resolution PPG spectrogram is detailed in Section IV. Model optimization is described in Section V. The results analysis, comparison with state-of-the-art approaches, results and discussion are described in Section VI. Finally, the conclusion and future work are discussed in Section VII.

II. Background and Objective

The main hurdle in properly utilizing PPG-based health monitoring devices is the suppression of motion artifacts to estimate HR accurately. Many signal processing techniques, such as independent component analysis [11], empirical mode decomposition [12], adaptive filtering [13], [14], short-time Fourier transform [15], and wavelet transform [16], have been proposed to suppress motion artifacts from the PPG signal. The state-of-the-art methods comprise a three-step process: 1) suppressing motion artifacts; 2) HR estimation; and 3) HR tracking [18], [19]. The above mentioned methods require a simultaneously recorded reference signal to remove noise [20]. The need for predefined heuristic threshold values or activity-based parameter optimization limits their usage in real-time monitoring devices.

The IEEE Signal Processing Cup 2015 (IEEE SPC) data set is a benchmark data set. The IEEE SPC data set contains simultaneously recorded reference accelerometer signals, two PPG sensor signals, and a gold standard ECG signal [17]. The IEEE SPC data set aims to provide motion artifact-contaminated PPG signal recordings to estimate HR. The ground truth HR (HR_{true}) calculated for an 8-s window from a simultaneously recorded ECG signal is also available with every recording of the IEEE SPC data set. The mean absolute errors (MAEs) of the above mentioned methods evaluated using the IEEE SPC data set ranges from 1 to 3 BPM. The above mentioned methods use traditional power spectral density to estimate HR. The reliable and accurate HR tracking assumes that the probability of a significant change in HR in consecutive windows is minimal. Thus, referencing the HR value with the immediately prior HR window is used to track HR in those windows severely affected by motion artifacts [21]. In [22], a hybrid approach combining CNN and LSTM estimates HR in real time. However, subject-specific training makes this approach complex and incompatible for implementation in personalized real-time monitoring devices. A fully binarized network that reduces computational complexity [23] is proposed to estimate HR. In [24], an end-to-end deep learning approach that computes the Fourier transform spectrum of input PPG and accelerometer signals is proposed to predict HR. The use of additional preprocessing steps increases the computational complexity of the method. The work proposed in [25] introduced a new data set called BAMI.

Approaches present in the literature require an additional sensor and a preprocessing unit to suppress motion artifacts from the acquired PPG signal to estimate HR accurately. The additional sensors and processing step adversely affect the computational complexity and energy requirements of the device [26]. Deep learning-based methods have recently been used to extract relevant features without additional signal-processing steps to suppress motion artifacts. However, the deep learning-based automatic learning approach requires reference accelerometer signals to estimate HR. The use of additional hardware poses limitations on the energy requirement, a key hurdle while designing wearable devices.

A single PPG sensor-based method that eliminates the additional accelerometer sensor to estimate HR is proposed in [27]. However, the requirement of sparse training for different hardware specifications limits the use of the method in real-time monitoring. In [28], a clean PPG signal is generated using ECG data from a given data set and trains the model with noisy PPG and clean PPG signal. Estimated HR is calibrated by using spectrum analysis. A calibration parameter is required to refine the estimated HR value, which is constant for a complete data set. Deep CNNs play a significant role in machine learning (ML). CNN can process images like a human brain. A fully automatic learning principle of CNN allows the network to extract relevant features of an input image across different layers. In the early stages of CNN-based HR estimation studies, the proposed models are trained only using the IEEE SPC data set. However, training models with a small data set cannot assure accurate estimation in real time. Thus, a recent study based on deep learning used additional publicly available data sets to improve the accuracy. In [29], a method is proposed to improve the reliability of a deep neural network to estimate HR. Conventional time and frequency-based signal processing methods are inaccurate and require fewer operations to process a signal at high rates. Extracting HR using conventional time-frequency approaches is challenging as these are designed with predefined conditions. The healthcare industry needs generalized approaches to estimate HR in real time. Due to the proliferation of real-time health monitoring wearable devices, implementing the Internet of Medical Things (IoMT) sensor at the edge layer is becoming a new phenomenon. Integrating IoMT with the wearable device allows the user to monitor HR during busy hours and be alert about changes in health conditions. Monitoring health conditions helps take timely preventive measures to save a life. Most denoising methods require motion artifact filtering and manual feature selection, which increase the computational complexity of the device. Hence, it cannot be implemented using edge-assisted IoMT sensors. In [30], a temporal convolutional network-based framework is proposed to estimate the HR using a PPG sensor-enabled wearable device. This work requires a post-processing stage to refine the estimated value of HR. The protocol used in the post-processing stage is fixed and the same for all subjects. Fixing a parameter value based on limited subjects does not indicate the work's generalized capability. Moreover, this method requires a reference accelerometer signal to compute HR. In [31], a deep neural network architecture search-based HR estimation approach is proposed.

This work shows extensive performance in estimating HR using the PPG signal but requires a reference signal. The need for a three-axis accelerometer sensor for reference signals increases the hardware and computational complexity of the framework. Further, maintaining a correlation between the accelerometer and PPG signals is challenging. In [32], the HR estimation framework is proposed using cascaded CNN and LSTM networks. The performance of the proposed network depends on three input signals: 1) the PPG signal; 2) the first derivative of the PPG signal; and 3) the second derivative of the PPG signal. Correlating three signals to suppress the effect of motion artifacts is challenging in real time. Moreover, the proposed work uses a GPU-based workstation to deploy the framework for HR estimation. Hence, deploying the method in [32] is not feasible on edge-based hardware.

In [33], a centralized state sensing algorithm-based HR estimation framework is proposed. The proposed framework uses a raw PPG signal to predict HR using CNN-based models. A GPU-based workstation is used to train and test the model for HR prediction. These GPU-based workstations increase the power consumption of the device. Wearable devices require low-power consumption to increase the extended battery life. The proposed work conceptualizes the potential of IoMT with edge computing to estimate HR in real time using PPG signals. This work proposes an end-to-end automatic feature extraction technique based on a deep learning approach. The proposed work trains the deep neural network model with the superlet transform based super-resolution time-frequency spectrogram to increase the accuracy of the model. Additionally, the proposed work, compressed and optimized the proposed deep neural network model using TFLite, ensures efficient deployment on memory-constrained wearable edge devices. This process enables faster inference, low-power consumption, and processes PPG signal near the subject (as a wearable device). The lightweight version of the proposed model requires less memory and computation time with identical performance to the uncompressed model at the edge device. The proposed method computes a super-resolution spectrogram of an input PPG signal using superlet-transform to estimate HR. The proposed method neither requires a reference accelerometer signal nor multiple PPG sensors.

Further, the proposed method inherently filters motion artifacts and does not require additional signal preprocessing steps. The proposed model also does not require manual feature extraction steps. The proposed work is a hybrid approach of superlet transform and deep learning-based lightweight HR estimation method. The proposed work is compared with a reference HR extracted from a simultaneously recorded ECG signal, used as a true label of the PPG spectrogram. The reference ECG signals are used as a model to learn the correlation between spectrogram and true HR value. To the best of our knowledge, the proposed framework, for the first time, introduces the development and design of a deep learning-based, edge-assisted model for real-time HR estimation.

The key highlights of the proposed work are the following.

1) The proposed framework is used to design an edge-based remote health monitoring device for real-time HR assessment.
2) For the first time in literature, this work introduces a computationally efficient deep control algorithm residing at the edge layer to process the subject's health in real time.
3) The proposed framework is tested with various dimensions of the input spectrogram to evaluate the variation in the accuracy of the model.
4) An optimized 2-D CNN-based deep model, centrally trained using two publicly available data sets, is transferred to the edge device for real-time HR estimation.

III. System Architecture

This section describes various blocks required to realize the proposed wearable device. Fig. 1 shows the proposed device as an edge device. This device proposes an edge-assisted wearable device that can sense, process, and configure the signal in real time.

A PPG optical sensor is used to acquire a PPG signal in real time. The analog PPG signal is digitized using a signal converter. The digitized PPG signal is first transformed into a time-frequency super-resolution spectrogram to separate the clean PPG signal component and motion artifact component from the raw PPG signal. The proposed device is designed

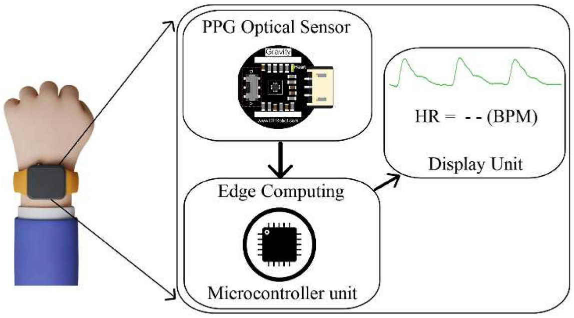

Fig. 1. Block diagram representation of the proposed framework.

to handle edge computation at the device level. As shown in Fig. 1, preprocessing of the signal, deep learning-based feature extraction and regression layer-based vital sign estimation are accomplished in the edge layer. The edge resides close to the sensor. The PPG signal from the sensor is processed and analyzed in the edge in real time, eliminating network latency. The display connected to the edge layer displays the estimated vital signs. The important information on vital signs can be further shared with a medical practitioner and others through the cloud. The deep learning CNN model is trained using the super-resolution spectrogram.

A. Core Components

The edge hardware is realized using a quad-core Cortex-A72 64-bit processor operating at 1.5 GHz. The following peripherals and functions associated with the signal conditioning unit complete the hardware setup.

1) A PPG optical sensor to acquire real-time PPG signal.
2) Analog to digital converter to digitize acquired analog PPG signal.
3) Recording and storing of real-time PPG signal.
4) Algorithm design to preprocess the acquired signal.
5) Conversion of preprocessing data to superlet transform-based 2-D spectrogram.
6) Training and testing the proposed model using the spectrograms obtained from publicly available data set.
7) Design an algorithm to process the acquired data through edge-assisted hardware.
8) Estimation and analysis of HR using design hardware.

A 64-GB memory fulfills the memory requirements of the proposed device. The complete prototype is shown in Fig. 2.

B. IoT Sensor Description

The first block is the front-end IoMT sensor module used to acquire real-time PPG signals and to provide reference HR value for performance analysis. The GRAVITY SEN0203$^{\mathrm{TM}}$ PPG sensor is attached to the right-hand wrist to acquire a real-time PPG signal. The PPG sensor interfaces with the edge unit to preprocess the acquired raw data. The sensor consists of an integrated circuit, SON1303, that uses reflective mode to record the PPG signals in real time.

The transmitter module consists of a double green LED of wavelength 570 nm. The receiver consists of a photodiode, low-noise preamplifier with a built-in optical amplifier with a peak sensitivity wavelength of 570 nm. To the left hand, a

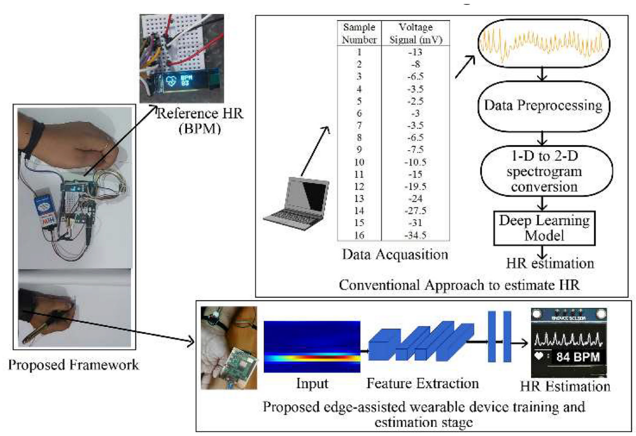

Fig. 2. Blockwise representation of the proposed framework.

Gravity MAX30102 HR sensor is attached to acquire a reference HR value to validate the performance of the proposed method. The sensor is interfaced with the processing unit to provide HR (BPM) in real time, as shown in Fig. 2.

C. Edge Layer

The edge hardware is realized using a quad-core Cortex-A72 64-bit processor. Fig. 2 shows the main processing blocks of the proposed wearable device on a system architecture level and depicts the step-by-step process performed after data acquisition on the edge device. The processing of the edge layer is divided into three parts. First, the acquired PPG signal is subjected to a preprocessing block. In the second part, in the edge layer, the 1-D PPG signal is converted into a 2-D spectrogram through preprocessing. The third layer consists of a deep CNN model for real-time HR estimation.

IV. METHODOLOGY

The proposed algorithm is tested using the IEEE SPC data set and BAMI data set. The algorithm is then implemented on the edge device. The PPG signals are recorded, and HR is estimated in real time using the proposed hardware setup. A complete description of the methodology is as follows.

A. Data Set

The IEEE SPC and the BAMI data sets are used to train and test the performance of the proposed algorithm. Both data sets contain multichannel PPG sensor signals and a simultaneously recorded three-axis accelerometer signal measured using a wearable device. Both data sets include reference HR named HRtrue measured for a window of 8 s using a simultaneously acquired ECG signal. The sampling frequency is 125 Hz in the IEEE SPC data set and 50 Hz in the BAMI data set. The proposed framework is tested using a small in-house recorded data set, including activities close to real-life activities, to check the generalized capability of the proposed method.

Eight subjects participated in the data collection: two female and six male subjects, aged 21–40. With the wearable hardware setup shown in Fig. 2, it is possible to collect data during daily life activities. Each subject follows a data collection protocol to maintain uniformity in data collection. The PPG signal is recorded using the right wrist PPG sensor. Each record is acquired for a total duration of 4 min. For subjects one to five, during the initial 30 s, the subject is at rest.

During the next 120 s, the subject writes something on paper. During the next 60 s, the subject bends down the finger to touch the finger base joint. During the last 30 s, the subjects are at rest. The subjects six to eight are at rest for the initial 30 s. During the next 30 s, the subject slightly rolls the arm in a 360° format. During the next 60 s, the subject bends the arm. During the next 30 s, the subjects are at rest. During the next 60 s, the subjects walk inside the lab. The subjects step up for the next 30 s with the left and right feet. This process continues to imitate a running pose in our lab for 60 s. The HR value obtained with the PPG signal acquired using the left hand is used as a ground truth HR. The left-hand remains stable to provide reference HR and further evaluate the proposed method. The sampling frequency of both the PPG signals is 100 Hz.

B. Preprocessing

During the preprocessing stage, the recorded PPG signal from the data set is divided into consecutive 8-s windows. After the first window, each consecutive PPG signal window shifts by 2 s. Thus, after the first window, a window of 8-s duration has a 6-s overlap with the previous window. The segmented 8-s PPG signal windows are subject to a fourth-order Butterworth bandpass filter with cutoff frequencies of 0.4 to 4 Hz [13]. The filtering stage filters out the signal components that lie outside the range of cardiac activity. The filtered signals are normalized to zero mean and unit variance to extract meaningful information from the amplitude-limited data.

C. Superlet Transform Spectrogram

PPG-based HR estimation is unfortunately affected by motion artifacts, thus reducing the utility of PPG as an HR estimation device in real time. The accurate and reliable estimation of HR in real time is the main feature of the proposed devices. Separation of heart and motion artifacts components is challenging as both PPG signal and motion artifacts signal components possess overlapping frequency spectra from 0.4 to 4 Hz. Due to spectral overlap between heart and motion artifacts components, estimation of HR may result in false information. A superlet represents the motion artifact contaminated PPG signal in the time-frequency domain by separating the peaks related to HR and motion artifacts. Thus, the superlet provides a robust approach to accurately estimating HR in real time. The wavelet is normalized to study different properties of the PPG signal in the time-frequency spectrogram. Normalization enables detecting self-similar features across scales (compressed or dilated). Normalization ensures that the features receive the same normalized amplitude in the representation if the feature has the same shape and peak amplitude for a different order of wavelet [34]. With normalization, a wavelet tends to concentrate at the dominant frequency in the signal, represented by a high-intensity lobe. The high-intensity lobe is where the scaled wavelet frequency coincides with the signal's local frequency.

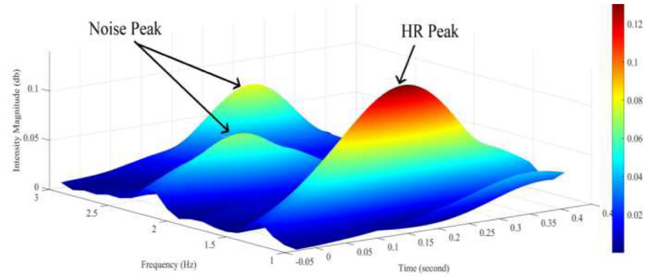

Fig. 3. Separation of noise peak and dominant HR peak using superlet transform.

Superlet transform involves multiple wavelets with a fixed center frequency to provide super-resolution by utilizing different cycles

$$\mathrm{SL}_{f,g} = \left\{\psi_{s,d_k} | d_k = d_1, d_2, \ldots, d_g\right\}. \tag{1}$$

The mathematical representation of a superlet is given by (1). Here, g represents the number of wavelets used in the superlet (order). The superlet transform decreases the redundancy of the representation for the higher frequency by increasing the order of the superlet. d_1 is the first wavelet base cycle used for the analysis. In superlet, the value of different cycles defining the order of the wavelet can be considered using a multiplicative or additive rule [35]. This work uses the multiplicative rule given by $d_i = i \times d,\ i = 1, 2, \ldots, g$.

With multiple wavelets of different cycles, the response of the superlet to the preprocessed PPG signal $S[n]$ is given by the geometric mean of the individual wavelet response represented in

$$R\left[\mathrm{SL}_{f,g}\right] = \sqrt[g]{\prod_{i=1}^{g} R\left[\psi_{s,d_i}\right]}. \tag{2}$$

The geometric mean of the time-frequency information of the PPG signal obtained with multiple wavelets represents a bright red peak. The bright red peak indicates a large amplitude used to estimate the HR. A dark blue or yellow peak will represent the component that does not have the same feature with multiple wavelets, such as noise.

Fig. 3 represents a 3-D spectrogram of a PPG signal obtained using a superlet plotted in the time-frequency domain. The color represents the amplitude. A bright red indicates a large amplitude, and a dark blue color depicts a small amplitude.

As observed from Fig. 3, the separation of the HR peak from a motion artifact peak in a corrupted PPG signal is evident. A corresponding 2-D view of the super-resolution spectrogram in the time-frequency domain is shown in Fig. 4. Fig. 4 is a 2-D representation of a 3-D spectrogram in which the amplitude (3-D) is represented by color intensity. HR modulates the PPG signal; hence, HR information is concentrated as lobes in the super-resolution spectrogram, centered on a frequency corresponding to the HR.

This 2-D spectrogram is subjected through a CNN using the true HR value as the predicted target.

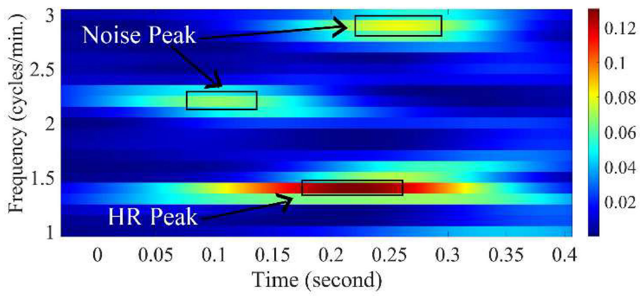

Fig. 4. 2-D representation of superlet transform spectrogram.

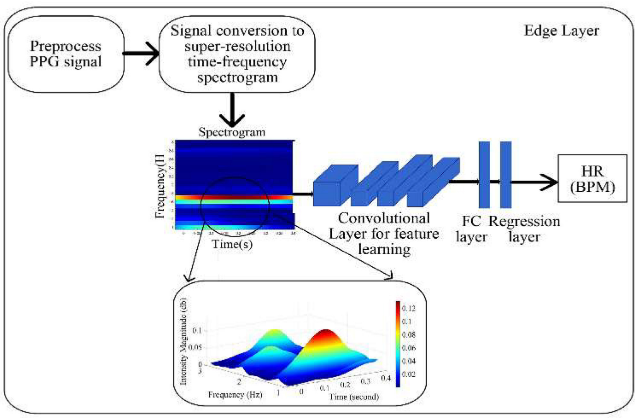

Fig. 5. Detailed flow diagram of proposed framework as an edge device.

During the training phase of the proposed work, the relationship between the change in color intensity of an 8-s window spectrogram of a PPG signal and the true HR computed from the ECG is learned. Instead of mapping the fixed image region with true HR value, the proposed work introduces a self-adaptive color intensity region selection framework by fusing high-intensity peak regions of different spectrograms for HR estimation. Once trained based on given inputs, the model predicts the HR for the test PPG data set. The obtained HR prediction values from the trained model are verified using the true HR value and the MAE, estimated in BPM over the number of observations.

The core idea of the proposed superlet transform-based spectrogram is to distinguish the periodicity of HR peaks and motion artifact peaks in the time-frequency domain to train the model for better accuracy. The 2-D-CNN layer in the deep learning technique learns the feature from the 2-D spectrogram. If the input spectrogram data is sufficient, the deep CNN model can predict the HR reliably and accurately. Fig. 5 shows the proposed framework as an edge device.

The proposed device eliminates the latency issue by introducing an edge platform more suitable for real-time human health monitoring. Edge computing technology brings the process data close to the user to reduce latency.

V. Model Architecture

The potential of CNN has been shown in many fields as CNN uses the both temporal and spatial correlation of input data. A convolutional layer slices the input into small parts

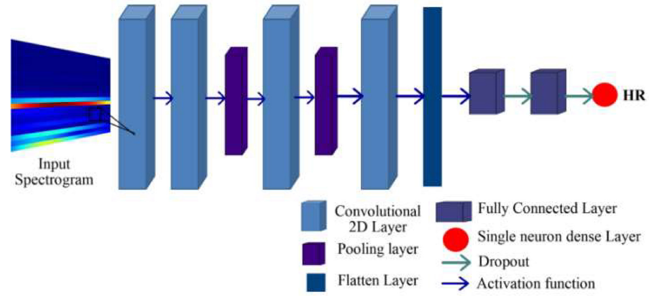

Fig. 6. Deep CNN layer architecture of the proposed CNN model.

(receptive fields). A convolutional layer extracts the required features. The convolutional layer's parameters consist of kernels or learnable filters. Each filter produces a 2-D activation map convolved across the input image volume, computing the dot product between filter and input entries. The activation map shows the features detected by learnable filters for a given input spectrogram.

A pooling layer allows the network to extract a combination of similar features extracted by the convolutional layer. Thus, combining the convolutional layer and pooling layer makes the CNN automatically extract features. The proposed framework acts as a supervised framework by converting the PPG signal into a superlet transform 2-D time-frequency spectrogram using deep neural networks. CNN models consist of 2-D layers characterized by convolutional filters that slide over the input spectrogram as per the assigned weights. The proposed CNN model consists of four convolutional layers. The kernel size for each layer is 3×3. After each convolutional layer, a maximum pooling layer is inserted with a 2×2 kernel size. A dropout layer is inserted after two convolutional layers. The input to a convolution layer is the previous layer's output, as shown in Fig. 6. During the training phase, the proposed model is executed for 250 epochs with batch size 32.

An early stopping functionality is imposed to avoid the model's overfitting during training. For a given number of epochs, if the model does not improve in metric with patience 4, the model reduces the learning rate by a factor of 0.5. All layers except the last layer use ReLU as an activation function. The last layer is the estimation unit, based on a single neuron-dense layer performing a regression task. During the training phase, the proposed CNN model learns the high-intensity peak pattern as HR patterns using the super-resolution 2-D superlet spectrogram to estimate the HR. The testing phase uses a super-resolution spectrogram from an independent testing data set.

The feature extracted from the convolutional layer is passed to the dropout layer with a dropout ratio of 0.2. This means that 20% of the neurons are ignored in the subsequent layer, thus making the system less sensitive to overfitting.

The output of the last convolutional layer is fed to the two fully connected layers with 128 and 64 neurons. The output of the fully connected layer is subjected to the regression task consisting of a single neuron to predict the HR value. The parameters of the CNN layer, such as spectrogram size, learning rate, filter size, and the number of fully connected layers, are optimized to maximize the performance of estimated HR efficiency on the training and test data sets.

MAE is used to confirm the performance of the proposed model as a loss function. MAE is the mean of the absolute difference between the HRtrue and the $\mathrm{HR}_{\text{estimated}}$ using the proposed framework given by

$$\mathrm{MAE} = \frac{1}{W}\sum_{k=1}^{W}|\mathrm{HR}_{\text{true}}(k) - \mathrm{HR}_{\text{estimated}}(k)|. \tag{3}$$

Here, W is the length of the total 8-s windows, and k is the window number. Root mean square error is also assessed to study the accuracy of the proposed model. The performance of the proposed method is analyzed by calculating these metrics.

VI. Results and Discussion

This section presents the performance evaluation of the proposed framework on a PPG signal acquired in real time. The HR is estimated using an edge-assisted hardware setup. The framework is trained and tested using the IEEE SPC and BAMI data sets. This work uses a single PPG sensor data. Thus, it does not require additional accelerometer or other sensor data for HR estimation. The proposed framework is extensively trained using signals from two data sets, making the model effectively learn physiology and physical exercises. The data set used in the testing phase is removed from the training phase to estimate how our model performs on any new data set. A tenfold cross-validation approach is used to split the train and test data sets. It shows a generalized framework of the proposed work to overcome the overfit and underfit problem of model training. Table I shows the performance comparison of the proposed work with state-of-the-art techniques. The Pearson correlation coefficient and the Bland–Altman plot analysis are considered to assess the efficacy of the proposed framework, as shown in Table I. A correlation value of 0.997 indicates a high similarity between $\mathrm{HR}_{\text{estimated}}$ and $\mathrm{HR}_{\text{true}}$. Upper limits of agreement (LOA) and lower LOA are used to compare $\mathrm{HR}_{\text{estimated}}$ and $\mathrm{HR}_{\text{true}}$. Table II compares the proposed work with state-of-the-art HR estimation algorithms using MAE as a metric. The MAE values of the proposed framework using IEEE SPC training, IEEE SPC test, BAMI-I, and BAMI-II data sets are 0.76, 1.01, 1.46, and 1.79 BPM, respectively.

The proposed edge-based IoMT framework outperforms all previously reported methods in Table II. The advantage of the proposed edge computing IoMT sensor-enabled wearable device to estimate HR in real time is that the proposed IoMT framework used the TFLite tool and post-quantization technique to compress and optimize the deep neural network model into the lightweight model.

The proposed framework demonstrated MAE for IEEE SPC training, IEEE SPC test, BAMI-I, and BAMI-II data set, exceeding the MAE reported in [25].

However, the work reported in [25] uses a reference accelerometer sensor signal to generate a reference signal to suppress the effect of motion artifact from the acquired PPG signal. The use of additional accelerometer sensors increases the computational complexity of the system. Moreover, the algorithm's accuracy proposed in [25] depends on the correlation between the PPG signal and the reference accelerometer sensor signal. Maintaining a high correlation between both signals in real time is challenging and increases overall system complexity and energy consumption. The efficacy of the work proposed in [8], [12], [13], [14], [17], [18], [19], [20], [26], and [36] depends on the post-processing stage used to refine

TABLE I
Performance Matrices Comparison With State-of-the-Art Techniques

Method	Dataset	Algorithm	MAE
TROIKA [17]	IEEE SPC Training IEEE SPC Test	Singular spectrum analysis	2.34 BPM
JOSS [18]	IEEE SPC Training IEEE SPC Test	spectral subtraction	1.28 BPM
Khan [12]	IEEE SPC Training	Signal decomposition	1.02 BPM
SpaMa [19]	IEEE SPC Training IEEE SPC Test	spectral filtering	0.89 BPM 3.36 BPM
Temko [13]	IEEE SPC Training IEEE SPC Test	Wiener filtering	1.02 BPM 3.01 BPM
Nathan [26]	IEEE SPC Training	Particle filter	1.56 BPM
FSM [20]	IEEE SPC Training	Wiener filtering	0.99 BPM
Motion [36]	IEEE SPC Training IEEE SPC Test	Recursive Wiener filtering	1.02 BPM 1.85 BPM
Arun [14]	IEEE SPC Training IEEE SPC Test	Adaptive filtering	1.03 BPM 1.89 BPM
FDM [8]	IEEE SPC Training IEEE SPC Test BAMI-I BAMI-II	Fourier decomposition and FFT	1.66 BPM 1.87 BPM 1.33 BPM 1.45 BPM
CNN [24]	IEEE SPC Training PPG-Dalia	CNN	4 BPM 7.65 BPM
PPGNet [34]	IEEE SPC Training IEEE SPC Test	Inception + LSTM	3.36 BPM 12.48 BPM
CorNet [22]	IEEE SPC Training IEEE SPC Test	CNN+LSTM	4.67 BPM 5.55 BPM
BinCor Net [23]	IEEE SPC Training IEEE SPC Test	Bin. CNN+LSTM	6.78 BPM 7.32 BPM
Chung [25]	IEEE SPC Test IEEE SPC Test BAMI-I BAMI-II	CNN+LSTM	0.67 BPM 0.86 BPM 1.39 BPM 1.46 BPM
Deep Heart[28]	IEEE SPC Training	DnCNN	1.61 BPM
Deep Pulse [29]	IEEE SPC Training IEEE SPC Test BAMI-II	TCNBest	2.76 BPM 5.05 BPM 2.38 BPM
Proposed work	IEEE SPC Training IEEE SPC Test BAMI-I BAMI-II Measured data	Super-resolution and CNN	**0.76 BPM** **1.01 BPM** **1.46 BPM** **1.79 BPM** **1.27 BPM**

TABLE II
COMPARISON OF MAE VALUES ESTIMATED USING THE PROPOSED TECHNIQUE WITH OTHER EXISTING METHODS

Method	Pearson correlation	Upper LOA (BPM)	Lower LOA (BPM)
TROIKA [17]	0.992	4.79	−7.26
JOSS [18]	0.993	5.41	−5.94
Nathan [26]	-	4.45	-4.75
FSM [20]	0.997	2.96	-2.60
Motion [36]	0.992	7.30	-7.29
Arun [14]	0.990	7.8	− 8.4
FDM [8]	0.993	7.79	−6.78
Chung [25]	0.996	4.66	-4.81
Deep Heart [28]	0.990	7.30	−6.68
Proposed Work	0.997	2.34	-2.23

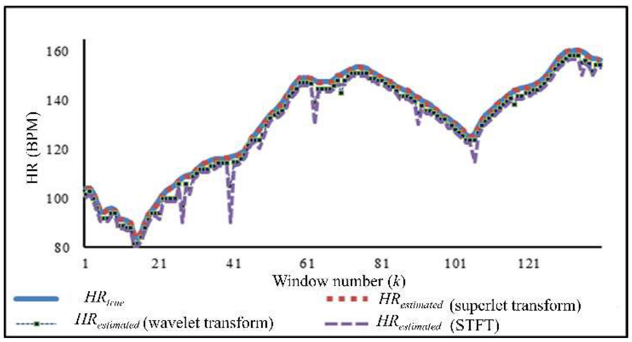

Fig. 7. Comparison between HR_{true} and $HR_{estimated}$ evaluated using state-of-the-art wavelets and STFT approach.

Fig. 8. Comparison between HR_{true} and $HR_{estimated}$ using the data processed using the proposed method.

the value of HR estimation. The need for a post-processing stage increases the computational complexity of the algorithm.

Moreover, optimizing the protocol in the post-processing stage is challenging for PPG signals acquired in real time. The literature listed in Table II lack generalized capabilities. None of these algorithms are deployed in a wearable device.

This article presents an edge-assisted complete deep learning framework for HR estimation in real time using PPG signal only. The proposed deep neural model is sequentially arranged with a 2-D convolutional layer, a max pooling layer, and a fully connected layer, which are incorporated to estimate HR. No additional layer structure is required to suppress motion artifacts. The performance of the super-resolution spectrogram-based HR estimation approach with traditionally proposed time-frequency approaches is further analyzed. The proposed framework is trained and tested separately with 2-D time-frequency spectrograms created using superlet, wavelet, and short-time Fourier transform. Fig. 7 compares the $HR_{estimated}$ obtained using all three trained models with the HR_{true} value of a randomly selected subject from the IEEE SPC data set.

Fig. 7 shows that estimated HR using superlet transform is accurate for most windows. Hence, the performance of the proposed framework is superior to conventional motion artifact suppression signal processing techniques. To further improve the results of the proposed framework, increase the number of fully connected layers of various depths and widths but find no changes in the performance metric. Most of the techniques in the literature require a PPG sensor and a reference accelerometer signal. However, for a real-time monitoring device, using an accelerometer signal to provide a reference signal to estimate HR has no real significance as the accelerometer signal intensity need not correlate with a person's daily life activity.

Nevertheless, in our results from IEEE SPC training, IEEE SPC test, BAMI-I, and BAMI-II data set, the HRs have estimated accurately during the process of motion artifacts affected windows, and even HRs estimation results accurate during the windows when true HR for those windows is randomly increased. None of the state-of-the-art techniques investigate the efficacy of their proposed model in real time as the acceleration sensor signal need not necessarily correlate with the exercises. The key highlight of the proposed device is that the model's accuracy in estimating HR does not depend upon any motion artifacts suppression signal processing algorithm and additional accelerometer sensor data.

All the above aspects are essential when designing an energy-efficient edge computing IoMT sensor-enabled wearable device to estimate HR in real time. Deep learning shows superior performance in vital sign estimation. However, high-power requirements due to multiple processing show challenges in designing the wearable device due to operating life. Shyam et al. [37] suggested that shifting the processing task to the cloud can reduce the computation burden of the device. However, the latency issue makes this approach impractical as the device has to monitor the HR in real time. Therefore, the proposed framework introduces a completely energy-efficient, edge-assisted module to estimate HR in real time.

In addition, the proposed framework downsizes the spectrogram sizes to reduce the computational parameter further. We test the model at different downsizes 320×320, 296×296, 224×224, 196×196, 144 ×144, and 128 ×128. The MAE value remains the same for 224×224 and higher image sizes. However, the loss function value drastically increases when the model tests for lower image sizes. Hence, 224×224 is considered to estimate HR for a different data set. The proposed work shows the advantage of image size selection during the design of the proposed device.

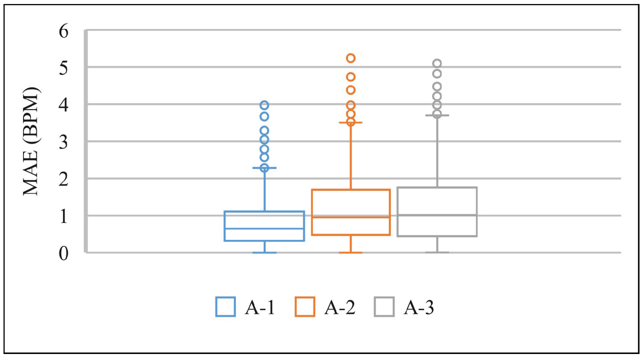

Fig. 9. Box plot representing MAE of different types of exercises.

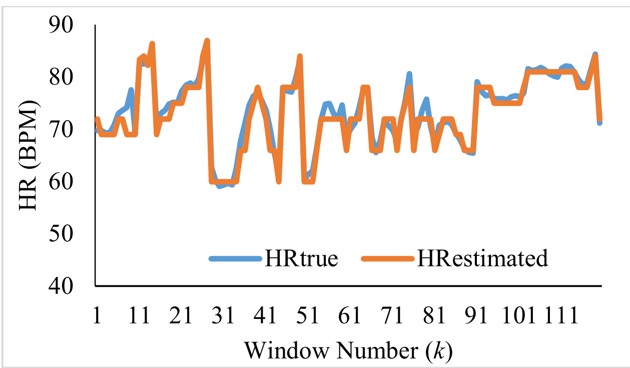

Fig. 10. Comparison between HR_{true} and $HR_{estimated}$ recorded with the proposed wearable device.

Fig. 8 shows a box plot of the HR_{true} and $HR_{estimated}$ using the data processed using the proposed method. The boxes and median value of HR_{true} and $HR_{estimated}$ are almost identical, demonstrating the potential of the proposed framework.

The box plot in Fig. 9 shows the MAE of proposed frameworks under different exercises. In the A-1 exercise database, the subjects run on a treadmill at various speeds.

In exercises A-2, subjects performed various forearm and upper arm exercises, such as push-ups, shaking hands, and stretching. In exercises A-3, subjects performed intensive forearm and upper arm movements such as boxing. Fig. 9 shows similar performance in all three types of exercise. The results show that the generalization of the proposed framework encompasses all types of signals recorded with different exercises without a significant deviation in the performance.

The proposed model is also tested on the PPG data acquired in real time. The HR value obtained using a reference HR device is considered HR_{true} to verify the performance of the proposed edge-assisted hardware. A total of 120 window spectrograms are used to estimate the HR in BPM ($HR_{estimated}$). For the same duration, the HR value of the reference device is considered as HR_{true}. Fig. 10 shows the comparison of $HR_{estimated}$ with HR_{true}. HRestimated accurately tracks the HRtrue for most windows, irrespective of the physical motion occurring while recording the data set. One of the limitations of this step is that no standard ground truth HR is available to compare the obtained results. Thus, in the future, we aim to involve an ECG device under the supervision of medical personnel to record ground truth HR using ECG simultaneously.

VII. Conclusion

The proposed framework uses two publicly PPG data sets to estimate HR and one short-duration in-house recorded data set. While recording these data sets, the exercises are close to real-life activities. Moreover, the proposed work significantly outperforms the state-of-the-art methods, showing the potential of super-resolution spectrogram-based HR estimation. The proposed framework for HR estimation incorporates the potential of both deep learning and signal processing approaches. The proposed device demonstrates better computational complexity and memory requirement performance. The proposed trained model is embedded in a virtualized edge layer connected to the physical layer. An edge-assisted health monitoring device processes the data on the wearable device itself. The edge-assisted wearable device does not transfer the recorded PPG data to any centralized server or cloud for processing. Thus, the latency is reduced as the computation is done on the device.

The proposed framework shows the proposed method's efficiency in estimating HR during the presence of motion artifacts during real-life activities. The proposed framework demonstrated compelling performance in HR estimation. The proposed device allows the work to be embedded in a user-centric, personalized healthcare device. Finally, the computationally efficient edge-assisted device is a novel contribution, providing features toward an embedded application to monitor the real-time CVD state.

References

[1] "Health topics: Cardiovascular diseases," Fact Sheet, World Health Org., Geneva, Switzerland. Accessed: Dec. 11, 2022. [Online]. Available: https://www.who.int/en/news-room/fact-sheets/detail/cardiovascular-diseases-(CVDs)

[2] Pankaj, A. Kumar, R. Komaragiri, and M. Kumar, "A review on computation methods used in photoplethysmography signal analysis for heart rate estimation," *Arch. Comput. Methods Eng.*, vol. 29, no. 2, pp. 921–940, May 2021.

[3] S. Nabavi and S. Bhadra, "A robust fusion method for motion artifacts reduction in photoplethysmography signal," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 12, pp. 9599–9608, Dec. 2020.

[4] C. H. Cheng, K. L. Wong, J. W. Chin, T. T. Chan, and R. H. Y. So, "Deep learning methods for remote heart rate measurement: A review and future research agenda," *Sensors*, vol. 21, pp. 1–32, Sep. 2021.

[5] P. Mohapatra, P. S. Premkumar, and M. Sivaprakasam, "A yellow–orange wavelength-based short-term heart rate variability measurement scheme for wrist-based wearables," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 5, pp. 1091–1101, May 2018.

[6] Pankaj, A. Kumar, R. Komaragiri, and M. Kumar, "Analysis of photoplethysmogram signal to estimate heart rate during physical activity using fractional Fourier transform—A sampling frequency independent and reference signal-less method," *Comput. Methods Programs Biomed.*, vol. 229, Jan. 2023, Art. no. 107294.

[7] A. John, S. J. Redmond, B. Cardiff, and D. John, "A multimodal data fusion technique for heartbeat detection in wearable IoT sensors," *IEEE Internet Things J.*, vol. 9, no. 3, pp. 2071–2082, Feb. 2022.

[8] Pankaj, A. Kumar, R. Komaragiri, and M. Kumar, "Reference signal less Fourier analysis-based motion artifact removal algorithm for wearable photoplethysmography devices to estimate heart rate during physical exercises," *Comput. Biol. Med.*, vol. 141, p. 5081, Feb. 2022.

[9] S. Sakib, M. M. Fouda, and Z. M. Fadlullah, "A rigorous analysis of biomedical edge computing: An arrhythmia classification use-case leveraging deep learning," in *Proc. IEEE Int. Conf. Internet Things Intell. Syst.*, Jan. 2021, pp. 136–141.
[10] S. Dewanto, M. Alexandra, and N. Surantha, "Heart rate monitoring with smart wearables using edge computing," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 3, pp. 141–148, Jan. 2020.
[11] B. S. Kim and S. K. Yoo, "Motion artifact reduction in photoplethysmography using independent component analysis," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 3, pp. 566–568, Mar. 2006.
[12] E. Khan, F. Al Hossain, S. Z. Uddin, S. K. Alam, and M. K. Hasan, "A robust heart rate monitoring scheme using photoplethysmographic signals corrupted by intense motion artifacts," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 550–562, Mar. 2016.
[13] A. Temko, "Accurate heart rate monitoring during physical exercises using PPG," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 9, pp. 2016–2024, Sep. 2017.
[14] K. R. Arunkumar and M. Bhasker, "Heart rate estimation from wrist-type photoplethysmography signals during physical exercise," *Biomed. Signal Process. Control*, vol. 57, p. 1790, Mar. 2020.
[15] D. Zhao, Y. Sun, S. Wan, and F. Wang, "SFST: A robust framework for heart rate monitoring from photoplethysmography signals during physical activities," *Biomed. Signal Process. Control*, vol. 33, pp. 316–324, Dec. 2016.
[16] A. Biswas, M. Singha Roy, and R. Gupta, "Motion artifact reduction from finger photoplethysmogram using discrete wavelet transform," in *Recent Trends in Signal and Image Processing: ISSIP*, vol. 727. Singapore: Springer, Jan. 2019, pp. 89–98.
[17] Z. Zhang, Z. Pi, and B. Liu, "TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 2, pp. 522–531, Feb. 2015.
[18] Z. Zhang, "Photoplethysmography-based heart rate monitoring in physical activities via joint sparse spectrum reconstruction," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 8, pp. 1902–1910, Aug. 2015.
[19] S. M. A. Salehizadeh, D. Dao, J. Bolkhovsky, C. Cho, Y. Mendelson, and K. H. Chon, "A novel time-varying spectral filtering algorithm for reconstruction of motion artifact corrupted heart rate signals during intense physical activities using a wearable photoplethysmogram sensor," *Sensors*, vol. 16, no. 1, p. 10, Dec. 2015.
[20] H. Chung, H. Lee, and J. Lee, "Finite state machine framework for instantaneous heart rate validation using wearable photoplethysmography during intensive exercise," *IEEE J. Biomed. Health Inform.*, vol. 23, no. 4, pp. 1595–1606, Jul. 2019.
[21] K. R. Arunkumar and M. Bhaskar, "CASINOR: Combination of adaptive filters using single noise reference signal for heart rate estimation from PPG signals," *Signal, Image Video Process.*, vol. 14, pp. 1507–1515, Nov. 2020.
[22] D. Biswas et al., "CorNET: Deep learning framework for PPG-based heart rate estimation and biometric identification in ambulant environment," *IEEE Trans. Biomed. Circuits Syst.*, vol. 13, no. 2, pp. 282–291, Apr. 2019.
[23] L. G. Rocha et al., "Binary CorNET: Accelerator for HR estimation from wrist-PPG," *IEEE Trans. Biomed. Circuits Syst.*, vol. 14, no. 4, pp. 715–726, Aug. 2020.
[24] A. Reiss, I. Indlekofer, P. Schmidt, and K. Van Laerhoven, "Deep PPG: Large-scale heart rate estimation with convolutional neural networks," *Sensors*, vol. 19, no. 14, p. 3079, Jul. 2019.
[25] H. Chung, H. Ko, H. Lee, and J. Lee, "Deep Learning for heart rate estimation from reflectance photoplethysmography with acceleration power spectrum and acceleration intensity," *IEEE Access*, vol. 8, pp. 63390–63402, 2020.
[26] V. Nathan and R. Jafari, "Particle filtering and sensor fusion for robust heart rate monitoring using wearable sensors," *IEEE J. Biomed. Health Inform.*, vol. 22, no. 6, pp. 1834–1846, Nov. 2018.
[27] M. Panwar, A. Gautam, D. Biswas, and A. Acharyya, "PP-Net: A deep learning framework for PPG-based blood pressure and heart rate estimation," *IEEE Sensors J.*, vol. 20, no. 17, pp. 10000–10011, Sep. 2020.
[28] X. Chang, G. Li, G. Xing, K. Zhu, and L. Tu, "DeepHeart: A deep learning approach for accurate heart rate estimation from PPG signals," *ACM Trans. Sens. Netw.*, vol. 17, pp. 1–18, Jan. 2021.
[29] D. Ray, T. Collins, and P. V. S. Ponnapalli, "DeepPulse: An uncertainty-aware deep neural network for heart rate estimations from Wrist-worn photoplethysmography," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Jul. 2022, pp. 1651–1654.
[30] A. Burrello et al., "Q-PPG: Energy-efficient PPG-based heart rate monitoring on wearable devices," *IEEE Trans. Biomed. Circuits Syst.*, vol. 15, no. 6, pp. 1196–1209, Dec. 2021.
[31] S. B. Song, J. W. Nam, and J. H. Kim, "NAS-PPG: PPG-based heart rate estimation using neural architecture search," *IEEE Sensors J.*, vol. 21, no. 13, pp. 14941–14949, Jul. 2021.
[32] B. Ngoc-Thang, T. M. T. Nguyen, T. T. Truong, B. L. H. Nguyen, and T. T. Nguyen, "A dynamic reconfigurable wearable device to acquire high quality PPG signal and robust heart rate estimate based on deep learning algorithm for smart healthcare system," *Biosens. Bioelectron. X*, vol. 12, Dec. 2022, Art. no. 100223.
[33] E. Lee and C.-Y. Lee, "PPG-based smart wearable device with energy-efficient computing for mobile health-care applications," *IEEE Sensors J.*, vol. 21, no. 12, pp. 13564–13573, Jun. 2021.
[34] V.V. Moca, H. Bârzan, A. Nagy-Dăbâcan, and R. C. Mureşan, "Time-frequency super-resolution with superlets," *Nat. Commun.*, vol. 12, p. 337, Jan. 2021.
[35] Pankaj, A. Kumar, M. Kumar, and R. Komaragiri, "STSR: Spectro-temporal super-resolution analysis of a reference signal less photoplethysmogram for heart rate estimation during physical activity," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–10, Jul. 2022.
[36] M. A. Motin, C. K. Karmakar, and M. Palaniswami, "PPG derived heart rate estimation during intensive physical exercise," *IEEE Access*, vol. 7, pp. 56062–56069, 2019.
[37] A. Shyam, V. Ravichandran, S. P. Preejith, J. Joseph, and M. Sivaprakasam, "PPGnet: Deep network for device independent heart rate estimation from photoplethysmogram," in *Proc. EMBC*, Mar. 2021, pp. 1899–1902.

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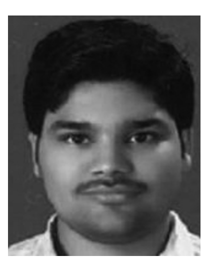

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