IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 8, 2022, accepted May 18, 2022, date of publication May 23, 2022, date of current version June 2, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3177539

Oscillometry-Based Blood Pressure Estimation Using Convolutional Neural Networks

MINHO CHOI [1] AND SANG-JIN LEE [2]
[1] Digital Health Research Division, Korea Institute of Oriental Medicine, Daejeon 34054, South Korea
[2] InBody Company Ltd., Seoul 06313, South Korea

Corresponding author: Minho Choi (minho17@kiom.re.kr)

This work was supported by the Korea Medical Device Development Fund Grant through the Korea Government (the Ministry of Science and ICT, the Ministry of Trade, Industry and Energy, the Ministry of Health and Welfare, and the Ministry of Food and Drug Safety) under Grant KMDF_PR_20200901_0212.

ABSTRACT Blood pressure measurement is required to monitor the cardiovascular state of a person, and it is commonly conducted in a noninvasive way using oscillometry-based blood pressure monitors (BPM). Blood pressure can be estimated by analyzing the oscillometric waveform (OMW) in the BPM, and many methods have been examined to increase their estimation accuracy. In this study, we proposed a new method that enhances estimation accuracy and requires no external user information, such as age and gender, in the test phase. In the method, the entire OMW was considered as an input to reduce information loss via feature extraction, and convolutional neural networks were utilized to effectively analyze the high-dimensional input. Additionally, the proposed method included a novel ensemble method to further increase the estimation accuracy. The performance of the proposed method was evaluated and compared with other studies via subject-independent tests considering real situations in which it is difficult to obtain preliminary information on a test subject. Data from 64 subjects were used in the test. The mean absolute error of the proposed method was 3.12 and 3.98 mmHg for systolic and diastolic blood pressure, respectively, which was superior to those reported in other studies conducted in similar conditions. Individuals can measure their blood pressure with higher precision using the proposed method with improved estimation performance. This can aid in reducing the risk of cardiovascular diseases.

INDEX TERMS Blood pressure estimation, convolutional neural network, noninvasive measurement, oscillometry.

I. INTRODUCTION

Blood pressure commonly refers to the pressure of blood in arteries, which are blood vessels containing blood from the heart. It changes according to the pumping action of the heart. Specifically, systolic blood pressure (SBP) and diastolic blood pressure (DBP) are defined as the highest and lowest blood pressure within a cardiac cycle, respectively [1]. The blood pressure is an important vital sign that represents the state of the cardiovascular system, and it is commonly measured in hospitals or homes [2]. An arterial catheter can be used to measure it directly; however, it is an invasive method and can lead to clinical risks such as infection, bleeding, and ischemia [3]. As a noninvasive method, the auscultatory method has been used in hospitals. It compresses the upper arm of the subject using a cuff and gradually reduces the air pressure in the cuff. A medical personnel then uses a stethoscope to hear Korotkoff sounds that appear when the cuff pressure is the same as SBP and disappears when the pressure is the same as DBP. The auscultatory method is accurate and considered as the gold standard for noninvasive blood pressure measurements. However, it can be affected by the listener's hearing ability, and a skilled personnel is required to measure the blood pressure [4]. Currently, automatic blood pressure monitors that do not require a medical personnel are widely used. They sense an oscillometric waveform (OMW) due to the vibrations of pulse waves in the brachial artery when the cuff pressure

The associate editor coordinating the review of this manuscript and approving it for publication was Norbert Herencsar.

is decreased after compression. Specifically, SBP and DBP are determined by analyzing OMW. Many algorithms have been proposed to obtain SBP and DBP from OMW, and the maximum amplitude algorithm (MAA) is the most conventional algorithm that has been used [5]. The pulse of OMW is enlarged when the cuff pressure is close to the mean arterial pressure (MAP), which is the average arterial blood pressure value in a cardiac cycle. The MAA simplifies the OMW and constructs an OMW envelope (OMWE) to find a maximum point corresponding to the cuff pressure that is close to the MAP. Then, the algorithm utilizes empirical coefficients to determine the SBP and DBP points from the maximum point. MAA is simple and has been used in many commercial devices; however, it is sensitive to noise. Additionally, it is not accurate for a subject because it utilizes fixed empirical coefficients for all subjects without considering the characteristics of OMW for each subject.

In some studies, SBP and DBP were estimated by analyzing the characteristics of OMW in more detail. In these studies, features from OMW or OMWE were extracted, and these features were used as inputs for machine learning techniques. For example, Forouzanfa *et al.* mathematically approximated OMWE with two Gaussian functions and used the model parameters for the input of two separate feed-forward neural networks (FFNN) to estimate blood pressure [6]. Alghamdi *et al.* extracted 27 features, including time, frequency domain, and chaotic features, and blood pressure values were obtained using Gaussian process regression (GPR) [7]. Lee and Chang extracted eight features and increased the feature data by applying them to the parametric bootstrap method [8]. SBP and DBP were then estimated using deep belief networks-deep neural networks (DBN-DNN). The study was conducted in different ways. Specifically, DBN-DNN-based fusion ensemble regression models using bootstrap-aggregation and adaboost techniques were proposed [9], [10], and deep Boltzmann machine (DBM)-based methods were introduced by the author [11], [12]. The OMWE can simplify the OMW and represent the morphological characteristics of the OMW. However, detailed information on each pulse of the OMW can be ignored. Therefore, Argha and Celler considered seven features extracted from each pulse of OMW and utilized these features for a long short-term memory recurrent neural network (LSTM-RNN)-based method [13]. The study was further developed, and improved results were reported by the author using the DBN-DNN [14]. These studies attempted to identify useful features that contain information on SBP and DBP. However, there might be valuable characteristics of OMW that cannot be extracted as features. By considering the possibility of information loss, Narus *et al.* used a simplified OMWE as the input of an artificial neural network for blood pressure estimation [15]. The extended input dimension can decrease information loss, but the complexity of the model should be increased to represent a complex relationship between the input and output.

Therefore, in this study, we utilized convolutional neural networks (CNN) for blood pressure estimation. A CNN is a popular deep learning technique that can construct a complex and deeper model that reduces the problems of conventional learning methods such as overfitting and vanishing gradient [16], [17]. Furthermore, CNNs have been widely used in image processing fields, and many studies have shown remarkable results by utilizing CNNs for the analysis of one-dimensional physiological signals, including electrocardiograms and electroencephalograms [18]–[22]. In this study, the entire OMW was used as input to prevent the omission of valuable information required for blood pressure estimation, and CNN models were constructed to obtain SBP and DBP by effectively utilizing the high-dimensional input. Additionally, the proposed method includes an ensemble technique to further increase the estimation performance. The ensemble method uses gender information of subjects. Gender information has already been used in many studies as a feature [9]–[12], and previous studies assumed that the gender information of a test subject can be known. However, gender information is external information that cannot be obtained by using the measured signal itself, and an additional process, such as feedback from users, is required. Our ensemble method uses gender information only in the training phase, and does not require an additional procedure. The gender information is utilized to adjust the weights of data differently, and three models are trained using the weights to increase the diversity of the models. Then, a model that is suitable for each test datum is selected to estimate blood pressure in the ensemble method. The model selection is conducted without prior information on the gender of a test subject, and only the estimation results from the three models are utilized to select a model for each test datum. The performance of the proposed method was evaluated and compared with other methods using a subject-independent test (SIT) [23]. SIT separates the data of all subjects such that the data of each subject are included only in the training or test set. This is performed to evaluate the performance of a model for the data of an unseen subject, similar to a real environment, where it is difficult to obtain information about a test subject in advance. Physiological signals, including OMW, generally exhibit characteristic differences for each subject, and it is important to utilize SIT in the performance evaluation of physiological signal-based systems.

The main contributions of this study can be listed as follows:

1) A CNN-based method for estimating SBP and DBP was proposed. This includes a method to construct input data from OMW and the structure of the CNN model that is suitable for dealing with the input data. To the best of our knowledge, this is the first study that uses the entire OMW as an input for deep learning-based blood pressure estimation. Hence, the results can be a valuable reference for applying deep learning techniques to blood pressure estimation in future studies

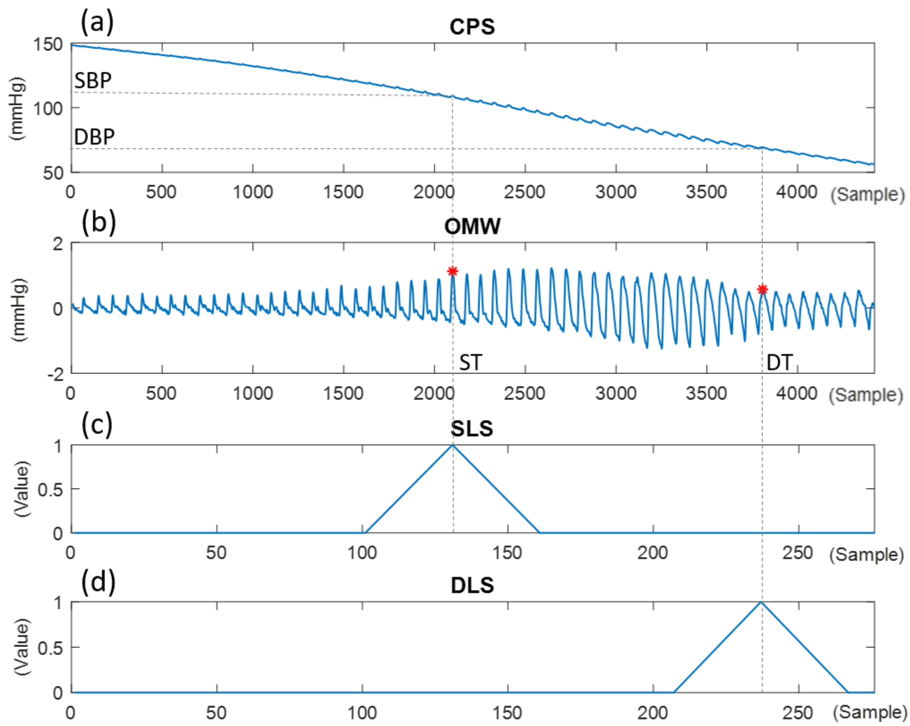

FIGURE 1. Preprocessing of data: (a) measured CPS, (b) extracted OMW, (c) constructed SLS, and (d) DLS. Red stars are two peaks corresponding to ST and DT.

2) A novel ensemble method was used to increase the performance of blood pressure estimation. It requires the gender information of subjects, but the information is used only in the training phase to expand the diversity of CNN models. Therefore, additional gender information of the test subject is not required, and the ensemble method can be used in real situations to improve the estimation accuracy of blood pressure.
3) The results of the proposed method were evaluated and compared with those of similar studies. SIT was utilized for evaluation, and readers were able to understand the advantages of the proposed method and the current level of oscillometry-based blood pressure estimation more precisely. The comparison results can also be viewed as a standard when the performance of a new blood pressure estimation method is evaluated in other studies.

The rest of this paper is organized as follows. A detailed explanation of the proposed method is described in Section II. The explanation includes data acquisition, preprocessing, data augmentation, the structure of the proposed CNN model, and an ensemble method. The effectiveness of the proposed method is described in Section III. The performance of the blood pressure estimation obtained using the proposed method is presented and compared with the results of other studies in this section. Finally, the conclusions and future work for this study are summarized in Section IV.

II. METHODS

A. DATA ACQUISITION

Blood pressure was measured using a commercial device (BPBIO480 KV, InBody). It uses one of two cuffs according to the arm circumference of the subject. The pressure signal of the cuff was obtained at a sampling rate of 100 Hz and saved in the USB memory of the device. The device can also acquire Korotkoff sounds, but the signals were not used in this study because they cannot be acquired in other blood pressure monitors. A total of 64 subjects (39 males and 25 females) participated in the experiment, and their ages ranged from 21 to 45 years. We obtained informed consent from all the subjects prior to the experiment, and blood pressure was measured four times for each subject using the device. A trained nurse used a stethoscope to simultaneously obtain SBP and DBP via the auscultatory method with the measurements of the device, and the values were used as the gold standard to compare the estimated blood pressure results obtained via the proposed method. For the rest of the experimental protocol, such as posture to measure blood pressure and rest time between measurements, the standards that are typically used for blood pressure measurements were utilized [24]. Among 256 records that were acquired from 64 subjects, 10 records were discarded because Korotkoff sounds, required to determine true SBP and DBP, were unclear or there was distortion in the measured cuff pressure signal (CPS) due to the motion of the subject.

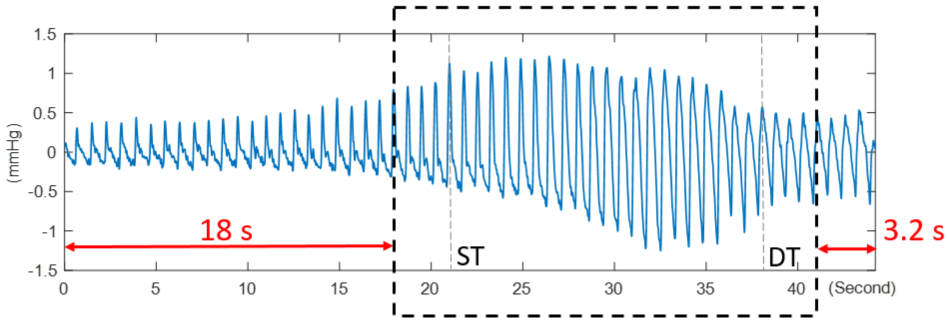

FIGURE 2. Example of data augmentation. The black dashed square represents the data from the ST - *margin* to the DT + *margin* in the OMW.

B. PREPROCESSING

The CPS contains two components (Fig. 1(a)). One of the components corresponds to a decreasing linear trend due to decompression of the cuff during blood pressure measurement, and the other component corresponds to OMW due to the vibrations of pulse waves from the body. OMW is extracted from CPS by using a band-pass filter with a pass band of 0.3–15 Hz (Fig. 1(b)), and it is used as the input to a CNN model for estimating blood pressure. Two time points are defined when the value of CPS is the same as SBP or DBP at the SBP time point (ST) and DBP time point (DT), respectively, and the model is used to determine the relationship between OMW and ST and DT by considering them as input and output. The model is used to find two pulse peaks with time points matching ST and DT in OMW. Then, SBP and DBP can be estimated by reading the CPS values corresponding to ST and DT, which are determined by the model. To train the model, the proposed method does not directly use ST and DT values as labels, and a signal is constructed and utilized as label data for SBP and DBP. The two signals for SBP and DBP are defined as the SBP label signal (SLS) and DBP label signal (DLS), respectively, and are constructed as follows (Fig. 1(c, d)):

1) Two time points which values are true SBP and DBP are identified and defined as pre-ST and pre-DT in the CPS.
2) Pulse peaks are detected in OMW, and two peaks, which are nearest to pre-ST and pre-DT, are identified and used as ST and DT.
3) SLS and DLS with a length of L/r are constructed as follows:

$$\mathrm{SLS}(i) = \begin{cases} 1 & \text{if } i = \mathrm{ST}/r, \\ 1 - \frac{|i-\mathrm{ST}/r|}{\alpha} & \text{if } |i - \mathrm{ST}/r| < \alpha, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

$$\mathrm{DLS}(i) = \begin{cases} 1 & \text{if } i = \mathrm{DT}/r, \\ 1 - \frac{|i-\mathrm{DT}/r|}{\alpha} & \text{if } |i - \mathrm{DT}/r| < \alpha, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where L denotes the length of OMW.

The SLS and DLS are used to intuitively provide the position information of ST and DT to the model, and the model can simplify the relationship between OMW and the ST and DT through the SLS and DLS. In addition, the SLS and DLS have values from zero to one, and it can limit the range of output values of the model without being affected by the length of OMW. L is normally very long when compared with the ST and DT points, and r is used to reduce dimensionality and remove unnecessary information in the SLS and DLS. Specifically, L corresponded to 6800 in our data, and r was set as 16 in this study. Even after reducing the dimensionality, the information of the two points remains sparse within SLS and DLS, and α is designated to expand the information of ST and DT. The values of SLS and DLS gradually decrease from around ST and DT, and the position information of ST and DT is represented as a triangular shape. It emphasizes the information of ST and DT and increases the proportion of meaningful information in the total, similar to the heatmap representation used in human pose estimation of image processing [25], [26]. Additionally, the probabilities of ST and DT can be estimated from the model trained using the SLS and DLS. It is needed in a proposed ensemble method, and a more detailed explanation of the proposed ensemble method is provided in Section II-E. The value of α was experimentally set as 30.

C. AUGMENTATION OF TRAINING DATA

Deep learning techniques, such as CNN, can construct a complex model, but a large dataset is required in the training process. Therefore, in this study, data augmentation is conducted to increase the training data size. The trained model determines ST and DT in OMW, and the data from ST to DT should be included in the input data. In the proposed method, the data from the ST - *margin* to the DT + *margin* are considered as essential information, and new data are constructed by sequentially trimming the original data with the exception of the essential information. Hence, we define the data before and after the essential information as D_{before} and D_{after}, respectively, which are continuously trimmed at a second unit, and new data are generated for all trimmed cases. The *margin* was set to a length of 3 s to include at

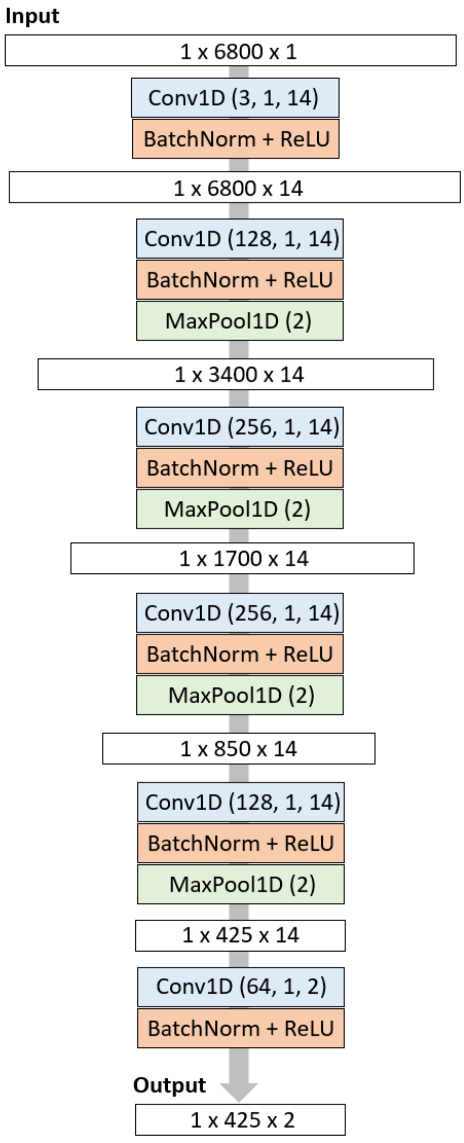

FIGURE 3. **Structure of the proposed CNN model for estimating ST and DT from OMW.**

least one more pulse in the OMW. Fig. 2 shows an example of the augmentation process. The length of the OMW is 44.2 s, and D_{before} and D_{after} exhibit lengths of 18 s and 3.2 s, respectively. Then, D_{before} can be trimmed 18 times, and D_{after} can be trimmed three times. Therefore, all possible trimmed cases correspond to $18 \times 3 = 54$, and a new set of 54 cases can be obtained via the augmentation process. The size of augmented data was 28,570 from 246 records of 64 participants in our study. Blood pressure monitors uses their own algorithm to decide maximum cuff pressure to be compressed and endpoint of measurement, and the length of the measured OMW might vary for each measurement. By using augmented data, the model can learn various cases of OMW of various lengths, and a more robust estimation is possible for OMW with a short length.

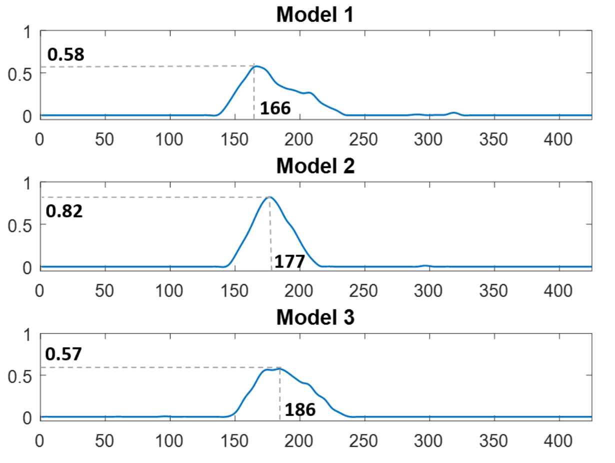

FIGURE 4. **Example of estimated SLS in the three CNN models trained using different datasets.**

D. STRUCTURE OF THE CNN MODEL

In the proposed model, input data size of $1 \times 6800 \times 1$ was used. OMW was normalized to a zero mean and unit variance, and zero padding was utilized for OMW whose length was shorter than 6800 to be used as the input data. The structure of the proposed model is shown in Fig. 3. The model is constructed to find the positions of ST and DT in OMW, and fully convolutional networks are utilized without fully connected layers to preserve the position information on ST and DT in each layer. The model consists of six CNN blocks constructed by combining a 1-D convolutional layer, batch normalization, ReLu activation function, and a 1-D max pooling layer. The first block uses a 1-D convolutional layer with a kernel size of $1 \times 3 \times 1$, stride of 1, and 14 filters. The purpose of this layer involves extracting detailed information on the OMW signal, and a small kernel is utilized. Then, batch normalization and ReLu activation function are attached to reduce the impact of the data scale and prevent the vanishing gradient problem [27]. Previous studies extracted features from the OMWE to determine ST and DT [6], [8]. This is because the analysis of the overall shape of the OMW can aid in estimating ST and DT. Therefore, wider kernels are used for the 1-D convolutional layers in the second to sixth blocks to acquire useful information in a wide region of OMW, similar to the OMWE-based features utilized in previous studies. The model investigates a wide range of OMW trends via successive broad kernels, and variable information on ST and DT is extracted. Similar to the first block, batch normalization and the ReLu activation function are also included in the blocks. The label data of this model are SLS and DLS with reduced dimensionality as explained in Section II-B. The length of the input data is decreased by four 1-D max pooling layers in the second to fifth blocks. The number of filters is set to two in the last convolutional layer to produce two signals with a length of $6800/r$, each corresponding to SLS and DLS.

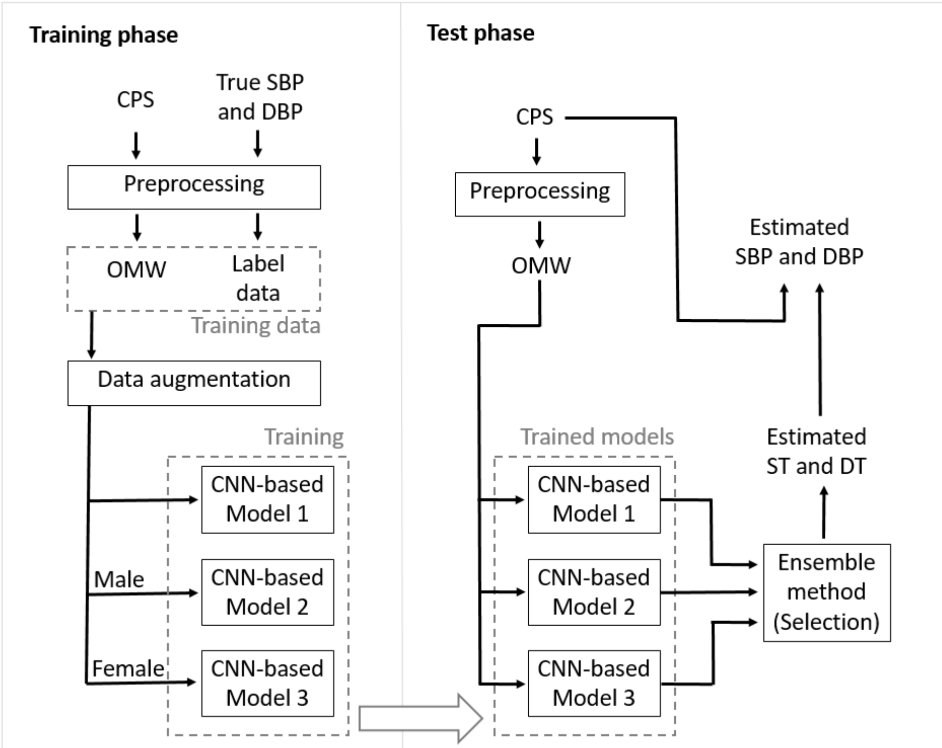

FIGURE 5. Overall block diagram of the proposed method.

E. ENSEMBLE METHOD USING GENDER INFORMATION

The output of the model could contain an outlier value, and a low-pass filter with a cutoff frequency of 0.5 Hz is used to smooth the output, that is the estimated SLS and DLS. ST and DT are obtained by determining a point with the maximum value in SLS and DLS, respectively. Then, SBP and DBP can be estimated by identifying the CPS values corresponding to ST and DT.

Only one model can be used to conduct the aforementioned estimation process; however, three models are trained and utilized in the proposed method. This is conducted to further improve the estimation performance using an ensemble method. The ensemble methodology is a common concept in machine learning. It involves building several diverse models and integrating the results of multiple models to increase the prediction performance and improve the robustness of prediction [28]. To construct models with diversity, the proposed method assigns different weights to training data using gender information. One model is trained considering the entire data with equal weights. However, the other two models separate the entire training data into male and female data and increase the weights of the male or female data to train each model. The usefulness of gender information in blood pressure estimation has been shown in previous studies [9]–[12], and gender information-based data manipulation was implemented in this study. Experimental protocols for blood pressure measurement normally require the gathering of gender information to analyze the results of blood pressure measurement according to gender [24], and the acquisition of the information is not abnormal or difficult. Therefore, the information was recorded in our experiment and utilized for the ensemble process. Furthermore, the information is required only in the training phase to construct diverse models, and the gender information of a test subject is not required to estimate SBP and DBP in the proposed method. This is a crucial advantage because gender information is external information that cannot be automatically obtained by using a blood pressure monitor in the test phase.

The proposed method simultaneously applies a test datum to the three models and selects the output of one model by comparing their reliability to obtain the ST and DT. It is to utilize the information of the three models with various characteristics regardless of the actual gender information of the test datum. A detailed explanation is presented in Fig. 4, which shows the three estimated SLS results from the three models. The original SLS used for training has a maximum value of one at ST, and the model is trained to produce an output similar to the SLS. Therefore, the maximum value of the estimated SLS will be close to one when reliable estimation is performed in the model. This idea is reflected in the proposed method, and the estimated SLS output of the model with the highest maximum value is selected among the three estimated SLS results from the three models. Then, ST is determined using the selected SLS output. This process utilizes the estimated SLS of each model as a signal representing the probability of ST, and the point with the highest probability is selected as ST. For example, the estimated SLS of model 2 exhibits the highest maximum value of 0.82 among the three estimated SLS results, and ST is designated as 177 in Fig. 4. The estimation of DT is conducted using the same process as above with the exception that estimated DLS is used as opposed to SLS. Other methodologies such as the weighted sum or morphology analysis of outputs can be used to merge the information of three models, but the selection method was utilized in this study, because the method is simple and dose not need any adjustable or empirical variables.

F. SUMMARY OF THE PROPOSED METHOD

The overall process of the proposed method is illustrated in this section (Fig. 5). The proposed method utilizes OMW and label data, consisting of SLS and DLS as training data, which are obtained via preprocessing. Then, data augmentation is implemented to increase the size of the training data by trimming the OMW into various lengths. The gender information is used to obtain three models having diversity. One model considers the entire training data equally, but the other two models increase the weights of male or female data for training, respectively. In the test phase, OMW is extracted from the measured CPS and applied to the three trained models. The output of the models is the estimated SLS and DLS, and the proposed ensemble method selects one of the results of the three models by comparing their reliability. The ST and DT are determined from the selected results. SBP and DBP are estimated by determining the pressure values corresponding to ST and DT in the measured CPS.

III. RESULTS AND DISCUSSIONS

A. SIMULATION ENVIRONMENT

Simulations were conducted to verify the proposed method using a computer with an Intel Core i7-6700 CPU and NVIDIA GeForce GTX 1060 graphics card. Preprocessing was conducted in MATLAB, and other steps, including the construction of the CNN models, training process, and blood pressure estimation from the estimation results of the models, were implemented in Python with TensorFlow and Keras. In the training, the batch size was set as 100, and the mean square error loss and Adam optimizer were utilized to update the weights of the models. The learning rate was 5×10^{-5} and it was reduced by 10% to as low as 10^{-8} if there was no improvement for three epochs. The total number of epochs for training was 100, but early stopping was activated when there was no improvement in the performance for ten epochs.

The performance of blood pressure estimation was verified using SIT. As mentioned in the introduction, SIT is used to identify the performance of a system on the data of unknown subjects, and the test data consist only data of subjects who do not belong to the training data. The evaluation process is similar to real situations, and it is important and necessary to apply SIT to verify a system that analyzes physiological signals such as OMW with inter-subject variation [29]. The data of 64 subjects were randomly divided into eight folds and cross-validated. The training data contained the data of 56 subjects to train the models in each fold. The data of eight subjects were tested for each fold, and the estimation errors of all subjects were collected. As mentioned at Section II-A, the auscultatory method was used to identify true SBP and DBP, and the estimation error was obtained as the difference between the true value and the estimated blood pressure for SBP and DBP, respectively. The auscultatory method cannot give true MAP, and the estimation and analysis were conducted for SBP and DBP. Subsequently, the mean error (ME), standard deviation of error (SDE), and mean absolute error (MAE) were calculated for SBP and DBP to represent the performance of blood pressure estimation as follows:

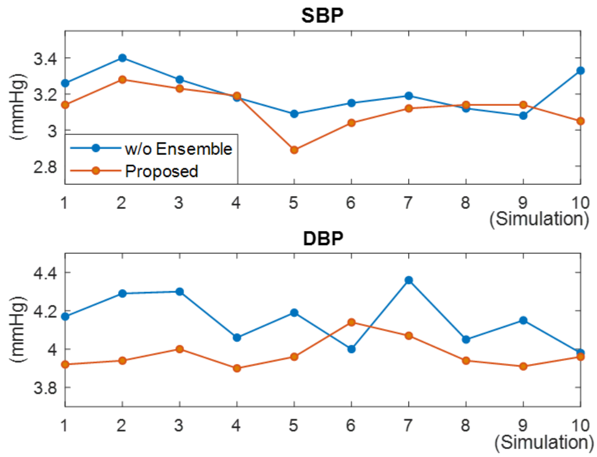

FIGURE 6. MAE of blood pressure estimation using the proposed method in ten simulations. The orange line denotes the results of the proposed method, including the ensemble method, and the blue line denotes the results when the ensemble method was not utilized.

$$e_i = y_i - \hat{y}_i \tag{3}$$

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N} e_i, \tag{4}$$

$$\mathrm{SDE} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(e_i - \mathrm{ME})^2}, \tag{5}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|e_i|, \tag{6}$$

where y_i, $\hat{y}_i$, e_i, and N denote the true value, estimated value, estimation error, and number of data, respectively. Then, the subject-wise cross-validation was repeated ten times to obtain a more generalized performance for the proposed method.

B. BLOOD PRESSURE ESTIMATION RESULTS OF THE PROPOSED METHOD

Fig. 6 shows the MAE of the proposed method for ten simulations of blood pressure estimation. It also contains the results of cases that excluded the ensemble method, and the effect of the ensemble method can be identified by comparing the two results. To calculate the results for the case without the ensemble method, ST and DT were estimated using only one

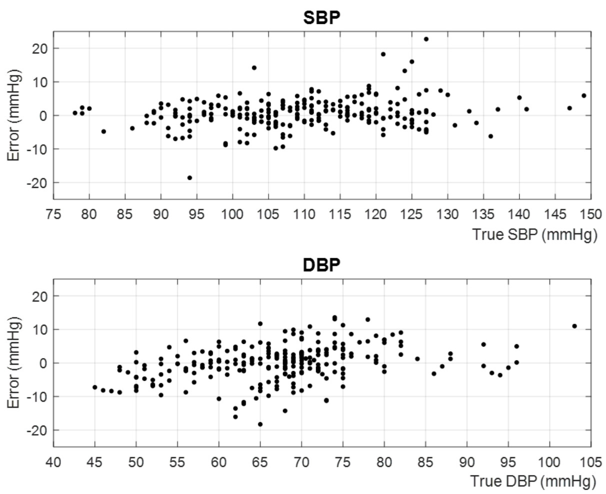

FIGURE 7. Bland–Altman plot showing the relationship between true blood pressure and estimation error.

TABLE 1. Averaged results of blood pressure estimation (mmHg) for ten simulations.

Method	SBP			DBP		
	ME	SDE	MAE	ME	SDE	MAE
MAA	3.92	6.48	5.51	4.59	5.99	6.23
w/o Ensemble	0.62	4.73	3.21	0.13	5.68	4.16
Proposed	0.72	4.57	3.12	0.06	5.27	3.98

model (Model 1 in Fig. 5), and SBP and DBP were obtained from ST and DT. The results varied slightly according to each simulation; however, there were no outliers. Overall, the MAE was low when the ensemble method was utilized in the results, and its effect was more noticeable for DBP than for SBP. The MAE of SBP estimation was lower than that of DBP when only one model was employed, and the improvement from the ensemble method was more prominent in DBP with more room for enhancement. A t-test was used to verify the statistical significance of the differences between the results with and without the ensemble method [30]. The calculated p values were 0.028 and 0.004 for SBP and DBP, respectively. The values were lower than 0.05, which shows that the use of the ensemble method has a statistical significance at the 95% confidence level in the results of blood pressure estimation. Furthermore, the advantages of the ensemble method can be confirmed by the averaged results (Table 1).

The results from MMA, which is a traditional method for blood pressure estimation, were computed to exhibit the superiority of the proposed method in Table 1. The MAE of the proposed method were 3.12 and 3.98 mmHg, and the values were 2.39 and 2.25 mmHg lower than MMA for SBP and DBP, respectively. Additionally, the proposed method could improve ME and SDE. The decrease in ME was the highest, and the differences in ME between MAA and the proposed method were 3.20 and 4.53 mmHg for SBP and DBP. MMA is simple and has an intuitive operating principle; however, it only analyzes the amplitude change in OSC pulses, and fixed empirical coefficients are used for all data. Conversely, the proposed method attempts to find valuable information in the entire OMW and utilizes the deep learning model and ensemble method to generate most of the input data. Therefore, the performance of the proposed method was better than that of MMA.

TABLE 2. Computational time (s) for training and test.

	T_{TR_F}	T_{TE_D}
w/o Ensemble	3,840.99	0.86
Proposed	12,500.01	4.47

TABLE 3. Percentage of distribution of absolute error.

	Absolute Error (%)		
	$\leq$ 5 mmHg	$\leq$ 10 mmHg	$\leq$ 15 mmHg
SBP	80.08	97.56	98.37
DBP	69.11	96.09	99.19

The distribution of the estimation error was investigated to analyze the performance of the proposed method in more detail. The results of the seventh simulation were used for the analysis, and the estimation error was plotted according to the true blood pressure (Fig. 7). There was no bias for true blood pressure in the figure, and R^2 was 0.0148 and 0.0002 for SBP and DBP, respectively. The results show that the estimation performance of the proposed method was rarely affected by the blood pressure value. Additionally, there were a few cases with errors higher than 20 mmHg for SBP, but most of the error values were less than 15 mmHg (Table 3). The British Hypertension Society established a standard for grading the performance of a blood pressure monitor [31]. Although there were some differences in the experimental protocol used in this study, it was possible to evaluate the proposed method by numerically comparing the results of the proposed method with the standard. The standard considers a blood pressure monitor as ‘A’ grade when it has more than 60, 85, and 95% absolute error with values lower than 5, 10, and 15 mmHg, respectively. The results of the proposed method satisfied the standard, indicating the superiority of the blood pressure estimation results obtained via the proposed method.

Computational time was investigated to provide more detailed information on the proposed method (Table 2). The proposed method was validated via the subject-wise eight-folds cross-validation, and average training time for each fold (T_{TR_F}) was calculated. The number of training data was 24,998.75 on average in each fold, and T_{TR_F} was 3,840.99 without the ensemble method. It increased approximately three times when using the ensemble method, because the three models were trained in the ensemble method. In the test phase, the time to estimate blood pressure was measured for each datum, and the averaged time was defined as T_{TE_D}. The T_{TE_D} was more than three time when using the ensemble method. This is because the time for comparing the results of the three models was necessary. The proposed method required the long training time, but the time for estimating blood pressure was relatively short. Therefore, the proposed

TABLE 4. Comparison results with other studies on OMW-based blood pressure estimation.

Method	SBP			DBP			SIT	External information
	ME	SDE	MAE	ME	SDE	MAE		
1. FFNN [6]	-	8.58	6.28	-	7.33	5.73	O	-
2. DBN-DNN [8]	0.01	6.35	-	0.03	5.28	-	O	-
3. GMR [32]	1.18	5.67	-	0.32	5.72	-	O	-
4. IGMR [33]	-0.34	5.79	4.52	0.73	4.32	3.32	O	Age
5. DBN-DNN-FE [9]	-0.01	5.74	-	-0.04	4.68	-	O	Age and gender
6. DBN-DNN-AE [10]	0.02	5.74	-	-0.03	4.67	-	O	Age and gender
7. DBR [11]	-0.50	5.96	-	0.21	4.82	-	O	Age and gender
8. DBMDS [12]	0.17	5.34	-	-0.11	4.36	-	O	Age and gender
9. GPR [7]	-	-	3.64	-	-	4.27	X	-
10. LSTM-RNN [13]	-1.2	5.9	3.8	1.8	8.8	7.3	X	-
11. DBN-DNN-BB [14]	0.4	2.9	1.1	-1.0	5.6	3.0	X	-
Proposed	0.72	4.57	3.12	0.06	5.27	3.98	O	-

method can be used in real situations by utilizing the models that were trained offline.

C. COMPARISON WITH OTHER STUDIES

Many studies that estimate blood pressure based on OMW have been conducted, and the effectiveness of the proposed method was compared with the results of previous studies (Table 4). The comparison considered 11 methods that used various techniques such as FFNN, DBN-DNN, Gaussian mixture regression (GMR), improved GMR (IGMR), DBN-DNN with a fusion ensemble estimator (DBN-DNN-FE), DBN-DNN with an asymptotic approach-based ensemble method (DBN-DNN-AE), DBM regression (DBR), DBM-based Dempster-Shafer fusion (DBMDS), GPR, LSTM-RNN, and DBN-DNN with beat-by-beat time domain features (DBN-DNN-BB).

The proposed method outperformed methods 1–3 that did not utilize external information. Methods 1–3 were validated via SIT, and all the performance indices of SBP and DBP were worse than those of the proposed method with the exception of the ME for method 2. The ME of method 2 was 0.71 lower than that of the proposed method for SBP. However, the ME and SDE of DBP were almost equal, and the SDE of SBP was 1.78 higher than that of the proposed method. Therefore, the proposed method exhibited a better performance in blood pressure estimation than method 2 overall. Furthermore, SBP results could be improved via the proposed method when compared with methods 4–8, but DBP results were better in methods 4-8. By comprehensively considering the results of SBP and DBP, the blood pressure estimation performance of the proposed method was similar to that of methods 4–8. However, methods 4–8 used external information, such as age and gender, and the information should be acquired and included in the input when blood pressure estimation is conducted for a test subject in a system that utilizes methods 4–8. On the other hand, the proposed method does not require any external information, and only the measured CPS is used in the testing phase. Nevertheless, the proposed method showed good performance similar to methods 4–8, and which is an advantage of the proposed method. Methods 9–11 did not utilize SIT in the performance evaluation, and the data of all subjects were classified into training and test data without considering the subject-wise separation of data. The evaluation process is advantageous for performance evaluation when compared to SIT for physiological data with inter-subject variation because the characteristics of subjects in the test data can be analyzed during training in advance. Therefore, it is difficult to rigorously compare the results of methods 9–11 with those of the proposed method. Despite this, all the results of SBP and DBP obtained via the proposed method were better than those obtained via methods 9 and 10.

IV. CONCLUSION

In this study, a CNN-based method was proposed to estimate blood pressure. The method analyzes OMW and does not require any external information on a subject in the test phase. The CNN model of the proposed method extracts useful information in the entire OMW and finds the pulse positions corresponding to SBP and DBP. Data augmentation was conducted to expand the size of the training data, and an ensemble method was utilized to further increase the performance of the blood pressure estimation in the proposed method. Simulations and comparisons with other studies were performed, and the effectiveness and superiority of the proposed method were confirmed. To the best of our knowledge, this is the first study in which a deep learning-based model is devised to analyze the entire OMW for blood pressure estimation. The method uses the entire OMW as input to prevent the omission of valuable information in the OMW. Furthermore, the excellent performance of the proposed method was identified via the results. The proposed method can be utilized in various forms of automatic blood pressure monitors and can improve the estimation performance of blood pressure values. This benefit can aid individuals in managing cardiovascular diseases by ensuring more accurate blood pressure monitoring. In future studies, we will validate the expanded size of real data and perform an in-depth analysis of outliers.

REFERENCES

[1] B. Zhang, Z. Wei, J. Ren, Y. Cheng, and Z. Zheng, "An empirical study on predicting blood pressure using classification and regression trees," *IEEE Access*, vol. 6, pp. 21758–21768, 2018.

[2] F. Tabei, J. M. Gresham, B. Askarian, K. Jung, and J. W. Chong, "Cuff-less blood pressure monitoring system using smartphones," *IEEE Access*, vol. 8, pp. 11534–11545, 2020.

[3] L. E. Klinker, T. S. Henriques, M. D. Costa, R. B. Davis, M. A. Mittleman, P. Mathur, and B. Subramaniam, "Comparison of invasive and noninvasive blood pressure measurements for assessing signal complexity and surgical risk in cardiac surgical patients," *Anesthesia Analgesia*, vol. 130, no. 6, p. 1653, 2020.

[4] M. Forouzanfar, H. R. Dajani, V. Z. Groza, M. Bolic, S. Rajan, and I. Batkin, "Oscillometric blood pressure estimation: Past, present, and future," *IEEE Rev. Biomed. Eng.*, vol. 8, pp. 44–63, 2015.

[5] G. Drzewiecki, R. Hood, and H. Apple, "Theory of the oscillometric maximum and the systolic and diastolic detection ratios," *Ann. Biomed. Eng.*, vol. 22, no. 1, pp. 88–96, Jan./Feb. 1994.

[6] M. Forouzanfar, H. R. Dajani, V. Z. Groza, M. Bolic, and S. Rajan, "Feature-based neural network approach for oscillometric blood pressure estimation," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 8, pp. 2786–2796, Aug. 2011.

[7] A. S. Alghamdi, K. Polat, A. Alghoson, A. A. Alshdadi, and A. A. A. El-Latif, "Gaussian process regression (GPR) based non-invasive continuous blood pressure prediction method from cuff oscillometric signals," *Appl. Acoust.*, vol. 164, Jul. 2020, Art. no. 107256.

[8] S. Lee and J.-H. Chang, "Oscillometric blood pressure estimation based on deep learning," *IEEE Trans. Ind. Informat.*, vol. 13, no. 2, pp. 461–472, Apr. 2017.

[9] S. Lee and J.-H. Chang, "Deep belief networks ensemble for blood pressure estimation," *IEEE Access*, vol. 5, pp. 9962–9972, 2017.

[10] S. Lee and J.-H. Chang, "Deep learning ensemble with asymptotic techniques for oscillometric blood pressure estimation," *Comput. Methods Programs Biomed.*, vol. 151, pp. 1–13, Nov. 2017.

[11] S. Lee and J.-H. Chang, "Deep Boltzmann regression with mimic features for oscillometric blood pressure estimation," *IEEE Sensors J.*, vol. 17, no. 18, pp. 5982–5993, Sep. 2017.

[12] S. Lee and J.-H. Chang, "Dempster–Shafer fusion based on a deep Boltzmann machine for blood pressure estimation," *Appl. Sci.*, vol. 9, no. 1, p. 96, Dec. 2018.

[13] A. Argha and B. G. Celler, "Blood pressure estimation from time-domain features of oscillometric waveforms using long short-term memory recurrent neural networks," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 3614–3622, Jun. 2020.

[14] A. Argha, J. Wu, S. W. Su, and B. G. Celler, "Blood pressure estimation from beat-by-beat time-domain features of oscillometric waveforms using deep-neural-network classification models," *IEEE Access*, vol. 7, pp. 113427–113439, 2019.

[15] S. Narus, T. Egbert, T.-K. Lee, J. Lu, and D. Westenskow, "Noninvasive blood pressure monitoring from the supraorbital artery using an artificial neural network oscillometric algorithm," *J. Clin. Monit.*, vol. 11, no. 5, pp. 289–297, Sep. 1995.

[16] Z. Ünal, "Smart farming becomes even smarter with deep learning—A bibliographical analysis," *IEEE Access*, vol. 8, pp. 105587–105609, 2020.

[17] X.-W. Chen and X. Lin, "Big data deep learning: Challenges and perspectives," *IEEE Access*, vol. 2, pp. 514–525, 2014.

[18] X. Xu, S. Jeong, and J. Li, "Interpretation of electrocardiogram (ECG) rhythm by combined CNN and BiLSTM," *IEEE Access*, vol. 8, pp. 125380–125388, 2020.

[19] O. Cheikhrouhou, R. Mahmud, R. Zouari, M. Ibrahim, A. Zaguia, and T. N. Gia, "One-dimensional CNN approach for ECG arrhythmia analysis in fog-cloud environments," *IEEE Access*, vol. 9, pp. 103513–103523, 2021.

[20] E. Eldele, Z. Chen, C. Liu, M. Wu, C.-K. Kwoh, X. Li, and C. Guan, "An attention-based deep learning approach for sleep stage classification with single-channel EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 809–818, 2021.

[21] X. Xu and H. Liu, "ECG heartbeat classification using convolutional neural networks," *IEEE Access*, vol. 8, pp. 8614–8619, 2020.

[22] W. Huang, Y. Xue, L. Hu, and H. Liuli, "S-EEGNet: Electroencephalogram signal classification based on a separable convolution neural network with bilinear interpolation," *IEEE Access*, vol. 8, pp. 131636–131646, 2020.

[23] M. Choi, G. Koo, M. Seo, and S. Kim, "Wearable device-based system to monitor a driver's stress, fatigue, and drowsiness," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 3, pp. 634–645, Mar. 2018.

[24] G. S. Stergiou *et al.*, "A universal standard for the validation of blood pressure measuring devices: Association for the advancement of medical instrumentation/European society of hypertension/International Organization for Standardization (AAMI/ESH/ISO) collaboration statement," *Hypertension*, vol. 71, no. 3, pp. 368–374, Jan. 2018.

[25] V. Belagiannis and A. Zisserman, "Recurrent human pose estimation," in *Proc. 12th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG)*, May 2017, pp. 468–475.

[26] L. Ke, M.-C. Chang, H. Qi, and S. Lyu, "Multi-scale structure-aware network for human pose estimation," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2018, pp. 713–728.

[27] S.-H. Wang, K. Muhammad, J. Hong, A. K. Sangaiah, and Y.-D. Zhang, "Alcoholism identification via convolutional neural network based on parametric ReLU, dropout, and batch normalization," *Neural Comput. Appl.*, vol. 32, no. 3, pp. 665–680, Feb. 2020.

[28] L. Rokach, "Ensemble-based classifiers," *Artif. Intell. Rev.*, vol. 33, nos. 1–2, pp. 1–39, 2010.

[29] M. Choi and J. J. Jeong, "Comparison of selection criteria for model selection of support vector machine on physiological data with inter-subject variance," *Appl. Sci.*, vol. 12, no. 3, p. 1749, Feb. 2022.

[30] A. Guzanová, G. Ižaríková, J. Brezinová, J. Živčák, D. Draganovská, and R. Hudák, "Influence of build orientation, heat treatment, and laser power on the hardness of Ti6Al4V manufactured using the DMLS process," *Metals*, vol. 7, no. 8, p. 318, Aug. 2017.

[31] E. O'Brien, J. Petrie, W. A. Littler, M. D. Swiet, P. L. Padfield, D. Altman, M. Bland, A. Coats, and N. Atkins, "The British hypertension society protocol for the evaluation of blood pressure measuring devices," *J. Hypertension*, vol. 11, no. 2, pp. S43–S62, 1993.

[32] S. Lee, S. Rajan, G. Jeon, J.-H. Chang, H. R. Dajani, and V. Z. Groza, "Oscillometric blood pressure estimation by combining nonparametric bootstrap with Gaussian mixture model," *Comput. Biol. Med.*, vol. 85, pp. 112–124, Jun. 2017.

[33] S. Lee, C.-H. Park, and J.-H. Chang, "Improved Gaussian mixture regression based on pseudo feature generation using bootstrap in blood pressure estimation," *IEEE Trans. Ind. Informat.*, vol. 12, no. 6, pp. 2269–2280, Dec. 2016.

MINHO CHOI received the B.S. degree from the Department of Electric and Electronic Engineering, Chung-Ang University, Seoul, South Korea, in 2012, and the Ph.D. degree from the Department of Creative IT Engineering, Pohang University of Science and Technology, Pohang, South Korea, in 2019.

From 2019 to 2021, he was a Senior Researcher at InBody Company Ltd., Seoul. Since 2022, he has been a Senior Researcher with the Digital Health Research Division, Korea Institute of Oriental Medicine, Daejeon, South Korea. His current research interests include sensing technology for biomedical measurements, the signal processing of physiological signals, and artificial intelligence for biomedical data.

SANG-JIN LEE received the B.S. and master's degrees from the Department of Electronics and Information Engineering, Korea University, Seoul, South Korea, in 2014 and 2016, respectively.

Since 2017, he has been working as a Researcher at InBody Company Ltd., South Korea. His current research interests include measurements and signal processing of physiological signals and algorithms for estimating blood pressure.